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IMPLEMENTATION OF GENETIC ALGORITHM FOR OPTIMAL UNIT COMMITMENT IN A POWER SYSTEM

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Abstract: The Genetic Algorithms (GA) are general optimization techniques based on principle inspired from the biological evolution. A simple GA algorithm implementation using the standard crossover and mutation operator could locate near optimal solutions but it most cases failed to converge to optimal solution. However, using the varying quality function techniques and adding problem specific operators, satisfactory solution was obtained. Test result, for systems of up to 100 units and comparisons with result obtained using Lagrangian relaxation and Dynamic programming are also reported. In this research, a genetic algorithm was applied to the unit commitment scheduling problem. A genetic It is hoped that the concurrent processing will enable the algorithm to operate within the needed response time of an electric utility power broker. The goal of this research is to determine if a genetic algorithm can be implemented to find good unit commitment schedules.
Keywords: Unit Commitment, Genetic Algorithm, Optimization, Load Forecast, Unit Scheduling.

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. The unit commitment problem in a power system involves determining the startup and shut down schedules of the thermal units to be used to meet forecasted demand over a future short-term period. The objective is to minimize total production cost while observing a large set of operating constraints. To solve the unit commitment problem the optimization methods are in the form of Lagrange relaxation (LR) and Dynamic programming (DP). The Dynamic programming and Lagrangianrelaxation have been used extensively to develop industry gradeunit commitment programs.These problems are defined mathematically as a non-linear, non-convex, large scaled, mixed integer combinatorial optimization problem after involving thousands of 0-1 decision values as well as continuous variables and a wide spectrum of equality and un-equality constraints. The optimal solution of such a complex combinatorial optimization problem can be obtained only by a global such techniques. The solution to the UCP is given as a set of binary decision variable assignments showing which generator units are online and which are offline for any given time slot. This solution is obtained through minimizing a cost objective while adhering to several constraints. Therefore, this problem can be seen as a search for feasible solutions which optimize an objective. It introduces genetic algorithms (GA) as a complete entity, in which knowledge of this emerging technology can be integrated together to form the framework of a design tool for industrial engineers (1), the aim of finding a general method for solving the unit commitment (UC) problem. The proposed algorithm employs the evolutionary programming (EP) technique in which populations of contending solutions are evolved through random changes, competition, and selection (2), new simulated annealing (SA) algorithm combined with a dynamic economic dispatch method has been developed for solving the short-term unit commitment (UC) problem. SA is used for the scheduling of the generating units, while a dynamic economic dispatch method is applied incorporating the ramp rate constraints in the solution of the UC problem (3), the unit commitment (UC) problem is one of the most difficult optimization problems in power system, because this problem has many variables and constraints. The objective is the minimization of the total production cost over the scheduling horizon while the constraints must be satisfied (4), a new approach via a new evolutionary algorithm known as imperialistic competition algorithm (ICA) to solve the unit commitment (UC) problem. In ICA the initial population individuals (countries) are in two types: imperialists and colonies that all together form some empires (5), a two layer approach to solve the unit commitment problem of a hydro-thermal power system. The first layer uses a genetic algorithm (GA) to decide the on/off status of the units. The second layer uses a nonlinear programming formulation solved by a Lagrangian relaxation to perform the economic dispatch while meeting all plant and system constraints (6), the task of optimizing a complex system presents at least two levels of problems for the system designer. First, a class of optimization algorithms must be chosen that is suitable for application to the system. Second, various parameters of the optimization algorithm need to be tuned for efficiency (7), a genetic algorithm (GA) solution to the unit commitment problem. GAs are general purpose optimization techniques based on principles inspired from the biological evolution using metaphors of mechanisms such as natural selection, genetic recombination and survival of the fittest (8), a new evolutionary algorithm known as the shuffled frog leaping algorithm is presented in this paper, to solve the unit commitment (UC) problem (9), a new binary particle swarm optimization (BPSO) approach inspired by quantum computing, namely quantum-inspired BPSO (QBPSO). Although BPSO-based approaches have been successfully applied to the combinatorial optimization problems in various fields, the BPSO algorithm has some drawbacks such as premature convergence when handling heavily constrained problems (10), a Hybrid Chaos Search (CS) immune algorithm (IA)/genetic algorithm (GA) and

Fuzzy System (FS) method (CIGAFS) for solving short-term thermal generating unit commitment (UC) problems (11), a genetic algorithm (GA) in conjunction with constraint handling techniques to solve the thermal unit commitment problem. To deal effectively with the constraints of the problem and prune the search space of the GA in advance, the difficult minimum up- and down-time constraints are embedded in the binary strings that are coded to represent the on-off states of the generating units (12), a discrete binary differential evolution (DBDE) approach to solve the unit commitment problem (UCP). The proposed method is enhanced by priority list based on the unit characteristics and heuristic search strategies to handle constraints effectively. The implementation of the proposed method for UCP consists of three stages (13), A Parallel Structure has been developed to handle the infeasibility problem in a structured and improved Genetic Algorithm (GA) which provides an effective search and therefore greater economy (14),an enhanced genetic algorithm for the Unit Commitment problem is presented. This problem is known to be a large scale, mixed integer programming problem for which exact solution is highly intractable (15), Large scale power systems Unit Commitment (UC) is a complicated, hard limit, mixed integer combinatorial and nonlinear optimization problem with many constraints. This paper presents an innovative and effective solution based on modification of the Harmony Search (HS) Algorithm to solve the strategic planning of Generating unit's commitment (16), the use of a memetic algorithm (MA), a genetic algorithm (GA) combined with local search, synergistically combined with Lagrangian relaxation is effective and efficient for solving large unit commitment problems in electric power systems (17).

II. LITERATURE SURVEY

K.E.Manet. al. introduces genetic algorithms (GA) as a complete entity, in which knowledge of this emerging technology can be integrated together to form the framework of a design tool for industrial engineers. An attempt has also been made to explain "why" and "when" GA should be used as an optimization tool[1].

N.D.Simopouloset. al.represent the aim of finding a general method for solving the unit commitment (UC) problem. The proposed algorithm employs the evolutionary programming (EP) technique in which populations of contending solutions are evolved through random changes, competition, and selection. In the subject algorithm an overall UC schedule is coded as a string of symbols and viewed as a candidate for reproduction. Initial populations of such candidates are randomly produced to form the basis of subsequent generations. The practical implementation of this procedure yielded satisfactory results when the EP-based algorithm was tested on a reported UC problem previously addressed by some existing techniques such as Lagrange relaxation (LR), dynamic programming (DP), and genetic algorithms (GAs). Numerical results for systems of up to 100 units are given and commented on[2].

K.A.Justeet. al. deals with new simulated annealing (SA) algorithm combined with a dynamic economic dispatch method has been developed for solving the short-term unit commitment (UC) problem. SA is used for the scheduling of the generating units, while a dynamic economic dispatch method is applied incorporating the ramp rate constraints in the solution of the UC problem. New rules concerning the tuning of the control parameters of the SA algorithm are proposed. Three alternative mechanisms for generating feasible trial solutions in the neighborhood of the current one, contributing to the reduction of the required CPU time, are also presented. The ramp rates are taken into account by performing either a backward or a forward sequence of conventional economic dispatches with modified limits on the generating units. The proposed algorithm is considerably fast and provides feasible near-optimal solutions. Numerical simulations have proved the effectiveness of the proposed algorithm in solving large UC problems within a reasonable execution time[3].

M.Eslamianet. al. represent the unit commitment (UC) problem is one of the most difficult optimization problems in power system, because this problem has many variables and constraints. The objective is the minimization of the total production cost over the scheduling horizon while the constraints must be satisfied, too. This paper employs a new evolutionary algorithm known as bacterial foraging (BF) for solving the UC problem. This new integer-code algorithm is on the base of foraging behavior of E-coli Bacteria in the human intestine. By integer coding of the problem, computation time decreases and the minimum up/down-time constraints may be coded directly, and therefore, there is no need to use penalty functions for these constraints. From simulation results, satisfactory solutions are obtained in comparison with previously reported results[4].

M.M. Hadji and B.Vahidi presents a new approach via a new evolutionary algorithm known as imperialistic competition algorithm (ICA) to solve the unit commitment (UC) problem. In ICA the initial population individuals (countries) are in two types: imperialists and colonies that all together form some empires. Imperialistic competitions among these empires converge to a state in which there exists only one empire. In the proposed ICA for the UC problem, the scheduling variables are coded as integers; therefore, the minimum up/down-time constraints can be handled directly. A new method for initializing the countries is proposed. To verify the performance of the proposed algorithm, it is applied to systems with number of generating units in range of 10 up to 100 in one-day scheduling period[5].

A.Rudolf and R.Bayrleithner presents a two layer approach to solve the unit commitment problem of a hydro-thermal power system. The first layer uses a genetic algorithm (GA) to decide the on/off status of the units. The second layer uses a nonlinear programming formulation solved by a Lagrangian relaxation to perform the economic dispatch while meeting all plant and system constraints. In order to deal effectively with the constraints of the problem and prune the search space of the GA in advance, the difficult minimum up/down-time constraints of thermal generation units and the turbine/pump operating constraint of storage power stations are embedded in the binary strings that are coded to represent the on/off-states of the generating units.

The other constraints are handled by integrating penalty costs into the fitness function. In order to save execution time, the economic dispatch is only performed if the given unit commitment schedule is able to meet the load balance, energy, and begin/end level constraints. The proposed solution approach was tested on a real scaled hydro-thermal power system over a period of a day in half-hour time-steps for different GA-parameters. The simulation results reveal that the features of easy implementation, convergence within an acceptable execution time, and a highly optimal solution in solving the unit commitment problem can be achieved[6].

John.J. Grefenslette presents the task of optimizing a complex system presents at least two levels of problems for the system designer. First, a class of optimization algorithms must be chosen that is suitable for application to the system. Second, various parameters of the optimization algorithm need to be tuned for efficiency. A class of adaptive search procedures called genetic algorithms (GA) has been used to optimize a wide variety of complex systems. GA's are applied to the second level task of identifying efficient GA's for a set of numerical optimization problems. The results are validated on an image registration problem. GA's are shown to be effective for both levels of the systems optimization problem[7].

S.A.Kazarliset. al. presents a genetic algorithm (GA) solution to the unit commitment problem. GAs are general purpose optimization techniques based on principles inspired from the biological evolution using metaphors of mechanisms such as natural selection, genetic recombination and survival of the fittest. A simple GA algorithm implementation using the standard crossover and mutation operators could locate near optimal solutions but in most cases failed to converge to the optimal solution. However, using the varying quality function technique and adding problem specific operators, satisfactory solutions to the unit commitment problem were obtained. Test results for power systems of up to 100 units and comparisons with results obtained using Lagrangian relaxation and dynamic programming are also reported[8].

J.Ebrahimiet. al. presents a new evolutionary algorithm known as the shuffled frog leaping algorithm is presented in this paper, to solve the unit commitment (UC) problem. This integer-coded algorithm has been developed to minimize the total energy dispatch cost over the scheduling horizon while all of the constraints should be satisfied. In addition, minimum up/down-time constraints have been directly coded not using the penalty function method. The proposed algorithm has been applied to ten up to 100 generating units, considering one-day and seven-day scheduling periods. The most important merit of the proposed method is its high convergence speed. The simulation results of the proposed algorithm have been compared with the results of algorithms such as Lagrangian relaxation, genetic algorithm, particle swarm optimization, and bacterial foraging. The comparison results testify to the efficiency of the proposed method[9].

III. OVERVIEW OF DIFFERENT TECHNIQUES

There are various techniques of optimization tried on the thermal unit commitment problem to get solution in which they range from heuristics such as complete knowledgeable which have more experienced one such as lagrangian multiple.

A. Exhaustive Enumeration

This problem is solved by tally generating units of all possible combination. When all the conditions and constraints of systems are considered then this method finds the optimal solution.

B. Priority List (PL)

In this method the generating unit in a ordering of startup heuristic which was arranged by combining transition cost and operating costs. Changes on this technique rank the units consecutively one after the others. The commitment utilization factor and classified average full load cost and economic index which is combined to find the order of priority commitment. The heuristic of ordering is explain into rules and carry out as an expert system. Since, any of this technique is treated as an expert system tool.

C. Dynamic Programming (DP)

This programming finds solution space which include unit status for an optimal solution. The search dynamic programming evaluate complete decision free matrix to optimize the problem. The search space continues in the forward and backward direction.

D. Integer Programming

The Integer programming solve unit commitment problem by reducing solution search space through dispose impracticable subsets. The general solution concept is based on linear programming solution and checking for integer solution. The linear problems and sub-problems are continuously solved if solution is not an integer.

E. Branch and Bound

This method finds the lower bound of the optimal solution and also finds a near-optimal workable commitment schedule. Information is obtained from the dual problem in producing dynamic priority lists.

F. Linear Programming

In this programming first of all, the problem is degrading into smaller sub-problems by Dantzing-Wolfe decomposition principal. Then each sub-problem is solved by this programming. This problem is also solved with revised simplex technique. By UC problem, this programming solve economic dispatch for calculation of production cost and optimal allocation of fuel.

G. Lagrangian Relaxation

This technique degraded UC problem into Master Problem which solved continue until near optimal solution is obtained. Each sub-problem finds out the single unit commitment.

IV. GENETIC ALGORITHM OVERVIEW

Genetic algorithms are randomized population base search technique that closely emulate the natural process of evolution. They are predominantly string or integer-based searches with each member of the population represented by a string or matrix of bits. The evolution process is accomplished by reproducing a new generation of members from the previous generation. Each member of the new population is derived from two members of the previous generation. Hence, the new member is the child of two parent members from the previous generation. This process of reproduction is driven by a fitness value associated with each member. The problem specifies play a role in genetic algorithms only in decoding the string or matrix of bits and constructing its fitness value from the string or matrix of bits. There are no restrictions on the domain of the decoded design space or the solution space. This flexibility and the robust nature of genetic algorithms make them very powerful optimization tools.

Mechanism of Genetic Algorithms

The mechanism of genetic algorithms is simple, involving copying string and swapping partial strings. Simplicity of operation are power of effect are two of the main attraction of genetic algorithm.

A genetic algorithm starts with a population of strings (of bits 0 & 1) randomly generated using successive toss (flip) of a coin. As an example; generate the initial population (S1 to S4) of size n=4 with the length of strings L=5 through L*n=20 successive toss of unbiased coin (head=1, tail=0)

S1 - 01101
S2 - 11000
S3 - 01000
S4 - 10011

After this random start of initial populations, successive population are generated using three basic operation of the genetic algorithm as

- Reproduction
- Cross over
- Mutation

V. GENETIC ALGORITHM FOR UNIT COMMITMENT

Given the initial status of a set of units, the purpose of the unit commitment activity is to find the feasible combinations of these units and operating policy that minimize the total cost (IC) over the given study periods.

The genetic UC problems are as follows-

Decrease operational cost subject to following constraints

a) System constraints of power balance.
b) System reserve requirements.
c) Unit starting conditions.
d) Unit low and high MW limits.
e) Unit minimum up and down time.
f) Unit status restrictions (must-run, fixed MW unavailable Rate limits).
g) Unit Rate limits.
h) Unit start up ramps.
i) Unit shut down ramps.
j) Unit flame stabilization fuel mix.
k) Unit dual or alternate fuel usage.
l) Unit or plant fuel availability.
m) Plant crew constraints.

Constraints (a) and (b) shows all the units of the power system which are called system or coupling constraints and constraints (c) through (m) shows individual units which are called local constrains. Plant crew constraints can also be classified along with local constraints, but they involve all units in a plant.

Objective Function

The objective functions of the UCproblem are composed of operating and startup costs of the generation units can be expressed as

$$\sum_{i=1}^{N}\sum_{i=1}^{N} \mathrm{U_{i,t}} * \mathrm{OC_i}(\mathrm{P_{i,t}}) + \mathrm{SC_i} * \mathrm{U_{i,t}} * (1 - \mathrm{U_{i,t}}) => > Min \qquad (1)$$

System Constraints

(a) Load Balance

$$\sum_{i=1}^{H} U_{i,t} * P_{i,t} = Dt \; t = 1 \dots\dots\dots H \qquad (2)$$

Dt - system load document at time step t [MW]

(b) Spinning Reserve

$$\mathrm{Dt} + \mathrm{Rt} \le \sum_{i=1}^{N} U_{i,t} * P_{\max\ i,t} \qquad (3)$$

$$\sum_{i=1}^{N} U_{i,t} * P_{\min\ i,t} \le Dt \qquad (4)$$

(c) Unit Constraints

1. Generation Output Limit

$$P_{mini,t} \le P \le P_{maxi,t} \qquad (5)$$

Ramp Rate Limits

$$P_{i.t} - P_{i.t-1} \le \text{up ramp}_{i,t} \qquad (6)$$

$$-P_{i.t} + P_{i.t-1} \le \text{down ramp}_{i,t} \qquad (7)$$

Minimum up-and down time constraints

$$U_{i,t=1} \sum_{t=ts}^{t=1} U_{i,t} \ge Min\ Up\ time_i \qquad (8)$$

$$U_{i,t=0} \sum_{t=ts}^{t=1} U_{i,t} \ge Min\ Down\ time_i \qquad (9)$$

$$\text{fitness} = \frac{1}{\{C(U) + \sum_{j=1}^{H} PF_{maxj} * g/g\ lim\}} \qquad (10)$$

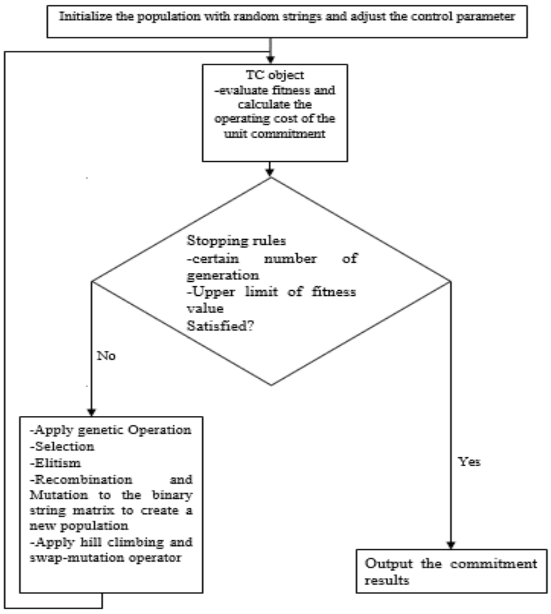

Fig: 1 Flowchart of the GA object

Penalty Functions

Penalty functions and their parameters affect the performance of the algorithm. The careful selection and grading of the parameter is important, well chosen, graded penalties which differentiate the relative performance of all the chromosomes should provide a better performance than harsh penalty functions. The penalty values are chosen sufficiently large to discourage the selection of solutions with violated constraints. Penalties function may be classified as:

(1) Constant Function:

PF = Fixed Constant Value

(2) Smooth and Gradual Penalty Function:

$PF_j \geq PF_{maxj} * g/g_{lim}$ (11)

(3) Smooth and Step Increasing Function:

$PF_j \geq PF_{minj} + I \times GEN$ (12)

(4) Exponential Function:

$PF = \{\sum_{t=1}^{t=H} [\, ExP(PF * h) - 1]\}$ (13)

VI. COMPUTER IMPLEMENTATION OF THE GENETIC ALGORITHM

Computer implementation of the Genetic Algorithm for solution to the unit commitment problem.

A genetic Algorithm has the following component/Steps.

(1) First generation counter is reset to Zero.

(2) Next initialize routine is called which initialized a random population of strings and calculate the statistics.

(3) Next a do while loop start which continues until the generation count exceeds the maxgen or maximum value of fitness reached.

Within this loop successive generation are produced and every time a better solution is found. This contains the following steps.

Generation count is incremented.

- Next, generation routine is called which produces next generation with the three genetic operators, reproduction, crossover and mutation.
- Next, new generated population replaces the old populations except population of maximum fitness by the routine advance generation.
- Swap Mutation operator selects a single arbitrary unit and flips its equivalent bit for the specific hour from '0' to '1' and vice-versa.
- HILL-climb operator selects arbitrary units U1, U2 and exchanges their bit if fitness is better.
- Next the statistics routine the old statistics.Report routine prints the population report

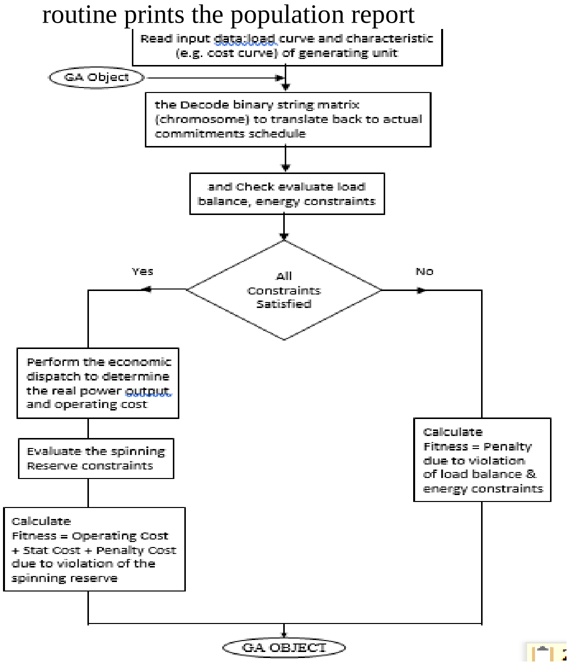

Fig.: 2 Flowchart of the TC Object

i. Next scalepop routine transforms the raw fitness to the scaled fitness for entire population.

ii. Iterate until the generation count exceeds the count limits.

iii. Lastly the solution found by genetic algorithm is printed.

VII. RESULT AND DISCUSSION

Simulation Result up to 10 units

Data Set: A set of 10 units was chosen with 24 hours demand schedule. This set is with demand schedule as shown in table 1 and 2.

Programming is conducted on reported UC problem. The GA used the advanced technique and operator for every problem set. In order to ignore misleading results due to stochastistic nature of GA 10 runs are made for each problem set, with each run starting with different random populations. In each set of problem every one of 10 runs was terminated at same generating limit. The limits rising with the number of units. The run was considered successfully if it assemble on a solution is better than or equal to LR algorithm.

If $MDT_i \leq DT_i \leq MDT_i + CSH_i$

$SC_i = HSC_i$

if $DT_i > MDT_i + CSH_i$

$SC_i = CSC_i$

They decide the regulation of GA results in Dynamic Programming algorithm (DP) with finished state enumeration is used for 10 units problem.

In order to use a success limit and fulfil as reference with Lagrangian relaxation algorithm also to decide the efficiency of GA result and compare to give the near optimal solution for each problem set.

Table 1 - Problem data for the 10-unit base UC problem

	U1	**U2**	**U3**	**U4**	**U5**
Pmax (MW)	455	455	162	130	130
Pmin (MW)	450	150	25	20	20
a ($/h)	1000	970	450	680	700
b ($IMWh)	16.19	17.26	19.7	16.5	16.6
c ($IMW2-h)	0.00048	0.00031	0.00398	0.00211	0.002
min up (h)	8	8	6	5	5
min dn (h)	8	8	6	5	5
hot start cost ($)	4500	5000	900	560	550
cold start cost ($)	9000	10000	1800	1120	1100
cold start hrs (h)	5	5	4	4	4
Initial status (h)	8	8	-6	-5	-5

	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 ($/h)	370	480	60	665	670
b ($IMWh)	22.26	27.74	25.92	27.27	27.79
c ($IMW2-h)	0.00712	0.00079	0.00413	0.00222	0.00173
min up (h)	3	3	1	1	1
min dn (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 - 2 Shows 24 hours with demand schedule

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

a, b, c are fuel cost function coefficients
($fc = a + b * P + c * P^2$)

Below tables shows comparisons of various methods for production cost with the number of units.

TABLE 3 - Comparison of various methods for production cost of 10 units

Method	**Best Cost**	**Average Cost**	**Worst Cost**	**Time**
	10 Units			
EP	5,64,551	5,65,532	5,66,231	100
LR	5,66,107	-	-	257
ICGA	5,66,404	-	-	7.4
SA	5,65,828	5,65,988	5,66,260	3
ICA	5,63,938	5,64,406	-	48
HS	5,65,828	-	-	-
GA	5,63,938	5,63,960	5,64,654	17

Tables above showns a comparison for different number of units generated with various methods i.e. Evolutionary Programming (EP), Lagrangian Relaxation (LR), Integer Coded Genetic Algorithm (ICGA), Simulated Anneling (SA), Imperialist Competitive Algorithm (ICA), Hydrothermal Scheduling (HS) and Genetic Algorithm (GA).

The generation cost of various methods is tabulated as compare and it is find that for all the methods, Genetic Algorithm results into minimum cost of production for number of units.

VIII. CONCLUSION

For Unit Commitment problem the Genetic Algorithm solution has presented. It was important to magnify at performance of standard GA with particular operator addition and varying technique of quality function to produce adequate UC solution. The advantage of GA that it can easily converted on parallel computer to work on it. Other advantage is the strechability that gives in modeling the time dependent and coupling constraints. The difference in the best and worst GA provides solution is small at most. Test results for the GA both of the best and worst solution provided are reported together with their difference as a percentage of best solution. Further the GA constantly outperforms the LR unit commitment.

Programming results reveal that optimal tuning of the GA parameters guarantees for convergence and a highly optimal solution is difficult and depends on the studied UC problem. Higher population size requires more evaluations per generation, resulting in a relatively slow rate of convergence. However, a small population would retain less variation of individuals and result in premature stopping of the GA.

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