

Solution of Unit Commitment Problem Using Enhanced Genetic Algorithm

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Abstract—In this paper, enhanced genetic algorithm (EGA) is used to solve the short-term unit commitment problem (UCP) and the enhanced lambda iteration (ELI) method is used to solve the economic dispatch (ED) sub-problem. Based on EGA, the problem specific operators have been integrated in the simple GA algorithm and thus, enhanced the quality of the solution. Performance of EGA is tested on 2 test systems comprising of 4-unit and 10-unit over the scheduling time horizon of 8 hours and 24 hours respectively. Results demonstrate that the proposed method is superior to the other reported methods in the literature.

Keywords—economic dispatch; genetic algorithm; unit commitment

I. INTRODUCTION

Unit Commitment Problem (UCP) is one of the most important optimization task which has to be performed by power engineers in a daily operation planning of power systems so that obtained generation schedule results in a great savings of dollars for power generation companies especially in a deregulated environment where each GENCO runs its own generator in order to obtain more profit. Since the load demand varies throughout the day and reaches to a different peak values from one day to another and thus, the total power generation can't be kept constant [1]. The main objective of conventional UCP is to minimize the total generation cost (operating fuel cost, start-up and shutdown costs) over the scheduling time horizon of 24-h or 168-h with 1-h time interval subject to the number of system (or coupling) and unit (or local) constraints.

Many optimization techniques have been proposed in the past to solve the UCP and mainly classified into three groups. These groups are classical (or mathematical) techniques, stochastic (or heuristic) techniques and hybrid techniques. The mostly used mathematical techniques are priority list (PL) method [2], dynamic programming (DP) [3], branch-and-bound (BB) method [4], mixed-integer linear programming (MILP) [5] and lagrangian relaxation (LR) method [6]. Out of which, PL method is fast but produces sub-optimal solution. DP faces dimensionality problem as the problem size increases. MILP requires large memory and suffers from great computation delay for large scale UCP. LR suffers from numerical convergence and solution quality problems. Although the solution produced by mathematical techniques is

accurate and optimal, but requires large computation time even for medium sized UCP. The stochastic techniques are highly heuristic in nature and mainly classified as simulated annealing (SA) [7], evolutionary programming (EP) [8], genetic algorithm (GA) [9,10], particle swarm optimization (PSO) [11], differential evolution (DE) [12], bacterial foraging algorithm (BFA) [13], imperialistic competition algorithm (ICA) [14], harmony search algorithm (HSA) [15] and artificial bee colony algorithm (ABC) [16]. Since these techniques are parameter sensitive and thus, require proper tuning in order to obtain the near global optimal solution in least execution time. Improper tuning of these parameters results in premature or slow convergence which may lead the solution to local optimum. Some hybrids of the methods have been also proposed in the past which utilizes the feature of one method to overcome the drawback of another method. The mainly consist hybrid methods are GA and LR [17], GA and tabu search (TS) [18], artificial neural network (ANN) and DP [19]. The hybridization reduces the search space for large scale UCP and thereby, reduces the execution time.

The GA is a population based search algorithm based on the mechanics of natural selection and genetics [9]. GA has been successfully applied to many non-linear large scale engineering optimization problems. In this work, enhanced GA (EGA) is used to decide the ON/OFF status of the thermal units in each hour of the scheduling time horizon and the power generation values of the committed units are determined by solving the economic dispatch sub-problem using enhanced lambda iteration (ELI) method adopted from [20]. Moreover, the performance of EGA for UCP has been enhanced by integrating the problem specific operators to the simple GA algorithm.

The rest of the work is organized as follows: Section II presents the unit commitment (UC) problem formulation, Section III presents the mapping of EGA for UCP, Section IV provides the simulation results and their discussions and finally Section V concludes the paper.

II. PROBLEM FORMULATION

A. Objective Function

The main objective of UCP is to determine the optimum ON/OFF schedule so as to minimize the total generation cost

(TC) over the scheduling time horizon of 24-h with 1-h time interval by satisfying various system and unit constraints. Mathematically the problem to be minimized [2] is

$$TC = \sum_{t=1}^T \sum_{i=1}^N [F_i(P_i^t) + SU_{i,t}(1-U_i^{t-1})] \times U_i^t \quad (1)$$

where

$$F_i(P_i^t) = a_i + b_i \times P_i^t + c_i \times (P_i^t)^2 \quad (2)$$

$$SU_{i,t} = \begin{cases} HS_i, & \text{if } T_{i,down} \leq T_{i,off}^t \leq T_{i,down} + T_{i,cold} \\ CS_i, & \text{if } T_{i,off}^t > T_{i,down} + T_{i,cold} \end{cases} \quad (3)$$

where $F_i(P_i^t)$ is the quadratic fuel cost function representing production cost of i^{th} unit at hour t in S/h, a_i , b_i and c_i are the fuel cost coefficients of i^{th} unit, P_i^t is the real power generation of i^{th} unit at hour t in MW, $SU_{i,t}$ is the start-up cost of i^{th} unit at hour t in S/h, HS_i and CS_i are the hot and cold start-up costs of i^{th} unit in S/h respectively, U_i^t is the ON/OFF status of i^{th} unit at hour t ($1 \rightarrow on$, $0 \rightarrow off$), N is the number of thermal units, T is the number of scheduling time intervals in hours, $T_{i,down}$ is the minimum-down time of i^{th} unit in hours, $T_{i,off}^t$ is the continuously-off time of i^{th} unit till time t in hours, $T_{i,cold}$ is the cold start-up time of i^{th} unit in hours.

B. Constraints

The various system and unit constraints imposed on the system are:

- 1) *Power balance constraint*: The generated power must be equal to the load demand as follows

$$\sum_{i=1}^N P_i^t U_i^t - P_D^t = 0 \quad (4)$$

where P_D^t is the load demand at hour t in MW.

- 2) *Spinning reserve constraint*: System spinning reserve is expressed as excess power generation as follows

$$\sum_{i=1}^N P_i^{\max} U_i^t \geq P_D^t + R^t \quad (5)$$

where P_i^{\max} is the maximum power generation capacity of i^{th} unit in MW, R^t is the system spinning reserve at hour t in MW.

- 3) *Generation limit constraint*: Each committed unit must be within its specified generation limits as follows

$$P_i^{\min} U_i^t \leq P_i^t \leq P_i^{\max} U_i^t \quad (6)$$

where P_i^{\min} is the minimum power generation capacity of i^{th} unit in MW

- 4) *Minimum up and down time constraint*: A unit must be on/off for a minimum number of hours before committing and decommitting as follows

$$U_i^t = \begin{cases} 0 \rightarrow 1, & \text{if } T_{i,off}^{t-1} \geq T_{i,down} \\ 1 \rightarrow 0, & \text{if } T_{i,on}^{t-1} \geq T_{i,up} \\ 0 \text{ or } 1, & \text{otherwise} \end{cases} \quad (7)$$

where $T_{i,up}$ is the minimum-up time of i^{th} unit in hours, $T_{i,on}^{t-1}$ is the continuously ON time of i^{th} unit till hour $(t-1)$ in hours.

III. ENHANCED GENETIC ALGORITHM (EGA) FOR UNIT COMMITMENT PROBLEM (UCP)

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

A. Representation of Chromosomes for UCP

In UCP, 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 binary values. A chromosome in a population itself represents an individual solution for UCP.

B. Population Initialization

For the complete N_p chromosomes, each chromosome X_j is randomly initialized as follows

$$X_j = [x_j^1 \ x_j^2 \dots x_j^d \dots x_j^n]; j \in \{1, 2, \dots, N_p\}; d \in \{1, 2, \dots, n\} \quad (8)$$

where j represents the chromosome in a population, d represents the dimension of a chromosome, n represents the total number of binary variables equals to $N \times T$ binary bits and N_p is the population size (number of chromosomes). The position of x_j^d is generated using a uniformly distributed random number, which generates either 0 or 1 and they are equally likely.

C. Fitness Function Evaluation

After generating the initial population, the economic dispatch (ED) has to be performed only on feasible chromosomes so as to economically dispatch the load demand in each hour of the scheduling time horizon. The enhanced lambda iteration (ELI) algorithm is used to solve the ED sub-problem and then the production cost can be calculated using (2). The fitness of each chromosome is the total generation cost (TC) which can be calculated using (1). The chromosome having least TC has the highest fitness value.

D. Generate trial solutions

In simple GA, the three basic operators viz. selection, crossover and mutation have been used to update the solution

of UCP throughout the generations whereas in EGA three more operators are proposed which are described as below:

- 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 parent genotype relative fitness within the population. Then, the new offspring genotypes are produced by means of two other genetic operators namely crossover and mutation.
- 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 are 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 have been formed.
- 3) *Mutation*: Mutation introduces new genetic material into the gene at some low rate. 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.
- 4) *Swap Window Operator*: This operator is applied to every genotype of the population with a probability of 0.2. The two units, a time window of width w (hours) and a random window position between $1, 2, \dots, T$ scheduling intervals are arbitrary selected from a genotype. The bits of the two selected units included in the window are exchanged and thus, a new offspring is formed. If a new offspring is better than the current one then the new one is selected else the old one is restored. This operator acts like a sophisticated mutation operator.
- 5) *Window mutation operator*: This operator is also applied to all the genotypes of the population with a probability of 0.2. In this operator, only one unit is randomly selected with time window of width w (hours) and a random window position between $1, 2, \dots, T$ scheduling intervals. Then, all the bits of that unit lie within the time window are flipped from 1 to 0 and vice-versa. This operator act as a multi-point mutation operator.
- 6) *Swap mutation operator*: This operator is applied only to the so-far found global best chromosome within the current population. The two units are randomly selected and their bits are exchanged for a specific hour i.e. their ON/OFF status is exchanged. If a better solution is obtained then the solution is kept otherwise it is restored to its old solution. This operator resembles the stochastic hill climbing method.

The above mentioned three advanced mutation operators worked simultaneously to generate the offsprings based on the two target probabilities $0 \leq p_{t1} \leq p_{t2} \leq 1$. If a uniformly

distributed random number $rand(0,1) \leq p_{t1}$ then, a swap window operator is to be performed else if $rand(0,1) \geq p_{t2}$ then, a swap mutation operator is to be performed else if $p_{t1} < rand(0,1) < p_{t2}$ then, a window mutation operator is to be performed. This will balance the exploration and exploitation process and thus, produce the near global optimal solution.

E. Repairing Infeasible Solutions

When the solution is randomly initialized and whenever the modification in the solution is made throughout the search process, the infeasible solutions have to be repaired in order to improve the solution quality at faster rate. The constraints in (5) and (7) have been repaired based on the strategies adopted from [11].

F. Elite Strategy

In order to avoid the losing of best solutions throughout the search process, an elite strategy has been adopted from [13]. 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.

G. Procedural Steps for UCP using EGA

The step by step procedure to solve the UCP using EGA is as follows:

- Step 1: Initialize EGA parameters like N_p, p_c, p_m, p_{t1} and p_{t2} and maximum generations (g_{max}) as termination criteria.
- Step 2: Randomly generate the N_p chromosomes by satisfying all the constraints from (4) to (7) with the structure shown in (8).
- Step 3: Perform ED on feasible chromosomes in order to determine the power generation values over the complete scheduling time horizon and then calculate the production cost of each unit in each hour using (2).
- Step 4: Evaluate the fitness function as in (1).
- Step 5: Select the parent chromosomes from the current population using Roulette wheel selection mechanism.
- Step 6: Perform 1-point crossover operation on the selected parent chromosomes to generate the offsprings.
- Step 7: Perform advanced mutation operators explained in previous section to modify the offsprings.
- Step 8: Repair infeasible solutions and then perform ED on the feasible offsprings to calculate the total production cost and then evaluate the fitness values of these offsprings.
- Step 9: Apply elite mechanism to preserve the best solutions found so far.

Step 10: If maximum number of generations (g_{\max}) are not reached then go to step 5, otherwise stop the procedure and print the optimal generation schedule.

IV. SIMULATION RESULTS

To demonstrate the feasibility and effectiveness of the proposed EGA method for UCP, EGA is applied to two test systems comprising of 4-unit and 10-units over the scheduling time intervals of 8-hour and 24-hour respectively. The spinning reserve is considered as 10 % of the total load demand in each hour of the scheduling time horizon and thus, reduced the probability of load interruptions [7]. The simulation is performed on Intel core2duo, 2.20 GHz processor PC and written in MATLAB 7.9.

A. Test System 1

This test system comprises of 4 thermal units over the scheduling time horizon of 8 hours with 1-h time interval. The cost characteristics and load demand are adopted from [1] and mentioned in Tables I and II 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 0.015 respectively. The range of two target probabilities are [0,1]. The best UC schedule along with the dispatch values, production cost (P_{cost}), start-up cost (SU) and total generation cost (TC) are listed in Table III. From Table III, it can be deduced that the obtained UC schedule has satisfied all the problem constraints and thus, produces the quality solution. Also, the total online capacity of generators in each hour of the scheduling time horizon is more than the load plus spinning reserve requirements. The same problem was also solved with GA and compared with EGA and the results are presented in Table IV which also presents the comparison of obtained results with that of LR. Since, it is a small system comprising of 4 thermal units, best cost was also achieved by GA but a marginal difference was found in CPU time.

TABLE I. UNIT CHARACTERISTICS FOR 4-UNIT SYSTEM [1]

	Unit 1	Unit 2	Unit 3	Unit 4
P_i^{\max} (MW)	80	250	300	60
P_i^{\min} (MW)	25	60	75	20
a_i (\$/h)	213.00	585.62	684.74	252.00
b_i (\$/MWh)	20.875	17.998	17.458	23.800
c_i (\$/MW ² h)	0.00396	0.00261	0.00289	0.0051
INS_i (h)	-5	8	8	-6
$T_{i,up}$ (h)	4	5	5	1
$T_{i,down}$ (h)	2	3	4	1
HS_i (\$)	150	170	500	0
CS_i (\$)	350	400	1100	0.02
$T_{i,cold}$ (h)	4	5	5	0

TABLE II. LOAD PATTERN FOR 4-UNIT SYSTEM [1]

Hour (h)	1	2	3	4	5	6	7	8
Load (MW)	450	530	600	540	400	280	290	500

TABLE III. OPTIMAL GENERATION SCHEDULE FOR 4-UNIT SYSTEM

T	Dispatch Values (MW)				P_{cost} (\$)	SU (\$)	TC (\$)
	U1	U2	U3	U4			
1	25	174.23	250.77	0	9782.53	150	9932.53
2	25	216.27	288.73	0	11303.69	0	11303.69
3	30	250	300	20	13003.46	0.02	13003.48
4	25	221.52	293.48	0	11495.29	0	11495.29
5	0	161.09	238.91	0	8573.23	0	8573.23
6	0	98.03	181.97	0	6332.32	0	6332.32
7	0	103.29	186.71	0	6517.54	0	6517.54
8	0	213.63	286.37	0	10470.83	0	10470.83
Total generation cost in 8-h (\$)					77,478.89	150.02	77,628.91

TABLE IV. COMPARISON IN TERMS OF COST (\$) AND CPU TIME (S)

Method	Cost (\$)	CPU time (S)
LR [6]	76,975.33	2.5
GA	77,628.91	3.96
EGA	77,628.91	3.62

B. 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 cost characteristics and load demand are adopted from [14] and presented in Tables V and VI respectively. In order to fine tune the EGA parameters, the simulation was repeated for 10 random trials. In each trial, the population size was kept 30 to show the effect of small population size and the maximum number of generations was kept 100, in order to reduce the computational efforts.

TABLE V. UNIT CHARACTERISTICS FOR 10-UNIT SYSTEM [14]

	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
HS_i (\$)	4500	5000	550	560	900
CS_i (\$)	9000	10000	1100	1120	1800
$T_{i,cold}$ (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
HS_i (\$)	170	260	30	30	30
CS_i (\$)	340	520	60	60	60
$T_{i,cold}$ (h)	2	2	0	0	0

TABLE VI. LOAD PATTERN FOR 10-UNIT SYSTEM [14]

Hour (h)	Load (MW)	Hour (h)	Load (MW)	Hour (h)	Load (MW)
1	700	9	1300	17	1000
2	750	10	1400	18	1100
3	850	11	1450	19	1200
4	950	12	1500	20	1400
5	1000	13	1400	21	1300
6	1100	14	1300	22	1100
7	1150	15	1200	23	900
8	1200	16	1050	24	800

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). When pre-mature convergence was observed, the crossover probability was lowered by 0.1 while mutation probability (per bit) is increased by 0.005. When excessive diversity occurs, the crossover probability is increased by 0.1 while mutation probability is lowered by 0.005. The two target probabilities range from 0 to 1.

TABLE VII. OPTIMAL GENERATION SCHEDULE FOR 10-UNIT SYSTEM

T	Generating Unit									
	1	2	3	4	5	6	7	8	9	10
1	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0
3	455	370	0	0	25	0	0	0	0	0
4	455	455	0	0	40	0	0	0	0	0
5	455	390	0	130	25	0	0	0	0	0
6	455	360	130	130	25	0	0	0	0	0
7	455	410	130	130	25	0	0	0	0	0
8	455	455	130	130	30	0	0	0	0	0
9	455	455	130	130	85	20	25	0	0	0
10	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	85	20	25	0	0	0
15	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0
20	455	455	130	130	162	33	25	10	0	0
21	455	455	130	130	85	20	25	0	0	0
22	455	455	0	0	145	20	25	0	0	0
23	455	425	0	0	0	20	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0

TABLE VIII. BEST COST SOLUTION FOR 10-UNIT SYSTEM

T	P_{cost} (\$/h)	SU (\$/h)	TC (\$/h)	T	P_{cost} (\$/h)	SU (\$/h)	TC (\$/h)
1	13683	0	13683	13	30058	0	30058
2	14555	0	14555	14	27251	0	27251
3	16809	900	17709	15	24150	0	24150
4	18598	0	18598	16	21514	0	21514
5	20020	560	20580	17	20642	0	20642
6	22387	1100	23487	18	22387	0	22387
7	23262	0	23262	19	24150	0	24150
8	24150	0	24150	20	30058	490	30548
9	27251	860	28111	21	27251	0	27251
10	30058	60	30118	22	22736	0	22736
11	31916	60	31976	23	17645	0	17645
12	33890	60	33950	24	15427	0	15427
Total generation cost in 24-h (\$)					559,848	4090	563,938

^a All decimals are rounded off to the nearest integers.

The simulation was again repeated 20 times on the best found parameters mentioned above. The best generation schedule obtained in a set of 20 independent runs is presented in Table VII whereas Table VIII shows the cost solution comprising of production cost (P_{cost}), start-up cost (SU) and total generation cost (TC) obtained on the best generation schedule mentioned in Table VII. From Table VII, it can be inferred that the obtained UC schedule has satisfied all the problem constraints imposed on the system and thus, produces the quality solution. Fig. 1 shows the convergence graph for simple GA and EGA for UCP and it is revealed that the quality of the solution has been enhanced by integrating the problem specific operators in simple GA. Fig. 2 shows the curves for total online capacity of units, load and spinning reserves and it is inferred that the sufficient amount of generation is available in each hour which can satisfy the load plus reserve requirements.

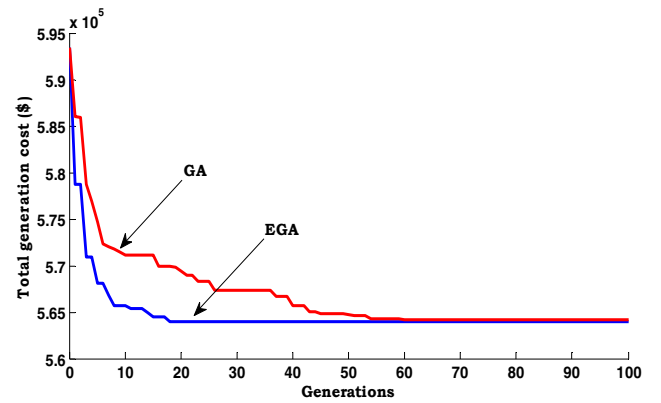


Fig. 1. Convergence characteristics of EGA and GA for 10-unit system.

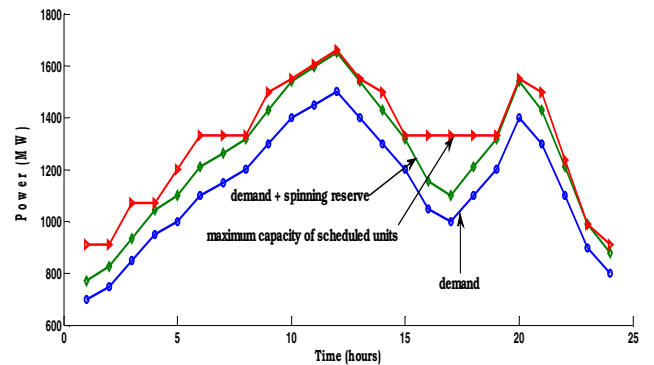


Fig. 2. Online capacity, load and spinning reserve curves for 10-unit system.

Table IX shows the comparison of EGA solution with the other classical and stochastic methods reported in the literature like enhanced priority list (EPL), lagrangian relaxation (LR), simulated annealing (SA), evolutionary programming (EP), improved binary particle swarm optimization (IBPSO), differential evolution (DE), bacterial foraging algorithm (BFA), imperialistic competition algorithm (ICA), harmony search algorithm (HSA), binary/real artificial bee colony algorithm (BRABC), hybrid of LR and GA (LRGA). From

Table IX, it is revealed that EGA produces quality solution in terms of total generation cost compared to most of the methods. Although the BRABC method produces approximately the same best cost solution, but computationally slow compared to the proposed EGA method. Moreover, the CPU time taken by EPL, LR and SA are less than that of EGA, but produce sub-optimal cost solutions compared to the proposed EGA method.

TABLE IX. PERFORMANCE COMPARISON OF PROPOSED EGA WITH THE OTHER METHODS FOR 10-UNIT SYSTEM

Method	Best Cost (\$)	Mean Cost (\$)	Worst Cost (\$)	Time (s)
EPL [2]	563,977	-	-	0.72
LR [6]	565,673.13	-	-	6.9
SA [7]	565,828	565,988	566,260	3.35
EP [8]	564,551	565,352	566,231	100
IBPSO [11]	563,977	564,155	565,312	27
DE [12]	563,938	-	-	27.4
BFA [13]	564,842	-	-	110
ICA [14]	563,938	564,408	-	48
HSA [15]	565,827	-	-	79
BRABC [16]	563,937.72	564,040	565,640	40.75
LRGA [17]	564,800	-	-	518
GA	564,217.08	564,377.21	564,878.96	31.11
EGA	563,937.57	564,082.12	564,248.22	14.56

V. CONCLUSIONS

In this paper, enhanced genetic algorithm (EGA) is successfully implemented to solve the unit commitment problem (UCP) for 4-unit and 10-unit test systems over the scheduling time horizon of 8 hours and 24 hours respectively and enhanced lambda iteration (ELI) method is used to solve the economic dispatch (ED) sub-problem. In order to enhance the exploration and exploitation process of the search space, the problem specific operators are integrated with the simple GA and thereby, reduced the chance of search to be trapped at local optimum solution. Moreover, the constraint repairing strategies keep the search space feasible and thus, accelerate the convergence process. The obtained results demonstrate the robustness of the proposed EGA algorithm for UCP.

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