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ORIGINAL ARTICLE

A novel hybrid PSO–GWO approach for unit commitment problem

Vikram Kumar Kamboj[1,2]

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Abstract Particle swarm optimization algorithm is a inhabitant-based stochastic search procedure, which provides a populace-based search practice for getting the best solution from the problem by taking particles and moving them around in the search space and efficient for global search. Grey Wolf Optimizer is a recently developed meta-heuristic search algorithm inspired by Canis-lupus. This research paper presents solution to single-area unit commitment problem for 14-bus system, 30-bus system and 10-generating unit model using swarm-intelligence-based particle swarm optimization algorithm and a hybrid PSO–GWO algorithm. The effectiveness of proposed algorithms is compared with classical PSO, PSOLR, HPSO, hybrid PSOSQP, MPSO, IBPSO, LCA–PSO and various other evolutionary algorithms, and it is found that performance of NPSO is faster than classical PSO. However, generation cost of hybrid PSO–GWO is better than classical and novel PSO, but convergence of hybrid PSO–GWO is much slower than NPSO due to sequential computation of PSO and GWO.

Keywords Grey Wolf Optimizer (GWO) · Particle swarm optimization (PSO) · Single-area unit commitment problem (SAUCP)

✉ Vikram Kumar Kamboj
kamboj.vikram@gmail.com

1 Department of Electrical Engineering, Punjab Technical University, Jalandhar, India

2 Department of Electrical Engineering, DAV University, Jalandhar, India

1 Introduction

In the modern power system networks, there are various generating resources like thermal, hydro and nuclear. Also, the load demand varies during a day and attains different peak values. Thus, it is required to decide which generating unit to turn on and at what time it is needed in the power system network and also the sequence in which the units must be shut down, keeping in mind the cost-effectiveness of turning on and shutting down of respective units. The entire process of computing and making these decisions is known as unit commitment (UC). The unit which is decided or scheduled to be connected to the power system network, as and when required, is known to be committed unit. Unit commitment in power systems refers to the problem of determining the on/off states of generating units to minimize the operating cost for a given time horizon [1].

Generators cannot be immediately turned on to meet up power demand. So it is required that the planning of generating units must be so prepared that there is enough generation available to fulfil the load demand along with an ample reserve generation to avoid failures and malfunctions under adverse conditions. Unit commitment knobs the unit generation schedule in electric power system for minimizing operational and fuel cost and satisfying system and physical constraints such as load demand and system reserve requirements over a set of time periods [2]. Unit commitment problem (UCP) is basically about finding the most suitable schedule to turn on or turn off the generating units to meet the electric power demand and at the same time keep the cost of generation as much minimum as possible. UCP is a nonlinear, large-scale, mixed-integer-constrained optimization problem [3] and happens to belong to combinatorial optimization problems. There are many constraints involved in UCP, and hence it is quite a complex and tedious task to compute or to find the optimal solution for UCP.

2 Unit commitment problem

The scheduling of the units together with the allocation of the generation quantities which must be scheduled to meet the demand for a specific period represents the UCP. The UCP is to determine a smallest cost turn-on and turn-off plan of a set of generating units to meet a power demand while satisfying system operational and physical constraints linked with various generating units. The production cost includes fuel, start-up, no load costs and shutdown cost. The operational constraints that must be taken into consideration are: (1) the total power generated must meet the power demand plus system losses. (2) There must be an adequate amount of spinning reserve to cover any shortfalls in power generation. (3) The loading of each unit must be within its minimum and maximum permissible rating. (4) The minimum up and downtimes of each unit must be pragmatic. The unit commitment is aimed to formulate a proper generator commitment schedule for electric power system over a period of 1 day to 1 week. The main objective of unit commitment is to minimize the total production cost over the study period and to satisfy the system and physical constraints imposed on the system such as spinning reserve, power generation–load balance, operating constraints, minimum uptime and minimum downtime. Several conventional methods are available to solve the UCP. But all these methods need the exact mathematical model of the system, and there may be a chance of getting stuck at the local optimum [4].

2.1 Literature review

Sriyanyong and Song [5] proposed particle swarm optimization (PSO) combined with Lagrange relaxation method for solving UCP. The proposed approach employs PSO algorithm for optimal settings of Lagrange multipliers. The feasibility of the proposed method is demonstrated for 4- and 10-unit systems, respectively. Xiong et al. [6] have applied multi-particle swarm to parallel arithmetic to produce particle to enhance the convergence speed and found the more efficient results than genetic algorithm. Jeong et al. [7] have discussed binary PSO-based approach for solving the UC problems. Ge [8] has proposed a new approach to solve ramp rate-constrained UCP by improving the method of PSO. Borghetti et al. [9] have suggested that there is no guarantee that the Tabu search will yield the global optimal result for large systems. There is a similar method named PSO proposed in [10]. Rajan et al. [11] proposed Neural-based Tabu search algorithm for the UCP and developed an improved version of Neural-based Tabu search approach [3]. Gaing [12] proposed binary particle swarm optimization (BPSO). The BPSO is used to solve the combinatorial unit on/off scheduling problem for operating fuel and transition costs. The ED subproblem is solved using the lambda iteration method for obtaining the total production cost. Zhao et al. [13] presented an improved particle swarm optimization algorithm (IPSO) for UC which utilizes more particle information to control the process of mutation operation. For proper selection of parameters, some new rules are also proposed. The proposed method combines LR technique to 0–1 variable. Lee et al. [14] presented a new approach for UCP named the iteration particle swarm optimization (IPSO). The proposed method improves the quality of solution in terms of total production cost and also improves the computation efficiency. A standard 48-unit system has been tested for validation. Samudi et al. [15] have presents a new approach of PSO algorithm for short-term hydro-thermal scheduling (HTS) problems. The proposed algorithm is ideally suitable for hydro-thermal coordination problems, hydro-economic dispatch problems with unit commitment, thermal economic dispatch with UCPs and scheduling of hydraulically coupled plants. Yuan et al. [16] proposed a new improved binary PSO (IBPSO). The standard PSO is improved using the priority list and heuristic search to improve the MUT and MDT constraints. The 10–100 units have been tested to validate the proposed approach. Numerical performance shows that the proposed approach is superior in terms of low total production cost and short computational time compared with other published results. Although no optimization algorithm can perform general enough to solve all optimization problems, each optimization algorithm has their own advantages and disadvantages. Particle swarm optimization (PSO) has simple concept, easy implementation, relative robustness to control parameters and computational efficiency [17]; although it has numerous advantages, it get trapped in a local minimum, when handling heavily constrained problems due to the limited local/global searching capabilities [18, 19]. Grey Wolf Optimizer (GWO) is a recently developed powerful evolutionary algorithm proposed by Mirjalili [19] and has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other prevailing techniques. Also, GWO has a good balance between exploration and exploitation that result in high local optima avoidance. Moved from these innovative ideas, a hybrid algorithm comprising of PSO and GWO is proposed to solve single-area UCP of electric power system.

3 Single-area unit commitment problem formulation

The foremost objective of unit commitment is to find the optimal schedule for operating the available generating units to regulate the total operating and generation costs of electric power utilities. Total operating cost of power generation includes fuel cost, shutdown and start-up costs. The fuel costs are calculated using the data of generating unit characteristics such as fuel price information, heat rate of generating utilities, turn-on, turn-off and initial status of units, which is mathematically a quadratic, nonsmooth and nonconvex equation of power output of each generator at each hour and can be determined by economic load dispatch (ELD) [20], as represented below:

$$F_{\text{cost}}(P_i) = c_i P_i^2 + b_i P_i + a_i \tag{1}$$

where a_i, b_i and c_i are the fuel cost coefficients of ith generating units.

The total fuel cost over the given time horizon 'H' is

$$\text{TFC} = \sum_{h=1}^{H} \sum_{i=1}^{\text{NG}} F_{\text{cost}} P_i * X_i(h) \tag{2}$$

where $X_i(h)$ is the position or status of ith unit at hth hour. Start-up cost is warmth dependent. Start-up cost is the cost which occurs while bringing the thermal generating unit online. It is expressed in terms of the time (in hours) for which the units have been shut down. On the other hand, shutdown cost is a fixed amount for each unit which is shut down. Mathematically, start-up cost can be expressed as:

$$\text{SUC}_{ih} = \begin{cases} \text{HSC}_i; \text{ for } \text{MDT}_i \le \text{MDT}_i^{\text{ON}} \le (\text{MDT}_i + \text{CSH}_i) \\ \text{CSC}_i; \text{ for } \text{MDT}_i^{\text{ON}} > (\text{MDT}_i + \text{CSH}_i) \\ \qquad (i \in \text{NG}; h = 1, 2, 3, \ldots, H) \end{cases} \tag{3}$$

where CSC_i and HSC_i are cold start-up and hot start-up costs of ith unit, respectively, and MDT_i is the minimum downtime of ith unit, MDT_i^{ON} is the number of hours that ith unit has been online since it was turned on earlier and CSH_i is the cold start hour of unit i. The various constraints linked with UCP are mentioned below:

3.1 Load balance or power balance constraints

The load balance or system power balance constraint requires that the sum of generation of all the committed units at hth hour must be greater than or equal to the demand at a particular hour 'h'

$$\sum_{i=1}^{\text{NG}} P_{ih} U_{ih} = D_h. \tag{4}$$

3.2 Spinning reserve constraints

Considering the important aspect of reliability, there is a provision of excess capacity of generation which is required to act instantly when there is a failure of already running unit or sudden load demand. This excess capacity of generation is known as spinning reserve and mathematically given as:

$$\sum_{i=1}^{N} P_{i(\max)} U_{ih} \ge D_h + R_h. \tag{5}$$

3.3 Thermal constraints

A thermal generation unit needs to undergo gradual temperature changes, and thus it takes some period of time to bring a thermal unit online. Also, the operation of a thermal unit is manually controlled. So a crew is required to perform the operation and maintenance of any thermal unit. This leads to many restrictions in the operation of thermal unit, and thus it gives rise to many constraints.

(1) Minimum uptime

If the units have already been shut down, there will be a minimum time before they can be restarted. This constraint is given as:

$$X_i^{\text{on}}(t) \ge \text{MUT}_i. \tag{6}$$

where $X_i^{\text{on}}(t)$ is duration for which unit i is continuously ON (in hours) and MU_i is unit i minimum uptime (in hours).

(2) Minimum downtime

Once the unit is decommitted, there is a minimum time before it can be recommitted. This constraint is given as:

$$X_i^{\text{off}}(t) \ge \text{MDT}_i. \tag{7}$$

where $X_i^{\text{off}}(t)$ is duration for which unit i is continuously OFF (in hours) and MDT_i is minimum downtime (in hours).

(3) Crew constraints

If a plant consists of two or more units, they cannot be turned on at the same time since there are no enough crew members to attend both units while starting up.

(4) Maximum and minimum power limits

Every unit has its own maximum/minimum power level of generation, beyond and below which it cannot generate.

$$P_{i(\min)} \le P_{ih} \le P_{i(\max)}. \tag{8}$$

(5) Initial operating status of generating units

The initial operating status of every unit should take the last day's previous schedule into account, so that every unit satisfies its minimum up/downtime.

4 Hybrid PSO–GWO algorithm for single-area unit commitment problem

4.1 Particle swarm optimizer

Particle swarm optimization, inspired by social behaviour of birds and shoals of fish, is swarm-intelligence-based optimization algorithm which provides a population-based search procedure for getting the best solution from the problem by taking particles and moving them around in the search space. In PSO, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of neighbouring particles, making use of the best position encountered by itself and its neighbours. The swarm direction of a particle is defined by the set of particles neighbouring the particle and its history experience [18]. PSO is a nondeterministic, stochastic optimization technique and provides a population-based search procedure for global optimization, having chief advantage of easy to perform and few parameters to adjust whose performance is comparable to genetic algorithm.

4.2 Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a recently developed metaheuristic search algorithm inspired by grey wolves (Canis-lupus) proposed by Mirjalili [19], to solve nonconvex engineering optimization problem, which simulate the social stratum and hunting mechanism of grey wolves in nature and based on three main steps of hunting: searching for prey, encircling prey and attacking prey.

5 Mathematical formulation of proposed algorithm

In proposed hybrid PSO–GWO algorithm, first the position of swarm is updated using the below-mentioned NPSO algorithms and then further updated using GWO algorithm.

Steps for updation of Position of Swarm using NPSO:

$Z = \mathrm{Zmax} - (\mathrm{Zmax} - \mathrm{Zmin}) * k/\mathrm{ITERmax}$;

$r1 = (\mathrm{fitness} < P\mathrm{fitness})$;

$r2 = (\mathrm{fitness} < G\mathrm{fitness})$;

Best_Position = Z*[r1*(Pbest-rand_Position) + $r2$*(Gbest-rand_Position)];

In order to mathematically model the social governance of wolves when designing Grey Wolf Optimizer (GWO), assume the fittest solution as the alpha (α). Consequently, the second and third best solutions are named beta (β) and delta (δ), respectively. The rest of the candidate solutions are assumed to be omega (ω), kappa (κ) and lambda (λ). In the GWO algorithm, the optimization (i.e. hunting) is guided by α, β and δ. The ω, κ and λ wolves trail these three wolves.

5.1 Encircling or trapping prey

As mentioned above, grey wolves encircle prey during the hunt. In order to mathematically model encircling behaviour, the following equations are proposed:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{\mathrm{Prey}}(t) - \vec{X}_{\mathrm{GWolf}}(t)\right| \tag{9}$$

$$\vec{X}_{\mathrm{GWolf}}(t+1) = \vec{X}_{\mathrm{Prey}}(t) - \vec{A} \cdot \vec{D} \tag{10}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_{\mathrm{Prey}}$ is the position vector of the prey, and $\vec{X}_{GWolf}$ 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 $\vec{r}_1$, $\vec{r}_2$ are random vectors between 0 and 1.

Therefore, a grey wolf can update its position inside the space around the prey in any random location by using Eqs. (9) and (10).

5.2 Hunting of prey

Grey wolves have the ability to recognize the location of prey and enclose or trap them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space, we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution), beta and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the delta, kappa and lambda) to update their positions according to the position of the best search agent. The score and positions of the first three search agents (i.e. alpha, beta and delta) can be updated using Eqs. (13), (14) and (15), respectively.

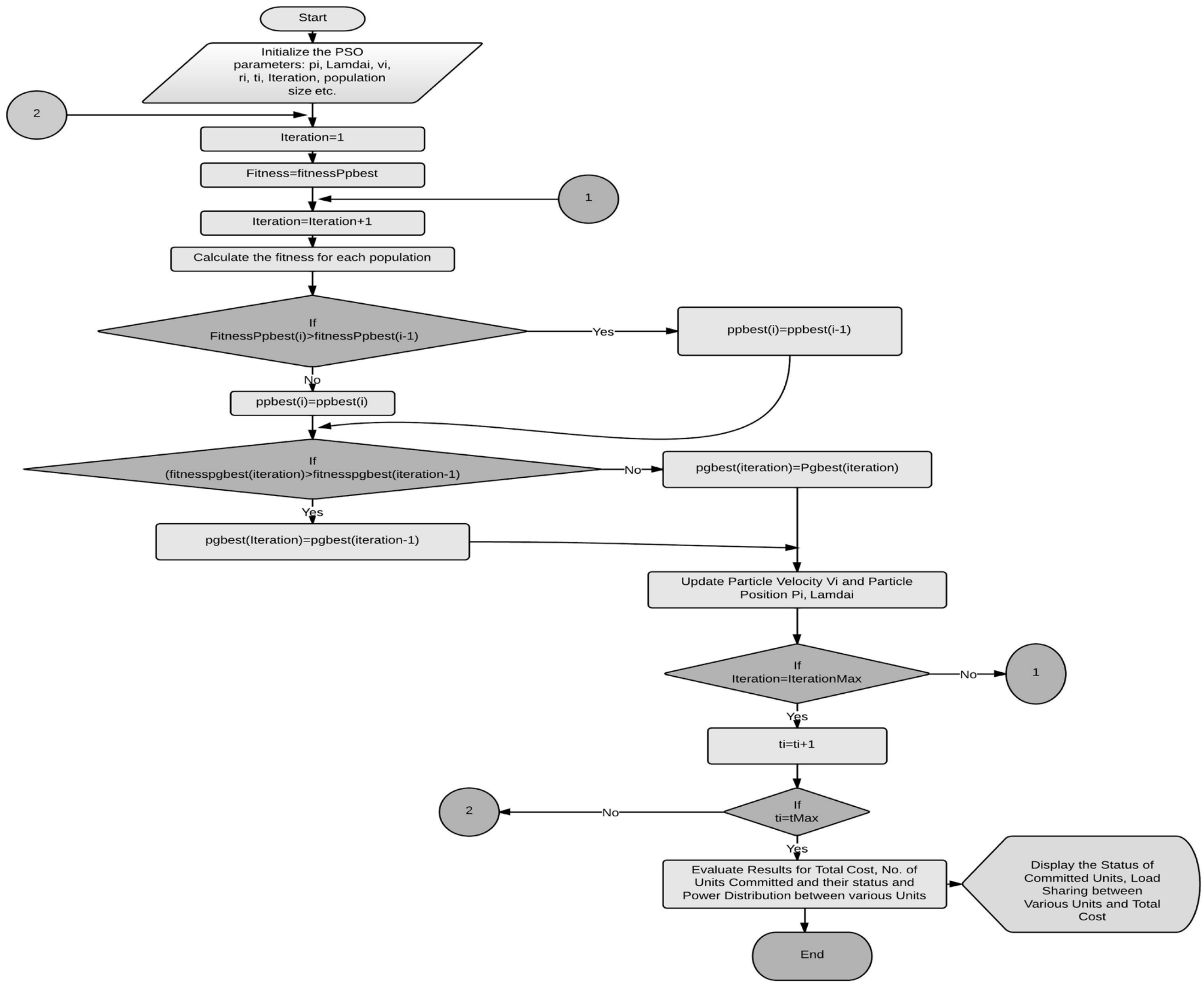

Fig. 1 Flow-chart for single-area unit commitment using NPSO

$$\vec{D}_{\text{Alpha}} = \left|\vec{C}_1 \cdot \vec{X}_{\text{Alpha}} - \vec{X}\right| \tag{13}$$

$$\vec{D}_{\text{Beta}} = \left|\vec{C}_2 \cdot \vec{X}_{\text{Beta}} - \vec{X}\right| \tag{14}$$

$$\vec{D}_{\text{Delta}} = \left|\vec{C}_3 \cdot \vec{X}_{\text{Delta}} - \vec{X}\right| \tag{15}$$

The position vector of prey with respect to alpha, beta and delta wolves can be calculated using the following mathematical formulation:

$$\vec{X}_1 = \vec{X}_{\text{Alpha}} - \vec{A}_1 \cdot (\vec{D}_{\text{Alpha}}) \tag{16}$$

$$\vec{X}_2 = \vec{X}_{\text{Beta}} - \vec{A}_2 \cdot (\vec{D}_{\text{Beta}}) \tag{17}$$

$$\vec{X}_3 = \vec{X}_{\text{Delta}} - \vec{A}_3 \cdot (\vec{D}_{\text{Delta}}) \tag{18}$$

The best position can be calculated taking average of alpha, beta and delta wolves as depicted below in Eq. (19)

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{19}$$

5.3 Basic steps of hybrid particle swarm optimization–Grey Wolf Optimizer algorithm

- Initialize the swarm and form the solution space
- Evaluate the fitness of each particle
- Update individual and global bests
- Take Best_Position as search agent current position and update the position of alpha, beta and gamma wolves using Grey Wolf Optimizer algorithm.
- Take alpha position as final position of swarms and alpha score as the best fitness
- Go to step 2, and repeat until termination condition

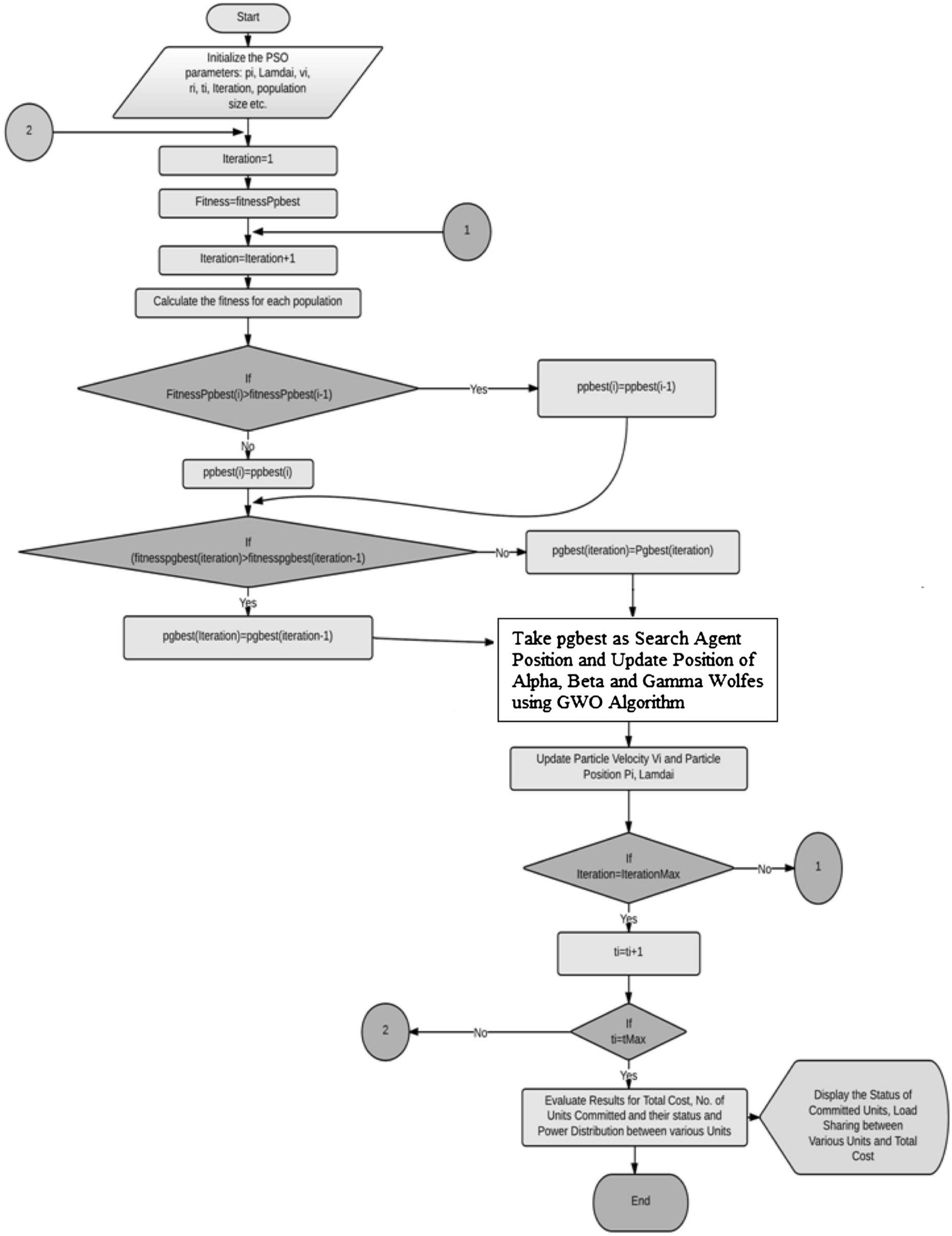

Fig. 2 Flow-chart for single-area unit commitment using hybrid PSO–GWO algorithm

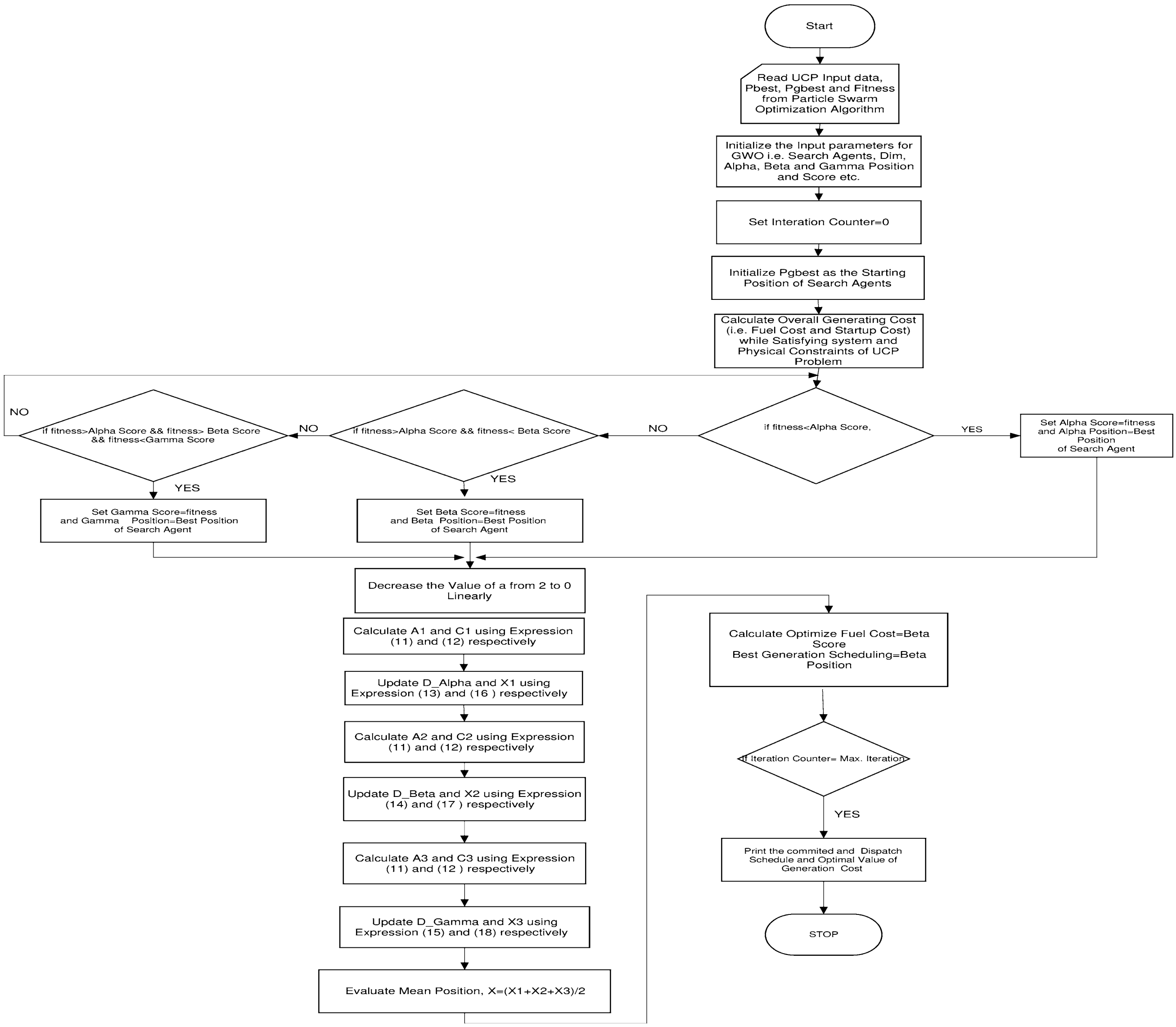

Fig. 3 Flow-chart for updating grey wolf position in GWO algorithm

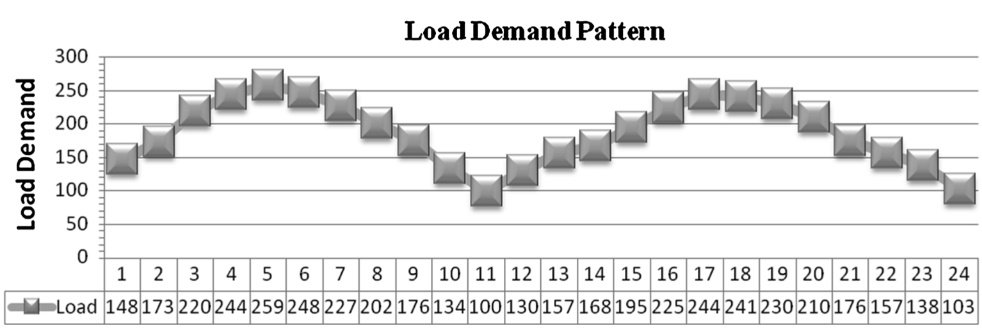

Fig. 4 Load demand pattern for 24 h for 14-bus system

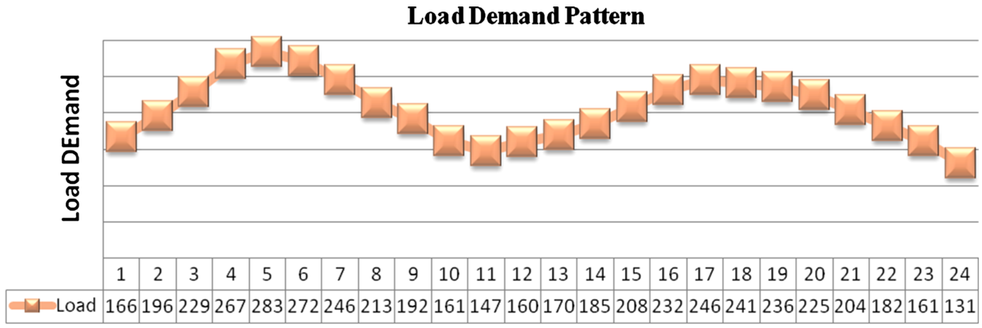

Fig. 5 Load demand pattern for 24 h for 30-bus system

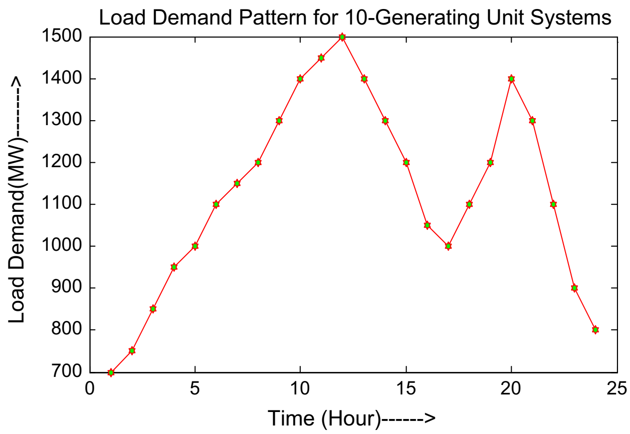

Fig. 6 Load demand pattern for 24 h for 10-unit system

6 Single-area unit commitment using novel and hybrid PSO

The flow chart for novel particle swarm optimization (NPSO) for single-area unit commitment problem is shown below in Fig. 1. The flow chart for hybrid PSO–GWO algorithm is shown in Fig. 2, and flow chart for updation of grey wolves position is shown in Fig. 3.

7 Test systems and results and discussion

In order to show the effectiveness of the NPSO and hybrid PSO–GWO algorithm for single-area unit commitment problem, three different types of test systems have been taken into consideration:

- The first test system consists of five generating units taken from IEEE 14-bus system [21] with a time-varying load demand for 24 h.
- The second test system consists of six generating units taken from IEEE 30-bus system [21] with a time-varying load demand for 24 h.
- The third test system consist of 10-generating-unit model [21] and load data for 24-h

The corresponding results have been obtained using novel particle swarm optimization technique using population size = 40 and maximum iteration = 10. The flow chart for

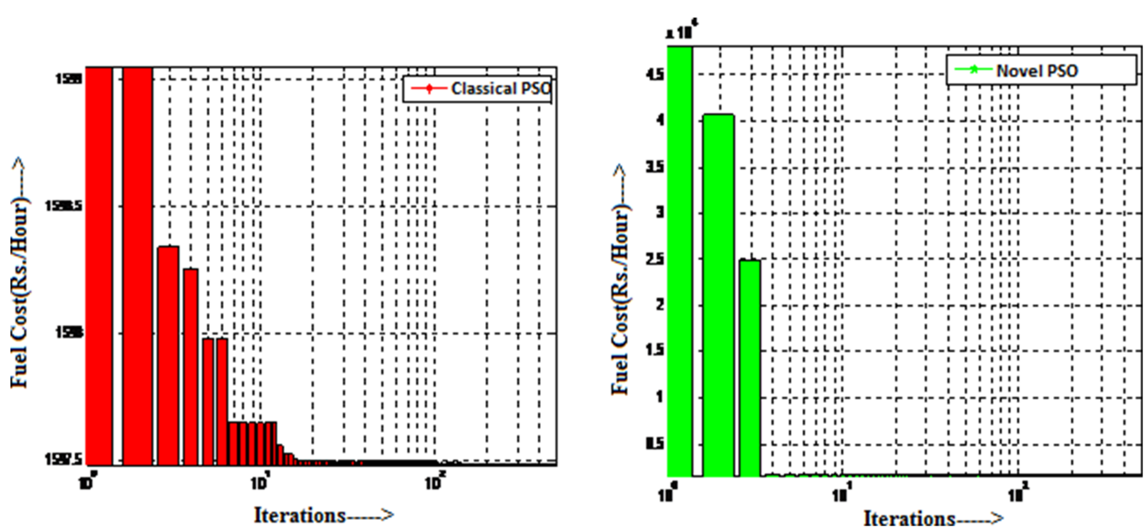

Fig. 7 Convergence of classical and novel PSO

Table 1 Test data for 5-unit, 14-bus system

Unit no.	P_{ih}^{max}	P_{ih}^{min}	a (\$/MW^2)	b (\$/MWh)	c (\$/h)	MUT$_i$	MDT$_i$	HSC$_i$	CSC$_i$	CSH$_i$	IS$_i$
U1	250	10	0.00315	2	0	1	1	70	176	2	1
U2	140	20	0.0175	1.75	0	2	1	74	187	2	−3
U3	100	15	0.0625	1	0	1	1	50	113	1	−2
U4	120	10	0.00834	3.25	0	2	2	110	267	1	−3
U5	45	10	0.025	3	0	1	1	72	180	1	−2

Table 2 Results for 14-bus system using NPSO

Hour	Commitment schedule for five-unit system					Generation schedule for five-unit system				
	U1	U2	U3	U4	U5	U1	U2	U3	U4	U5
1	1	0	0	0	0	148	0	0	0	0
2	1	0	0	0	0	173	0	0	0	0
3	1	0	0	0	0	220	0	0	0	0
4	1	1	0	0	0	104	140	0	0	0
5	1	1	0	0	0	119	140	0	0	0
6	1	1	0	0	0	108	140	0	0	0
7	1	0	0	0	0	227	0	0	0	0
8	1	0	0	0	0	202	0	0	0	0
9	1	0	0	0	0	176	0	0	0	0
10	1	0	0	0	0	134	0	0	0	0
11	1	0	0	0	0	100	0	0	0	0
12	1	0	0	0	0	130	0	0	0	0
13	1	0	0	0	0	157	0	0	0	0
14	1	0	0	0	0	168	0	0	0	0
15	1	0	0	0	0	195	0	0	0	0
16	1	0	0	0	0	225	0	0	0	0
17	1	1	0	0	0	104	140	0	0	0
18	1	1	0	0	0	101	140	0	0	0
19	1	0	0	1	0	220	0	0	10	0
20	1	0	0	1	0	200	0	0	10	0
21	1	0	0	0	0	176	0	0	0	0
22	1	0	0	0	0	157	0	0	0	0
23	1	0	0	0	0	138	0	0	0	0
24	1	0	0	0	0	103	0	0	0	0
Total cost = 12,281										

Table 3 Test data for 30-bus system

Unit no.	P_{ih}^{max}	P_{ih}^{min}	a (\$/MW^2)	b (\$/MWh)	c (\$/h)	MUT$_i$	MDT$_i$	HSC$_i$	CSC$_i$	CSH$_i$	IS$_i$
U1	200	50	0.00375	2	0	1	1	70	176	2	1
U2	80	20	0.0175	1.7	0	2	2	74	187	1	−3
U3	50	15	0.0625	1	0	1	1	50	113	1	−2
U4	35	10	0.00834	3.25	0	1	2	110	267	1	−3
U5	30	10	0.025	3	0	2	1	72	180	1	−2
U6	40	12	0.025	3	0	1	1	40	113	1	−2

Table 4 Results for 30-bus system using NPSO

Hour	Commitment schedule for six-generating unit system					Generation schedule for six-generating unit system				
	U1	U2	U3	U4	U5	U1	U2	U3	U4	U5
1	1	0	0	0	0	166	0	0	0	0
2	1	1	0	0	0	116	80	0	0	0
3	1	1	0	0	0	149	80	0	0	0
4	1	1	1	0	0	197	20	50	0	0
5	1	1	1	0	0	153	80	50	0	0
6	1	1	1	0	0	142	80	50	0	0
7	1	0	1	0	1	156	0	50	0	40
8	1	0	0	0	1	200	0	0	0	13
9	1	1	0	0	0	112	80	0	0	0
10	1	1	0	0	0	81	80	0	0	0
11	1	0	0	0	0	147	0	0	0	0
12	1	0	0	0	0	160	0	0	0	0
13	1	0	0	0	0	170	0	0	0	0
14	1	1	0	0	0	105	80	0	0	0
15	1	1	0	0	0	128	80	0	0	0
16	1	1	0	0	0	152	80	0	0	0
17	1	1	0	0	0	166	80	0	0	0
18	1	1	0	0	0	161	80	0	0	0
19	1	1	0	0	0	156	80	0	0	0
20	1	1	0	0	0	145	80	0	0	0
21	1	1	0	0	0	124	80	0	0	0
22	1	1	0	0	0	102	80	0	0	0
23	1	0	0	0	0	161	0	0	0	0
24	1	0	0	0	0	131	0	0	0	0
Total cost = 13,600										

Table 5 Test data for 10-unit system

Unit no.	$P_{ih}^{\max}$	$P_{ih}^{\min}$	a (\$/MW^2)	b (\$/MWh)	c (\$/h)	MUT$_i$	MDT$_i$	HSC$_i$	CSC$_i$	CSH$_i$	IS$_i$
U1	455	150	0.00048	16.19	1000	8	8	4500	9000	5	8
U2	455	150	0.00031	17.26	970	8	8	5000	10,000	5	8
U3	130	20	0.002	16.6	700	5	5	550	1100	4	−5
U4	130	20	0.00211	16.5	680	5	5	560	1120	4	−5
U5	162	25	0.00398	19.7	450	6	6	900	1800	4	−6
U6	80	20	0.00712	22.26	370	3	3	170	340	2	−3
U7	85	25	0.00079	27.74	480	3	3	260	520	2	−3
U8	55	10	0.00413	25.92	660	1	1	30	60	0	−1
U9	55	10	0.00222	27.27	665	1	1	30	60	0	−1
U10	55	10	0.00173	27.79	670	1	1	30	60	0	−1

Table 6 Load demand pattern for 24 h for 10-unit system

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Demand	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Hour	13	14	15	16	17	16	19	20	21	22	23	24
Demand	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

Table 7 Commitment schedule of 10-unit test system using hybrid PSO–GWO algorithm

Commitment schedule for 10-generating unit system

U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
1	1	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0
1	1	0	0	1	0	0	0	0	0
1	1	0	0	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	1	0	0	1
1	1	1	1	1	1	1	0	1	0
1	1	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	0	0	1	0	0
1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	0	0	0
1	1	0	0	1	1	1	0	0	0
1	1	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0

Total cost = 56,5210

Table 8 Generation schedule of 10-unit test system using NPOS

Generation schedule for 10-generating unit system

U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
455	245	0	0	0	0	0	0	0	0
455	295	0	0	0	0	0	0	0	0
455	370	0	0	25	0	0	0	0	0
455	455	0	0	40	0	0	0	0	0
455	390	130	130	25	0	0	0	0	0
455	360	130	130	25	0	0	0	0	0
455	410	130	130	25	0	0	0	0	0
455	455	130	130	30	0	0	0	0	0
455	455	130	130	95	0	25	0	0	10
455	455	130	130	162	33	25	0	10	0
455	455	130	130	162	73	25	10	10	0
455	455	130	130	162	80	25	43	10	10
455	455	130	130	162	33	25	10	0	0
455	455	130	130	85	20	25	0	0	0
455	455	130	130	30	0	0	0	0	0
455	310	130	130	25	0	0	0	0	0
455	260	130	130	25	0	0	0	0	0
455	350	130	130	25	0	0	10	0	0
455	455	130	130	30	0	0	0	0	0
455	455	130	130	162	33	25	10	0	0
455	455	130	130	85	20	25	0	0	0
455	455	0	0	20	20	25	0	0	0
455	320	0	0	0	0	0	0	0	0
455	345	0	0	0	0	0	0	0	0

Table 9 Comparison of results for 10-generating unit system (for 10 % spinning reserve)

S. no.	Method	Overall generation cost ($)			Average time (s)
		Best	Average	Worst	
1	Genetic-based method [22]	NA	623,441	–	–
2	Hybrid continuous relaxation and genetic algorithm (CRGA) [23]	NA	563,977	–	46
3	Continuous relaxation and genetic algorithm (CRGA) [24]	–	563,977	–	–
4	Integer-coded genetic algorithm (ICGA) [25]	–	566,404	–	–
5	Lagrangian search genetic algorithm (LSGA) [26]	609,023.69	–	–	–
6	Improved binary particle swarm optimization (IBPSO) [27]	599,782	–	–	14.48
7	New genetic algorithm [28]	591,715	–	–	677
8	PSO [29]	581,450	–	–	–
9	Binary particle swarm optimization with bit change mutation (MPSO) [30]	574,905	–	–	15.73
10	HPSO [31]	574,153	–	–	–
11	LCA–PSO [32]	570,006	–	–	18.34
12	Two-stage genetic-based technique (TSGA) [33]	568,315	–	–	–
13	Hybrid PSO-SQP [34]	568,032.3	–	–	–
14	BCGA [25]	567,367	–	–	–
15	SM [35]	566,686	566,787	567,022	–

Table 9 continued

S. no.	Method	Overall generation cost ($)			Average time (s)
		Best	Average	Worst	
16	LR [35]	566,107	566,493	566,817	–
17	GA [35]	565,866	567,329	571,336	–
18	Genetic algorithm (GA) [36]	565,852	–	570,032	221
19	Enhanced simulated annealing (ESA) [37]	565,828	565,988	566,260	3.35
20	Lagrangian relaxation (LR) [36]	565,825	–	–	–
21	Dynamic programming (DP) [36]	565,825	–	–	–
22	Improved Lagrangian relaxation (ILR) [38]	565,823.23	–	–	–
23	LRPSO [38]	565,275.2	–	–	–
24	NPSO [proposed method 1]	565,213.00	–	–	–
25	Hybrid PSO–GWO [proposed method 2]	565,210.2564	–	–	–

single-area unit commitment problem using NPSO is shown in Fig. 1, and flow chart for hybrid PSO–GWO algorithm is shown in Fig. 2. The MATLAB simulation software 7.12.0 (R2011a) is used to obtain the corresponding results (Figs. 4, 5, 6, 7) (Tables 1, 2, 3, 4, 5, 6, 7, 8, 9).

8 Conclusion

In this paper, researchers have presented the solution of single-area unit commitment problem using novel particle swarm optimization algorithm. The results for standard IEEE bus system of 14-bus system, 30-bus system and 10-generating unit model have been successfully evaluated using proposed NPSO and hybrid PSO–GWO algorithms. It is observed that performance of proposed NPSO is much better than conventional PSO, PSOLR, HPSO, hybrid PSOSQP, MPSO, IBPSO, LCA–PSO, DP, SA, GA, TSGA, BCGA, ICBCGA, CRGA, LR, ILR and ESA algorithm, and convergence of proposed NPSO is faster than classical PSO. However, generation cost of hybrid PSO–GWO is better than classical and novel PSO, but convergence of hybrid PSO–GWO is much slower than NPSO due to sequential computation of PSO and GWO.

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