Optimal Generation Scheduling Considering Renewable Energy Sources

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Abstract- This paper presents a competent approach to solve the unit commitment problem with consideration of wind and solar energy systems. The integration of wind and solar energy in the existing power system is considered to reduce the thermal unit operating cost. Abundant literatures have been reported for the thermal Unit Commitment (UC) solution. The Renewable Energy Source Integrated UC (RESIUC) problem is more complex in nature that requires a competent optimization tool. Hence, the novel swarm intelligence technique known as Grey Wolf Optimization (GWO) algorithm has been applied to determine optimal solution for the intended UC problem. The potential of the GWO algorithm has validated using standard 10-unit system. Numerical results show a considerable improvement in the quality of the solution obtained.

Keywords – Generation Scheduling, Grey Wolf Optimization, Renewable Energy, Unit Commitment

I. INTRODUCTION

The objective of the Unit commitment (UC) problem is to determine optimum schedule of all the units. The committed units must meet the system demand and reserve requirements at minimum operating cost, subject to a variety of constraints. UC is a vital optimization problem for daily economic operation and planning of modern power systems. Since UC problem involves many variables and constraints, it is complicated to determine the optimum start-up and shut down schedules of generating units. The augment of ecological shield and the progressive exhaustion of conventional power plants have increased the interest in incorporating Renewable Energy Sources (RES) into existing power system.

The UC is a non-convex, large-scale mixed integer nonlinear programming problem. It is difficult to determine the best feasible scheduling for UC problem within reasonable computational time and memory requirement. Abundant methods have been evolved to solve the UC problems. They can be categorized into traditional, soft computing and hybrid techniques.

The deterministic methods for thermal UC include Integer Programming (IP) [1], Branch-and-Bound (BB) [2], Priority List (PL) [3], Dynamic Programming (DP) [4], Mixed Integer Programming (MIP) [5] and Lagrangian Relaxation (LR) [6] methods. Most of the above approaches face the problem of dimensionality, particularly in case of large-scale systems. The soft computing techniques are used to address the demerits of mathematical approaches. Soft computing techniques such as Genetic Algorithm (GA) [7], Simulated Annealing (SA) [8], Neural Network (NN) [9], Differential Evolution (DE) [10], Ant Colony System (ACS) algorithm [11], Bacterial Foraging Algorithm (BFA) [12], Shuffled Frog Leaping Algorithm (SFLA) [13], Particle Swarm Optimization (PSO) [14], Quasi-Oppositional Teaching Learning Based Optimization (QOTLBO) algorithm [15] and Invasive Weed Optimization (IWO) [16] and Fireworks Algorithm [17] have been reported in the field of thermal UC.

Hybrid methods include Hybrid Taguchi (HT) - ACS [18], LR and PSO [19], hybrid harmony search/random search algorithm [20] and LR-DE [21] have been reported to solve thermal UC problems.

Soft computing techniques have become very popular in the past two decades. Recently, a new optimization algorithm, namely Grey Wolf Optimization (GWO) [22] has been developed. This is inspired by democratic behavior and the hunting mechanism of gray wolves in the nature. In a pack, the wolves follow social leadership hierarchy. *Seyedali Mirjalili et al.*, have proposed the GWO algorithm and the algorithm is inspected with standard test functions. It yields competitive solutions compared with other heuristic algorithms. The merits of the GWO are simple, easy implementation and require few parameters to adjust.

The remainder of the paper is organized as follows: The UC problem formulation is presented in Section II. In Section III, general GWO is given. Section IV details the numerical simulations and discussions. Finally, Section V summarizes the conclusion.

II. PROBLEM FORMULATION

2.1. Objective Function

Accordingly, the overall objective function of the UC problem is stated as:

$$\min\ F_t = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[F_i(P_i(t)) + SC_i(t) + SD_i(t)\right] \tag{1}$$

Generally, the fuel cost, $F_i(P_i(t))$ of unit i in any given time interval t is a function of the generator power output and can be expressed as:

$$F_i(P_i(t)) = a_i + b_i P_i(t) + c_i P_i^2(t) \tag{2}$$

The start up cost is defined as follows:

$$SC_i = \begin{cases} h-cost_i\ ;\ T_i^{off} \le X_i^{off} \le T_i^{off} + c-s-hour_i \\ c-cost_i\ ;\ X_i^{off} > T_i^{off} + c-s-hour_i \end{cases} \tag{3}$$

In this paper, the *SD* cost has been taken equal to zero for each unit.

The objective function, i.e., minimization of total cost F_t is subject to the system and generating unit constraints which are as follows:

2.2. System Constraint

a) Power Balance Constraint:

$$Pd(t) = \sum_{i=1}^{N} P_i(t) + P_W + P_S \tag{4}$$

2.3. Unit Constraints

a) Generation Limits:

$$P_{i\min} \le P_i(t) \le P_{i\max} \tag{5}$$

$$P_{w\min} \le P_w(t) \le P_{w\max} \tag{6}$$

b) Unit Minimum Up/Down Time Constraints:

$$\begin{aligned} T_i^{on} &\le X_i^{on} \\ T_i^{off} &\le X_i^{off} \end{aligned} \tag{7}$$

c) Up/Down Ramp Limits:

$$-DR_i \le P_i(t) - P_i(t-1) \le UR_i \tag{8}$$

d) Unit Initial Status:

The initial status at the start of the scheduling period must be taken into account.

III. GREY WOLF OPTIMIZATION

3.1 Inspiration

Grey wolf (Canis lupus) belongings to family of Canidae is deem as apex predator predominantly prefer to live in a pack. The group size is 5–12 on average and they follow a very stringent social dominant hierarchy.

The leaders of a pack called alphas are mainly liable for making decisions on hunting, sleeping place, time to wake and so on. The decisions of alphas are dictated to the pack. The alpha wolves are also called the dominant wolves since the pack should follow their commands. In gatherings, by holding their tails down, the entire pack accepts the alpha. The alpha is best in terms of managing the pack and not essentially the strongest member of the pack. This reveals that the organisation and discipline of a pack is much more essential than its strength.

The betas are second level in the grey wolves hierarchy. They are subordinate wolves that assist the alpha in decision-making or other pack activities. The beta wolf is possibly the best candidate to become the alpha in case one of the alpha wolves passes away or becomes very aged. The beta wolves should respect the alpha, however the other lower-level wolves obey the commands of them. They act as an advisor to the alpha and discipliner for the pack. The beta emphasizes the alpha’s commands throughout the pack and gives feedback to the alpha.

The lowest ranking grey wolf is omega. Omega wolves always have to submit to all the other dominant wolves. They are allowed to eat at last. It may seem the omega is not a significant member in the pack, however the whole pack faces internal fighting and problems in case of losing the omega. This is due to the venting of violence and frustration of all wolves by the omega(s). This helps satisfying the entire pack and maintaining the dominance structure.

If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts are liable for watching the boundaries of the territory and warning the pack in case of any danger. Sentinels protect and guarantee the safety of the pack. Elders are the experienced wolves who used to be alpha or beta. Hunters help the alphas and betas when hunting prey and providing food for the pack. Caretakers are responsible for caring for the weak, ill, and wounded wolves in the pack.

The hunting technique and the social hierarchy of grey wolves are mathematically modelled in order to design GWO and perform optimization.

3.2 Mathematical Model

a) Social hierarchy

The design of social hierarchy of wolves is made based on the fittest solutions. The fittest solution is considered as alpha (α), consequently, the second and third best solutions are named as beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω).

b) Encircling prey

Grey wolves encircle prey during the hunt. In order to mathematically model encircling behavior, the following equations are proposed:

$$\vec{D}=\left|\vec{C}.\vec{X}_P(t)-\vec{X}(t)\right| \tag{9}$$

$$\vec{X}(t+1)=\vec{X}_P(t)-\vec{A}\vec{D} \tag{10}$$

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_P$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf.

The vectors, $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2.\vec{a}.\vec{r}_1 - \vec{a} \tag{11}$$

$$\vec{C} = 2.\vec{r}_2 \tag{12}$$

Where, components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in the range [0, 1]. A grey wolf can update its position inside the space around the prey in any random location by using eequations (9) and (10). The same concept can be extended to a search space with n dimensions, and the grey wolves will move in hyper-cubes (or hyper-spheres) around the best solution obtained so far.

c) Hunting

Grey wolves have the ability to recognise the location of prey and encircle them. Usually the alpha guides the hunt. However, occasionally the beta and delta might also participate in this process. To simulate the mathematical model of the hunting behaviour of grey wolves, it is assumed that the alpha (best candidate solution), beta and delta have better knowledge about the potential location of prey. Therefore, the first three best solutions obtained so far are saved and they oblige other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are proposed to mathematically simulate the hunting behaviour of grey wolves.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|,\ \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|,\ \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{13}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha),\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta),\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{14}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15}$$

It can be observed that the final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words, alpha, beta, and delta estimate the position of the prey, and other wolves update their positions randomly around the prey.

d) Attacking prey

While the prey stops moving, the grey wolves attack it and finish hunting. The value of $\vec{a}$ is decreased to mathematically model approaching the prey. The fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. When random values of $\vec{A}$ are in range [-1, 1], the next position of a search agent can be in any position between its current position and the position of the prey.

e) Search for prey

The position of the alpha, beta and delta helps in the searching of grey wolves. Generally grey wolves diverge from each other and converge to search and attack prey respectively. In order to mathematically model divergence, $\vec{A}$ is utilized with random values greater than 1 or less than -1 to oblige the search agent to diverge from the prey. This emphasizes exploration and allows the GWO algorithm to search globally.

The $\vec{C}$ contains random values in [0, 2].This component provides random weights for prey in order to stochastically emphasis (C> 1) or deemphasize (C < 1) the effect of prey in defining the distance in equation (9). This assists GWO to show a more random behavior throughout optimization, favoring exploration and local optima avoidance. It is worth mentioning here that C is not linearly decreased in contrast to A. It is deliberately requiring C to provide random values at all times in order to emphasize exploration during initial and final iterations. This component is very helpful in case of local optima stagnation, especially in the final iterations.

The effect of obstacles to approach prey in nature is considered in the $\vec{C}$. The obstacles appear in the hunting paths of wolves prevent them from rapidly and conveniently approaching prey. This is exactly done by $\vec{C}$. Depending on the position of a wolf, it can randomly give the prey a weight and make it harder and farther to reach for wolves, or vice versa.

To sum up, the search process commences with generating a random population of grey wolves (candidate solutions) in the GWO algorithm. Over the course of iterations, alpha, beta and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance from the prey. The parameter $\vec{a}$ is decreased from 2 to 0 in order to emphasis' exploration and exploitation, respectively. Candidate solutions tend to diverge from the prey when $|\vec{A}| > 1$ and converge towards the prey when $|\vec{A}| < 1$. Finally, the GWO algorithm is terminated by the satisfaction of an end criterion. The computational flow of GWO algorithm is illustrated in Fig. 1.

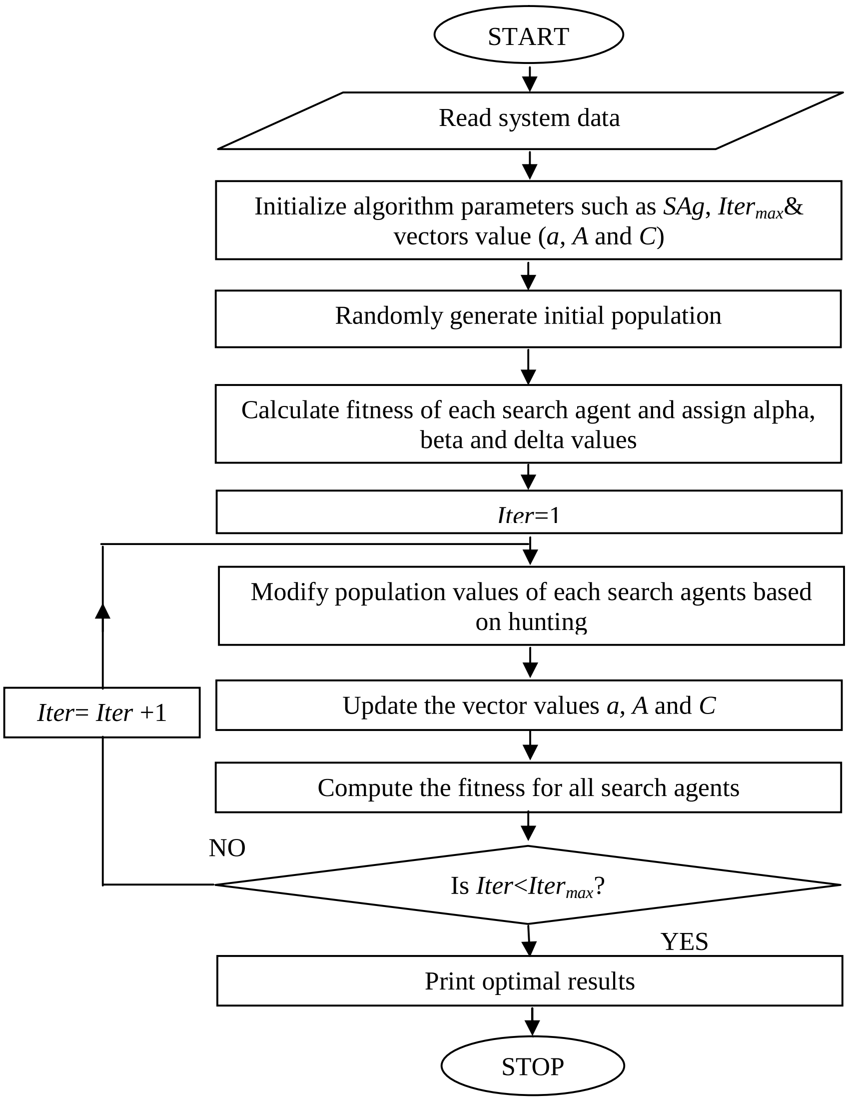

Figure 1. Generalized flow chart of GWO

IV. SIMULATION RESULTS AND DISCUSSIONS

The algorithm is developed in Matlab platform which is executed on a personal computer configured with Intel core i3 processor 2.20 GHz and 4 GB RAM. The performance of the GWO method is tested on the standard test system which consists of ten thermal generating units, one wind farm and solar plant over a planning horizon of 24 hours. The generating unit data and load demands are adopted from [7]. The wind power generation data [23] are provided in Fig. 2. The solar outputs are obtained from [24].

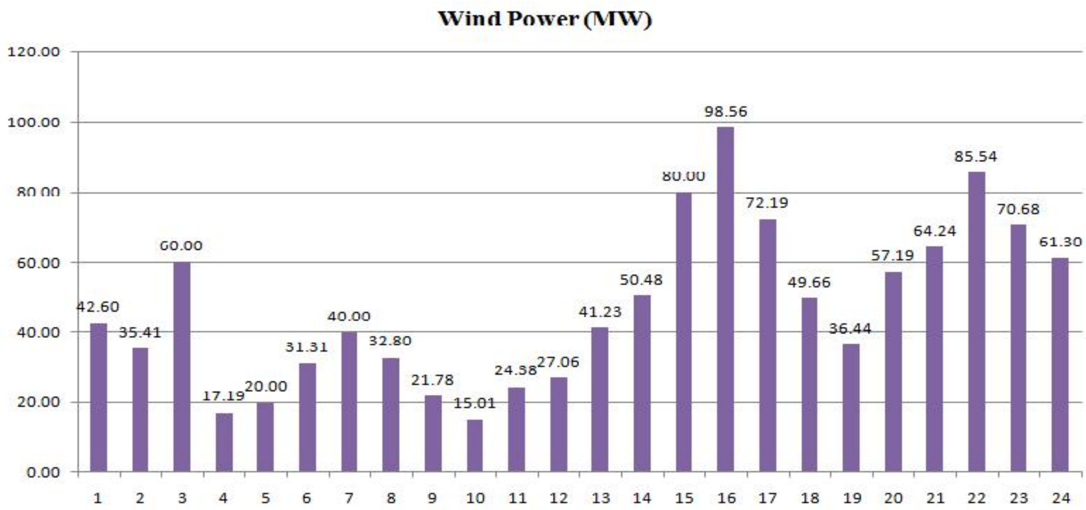

Figure 2. Wind power generation data

For each problem set, 50 test trials are made with random initial population for each run. Multiple runs have been performed, to verify the robustness of the GWO in solving UC problem.

4.1 RES Integrated UC

Table 1 illustrates the optimum UC schedule obtained by GWO. It shows that the minimum up/down time constraints of all thermal units are satisfied for entire scheduling horizon. Since the commitment priorities of P1 and P2 are high, they are switched ON for whole planning period. The introduction of wind farm and solar plant with thermal generating units significantly reduces the total operating cost and emission from the fossil fuel plants. The load demand is also satisfied for every time period. The total cost obtained in this case is $ 503592.10.

4.2 RES Integrated UC Condering Ramp Rate

In general, the amount of power generated by thermal units at each time period will not consider the dynamic of thermal units. But it is necessary to include ramp rate constraints in large practical UC problem. These constraints enforce limitation on drastic change in thermal unit generation output in successive time interval. Thus ramp rate restricts the rate of increase or decrease of power generation of each unit considering the thermal and mechanical inertia of the thermal units. However, this reduces the search space for obtaining more and better feasible solutions. When the ramp rate constraints are included, it has been assumed that the value of DR and UR of each unit is same [25]. The ramp rate limits of each unit are presented in the Table 2. The introduction of ramp rate constraints make changes in the real power dispatch of the thermal generating units and no change in scheduling of committed units. Fig. 3 illustrates the operating schedule of the thermal generating units for both cases. The total cost obtained in this case is $ 503651.80.

Table -1 Optimum RESIUC schedule

Hour	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	0	0	1	0	0	0	0	0
4	1	1	0	0	1	0	0	0	0	0
5	1	1	0	1	1	0	0	0	0	0
6	1	1	1	1	1	0	0	0	0	0
7	1	1	1	1	1	0	0	0	0	0
8	1	1	1	1	1	0	0	0	0	0
9	1	1	1	1	1	0	0	0	0	0
10	1	1	1	1	1	0	0	0	0	0
11	1	1	1	1	1	0	0	0	0	0
12	1	1	1	1	1	0	0	0	0	0
13	1	1	1	1	1	0	0	0	0	0
14	1	1	1	1	1	0	0	0	0	0
15	1	1	1	1	1	0	0	0	0	0
16	1	1	1	1	1	0	0	0	0	0
17	1	1	1	1	1	0	0	0	0	0
18	1	1	1	1	1	0	0	0	0	0
19	1	1	1	1	1	0	0	0	0	0
20	1	1	1	1	1	1	1	1	0	0
21	1	1	1	1	1	1	1	0	0	0
22	1	1	0	0	1	1	1	0	0	0
23	1	1	0	0	0	1	0	0	0	0
24	1	1	0	0	0	0	0	0	0	0

Table 2. Ramp rate limits of thermal generating units

Unit	Up/Down ramp rate (MW/hr)	Unit	Up/Down ramp rate (MW/hr)
P1	160	**P6**	60
P2	160	**P7**	60
P3	100	**P8**	40
P4	100	**P9**	40
P5	100	**P10**	40

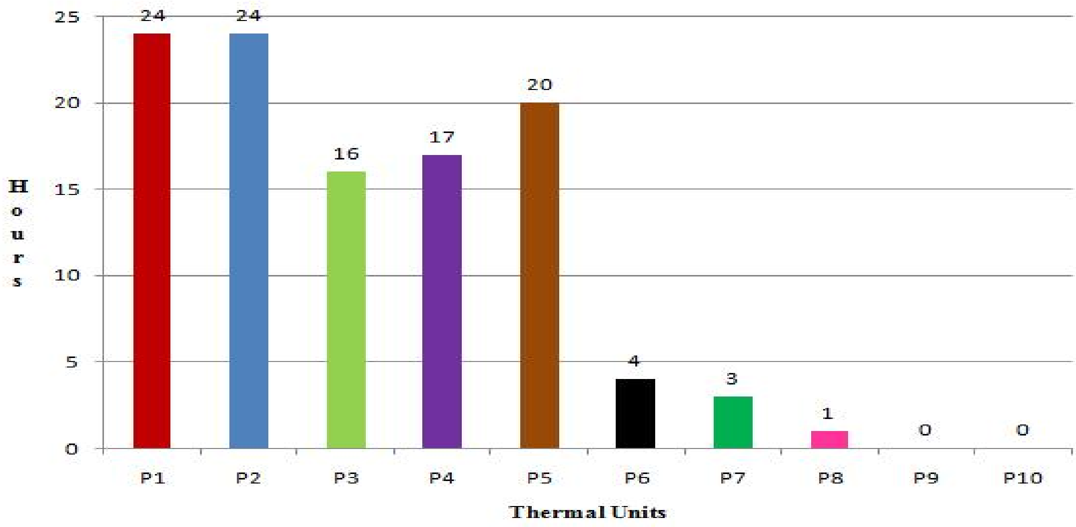

Figure 3. Thermal units operating schedule

V. CONCLUSIONS

Thus, it proves that the most efficient operation can be realised by using the proposed model and it is a well appropriate model for power production industries to improve their operational schemes. The implementation of GWO is simple and it successfully handled the operational constraints. The optimum solution for RESIUC problem can be consistently obtained by GWO. Results illustrate that intended algorithm is a powerful tool for solving RESIUC problem.

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