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Generator scheduling under competitive environment using genetic algorithm

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Abstract

In this paper, genetic algorithm (GA) is used to solve the GENCOs profit based unit commitment problem (PBUCP) in a day-ahead competitive electricity markets considering power and reserve generations simultaneously, whereas enhanced lambda iteration (ELI) method is used to solve the economic dispatch (ED) sub-problem. The proposed algorithm helps GENCO to take decision regarding how much power and reserve must be put up for sale in the markets to receive the maximum profit. Moreover, two types of market strategies based on the demand constraint are discussed and implemented. Performance of GA is tested on 3-unit, 12-h and 10-unit, 24-h test systems. Results demonstrate that the proposed method is superior to the other methods reported in the literature.

Keywords: Competitive electricity market, Economic dispatch, Genetic algorithm, Unit commitment.

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1. Introduction

Modern power systems have been deregulated throughout the world and thus, shift in the operation from monopolistic vertically integrated systems to free and competitive market systems (Shahidehpour *et al.*, 2002). The main goal of deregulation is to create competition among power generation companies (GENCOs) and provide choice to consumers at cheaper price. In the past, electric utilities run unit commitment (UC) and economic dispatch (ED) programs to satisfy the load demand over the complete scheduling time horizon in such a way that the total operating cost is minimum (Singhal and Sharma, 2011), whereas in a deregulated environment, GENCOs schedule their generators with an objective to maximize their own profit without any regard for system social benefit. Therefore, GENCOs have no more an obligation to satisfy the hourly load demand. In this new paradigm, the signal that would enforce units on/off status would be the forecasted energy and ancillary service prices.

Many methods have been proposed in the past to solve the GENCOs profit based unit commitment problem (PBUCP) and mainly classified into three groups. These groups are classical (or mathematical) methods, stochastic (or heuristic) methods and hybrid methods. The mostly used classical methods are dynamic programming (DP) (Pokharel *et al.*, 2005), lagrangian relaxation (LR) method (Singhal, 2011), mixed-integer linear programming (MILP) (Li and Shahidehpour, 2005). Out of these, DP faces a dimensionality problem as the problem size increases. LR suffers from numerical convergence and solution quality problems and MILP requires large memory and suffers from great computational delay for large scale UCP. The frequently used stochastic techniques for PBUCP are classified as genetic algorithm (GA) (Richter Jr. and Sheble, 2000), evolutionary programming (EP) (Hernandez and Maldonado, 2006), muller method (Chandram *et al.*, 2008), ant colony optimization (ACO) (Ketabi *et al.*, 2010), simulated annealing (SA) (Venkatesan and Rajan, 2005), shuffled frog leaping algorithm (SFLA) (Selvakumar *et al.*, 2012), particle swarm optimization (PSO) (Harison and Sreerengaraja, 2013), and artificial bee colony (ABC) algorithm (Govardhan and Roy, 2013). In order to globally optimize the search space of PBUCP, some hybrid methods have been proposed in the past that utilizes the feature of one method to overcome the drawback of another method. Some hybrid methods are GA and artificial immune system (AIS) (Lakshmi and Vasantharathna, 2013), LR and EP (Attaviriyanupap *et al.*, 2003), LR and GA (Yamin and Shahidehpour, 2004).

The GA is a population based search algorithm based on the mechanics of natural selection and genetics. GA has been successfully applied to many non-linear large scale engineering optimization problems and also applied to solve PBUCP (Richter Jr. and Sheble, 2000). But, in (Richter Jr. and Sheble, 2000), only energy (spot) market has been considered and ancillary services have been ignored, whereas in this work, both the energy and reserve markets are considered in problem formulation and implementation phase, which provide options for GENCOs to sell their power in any of the two markets in order to surplus the profit. Here, GA is used to decide the on/off status of the thermal units in each hour of the scheduled time horizon and the power and reserve generation values of the committed units are determined by solving the economic dispatch sub-problem using enhanced lambda iteration (ELI) method adopted from (Singhal *et al.*, 2014).

The rest of this work is organized as follows: Section II presents the profit based unit commitment problem (PBUCP) formulation whereas Section III presents the mapping of GA for PBUCP, Section IV provides the simulation results and their discussions and finally the Section V concludes the paper.

2. Problem Formulation

2.1 Objective function: In a deregulated environment, the main objective of PBUCP is to determine the optimal unit commitment schedule, thereby maximizing GENCOs profit in a day-ahead electricity market by satisfying various system and unit constraints. The problem formulation is given as follows:

$$\text{Maximize } PF = RV - TC \tag{1}$$

There are many types of payment in power market. We have only considered the payment for reserve allocated to calculate the GENCOs revenue (RV) and total operating cost (TC). In this strategy, GENCO receives the reserve price per unit of reserve for each hour that the reserve is allocated and not used. When the reserve is used, GENCO receives the spot (energy) price for the reserve that is generated. In this method, reserve price is much lower than the spot price (Attaviriyanupap *et al.*, 2003). Revenue and costs in (1) can be calculated as follows:

$$RV = \sum_{t=1}^{T}\sum_{i=1}^{N}(P_i^t \cdot SP^t)\cdot U_i^t + \sum_{t=1}^{T}\sum_{i=1}^{N}[(1-r)\cdot RP^t + r\cdot SP^t]\cdot R_i^t \cdot U_i^t \tag{2}$$

$$\text{TC} = \sum_{t=1}^{T}\sum_{i=1}^{N}\Big[(1-r)\cdot F_i(P_i^t) + r\cdot F_i(P_i^t + R_i^t) + (1-U_i^{t-1})\cdot SU_{i,t}\Big]\cdot U_i^t \tag{3}$$

where

$$F_i(P_i^t) = a_i + b_i \times P_i^t + c_i \times (P_i^t)^2 \tag{4}$$

$$SU_{i,t} = \begin{Bmatrix} HS_i,\ if\ \ T_{i,down} \le T_{i,off}^t \le T_{i,down} + T_{i,cold} \\ CS_i,\ if\ \ T_{i,off}^t > T_{i,down} + T_{i,cold} \end{Bmatrix} \tag{5}$$

2.2 Constraints: The various constraints imposed on the PBUCP are as follows:

2.2.1 Power balance constraint:

$$\sum_{i=1}^{N} P_i^t U_i^t \le P_D^t \qquad ;\ t = 1, 2, \ldots, T \tag{6}$$

2.2.2 Spinning reserve constraint:

$$\sum_{i=1}^{N} R_i^t \cdot U_i^t \le SR^t \quad ;\ t = 1, 2, \ldots, T \tag{7}$$

2.2.3 Generation Limit Constraint: Each online unit must be within its specified generation limits as follows:

$$P_i^{\min} U_i^t \le P_i^t \le P_i^{\max} U_i^t \tag{8}$$

2.2.4 Reserve Generation Limit Constraint:

$$0 \leq R_i^t \leq (P_i^{\max} - P_i^t) \cdot U_i^t \tag{9}$$

2.2.5 Minimum Up and Down Time Constraint: A unit must be on/off for a minimum number of hours before committing and decommitting as follows:

$$U_i^t = \begin{cases} 0 \rightarrow 1, \ if \ \ T_{i,off}^{t-1} \geq T_{i,down} \\ 1 \rightarrow 0, \ if \ \ T_{i,on}^{t-1} \geq T_{i,up} \\ 0 \ or \ 1, \ otherwise \end{cases} \tag{10}$$

3. Implementation of GA for Profit Based Unit Commitment Problem (PBUCP)

In this section, the implementation of GA for PBUCP has been presented. The control parameters involved in GA are population size (number of chromosomes), selection mechanism, crossover and mutation probabilities and the maximum number of generations required for obtaining the optimal solution.

3.1 Representation of chromosomes for PBUCP: In PBUCP, the decision variables are binary strings which show the on/off status of the thermal units over the complete scheduling time horizon. If N is the total number of thermal units and T is the complete scheduling time intervals, then a chromosome in a population consist of $N \times T$ binary bits. Each bit in a chromosome represents a gene having 1 or 0 value. A chromosome in a population itself represents an individual solution for PBUCP.

3.2 Population initialization: For complete P chromosomes, each chromosome X_j is randomly initialized as follows

$$X_j = [x_j^1 \ x_j^2 \ldots x_j^d \ldots x_j^n] \ ; \ j \in \{1, 2, \ldots, P\} \ ; d \in \{1, 2, \ldots, n\} \tag{11}$$

3.3 Fitness function evaluation: After generating an initial population, the economic dispatch (ED) has to be performed so as to economically dispatch the load demand in each hour of the scheduling time horizon. In conventional environment, ED is performed to optimally dispatch the load demand among the committed units (Singhal *et al.*, 2015), whereas in a deregulated environment, ED is performed to dispatch the load and reserve demands among the committed units over the complete scheduling time horizon. The enhanced lambda iteration (ELI) algorithm is used to solve the ED sub-problem and then the GENCOs profit is calculated using (1). The fitness of each chromosome is the total generation cost (*TC*) which can be calculated using (1). The chromosome having maximum profit has the highest fitness value in a population.

3.4 Generate trial solutions: In GA, the three basic operators, namely selection, crossover and mutation have been used to update the solutions of PBUCP throughout the generations which are described as below:

3.4.1 Selection: The parent chromosomes are selected based on their fitness values using Roulette wheel selection mechanism. The chromosomes are selected based on the probability proportional to the relative fitness value of the parent genotype within the population. Then, the new offspring genotypes are produced by means of two other genetic operators namely crossover and mutation.

3.4.2 Crossover: The selected parent chromosomes from the current population form a mating pool to produce the new offsprings. The crossover operation is a random process of recombination of parent chromosomes and their bit values is exchanged at the crossover sites based on the crossover probability (p_c) to produce offsprings. These offsprings have the feature of two parent genotypes and thus, may have better fitness. After performing the crossover operation, a new population of offsprings has been formed. In this work, 2-point crossover operator is used.

3.4.3 Mutation: It is used to specify small random changes in population to create mutation children. With a small mutation probability (p_m), randomly chosen bits of the offspring genotypes change from 0 to 1 and vice versa, and thus, introduce the diversity in the solution search space of PBUCP.

3.4.4 Penalty factor: If constraints are not satisfied in any chromosome within the population, then a penalty factor is subtracted from the total profit of that string in order to eliminate that string as soon as possible. In this work, the fixed value of the penalty is chosen as 10,000 for 1st test system and 100,000 for 2nd test system.

In this work, instead of choosing the fixed values of p_c and p_m, the dynamic values are considered that varies linearly throughout the generations from a higher value to the lower value. This process balances the exploration and exploitation process and thus, produces the near global optimal solution.

3.5 Elite strategy: In order to avoid the loosing of the best solutions throughout the iterative process, an elite strategy has been adopted. In this strategy, the parent and offspring chromosomes are first combined together and sorted according to their fitness values. Then, the first 50 % of the best solutions of the combined population are selected as the population for the next generation.

3.6 Procedural steps for PBUCP using GA:

Step 1: Scan the input generation and load data and initialize the GA parameters like population size (*P*), crossover probability (p_c) and mutation probability (p_m) whereas maximum generation count ($g_{\max}$) as a termination criteria.

Step 2: Randomly generate the initial population of *P* chromosomes using (11).

Step 3: Perform ED on feasible chromosomes to determine the power and reserve generation values over the complete scheduling time horizon and then evaluate the fitness function using (1).

Step 4: Select the parent chromosomes from the current population using Roulette wheel selection mechanism.

Step 5: Perform crossover operation on the selected parent chromosomes to generate the offsprings.

Step 6: Perform mutation operation to modify the offsprings.

Step 7: Apply penalty factor to infeasible solutions and then perform ED on feasible offsprings and then evaluate the fitness values of these offsprings.

Step 8: Apply elite mechanism to preserve the best solutions found so far.

Step 9: If the maximum number of generations ($g_{\max}$) are not reached then go to step 4, otherwise stop the procedure and print the optimal generation schedule.

4. Simulation Results

To demonstrate the feasibility and effectiveness of the proposed GA for PBUCP, GA is applied to 2 test systems comprising of 3-unit and 10-units over the scheduled time intervals of 12-hour and 24-hour respectively. The fuel cost function is considered quadratic in nature as in (4) for both the systems. The simulation is performed on Intel core2duo, 2.20 GHz processor PC and written in MATLAB 7.9.

4.1 Test system 1: This test system comprises of 3 thermal units over the scheduled time horizon of 12 hours with 1-h time interval. The unit data, forecasted load, reserve and spot prices are adopted from (Attaviriyanupap *et al.*, 2003) and shown in Tables 1 and 2 respectively. For this system, the population size was kept 10 and the maximum generation count was kept 100. The crossover and mutation probabilities were kept 0.7 and 0.01 respectively. The effects of probability that the reserve is called & generated (*r*) and the reserve price (RP^t) are investigated and the obtained results are presented in Table 3. Here, two cases based on the load demand are considered. In first case, the load demand is completely satisfied, whereas in the second case, load demand need not to be satisfied. Firstly, the reserve price (RP^t) is kept fixed at 0.1 times the spot price when *r* is varied. Secondly, the value of *r* is kept fixed at 0.005 when reserve price is varied. Since, the reserve is paid in each hour either it is used or not in the considered payment method and therefore, the profit is more sensitive when RP^t is varied.

Table 1. Unit data for 3-unit system (Attaviriyanupap *et al.*, 2003)

	Unit 1	Unit 2	Unit 3
$P_i^{\max}$ (MW)	600	400	200
$P_i^{\min}$ (MW)	100	100	50
a_i ($/h)	500	300	100
b_i ($/MWh)	10	8	6
c_i ($/MW^{2}h)	0.002	0.0025	0.005
INS_i (h)	-3	3	3
$T_{i,up}$ (h)	3	3	3
$T_{i,down}$ (h)	3	3	3
SU ($)	450	400	300

Table 2. Forecasted load, reserve and spot prices 3-unit, 12-h system (Attaviriyanupap *et al.*, 2003)

T	P_D^t (MW)	SR^t (MW)	SP^t ($/MW-h)	T	P_D^t (MW)	SR^t (MW)	SP^t ($/MW-h)
1	170	20	10.55	7	1100	100	11.30
2	250	25	10.35	8	800	80	10.65
3	400	40	9.00	9	650	65	10.35
4	520	55	9.45	10	330	35	11.20
5	700	70	10.00	11	400	40	10.75
6	1050	95	11.25	12	550	55	10.60

Table 3. Effect of r and reserve price (RP^t) for 3-Unit System

Effect of r			Effect of reserve price		
r	With demand satisfaction	With GENCOs profit	RP^t (times of spot price)	With demand satisfaction	With GENCOs profit
	Profit ($)	Profit ($)		Profit ($)	Profit ($)
0.005	4761.61	9213.23	0.02	4190.23	9088.82
0.015	4762.84	9214.11	0.04	4333.08	9119.92
0.025	4763.15	9214.97	0.06	4475.92	9151.02
0.035	4764.73	9215.85	0.08	4618.76	9182.13
0.045	4765.42	9216.72	0.10	4761.61	9213.23

The optimal power and reserve generation schedule is presented in Table 4. From Table 4, it is observed that the GENCOs choose to off unit 1 in each hour in order to surplus the profit. Moreover, the GENCOs profit is increased by almost 2 times when load is not necessary to satisfy in each hour. The comparison of obtained GENCOs total profit using GA is compared with other methods reported in literature and presented in Table 5. From Table 5, it is deduced that the proposed GA has produced quality solution in less execution time.

Table 4. Optimum power and reserve generation schedule of 3-unit system using GA (r = 0.005, reserve price = 0.1 $\times$ spot price)

T	Traditional unit commitment						Profit based unit commitment					
	Power (MW)			Reserve (MW)			Power (MW)			Reserve (MW)		
	U1	U2	U3	U1	U2	U3	U1	U 2	U 3	U1	U2	U3
1	0	100	70	0	0	20	0	0	170	0	0	20
3	0	100	150	0	0	25	0	0	200	0	0	0
3	0	200	200	0	40	0	0	0	200	0	0	0
4	0	320	200	0	55	0	0	0	200	0	0	0
5	100	400	200	70	0	0	0	400	200	0	0	0
6	450	400	200	95	0	0	0	400	200	0	0	0
7	500	400	200	100	0	0	0	400	200	0	0	0
8	200	400	200	80	0	0	0	400	200	0	0	0
9	100	350	200	15	50	0	0	400	200	0	0	0
10	130	0	200	35	0	0	0	130	200	0	35	0
11	200	0	200	40	0	0	0	200	200	0	40	0
12	350	0	200	55	0	0	0	350	200	0	50	0
Total profit in 12 hours = $ 4,761.61							Total profit in 12 hours = $ 9,213.23					

Table 5. Comparison in terms of cost ($) and CPU time (s)

Method	Profit ($)	CPU time (s)
Muller (Chandram *et al.*, 2008)	9030.5	0.078
LR-EP (Attaviriyanupap *et al.*, 2003)	9136	-
GA	9213.23	0.023

4.2 Test system 2: This test system comprises of 10 thermal units over the scheduling time horizon of 24 hours with 1-h time interval. The unit data, forecasted load and spot prices are adopted from (Attaviriyanupap *et al.*, 2003) and presented in Tables 6 and 7 respectively. The spinning reserve is considered as 10 % of the hourly load demand. For this system, the population size was kept 20 and the maximum generation count was kept 100. The range for crossover probability was kept 0.4 to 0.9 (per genotype) and the range for mutation probability was kept 0.005 to 0.025 (per bit).

Table 6. Unit data for 10-unit system (Attaviriyanupap *et al.*, 2003)

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
P_i^{max} (MW)	455	455	130	130	162
P_i^{min} (MW)	150	150	20	20	25
a_i (\$/h)	1000	970	700	680	450
b_i (\$/MWh)	16.19	17.26	16.60	16.50	19.70
c_i (\$/MW^{2}h)	0.00048	0.00031	0.00200	0.00211	0.00398
INS_i (h)	8	8	-5	-5	-6
$T_{i,up}$ (h)	8	8	5	5	6
$T_{i,down}$ (h)	8	8	5	5	6
SU (\$)	4500	5000	550	560	900
$T_{i,cold}$ (h)	5	5	4	4	4
	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P_i^{max} (MW)	80	85	55	55	55
P_i^{min} (MW)	20	25	10	10	10
a_i (\$/h)	370	480	660	665	670
b_i (\$/MWh)	22.26	27.74	25.92	27.27	27.79
c_i (\$/MW^{2}h)	0.00712	0.00079	0.00413	0.00222	0.00173
INS_i (h)	-3	-3	-1	-1	-1
$T_{i,up}$ (h)	3	3	1	1	1
$T_{i,down}$ (h)	3	3	1	1	1
SU (\$)	170	260	30	30	30
$T_{i,cold}$ (h)	2	2	0	0	0

Table 7. Forecasted load and spot prices for 10-unit, 24 hour system (Attaviriyanupap *et al.*, 2003)

T	P_D^t (MW)	SP^t (\$/MW-h)	T	P_D^t (MW)	SP^t (\$/MW-h)
1	700	22.15	13	1400	24.60
2	750	22.00	14	1300	24.50
3	850	23.10	15	1200	22.50
4	950	22.65	16	1050	22.30
5	1000	23.25	17	1000	22.25
6	1100	22.95	18	1100	22.05
7	1150	22.50	19	1200	22.20
8	1200	22.15	20	1400	22.65
9	1300	22.80	21	1300	23.10
10	1400	29.35	22	1100	22.95
11	1450	30.15	23	900	22.75
12	1500	31.65	24	800	22.55

When premature convergence was observed, the crossover probability was lowered by 0.1 while the mutation probability (per bit) is increased by 0.005. When excessive diversity occurs, the crossover probability is increased by 0.1 while the mutation probability is lowered by 0.005. Figure 1 shows the convergence graph of GA for PBUCP and it is revealed that the GA steadily reaches the optimal solution in less iteration. Figure 2 illustrates the curves for revenue, total operating cost and profit in each hour and it is observed that the GENCO succeeded to make profit in each hour.

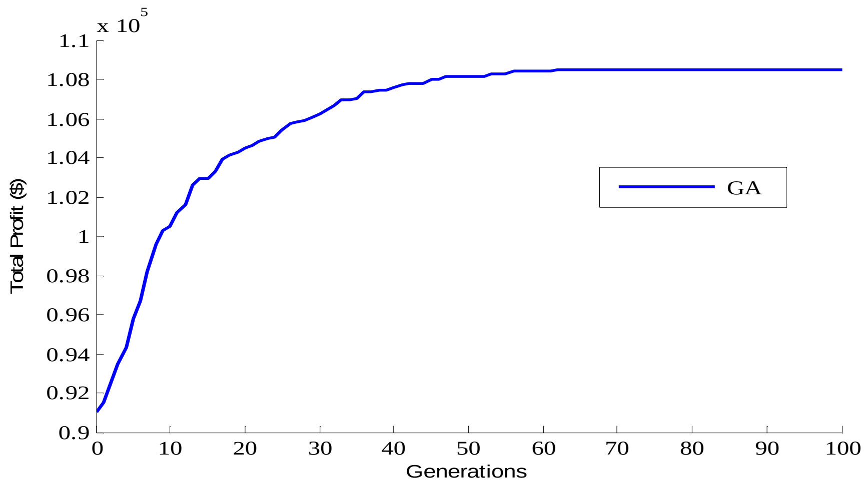

Figure 1. Convergence characteristics of PBUCP using GA for 10-unit system

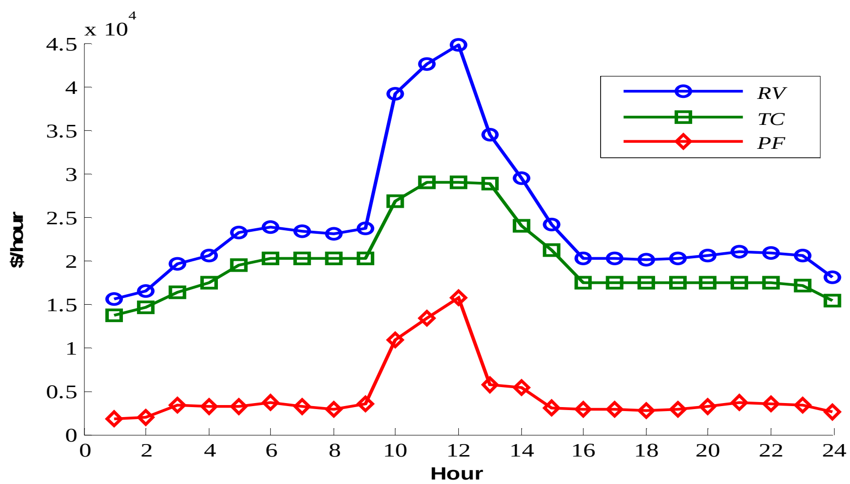

Figure 2. Revenue, total operating cost and profit in dollars for 10-unit system

Table VIII shows the comparison of GA solution with the other methods reported in the literature like muller method, hybrids of artificial immune system and genetic algorithm (AIS-GA) and lagrangian relaxation and evolutionary programming (LR-EP). From Table VIII, it is revealed that GA produces quality solution in terms of total profit compared to other methods. Since no information regarding execution time was available in the mentioned methods and thus, can't be compared.

Table 8. Performance comparison of proposed GA with other methods for 10-unit system

Method	Profit ($)	CPU time (s)
Muller (Chandram *et al.*, 2008)	103,296	-
AIS-GA (Lakshmi and Vasantharathna, 2013)	107,316.11	-
LR-EP (Attaviriyanupap *et al.*, 2003)	107,838.57	-
GA	108,483.15	15.75

4. Conclusions

In this paper, the genetic algorithm (GA) is successfully implemented to solve the GENCOs profit based unit commitment problem (PBUCP) for 3-unit and 10-unit test systems over the scheduling time horizon of 12 hours and 24 hours respectively, and an enhanced lambda iteration (ELI) method is used to solve the economic dispatch (ED) sub-problem. Both the energy and reserve markets are considered simultaneously and thus provide more flexible PBUCP schedules. Two strategies based on the demand constraint have been simulated and discussed. The simulation results obtained with the proposed GA have been compared with the existing methods and it is deduced that the proposed GA has provided the maximum GENCOs profit in reasonable execution time.

Nomenclature

a_i, b_i, c_i	Fuel cost coefficients of i^{th} unit
CS_i	Cold start-up cost of i^{th} unit in $
d	index for dimension of a chromosome
$F_i(P_i^t)$	Quadratic fuel cost function representing production cost of i^{th} unit at hour t in $
HS_i	Hot start-up cost of i^{th} unit in $
j	index for chromosome in a population
n	Total number of binary variables equals to $N \times T$ bits
N	Number of thermal units
P	Population size
P_D^t	Load demand at hour t in MW
P_i^t	Real power generation of i^{th} unit at hour t in MW
$P_i^{\min}$	Minimum power generation capacity of i^{th} unit in MW
$P_i^{\max}$	Maximum power generation capacity of i^{th} unit in MW
r	Probability that the reserve is called and generated
R_i^t	Reserve allocated at the output of i^{th} unit at hour t in MW
RP^t	Forecasted reserve price in $
SP^t	Forecasted spot price in $
SR^t	System reserve at hour t in MW
$SU_{i,t}$	Start-up cost of i^{th} unit at hour t in $
T	Number of scheduling time intervals in hours
$T_{i,down}$	Minimum-down time of i^{th} unit in hours
$T_{i,off}^t$	Continuously-off time of i^{th} unit till time t in hours
$T_{i,cold}$	Cold start-up time of i^{th} unit in hours
$T_{i,up}$	Minimum-up time of i^{th} unit in hours
$T_{i,on}^{t-1}$	Continuously-on time of i^{th} unit till time (t-1) in hours
U_i^t	On/Off status of i^{th} unit at hour t ($1 \rightarrow on$, $0 \rightarrow off$)

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