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ELECTRICITY GENERATION SCHEDULING AN IMPROVED FOR FIREFLY OPTIMIZATION ALGORITHM

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Abstract: *Thermal power plants are considered to be the conventional plants to produce electric powers in early days. But employing conventional plants is not much economical and also extinction of fossil fuels increases the need for renewable energy sources for electric power production. Thus coordination of thermal plant with some renewable plant will be beneficial. Power generation using wind energy is the most employing power plant in our country. This algorithm is a type of swarm intelligence algorithm based on the reaction of a firefly to the light of other fireflies. 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).*

Key Words: Thermal Power Plant, Wind Power System, Firefly Algorithm, Integrating System

1. INTRODUCTION

Optimization problem is one of the most challenging problems in the field of operation research. The goal of the optimization problem is to find the set of variables that results into the optimal value of the objective function, among all those values that satisfy the constraints. Many new types of optimization algorithms have been explored. One of them is a nature-inspired type. A new algorithm that belongs in this category of the so-called nature inspired algorithms is the firefly algorithm which is based on the flashing light of fireflies. Algorithms of this type are such as an ant colony optimization (ACO) algorithm proposed by Marco Dorigo in 1992 which has been successfully applied to scheduling problems. ACO is inspired by the ants' social behavior of finding their food sources and the shortest paths to their colony, marked by their released pheromone. Another example of this type of algorithms is a particle swarm optimization (PSO) algorithm developed by Kennedy and Eberhart in 1995. PSO is based on the swarming behavior of schools of fish and bird in nature. PSO has been successfully applied to a wind energy forecasting problem where wind energy is estimated based on two meta-heuristic attributes of swarm intelligence. A firefly algorithm is yet another example. Fireflies communicate by flashing their light. Dimmer fireflies are attracted to brighter ones and move towards them to mate. FFO is widely used to solve reliability and redundancy problems. Firefly algorithm is developed based on the flashing behavior of fireflies. FA developed by yang is used to solve constrained engineering problems. Until now many researches have been carried out to find the closest optimum result in determining the power generation of each generator using FA and it was inferred that the FA is the efficient in determining the optimal load scheduling. A species of firefly called Lampyride also used pheromone to attract their mate. Another well-known nature-inspired algorithm is genetic algorithm (GA). GA is inspired by the process of natural evolution. It starts with a population of chromosomes and effects changes by genetic operators.

Three key genetic operators are crossover, mutation, and selection operators. Our algorithm proposed in this paper combines attributes of firefly mating and its pheromone dispersion by the wind with the genetic algorithm. GA is used as the core of our algorithm while the attributes mentioned are used to compose a new selection operator.

1.1 Integrated Wind Power System

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.

1.2 Generation 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 minimizing utility wide production costs while meeting system and unit constraints. The generation scheduling function has to satisfy the main objective of economics, which involves an optimization of cost over a future period of time. The economic dispatch sub function which optimizes operation cost over a much shorter time interval is embedded in the generation scheduling function.

2 PROBLEM FORMULATION

2.1 Objective Function

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,

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

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.

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.

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

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.,

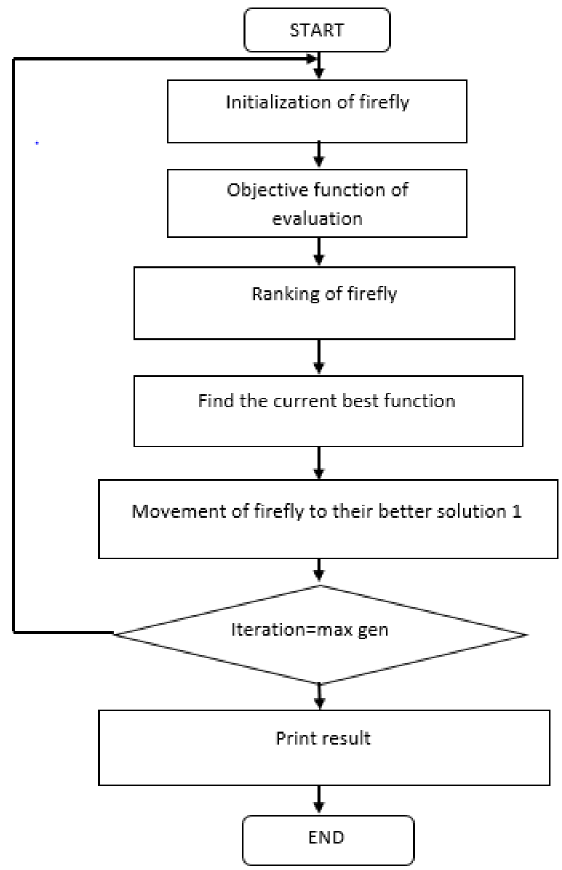
$$P_{Gg,min} \leq P_{GD}(g,t) + P_{GR}(g,t) \leq P_{Gg,max}$$

3 FIREFLY OPTIMIZATION ALGORITHM

Firefly algorithm is one of the swarm intelligence that evolve fast for almost area of optimization and engineering problems. Stand-alone firefly algorithm already has managed to solve problems. For problems that have multi-dimensional and nonlinear problem, some modification or even hybridization with the other metaheuristic is advisable. This modification and hybridization is to aim for help for the computational constrain and it will become more flexible and more efficient. Firefly is an insect that mostly produces short and rhythmic flashes that produced by a process of bioluminescence. The function of the flashing light is to attract partners (communication) or attract potential prey and as a protective warning toward the predator. Thus, this intensity of light is the factor of the other fireflies to move toward the other firefly. The light intensity is varied at the distance from the eyes of the beholder. It is safe to say that the light intensity is decreased as the distance increase

- Fireflies are attracted toward each other's regardless of gender.
- The attractiveness of the fireflies is correlative with the brightness of the fireflies, thus the less attractive firefly will move forward to the more attractive firefly.
- The brightness of fireflies is depend on the objective function.
- All the fireflies are unisex so it means that one firefly is attracted to other
- Firefly irrespective of their sex.

The firefly algorithm (FA) is another swarm intelligence algorithm, developed by Xin-She Yang. This new intelligent algorithm is intriguing because its author has shown that it is not only faster than Particle Swarm Optimization, but also that it provides better, more consistent results. It is also interesting that, given the right parameters, the FA essentially becomes PSO. This means that the FA is a more general form of PSO, and can be adapted better to a given problem.



Flow Chart of Firefly Algorithm to Find Optimal Solution

The Firefly Algorithm was inspired by the flashing of fireflies in nature. There are over 2000 species of fireflies, most of which produce a bioluminescence from their abdomen. Each species of firefly produces its own pattern of flashes, and although the complete function of these flashes is not known, the main purpose for their flashing is to attract a mate. For several species the male is attracted to a sedentary female. In other species, the female can copy the signal of a different species, so that the males of that species are lured in. The female then preys on these males. The flashing can also be used to send information between fireflies. The idea of this attractiveness and information passing is what leads to the inspiration for the FA.

The FA idealizes several aspects of firefly in nature. First, real fireflies flash in discrete patterns, whereas the modeled fireflies will be treated as always glowing. Then, three rules can be made to govern the algorithm, and create a modeled firefly's behavior.

1. The fireflies are unisex, and so therefore potentially attracted to any of the other fireflies.

2. Attractiveness is determined by brightness, a less bright firefly will move towards a brighter firefly.

3. The brightness of a firefly is proportional to the value of the function being maximized.

When comparing the brightness of any two fireflies, the locations of the fireflies must be considered. In the real world, if a firefly is searching for another, it can only see so far. The farther another firefly is from it, the less bright it will be to the vision of the first firefly. This is due to the light intensity decreasing under the inverse square law. The air will also absorb part of the light as it travels, further reducing the perceived intensity.

4 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.

4.1 Test System:

This test system has 34 generating systems in total, which includes 30 conventional units and 4 wind 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 4.1 shows the load pattern, reserve requirement and wind farm output. Each wind farms hold 30 wind 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 4.1 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	88	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 6.2 for five different populations. Table 4.1 shows the best result of this GS problem utilizing 100 iterations and 100 trails.

On comparing results of all five populations obtained by FFO method, we can conclude that the proposed FFO has a total cost which is less for population size 10 than the other populations' say 20, 30, 40 & 50.

That is, the total cost value decreases with decrease in population size. The accuracy of the results of all trails for five different populations in FFO method is also tabulated in Table 4.2.

The equation for calculating accuracy of the results is as follows :

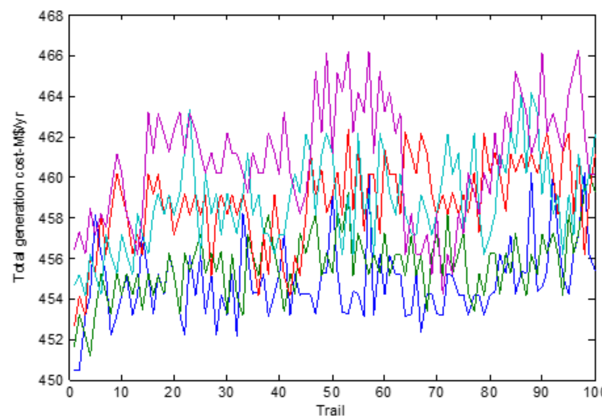
$$\text{Accuracy}=\sum_r \frac{[FE(r)-FE_{min}]}{FE_{max}-FE_{\min}}\ \forall r$$

Optimal generation scheduling results for Supplying Load (reserve) Contribution for test system is tabulated in table A 1.4. This table includes the data for one year (12 months). The optimal generation scheduling results for supplying load contribution in test system has 34 generating units.

Table 4.2 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	450.058	1.899346	47.36615
	20	451.11	455.272	2.40502	45.14859
	30	452.67	459.734	3.248308	48.18827
	40	454.12	459.140	2.691213	49.16466
	50	455.18	461.743	2.957839	59.37484

The unit capacity, fixed O&M cost and variable O&M cost for the test system holding 30 conventional units and 4 wind farms having total load of 5260MW is tabulated in table A 1.2.

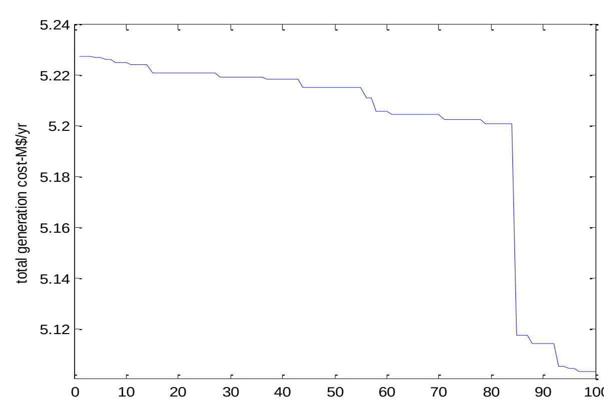


Pop 10	Pop 20	Pop 30	Pop 40	Pop 50

Sensitivity Analysis of Parameters' Selection for Proposed GWO in Test System

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.6.3 for different population sizes in test system solved by FFO method.



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

The values of population size and number of iterations in Fig.6.3. are (10,100) in the test system. On comparing the convergence characteristics of proposed FFO method with the convergence characteristics of PSO method [4], it is seen that the PSO method results in premature convergence and is trapped in local optimum, while the proposed FFO method converges toward the global optimum.

5 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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