An Enhanced Particle Swarm Optimization Approach for the Unit Commitment Problem

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Abstract

This paper proposes an Enhanced Particle Swarm Optimization (EPSO) approach to the Unit Commitment Problem (UCP). The BPSO algorithm for on/off decision and the PSO algorithm for the economic load dispatch problem are enhanced to find the optimal solution and reduce the overall computation time. The proposed technique is tested on real-world data obtained from the Turkish interconnected power network system with 8 units and an 8-h scheduling horizon as well as on 10 and 20 unit systems with a 24-h scheduling horizon. The results of the EPSO on the benchmark datasets are comparable with the results of other heuristic approaches found in the literature. This preliminary experimental study shows that EPSO is suitable for the UCP and the promising results promote further study.

1. Introduction

The unit commitment problem (UCP) is a mixed integer combinatorial optimization problem in which the purpose is to schedule the turning on and off of generating units to minimize the operating cost for a given time horizon under various operating constraints. The UCP can be considered as two linked optimization decision processes, namely the unit-scheduled problem, which determines the on/off status of generating units in each time period of the planning horizon, and the economic load dispatch problem. Mathematically, the UCP is formulated as a complex nonlinear mixed integer combinational optimization problem with 0–1 variables that represent unit status and continuous variables that represent unit power and the equality and inequality constraints [1].

Over recent decades, many methods have been developed for solving the UCPs. The exact solution to the problem can be obtained by complete enumeration, but this cannot be applied to real power systems due to the computational time required [1]. The solution for UCPs can be divided into two categories: one is the numerical optimization techniques, such as priority list methods [2-3], dynamic programming [4], Lagrange relaxation methods [5], branch-and-bound methods [6-7], and mixed-integer programming [8]; the other is the stochastic methods based on heuristic search, such as genetic algorithms [9-11], evolutionary programming [12-13], simulated annealing [14] particle swarm optimization [15-18] and ant colony optimization [19].

In this paper, an enhanced PSO (EPSO) approach is proposed which combines the binary PSO and the continuous PSO in order to find the final global best value faster than other techniques.

This paper is organized as follows: In section 2, the UCP is explained. In section 3, the PSO and BPSO methods are explained briefly. Section 4 introduces the EPSO approach used in this study. In section 5, the experiments and results are given. Section 6 concludes the paper.

2. Unit Commitment Problem Formulation

The objective of the UCP is to find the optimal combination of power generation that minimizes the total generation costs while satisfying the equality and inequality constraints. The total costs consist of the fuel costs and the start-up costs. The following parameters are used to formulate the UCP:

P_u^t : generated power by u-th unit at time t

F_u^t : cost of producing P_u^t MW power by u-th unit at time t

s_u^t : status of u-th unit at time t (1-0)

Sx_u^t : start-up cost of u-th unit at time t

$Pload^t$: power demand at time t

$Preserve^t$: power reserve at time t

$Pmin_u$: minimum generation limit of u-th unit

$Pmax_u$: maximum generation limit of u-th unit

Sh_u : hot start-up cost of u-th unit

Sc_u : cold start-up cost of u-th unit

$toff_u^t$: duration that u-th unit has been offline since hour t

ton_u^t : duration that u-th unit has been online since hour t

$tcold_u$: duration that u-th unit needs to cool down

a_u, b_u, c_u : fuel cost parameters of u-th unit

The objective function to be minimized is the total cost over the scheduling period. The total cost is the sum of fuel costs and start-up costs of all units, as follows:

$$Minimize \ \ Ftotal = \sum_{t=1}^{NT}\sum_{u=1}^{NU} F_u^t(P_u^t)\cdot s_u^t + Sx_u^t \cdot s_u^t \cdot (1 - s_u^{t\text{-}1}) \quad (1)$$

Total generated power by units must be equal to the load demand. The power balance constraint is as follows:

$$Pload^t = \sum_{u=1}^{NU} P_u^t \cdot s_u^t \quad (2)$$

The generated power by unit must be within its minimum and maximum generation limits. The power limit constraint is as follows:

$$Pmin_u \cdot s_u^t \le P_u^t \le Pmax_u \cdot s_u^t \tag{3}$$

The start-up cost occurs when the unit is turned on after an off period. If the unit has been shut down for a long time, a cold start-up occurs and more fuel is consumed to warm up the boiler; the Sc_u cost is incurred for a cold start-up. If the unit has only been shut down for a short time, a hot start-up occurs and less fuel is consumed to warm up the boiler; Sh_u cost is incurred for a hot start-up. The start-up cost is determined as follows:

$$Sx_u^t = \begin{cases} Sh_u, & if \quad toff_u^t \le tcold_u \\ Sc_u, & otherwise \end{cases} \tag{4}$$

To maintain the system reliability, a sufficient amount of reserve power is required. The spinning reserve constraint is as follows:

$$Pload^t + Preserve^t \le \sum_{u=1}^{NU} Pmax_u^t \cdot s_u^t \tag{5}$$

Once the unit is committed, it should stay online for a stated number of hours. Unit also should stay offline for a stated number of hours after it is decommitted. The minimum up and down time constraints are as follows:

$$s_u^t = \begin{cases} 1, & if \quad toff_u^{t-1} < tdown_u \\ 0, & if \quad ton_u^{t-1} < tup_u \\ 0 \text{ or } 1, \text{ otherwise} & \end{cases} \tag{6}$$

The fuel cost of a unit is expressed as a second order function of the generated power by unit. The fuel cost is formulated as follows,

$$F_u^t(P_u^t) = a_u + b_u \cdot P_u^t + c_u \cdot P_u^{t\,2} \tag{7}$$

3. Particle Swarm Optimization

PSO was first proposed by Kennedy and Eberhart and is a swarm intelligence optimization method inspired by the social behaviours of birds flocking in search of food. The PSO algorithm initializes the positions and velocities of a group of particles in a solution space. Particles' positions represent the solution to the objective function. Particles' velocities represent particle flight direction and distance.

3.1. Overview of Classical PSO

In classical PSO, each particle i represents a potential solution to the problem, and is expressed as a D-dimensional vector for which the position and velocity are, respectively, $\boldsymbol{x_i(t)=[\,x_{i1}, x_{i2},\dots, x_{iD}\,]}$ and $\boldsymbol{v_i(t)=[\,v_{i1}, v_{i2},\dots, v_{iD}\,]}$. Each particle is associated with a fitness value to indicate its advantage among the swarm. The movements of the particles are guided by their own best known positions $\boldsymbol{xpbest_i(t)=[\,xpbest_{i1}, xpbest_{i2},\dots, xpbest_{iD}\,]}$ and the entire swarm's best known position $\boldsymbol{xgbest_i(t)=[\,xgbest_{i1}, xgbest_{i2},\dots, xgbest_{iD}\,]}$. When better positions are being discovered, these will guide the movements of the swarm. The updated velocity of each individual particle can be calculated using the current velocity and the distance from personal best position and global best position as follows:

$$\begin{aligned} v_i(t+1) = w \cdot v_i(t) + c1 \cdot r1 \cdot (xpbest_i(t) - x_i(t)) \\ + c2 \cdot r2 \cdot (xgbest_i(t) - x_i(t)) \end{aligned} \tag{8}$$

The position of each particle is updated in every iteration, as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{9}$$

$c1$ is the cognitive factor, $c2$ is the social factor, $r1$ and $r2$ are two random numbers uniformly distributed in the range of [0, 1]. The velocities of the particles are restrained in [$vmin$, $vmax$] which prevents the particle from moving too fast or too slow and, as a result, retaining a balance between exploration and exploitation.

$$v\min \le v_i \le v\max \tag{10}$$

w is the inertia weight which shows the effect of the previous velocity on the new velocity. w is calculated as follows:

$$w = \frac{wmax - wmin}{iter_{max}} \cdot iter \tag{11}$$

3.2. Overview of Binary PSO

Kennedy and Eberhart proposed a discrete binary version of PSO for binary problems. In binary PSO, particle and global best positions and velocities are updated continuously. Updated velocity is restricted within the range of [0, 1]. If v_i is higher, the individual is more likely to choose 1, while lower values favour the choice of 0. To map the real velocity value to the range of [0, 1], a sigmoid function is used as follows:

$$sig(v_i(t+1)) = \frac{1}{1+\exp(-v_i(t+1))} \tag{12}$$

If a random number, selected from a uniform distribution in [0, 1] is lower than the value of the sigmoid function, the position is set to 0, otherwise it is set to 1. In the BPSO, the position is updated as follows:

$$x_i(t+1) = \begin{cases} 1, & if \quad rand \le sig(v_i(t+1)) \\ 0, & otherwise \end{cases} \tag{13}$$

4. Proposed Enhanced PSO Algorithm

Various researchers [15-18] have proposed the applications of PSO to UC problems. PSO applications differ in the representation of the problem, cost evaluation and handling of constraints. The UC problem can be considered as two enhanced optimization sub problems, which are unit scheduling problem and economic load dispatch problem. The proposed technique is a combination of the binary PSO to determine unit scheduling problem and the continuous PSO for handling of economic load dispatch problem. The infeasible particles will be penalized for the constraint violation by adding a penalty term to the fitness value.

4.1. Algorithmic Steps of BPSO

Unit on/off scheduling is determined by the BPSO algorithm. Minimum up/down time constraints and spinning reserve constraints are handled at this section of algorithm as shown in Fig. 1.

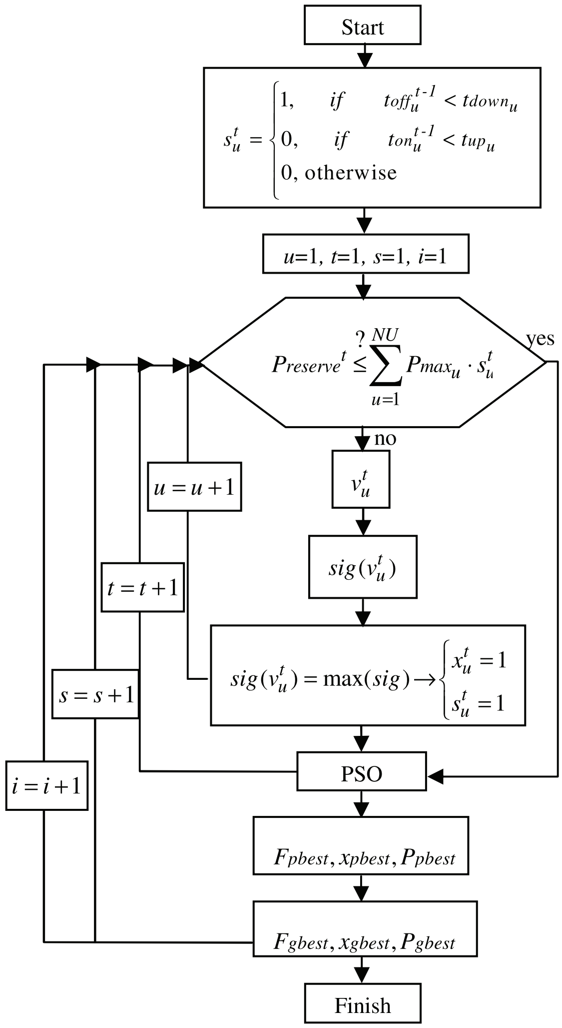

Fig. 1. Flowchart of BPSO algorithm

4.1. Algorithmic Steps of PSO

The economic load dispatch problem of the unit commitment is solved by the classical PSO algorithm. The total power demand constraints and unit generation limit constraints are also handled in this section. The hourly total costs are calculated from generation costs and the start-up costs and best positions are determined as shown in Fig. 2.

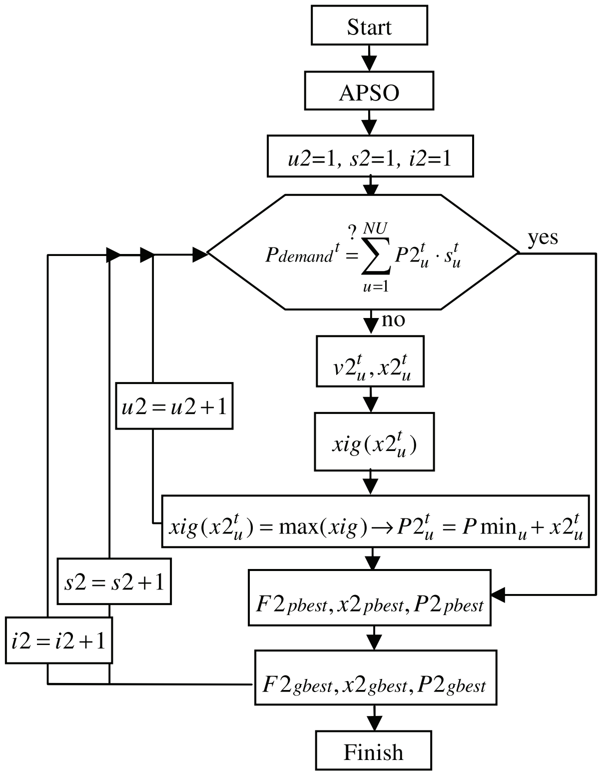

Fig. 2. Flowchart of PSO algorithm

5. Simulation Results

The fitness values of the particles are calculated as the sum of the fuel cost, the cost of the start-up and a penalty cost. For each hour, depending on whether the start-up is a cold start or a hot start, the appropriate cost is added to the total cost. A penalty cost is added if one of the constraints is violated to avoid considering a faulty solution.

The parameters defined at the beginning of the algorithm have an important influence on the solution quality in terms of both cost and time. Accordingly, the algorithm is run several times with different BPSO and PSO parameters, which are swarm, iteration, c1, c2, wmin and wmax values. The parameter combinations which provide the best solutions are given in tables for the test systems.

5.1. Turkey Test System

As the first test system, real-world data from the Turkish interconnected network system is used. There are 8 generating units and a time horizon of 8 hours. The data for this test system is given in Tables 1 and 2. The parameters and the results are given in Tables 3 and 4. The computation time is 32 seconds.

Table 1. Data-set for Turkey test system

	Unit 1	Unit 2	Unit 3	Unit 4
Pmax (MW)	1120	1350	1432	600
Pmin (MW)	190	245	318	150

a ($/MWH)	6995.5	7290.6	6780.5	1564.4
b ($/MWH)	70063	72.592	5682	31.288
c ($/MWH)	0.0168	0.0127	0.0106	0.0139
min up (h)	8	1	1	10
min down (h)	2	0.5	0.5	3
hot start cost ($)	800	800	600	400
cold start cost ($)	1600	1600	1200	800
cold start hrs (h)	8	1	1	10
initial status (h)	4	-4	-4	-4

	Unit 5	**Unit 6**	**Unit 7**	**Unit 8**
Pmax (MW)	990	420	630	630
Pmin (MW)	210	110	140	140
a ($/MWH)	5134.1	1159.5	1697	1822.8
b ($/MWH)	6.232	33.128	32.324	3.472
c ($/MWH)	0.0168	0.021	0.013	0.0147
min up (h)	10	10	10	10
min down (h)	3	3	3	3
hot start cost ($)	500	400	400	400
cold start cost ($)	1000	800	800	800
cold start hrs (h)	10	10	10	10
initial status (h)	-4	-4	-4	-4

Table 2. Demand-reserve data for Turkey test system

Hour	Demand(MW)	Reserve(MW)
1	2000	200
2	3000	300
3	6500	650
4	1500	150
5	4200	420
6	5100	510
7	2700	270
8	1750	175

Table 3. Parameters for Turkey test system

	s	*i*	*c1*	*c2*	*wmin*	*wmax*
APSO	40	50	2	2	0.1	1
PSO	10	40	1.1	1.1	0.1	0.92

Table 4. Results for Turkey test system

Algorithm	Best Cost	Worst Cost	Average Cost
ES[13]	530392	530392	530392
SSGA[13]	530392	530392	530392
PSO	531211	531858	531340,4
BDE1[13]	532142	-	-

5.2. Test System with 10 Units

As the second test system, a system commonly used in the literature is used. The system consists of 10 generating units and a time horizon of 24 hours. The data for this test system is given in Tables 5 and 6. The parameters and the comparison results are given in Tables 7 and 8. The computation time is 41 seconds and the best result obtained is $567,029.

Table 5. Parameters for test system with 10 units

	Unit 1	**Unit 2**	**Unit 3**	**Unit 4**	**Unit 5**
Pmax (MW)	455	455	130	130	162
Pmin (MW)	150	150	20	20	25
a ($/MWH)	1000	970	700	680	450
b ($/MWH)	16.19	17.26	16.60	16.50	19.70
c ($/MWH)	0.00048	0.00031	0.002	0.00211	0.00398
min up (h)	8	8	5	5	6
min down (h)	8	8	5	5	6
hot start cost ($)	4500	5000	550	560	900
cold start cost ($)	9000	10000	1100	1120	1800
cold start hrs (h)	5	5	4	4	4
initial status (h)	8	8	-5	-5	-6

	Unit 6	**Unit 7**	**Unit 8**	**Unit 9**	**Unit 10**
Pmax (MW)	80	85	55	55	55
Pmin (MW)	20	25	10	10	10
a ($/MWH)	370	480	660	665	670
b ($/MWH)	22.26	27.74	25.92	27.27	27.79
c ($/MWH)	0.00712	0.00079	0.00413	0.00222	0.00173
min up (h)	3	3	1	1	1
min down (h)	3	3	1	1	1
hot start cost ($)	170	260	30	30	30
cold start cost($)	340	520	60	60	60
cold start hrs (h)	2	2	0	0	0
initial status (h)	-3	-3	-1	-1	-1

Table 6. Demand-reserve data for test system with 10 units

Hour	Demand (MW)	Reserve (MW)	Hour	Demand (MW)	Reserve (MW)
1	700	70	**13**	1400	140
2	750	75	**14**	1300	130
3	850	85	**15**	1200	120
4	950	95	**16**	1050	105
5	1000	100	**17**	1000	100
6	1100	110	**18**	1100	110
7	1150	115	**19**	1200	120
8	1200	120	**20**	1400	140
9	1300	130	**21**	1300	130
10	1400	140	**22**	1100	110
11	1450	145	**23**	900	90
12	1500	150	**24**	800	80

Table 7. Parameters for test system with 10 units

	s	*i*	*c1*	*c2*	*wmin*	*wmax*
APSO	20	140	2.4	2.82	0.1	2.81
PSO	2	2	2.5	2	0.1	4.835

Table 8. Results for test system with 10 units

Algorithm	Best Cost	Worst Cost	Average Cost
LR1[9]	565825	N/A	N/A
GA2[12]	565825	570032	-
ES[13]	565827	571312	569199

GA1[12]	565866	571366	567329
PSO	567029	567436	567191.8
LR2[12]	567663	N/A	N/A

5.3. Test System with 20 Units

In the third test system, there are 20 generating units and a time horizon of 24 hours. The data for test system with 20 units is obtained by duplicating the data of 10-unit system and adjusting the load demand in proportion to the system size. The parameters and the comparison results are given in Tables 9 and 10. The computation time is 75 seconds and the best result obtained is $1,134,886.

Table 9. Parameters for test system with 20 units

	s	*I*	*c1*	*c2*	*wmin*	*wmax*
APSO	50	200	2.2	2.6	0.1	2.43
PSO	4	4	2.5	2	0.1	4.41

Table 10. Results for test system with 20 units

Algoritm	Best Cost	Worst Cost	Average Cost
GA2[12]	1126243	1132059	-
GA1[12]	1128876	1131565	1130160
LR2[12]	1129633	N/A	N/A
LR1[9]	1130660	N/A	N/A
PSO	1134886	119163	114453

6. Conclusion

This paper presented a new BPSO-PSO-based algorithm and applied it to the unit commitment problem in power systems. The proposed algorithm integrates the features of swarm intelligence for solving combinational optimization problems. The algorithm is based mainly on the PSO with the use of BPSO to arrange the ON/OFF status of the units and the classical PSO is used for power output estimation and to find an optimal solution for problem. The proposed EPSO is applied to UC problems in 3 test systems. The results of the test systems consisting of 8, 10 and 20 units with both 8-h and 24-h load demands were compared with those of previous works. The simulation results clearly reveal that the proposed EPSO algorithm can be used as a good optimizer in solving UC problems.

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