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Generation Scheduling With Renewable Energy Sources an Improved Fire fly Optimization Algorithm

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Abstract
Many optimization methods are employed in power system scheduling of generating units. Here in this paper firefly algorithm is proposed for solving the generation scheduling (GS) problem to obtain optimal solution in power systems by considering the reserve requirement, wind power availability constraints, load balance, equality and inequality constraints in wind thermal coordination. The firefly algorithm is a new meta-heuristic and swarm intelligence based on the swarming behavior of fish and bird in nature. The proposed firefly algorithm method is applied to a different test system holds 30 conventional units and 4 wind farms. The performance of proposed FFO is found for the test system by comparing the results of it with different trails and various iterations among five different populations say 10, 20, 30, 40 and 50.Computation of the solution for different populations in the system reveal that the best schedules attained by applying the firefly algorithm method. It also shows that as population size decreases the total cost value is also decreasing. The performance of FFO algorithm is efficiently proved by comparing the result obtained by FFO with the particle swarm optimization method (PSO).

1. Introduction

Electricity is regarded as the invention that changed the world. Currently electricity is virtually present in all our activities. With the advanced technology on the hand and population growth on the other hand, these two factors have made the world voracious and ravenous appetite for electricity. Energy policy plays a vital role to mitigate the impacts of global warming and crisis of energy availability. The problem which has received much attention. It is of current interest of many utilities and it has been marked as one of the most operational needs. Recently many countries throughout the world have concentrated on the reduction of the quantity of pollutants from fossil fuel to the production of electrical energy of each unit.In traditionally generation scheduling problem of the operating cost is reduced by the suitable attribution of the quantity of power to be produced by different generating units. However the optimal production cost cannot be the best in terms of the environmental criteria. Optimal management of power produced by conventional power plants by an improved firefly algorithm (FFA). Simulation results on the 34units power system prove the efficiency of this method thus confirming its capacity to solve the generation scheduling problem with the renewable energy.

2. Requirement of Wind Power Integration

The nature of wind power is that it is produced when the wind blows and not in correlation to on-going power consumption. The unpredictability of wind power makes it necessary to have the capability to regulate both up and down so as to accommodate deviations in wind power forecasts. In addition, there must be both appropriate access to reserves for voltage and frequency regulation and automatic and manual reserves. The reserve categories listed are all integrated elements in the operation of the power system, regardless of the share of wind power in the system. However, it is essential to use the reserves most appropriately by using the newest prognosis information available and acting surprisingly large imbalance with the hour of operation. An effective of the power system can make the system more adapt to larger shares of variable renewable power. System operation is done day to day, hour to hour and minute to minute by the transmission system operator and includes various aspects and features with relevance for a successful integration of wind power into the grid.

The integration of a significant share of variable renewables into power grids requires a substantial transformation of the existing networks in order to:

1. Allow for a bi-directional flow of energy; that is top-down (from generators to users) and bottom-up (with end-users contributing the electricity supply) aimed at ensuring grid stability when installing distributed generation;
2. Establish an efficient electricity-demand and grid management mechanisms aimed at reducing peak loads, improving grid flexibility, responsiveness and security of supply in order to deal with increased systemic variability;
3. Improve the interconnection of grids at the regional, national and international level, aimed at increasing grid balancing capabilities, reliability and stability;
4. Introduce technologies and procedures to ensure proper grid operation stability and control (e.g. frequency, voltage, power balance) in the presence of a significant share of variable renewables; and e) introduce energy storage capacity to store electricity from variable renewable sources when power supply exceeds demand and aimed at increasing system flexibility and security of supply.

The share of renewable energy sources in the electricity generation system is usually measured by the:

- Renewable share in the annual electricity generation: that is, the ratio of renewable-based electricity generation to the total annual electricity generation.
- Renewable share in the installed power capacity: that is, the ratio of nominal installed (connected) renewable power capacity to the total power capacity.
- Instantaneous renewable share in the current load: that is, the ratio of the total power output of operating renewable units to the load at a certain point in time.
- The problem of unit commitment and the economic dispatch includes in the generation scheduling problem. The optimal generation scheduling problem attempts to minimize the cost of electric power production while meeting the system demands and reserve requirements by determining the commitment and generation of all schedulable power resources over a scheduling horizon subject to various operational constraints and physical limitations on the power system components.

3. Generation Scheduling

Generation scheduling tools analyze the electric power system network operations and the economic dispatch of each power plant to optimize overall energy delivery under given constraints such as carbon dioxide emissions or transmission stability limits. Generation scheduling tools support different planning horizons, such as hourly, daily, weekly, monthly, and annually as well as 10 years plans for long term unit commitment and maintenance scheduling.

The generation scheduling function is one of the core components of a modem power system energy management system (EMS). The EMS helps in the determination of the generation level of each unit by minimising utility wide production costs while meeting system and unit constraints. The generation scheduling function has to satisfy

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the main objective of economics, which involves an optimisation of cost over a future period of time. The economic dispatch sub function which optimises operation cost over a much shorter time interval is embedded in the generation scheduling function.

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The problem of unit commitment involves finding the least cost dispatch of available generation resources to meet the electrical load and economic dispatch is the short-term determination of the optimal output of a number of electricity generation facilities, to meet the system load, at the lowest possible cost, while serving power to the public in a robust and reliable manner.

4. Significance of Firefly Algorithm

The Firefly Algorithm (FA) is a metaheuristic, nature-inspired, optimization algorithm which is based on the social (flashing) behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions. It was developed by Dr. Xin-She Yang at Cambridge University in 2007, and it is based on the swarm behavior such as fish, insects, or bird schooling in nature. In particular, although the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization (PSO), Artificial Bee Colony optimization (ABC), and Bacterial Foraging (BFA) algorithms, it is indeed much simpler both in concept and implementation. Furthermore, according to recent bibliography, the algorithm is very efficient and can outperform other conventional algorithms, such as genetic algorithms, for solving many optimization problems; a fact that has been justified in a recent research, where the statistical performance of the firefly algorithm was measured against other well-known optimization algorithms using various standard stochastic test functions.

Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles (i.e., the fireflies), and as a result, it seems more effective in multi-objective optimization such as the economic emissions dispatch problem in our case.

5. Problem Formulation

The objective function of the GS problem is to minimize the total production cost including fuel cost, operating and maintenance cost of the generating units for the specified period under the operating constraints. The time horizon for study of this problem is one year with monthly intervals for major changes in the schedules. Due to the longer time intervals in the scheduling than the time interval of change in any generating unit, the ramp rate and minimum up/down constraints on output of the generating units are all ignored. The equation of objective function is given by,

$$\min J = \sum_{t=1}^{T}\sum_{g=1}^{N_G}\{F(P_{GD}(g,t)).n(t)\}.U(g,t)$$
$$+\sum_{t=1}^{T}\sum_{g=1}^{N_G}\{(P_{GD}(g,t)+P_{GR}(g,t)).OMVCT(g).n(t)\}.U(g,t)$$
$$+\sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{\frac{PGg.\max(g).OMFCT(g).n(t)}{8760}\right\}$$
$$+\sum_{t=1}^{T}\sum_{g=1}^{N_W}\{P_W(w,t).OMVCW(w).n(t)\}.V(w,t)$$
$$+\sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{\frac{P_W,\max(w).OMFCW(w).n(t)}{8760}\right\}$$

where,

$$F(P_{GD}(g,t)) = a_g + b_g.P_{GD}(g,t) + c_g.(P_{GD}(g,t))^2$$

The equation of this objective function is subject to the number of systems and its unit constraints. The following equation should be satisfied to meet the load demand.,

$$Pd(t) = \sum_{g=1}^{N_G} P_{GD}(g,t).U(g,t) + \sum_{W=1}^{N_W} P_W(w,t).V(w,t)$$

Where, t=1, 2, 3… T

The reserve requirement should also be satisfied. The reserve in a system is needed to provide for any feasible unpredicted generation shortage. The accuracy of the load and wind power forecasts will have a significant bearing on the system reserve levels. Increasing amounts of wind capacity causes a greater increase in the required reserve. In this paper, there are two parts in operating reserve requirement .1. Percentage of the total system load (eg., 5% of system load) 2. Surplus/Excess reserve is chosen to balance the inequality among the predicted wind electric power production and its actual value.

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The percentage of total wind power availability (RESW) is used in this paper to find the second part of the operating reserve. The error due to wind power forecasting is compensated using the factor (RESW). It is assumed to be 10% of the total wind power availability in each wind farm. The conventional units (40 units) in the system are responsible for both the parts of the operating reserve requirement.

$$\sum_{g=1}^{N_G} P_{GR}(g,t).U(g,t) \geq P_{R(t)} + RESW \times \sum_{w=1}^{N_W} P_W(w,t).V(w,t)$$

Where, t=1, 2, 3… T

The generating unit constraints should also be satisfied. Therefore the equation satisfies the wind power availability is given by,

$$P_W(w,t) \leq W_{av}(w,t)$$

Where,

t =1, 2, 3… T

The equation showing the maximum and minimum generation in the generating units is as follows.,

$$P_{Gg,min} \leq P_{GD}(g,t) + P_{GR}(g,t) \leq P_{Gg,max}$$

6. Description of Test System

The performance effectiveness of the proposed optimization algorithm (FFO) is evaluated in two parts by applied it to a model system. The two parts are; Initialization and simulation parts. Five different populations say 10, 20, 30, 40, and 50 in a test system was tested to find and verify the feasible optimal solution of the proposed FFO algorithm to solve the GS problem. The results obtained from FFO method is compared among each population and the best result is compared with the result obtained by Particle Swarm Optimization method (PSO) to prove that FFO has better efficiency.

Test System:

This test system has 34 generating systems in total, which includes 30 conventional units and 4wind farms (units31, 32, 33 and 34) (30C+4W). The input data for 30 conventional units and 4 wind farms

in this test system are respectively and are tabulated in table A 1.3 and A1.1 respectively.

For this test system, the total load is considered as 5260MW. Table 1 shows the load pattern, reserve requirement and wind farm output. Each wind farms hold 30wind turbine units with 4MW capacities. Here, the value of RESW is assumed to be 10% of total wind power availability of each wind farms. For illustration, reserve requirement of this test system at third period is 232.9323MW. It is found by summing two parts. ie., 1. 230.914(5% of total load) and 2. 2.0183 (10% of wind power availability).

Table 1 Load Pattern, Reserve Requirement and Wind Farm Output.

Period (Month)	Percentage of annual peak load (%)	Reserve Requirement (MW)	Wind power availability (MW)			
			Unit 31	Unit 32	Unit 33	Unit 34
1	87.8	117.4753	3.576	16.607	3.576	16.607
2	88	117.5105	2.23	15.675	2.23	15.675
3	75	101.5685	3.717	25.718	3.717	25.718
4	83.7	113.3548	9.817	23.076	9.817	23.076
5	90	121.4711	14.604	16.607	14.604	16.607
6	89.6	119.9943	11.905	9.798	11.905	9.798
7	8	117.5243	10.13	7.913	10.13	7.913
8	80	109.0324	9.122	29.202	9.122	29.202
9	78	105.3326	12.097	15.529	12.097	15.529
10	88.1	117.9571	4.937	16.119	4.937	16.119
11	94	126.3822	6.007	21.715	6.007	21.715
12	100	135.6649	8.973	32.676	8.973	32.676

The minimum, average and standard deviation of the objective function of GS problem solved by FFO method is calculated and are tabulated in Table 2 for five different populations. Table 2 shows the best result of this GS problem utilizing 100 iterations and 100 trails.

Table 2: The Simulation Results For Different Population Sizes Of FFO Algorithm For 100 Iterations And 100 Trails In Test System (30C+4W).

		Total Cost (M$)			
Approach	Population	Minimum Cost	Average Cost	Standard Deviation	Accuracy
FFO	10	450.44	450.05	1.89934	47.3661
	20	451.11	455.27	2.40502	45.1485
	30	452.67	459.73	3.24830	48.1882
	40	454.12	459.140	2.691213	49.16466
	50	455.18	461.743	2.957839	59.37484

The simulations are made for several population sizes with different trails and various iterations are performed to find the convergence characteristics of the proposed FFO method.

The result of sensitivity analysis of acceleration parameters is presented in Fig.1 for different population sizes in test system solved by FFO method.

In this paper, the best results are verified through comparison of the results of all the five populations in the test system solved using proposed FFO method.

All the results are found via a process which involves 100 trails. It is observed that the population size of 10 led to the best results, due to the best fitness and the least calculation time.

The comparison of test system with the PSO method using the common population size 10 is tabulated in table 3.

On observing table 3, it is clear that the total cost is reduced in test system (30C+4W) than the total cost of GS problem solved by PSO method.

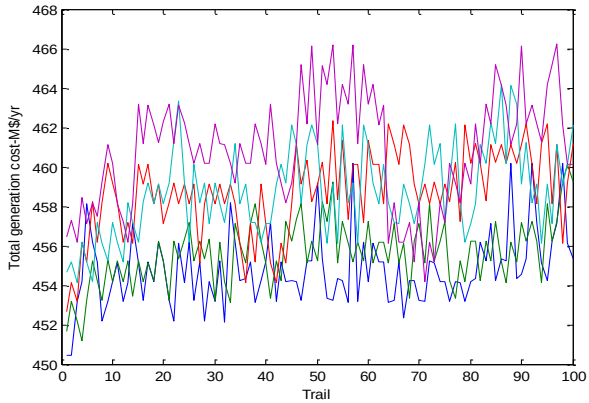

Fig.1: Sensitivity Analysis of Parameters' Selection for Proposed GWO in Test System:

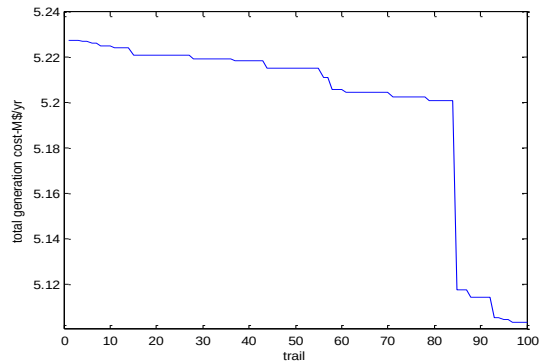

Fig.2: Convergence Characteristics of Proposed FFO in Test System with 100 Iterations.

Table 3: Best Results in Test System of FFO algorithm Along with PSO for 100 Trails**.**

Test System	Method	Pop. Size	Total Cost(M$)			Accuracy (%)
			Min. Cost	Avg. Cost	Std Dev.	
30C+4W	PSO	10	452.212	457.243	1.6538	43.539
30C+4W	Proposed FFO	10	450.44	455.058	1.8993	47.366

7. Conclusions

A new optimization method called FFO algorithm is employed for solving the generation scheduling (GS) problem and the formulation and implementation of the solution method is carried out successfully for the integrated wind thermal power generating system. A new position update tactic that is integrated in the FF method is employed to satisfy the constraints by the solutions of this problem.

The output of FFO method in a test system (30C+4W) is compared among the results obtained for different population sizes say 10, 20, 30, 40 & 50. From this it is noted that the population size 10 led to the best optimal solution. The above simulation results show that the proposed meta-heuristic and swarm intelligence based FFO algorithm has better computational efficiency and it is shown that the firefly (FFO) algorithm obtains near optimal solutions for GS problems**.**

Using the common population size 10, the performance of the proposed FFO method is compared with the performance of PSO method to prove that the FFO has better computational efficiency in reducing the total cost.

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