Grey Wolf Optimizer Applied to Dynamic Economic Dispatch Incorporating Wind Power

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Abstract
This article presents a new evolutionary optimization approach called gray wolf optimizer (GWO), which is based on gray wolf behavior for an optimal generating operation strategy. The GWO algorithm does not require any information about the gradient of the objective function, when searching for an optimal solution. The concept of the GWO algorithm, it seems a powerful and reliable optimization algorithm is applied to dynamic economic dispatch (DED) problem considering wind power. Many practical constraints of generators such as valve-point effects, ramp rate limits, and transmission losses are considered. The proposed algorithm is implemented and tested on two test systems that have 5-unit and 10-unit generators. The results confirm the potential and effectiveness of the proposed algorithm compared to various other methods are available in the literature. The results are very encouraging and prove that the GWO algorithm is a very effective optimization technique for solving various DED problems.

Index terms— gray wolf optimizer, dynamic economic dispatch, wind power, ramp rate limits, valvepoint effects.

Introduction he electric power system is one of the most vital needs in human life. The demand for electricity continues to increase causing electricity to be supplied by power plants to be very large. On the other hand renewable energy sources are the deciding factors in industrial development that can improve people's living standards. In addition, technological advances and developments have also contributed greatly to increasing electricity demand. Power system planning, power system management, and distribution of power system are required to meet consumer demand for an increase in the quantity and quality of electric power produced. Improving the quality of electric power is also very influential in increasing the efficiency and reliability of the system. Optimization of generator scheduling in the electric power system is very necessary, because the generation and distribution process in the electric power system requires a very large cost. Coordination between power plants is needed in an effort to optimize generator scheduling to get the minimum cost. Dynamic economic dispatch (DED) is the change in real-time load on an electric power system. The DED is a development of conventional ED involving ramp rate parameters. DED is used to determine the economic distribution of generating units within a certain timeframe of the generating units. The parameter to be considered is transmission losses. In fact, the distribution of electrical power to the load always causes power losses on the transmission line, therefore, transmission losses need to be calculated so that the generator can generate power that can meet the load requirements by considering the transmission loss. In general, the cost function for each generator is represented by a quadratic function, and the valve-point effect is ignored in solving the DED problem. If the DED problem includes the valve-point effect, then the problem becomes a non-convex optimization problem with nonconvex characteristics, which introduces difficulties in finding global optimal solutions [1][2][3].

Renewable energy is energy resource that comes from sustainable natural processes, such as energy from wind energy, solar energy, hydropower, biomass and geothermal energy. Renewable energy began to attract the attention of people and policy makers as an alternative energy resource after the world oil crisis in 1973. The use of renewable energy then rapidly developed when the United Nations Framework Convention on Climate Change (UNFCCC) was formed by the United Nations as a movement to reduce gas greenhouse. This institution continues to consistently voice the shift towards environmentally friendly energy through the Millennium Development Goals (MDGs) and Sustainable Development Goals (SDGs) issued by the United Nations. Climate change is currently a major concern of the world community due to its effect which causes an unnatural rise in world temperatures. The main cause of climate change is electricity production activities which are dominated by coal-fired power plants and natural gas power plants which account for around 30% of total gas emissions that cause global warming. Wind energy is a clean and rapidly growing renewable energy resources. They have shown great prospects in decreasing fuel consumption as well as reducing pollutants emission. However, the expected wind power is difficult to predict accurately, primarily due to the intermittent nature of the wind speed, coupled with the highly non-linear wind energy conversion. In order to adjust unforeseeable nature of the wind power, planned productions and uses in electricity market must be improved during the real operation of the power system. Due to the intermittent characteristic of wind power, DED is very suited for formulate the problem of optimal scheduling of generating units by including wind power. Several related studies have been conducted to overcome the problem of ED and DED by including renewable energy sources to the power system [4][5][6][7][8][9][10][11].

Over the past few years, a number of approaches have been developed to solve this DED problem using mathematical programming, namely, the lambda iteration method, linear programming, quadratic programming and the gradient projection method [12][13][14]. Most of the methods that have been applied do not apply to non-convex or non-smooth cost functions. Many heuristic optimization techniques known such as genetic algorithms (GA), simulated annealing (SA), differential evolution (DE), particle swarm optimization (PSO), artificial bee colony (ABC) algorithm, hybrid evolutionary programming (EP) and sequential quadratic programming (SQP), deterministically guided PSO, hybrid PSO and SQP, hybrid seeker optimization algorithm and sequential quadratic programming (SOA-SQP), imperialist competitive algorithm (ICA), hybrid harmony search (HHS) algorithm, artificial immune system (AIS), and glowworm swarm optimization (GSO) have been successfully used to solve the DED problems [15][16][17][18][19][20][21][22][23][24][25][26][27][28].

More recently, a new meta-heuristic search algorithm, called Gray Wolf Optimizer (GWO) [29], has no affinity for sticking to local optimal points in complex multimodal optimization problems and which provides a more diverse search of space the solution. The GWO is based on gray wolf behavior. Better optimal solutions with lower computational loads can be found at GWO compared to the stochastic search techniques mentioned above. In this paper, the GWO algorithm has been applied to solve the DED problem considering wind power. The performance of the proposed approach has been demonstrated in the 5-unit and 10unit generating systems. The results obtained from the proposed algorithm are compared with other optimization results reported in the literature. The comparison shows that the proposed GWO-based approach provides the best solution in terms of minimum production cost and power loss.

1 II.

2 Problem Formulation

The objective of DED problem is to find the optimal schedule of output powers of online generating units with predicted power demands over a certain period of time to meet the power demand at minimum operating cost. The objective function of the DED problem is, ( )T t N i c P b P a P F F T t N i i t i i t i i T t N i t i t i T , ,**2 , 1 ; , , 2 , 1 for) (1 1 , 2 , 1 1**

, ,? ? = = + + = = ?? ?? = = = = (1)

where F i,t (in \$/h) is the operating cost of ith unit at time interval t, a i , b i , and c i are the cost coefficients of generating ith unit, P i,t (in MW) is the real power output of generating ith unit at time period t, and N is the number of generators. T is the total number of hours in the operating horizon. The fuel cost function of ith unit with valve-point effects is represented as follows [9,21,22]:( ) ( ) ?? = = ? ? ? ? ? ? ? ? ? ? × × + + + = T t N i t i i i i i t i i t i i T P P f e c P b P a F 1 1 , min , , 2 , sin) (**(2)**

where F T (in \$/h) is total operating cost of generation including valve point loading, e i and f i are fuel cost coefficients of ith unit reflecting valve-point effects.

3 a) Power Balance

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

( )t L t D N i t w t i P P P P , ,**1**

, ,+ = + ? =**(3)**

where P w,t is power output of wind farm at time interval t; P D,t is the load demand at time interval t; P L,t is the transmission loss at time interval t that can be represented using the B-coefficients:?? = = = N i N j t j ij t i t L P B P P 1 1 , , ,**(4)**

where B ij , is the loss-coefficient matrix.

4 b) Generation Limits

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is max , , min , i t i i P P P ? ? (5) where P i, min and P i, max are the minimum and maximum capacity of unit i, respectively.

5 c) Ramp Rate Limits

The actual operating ranges of all on-line units are restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as (**??**) and (7), respectively.up i t i t i R P P , 1 , , ? ? ? (6) down i t i t i R P P , , 1 , ? ? ? (7)

where P i,t and P i,t-1 are the present and previous power outputs, respectively. R i,up and R i,down are the ramp-up and ramp-down limits of unit i. The fuel cost is minimized subjected to the following constraints:

To consider the ramp rate limits and power output limits constraints at the same time, therefore, equations (**??**), (**??**) and (**??**) can be rewritten as follows:} , min{ } , max{ , 1 , max , , , 1 , min , up i t i i t i down i t i i R P P P R P P + ? ? ? ? ? (8) III.

6 Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a new population based meta-heuristic algorithm proposed by **??**irjalili et al. in 2014 [29]. The grey wolves mostly like to live in a pack and one of the most important features is their very strict social hierarchy. The main leader of the pack is called alpha. The alpha wolf is the most predominant wolf in the pack as his/her orders were followed by rest of the pack. The alpha wolf is one of the most important members in terms of managing the pack.

The second important one is called beta. They are also known as sub-ordinate wolves as they help alpha in their respective work. They act as advisor to alpha and commander to the rest of the wolves in the pack. The third one are called delta. They submitted themselves to the alphas and betas but dominate the omegas. The fourth one which are lower ranking wolves are called omega. They have to submit themselves to all other members in the pack.

In another important thing among the grey wolves is their hunting mechanism which includes tracking, chasing, encircling and harassing the prey until they stop moving. Then they attack the prey. The mathematical model of this model is discussed as following.

7 a) Social Hierarchy

In order to mathematically model the social hierarchy of wolves when designing GWO that would consider the first fitness solution as alpha (?), the second best solution as beta (?), and the third best solution as delta (?). The rest of the solutions are assumed as omega (?). The hunting mechanism is decided by ?, ?, and ?, and the ? wolves have to follow them.

8 b) Encircling Prey

As the grey wolves encircle prey during the hunt, so their mathematical model which represents their encircling behavior is discussed as below: is linearly decreased from 2 to 0. The grey wolf can update their position according to equation (**??**) and (10).) ( ) (t X t X C D w p ? ? ? ? ? ? = (9) D A X t X p w ? ? ? ? ? ? = +) 1 ((**10**

9 c) Hunting

As we know that the grey wolf firstly recognizes the prey and then encircles them to hunt. The hunt is usually decided by alpha and beta, delta also participate in hunting occasion. So mathematically in the hunting procedure we take alpha, beta and delta as the best candidate solution and omega have to update its position according to the best search agent. The mathematical model for hunting is shown below:) (1 t X X C D ? ? ? ? ? ? = ? ? (13)) (2 t X X C D ? ? ? ? ? ? = ? ? (14)) (3 t X X C D ? ? ? ? ? ? = ? ? (15) ? ? D A X X ? ? ? ? ? ? = 1 1 (16) ? ? D A X X ? ? ? ? ? ? = 2 2 (17) ? ? D A X X ? ? ? ? ? ? = 3 3 (18) ( ) 3 1 3 2 1 X X X t X ? ? ? ? + + = + (19) where ? X ? is the position of the alpha, ? X ? is the position of the beta, ? X ? is the position of the delta, 1 C ? , 2 C ? , 3 C ? , 1 A ? , 2 A ? , and 3 A ? are all random vectors, X

? is the position of the current solution, and t is the iteration number.

10 d) Search for Prey

As we know that the grey wolves finishes their hunt by attacking the prey. In mathematical model we have A ? is a random variable having values in the interval [-2a, 2a] where a is decreased from 2 to 0 over the course of iterations. When the random value of A ? are in [-1, 1] then the next position of search agent is between its current position and position of prey. The pseudo code of the GWO algorithm is presented in Figure 1. IV.

11 Simulation Results

In order to demonstrate the performance of the GWO algorithm, two testing systems consisting of a 5unit and 10-unit generating system with non-smooth cost functions are taken into account. The GWO algorithm is implemented in MATLAB 2016a on a Pentium IV personal computer with a processor speed of 3.6 GHz and 4 GB RAM. The time horizon for scheduling is one day divided into 24 periods every one hour. The iteration performed for each test case is 1000 for the 5-unit system and 500 for the 10-unit system; and the number of search agents (population) taken in both test cases is 30.

12 a) Test System 1

In this section a 5-unit system is tested considering the valve-point effects, the ramp rate limits, and transmission losses. All technical data generating units are given in Appendix, which is taken from [16]. The optimal dispatch of real power for the given scheduling horizon using the proposed GWO algorithm is given in Table 1. Figure 2 shows the convergence characteristic of GWO technique for DED problem. The comparison results between the proposed GWO algorithm and other methods are shown in Table 2. It is clear that the proposed GWO algorithm has achieved lower minimum production cost. [16] 47356 APSO [25] 44678 DE [17] 43213 ICA [25] 43117.05 PSO [19] 50124 HHS [26] 43154.8554 ABC [20] 44045.83 GSO [28] 43414.12 AIS [25] 44385.43 GWO 42709.4563 In this section a 10-unit system is tested considering the valve-point effects, the ramp rate limits, and transmission losses. All technical data generating units are adopted from [30], as given in Appendix. The optimal dispatch of real power for the given scheduling horizon using proposed GWO algorithm is given in Table 3. Table 4 shows hourly production cost and power loss obtained from GWO algorithm. Figure **??** shows the cost convergence characteristic of GWO technique for 10-unit system. The comparison of different methods with the proposed GWO algorithm in terms of the best cost is given in Table 5. Clearly from the results, the proposed GWO algorithm produces a higher quality solution in terms of minimum production costs. [27] 2596847.38 PSO [27] 2580148.25 MBFA [27] 2544523.21 AIS [27] 2500684.32 GWO 2463046.3595 c) DED with wind power In testing the following system, wind power connected to the network is considered. The total installed capacity of wind power connected to the network is 100 MW, with a total of 50 wind turbines [11]. The best results obtained from the proposed GWO technique for the DED model without and with wind power are summarized in Table 6. The cost convergence characteristics of the DED model with wind power for the two systems are shown in Figures **??** and 5, respectively.

To realize the rationality of the integration of wind power into the power system, the comparison results of the two DED models are presented in Table 6.

From Table 6, it can be seen that when compared to the DED model without wind power for the 5-unit system, the savings in operating costs per day are obtained 2780.5154 $ and transmission losses reduced by 25.7935 MW (down 13.2982%). For the 10-unit system, the operating cost savings per day were 128069.3605 $ and transmission losses were reduced by 121.0233 MW (9.2037% decrease).

13 Conclusion

This paper has successfully applied the GWO algorithm to solve the DED problem. Different constraints such as the valve-point effects, ramp rate limits, and transmission loss are taken into consideration to solve the DED problem without and with wind power. The feasibility of the proposed method was demonstrated with 5-unit and 10-unit generating system and compared with other optimization methods reported in the literature. The results obtained show that the GWO algorithm has a much better performance in terms of minimum production cost. The main advantage of the proposed GWO algorithm is the good ability to find the best solution. [1]

Initialize the grey wolf population X i (i=1, 2, ..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
X a = the best search agent
X ß = the second best search agent
X ? = the third best search agent
while (t < Max number of iterations)
for each search agent
Update the position of the current search agent by equation (19)
end for
Update a, A, and C
Calculate the fitness of all search agents
Update X ? , X ? , and X ?
t=t+1
end while
Return X ?

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Figure 1:

1

H	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Cost ($)	Ploss (MW)
1	27.4519	98.5642	112.6621	124.9061	50.0400	1290.9632	3.6243
2	40.8780	20.6864	112.6565	124.8953	139.7611	1377.0230	3.8773
3	10.0011	93.0222	112.4978	124.6033	139.6305	1390.6017	4.7549
4	60.1566	98.3944	112.6397	124.8896	139.7547	1585.5829	5.8351
5	10.0244	88.7822	112.0767	124.8338	228.9681	1617.1250	6.6853
6	50.1727	98.5283	112.7020	124.9175	229.5269	1781.1620	7.8474
7	73.6823	98.4360	112.6268	209.7858	139.7856	1784.5556	8.3165
8	12.3970	98.7988	112.6697	209.8054	229.5890	1798.0200	9.2598
9	49.5491	98.5680	112.6757	209.7783	229.5974	1978.6326	10.1685
10	72.2391	20.0936	112.6555	209.8019	300.0000	2135.0457	10.7901
11	74.9901	22.4924	123.6426	210.0779	300.0000	2244.7025	11.2030
12	74.9978	124.6737	112.6965	209.7741	229.5776	2180.7454	11.7197
13	64.1287	98.5337	112.5886	209.8145	229.4943	1997.0867	10.5597
14	49.6763	98.5417	112.6029	209.7535	229.5338	1978.2501	10.1681
15	12.4498	98.6583	112.8169	209.8146	229.5189	1797.7365	9.2584
16	21.4368	98.5737	112.7391	124.9316	229.5195	1654.7180	7.2007
17	11.9769	83.8383	30.9181	208.9142	229.6487	1660.5675	7.2962
18	42.6229	21.2725	112.7108	209.8011	229.5037	1797.6510	7.9110
19	12.5602	98.5976	112.7763	209.8092	229.5146	1797.6550	9.2580
20	64.1452	98.4801	112.6121	209.8090	229.5131	1997.1149	10.5595
21	54.9786	20.3704	174.9802	209.8063	229.4998	2086.0725	9.6354
22	47.2316	98.4822	112.6528	124.8810	229.5265	1773.6759	7.7741
23	56.9070	98.5339	112.6500	124.9057	139.7739	1581.7362	5.7705
24	10.0019	80.8739	112.2489	124.8239	139.5408	1423.0320	4.4894
		Total cost & losses				42709.4563	193.9628

Figure 2: Table 1 :

2

Method	Fuel cost ($)	Method	Fuel cost ($)
SA			

Figure 3: Table 2 :

3

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H 1 150.0153 135.1646 81.6951 P1 (MW) P2 (MW) P3 (MW) P4 (MW) P5 (MW) P6 (MW) P7 (MW) P8 (MW) 78.1106 171.7151 157.6784 130.0000 120.0000 21.1887 10.0431 P9 (MW) P10 (MW) 2 150.0339 135.0000 88.1448 99.2764 210.5885 159.5589 130.0000 120.0000 21.5715 18.2262 3 150.0220 135.4325 145.4896 143.4040 242.7314 160.0000 130.0000 120.0000 48.7274 10.6402 4 150.0218 136.1829 226.6413 212.9782 243.0000 160.0000 130.0000 120.0000 39.1587 23.4546 5 150.0237 138.2234 262.7324 217.9014 242.8597 160.0000 129.9846 119.7323 75.2897 22.6374 6 150.1772 137Global Journal

Figure 4: Table 3 :

4

H	Cost ($)	Ploss (MW)	H	Cost ($)	Ploss (MW)
1	60618.6976	19.6109	13	141137.7122	84.4640
2	64038.9120	22.4001	14	121076.9722	70.5684
3	71273.7775	28.4469	15	104451.0947	58.3985
4	79124.4204	35.4374	16	87490.3301	43.5525
5	83318.3071	39.3846	17	83283.8259	39.3461
6	91979.1098	48.0402	18	91920.5131	48.0091
7	97395.8194	52.9469	19	104451.0565	58.3995
8	104451.4185	58.4004	20	141139.6650	84.4762
9	121076.9983	70.5655	21	121076.9045	70.5676
10	141138.1957	84.4707	22	91902.9362	48.0466
11	152498.7538	92.0713	23	75066.7055	31.7975
12	165433.1451	100.0750	24	67701.0884	25.4654

Figure 5: Table 4 :

5

Method	Fuel cost ($)
GA	

Figure 6: Table 5 :

6

Models	5-unit system Fuel cost ($)	Ploss (MW)	10-unit system Fuel cost ($)	Ploss (MW)
DED without wind power	42709.4563	193.9628	2463046.3595	1314.9416
DED with wind power	39928.9419	168.1693	2334976.9990	1193.9183
V.				

Figure 7: Table 6 :

A4

1	410	7	626	13	704	19	654
2	435	8	654	14	690	20	704
3	475	9	690	15	654	21	680
4	530	10	704	16	580	22	605
5	558	11	720	17	558	23	527
6	608	12	740	18	608	24	463

Unit	P i,min (MW)	P i,max (MW)	R i,up (MW/h)	R i,down (MW/h)	a i ($/MW 2 hr)	b i ($/MWhr)	c i ($/hr)	e i ($/hr)	f i (rad/MW)
1	150	470	80	80	0.1524	38.5397	786.7988	450	0.041
2	135	470	80	80	0.1058	46.1591	451.3251	600	0.036
3	73	340	80	80	0.0280	40.3965	1049.9977	320	0.028
4	60	300	50	50	0.0354	38.3055	1243.5311	260	0.052
5	73	243	50	50	0.0211	36.3278	1658.5692	280	0.063
6	57	160	50	50	0.0179	38.2704	1356.6592	310	0.048
7	20	130	30	30	0.0121	36.5104	1450.7045	300	0.086
8	47	120	30	30	0.0121	36.5104	1450.7045	340	0.082
9	20	80	30	30	0.1090	39.5804	1455.6056	270	0.098
10	10	55	30	30	0.1295	40.5407	1469.4026	380	0.094

Table A-5: Load demand for 24 hours (10-unit system)

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	1036	7	1702	13	2072	19	1776
2	1110	8	1776	14	1924	20	1972
3	1258	9	1924	15	1776	21	1924
4	1406	10	2022	16	1554	22	1628
5	1480	11	2106	17	1480	23	1332
6	1628	12	2150	18	1628	24	1184

Figure 8: Table A - 4 :

.1 Appendix

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