A New Genetic Algorithm With Lamarckian Individual Learning for Generation Scheduling

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***Abstract*—Unit Commitment (UC) is an important optimization task in the daily operation planning of the utilities. In mathematical terms, UC is a nonlinear optimization problem with a varied set of constraints. In recent years, Genetic Algorithm (GA), as a powerful tool to achieve global optima, has been successfully used for the solution of this complex optimization problem. Nevertheless, since the GA does not effectively use all the available information, usually the searching process does not have satisfactory convergence. In this research work, in order to improve the convergence of the GA, a new local optimizer for the UC problem based on Lamarck theory in the evolution, has been proposed. This local optimizer, which tries to improve the fitness of one chromosome in the population, effectively uses the information generated in calculating the fitness. The simulation results show that by implementing this local search method in the form of a new genetic operator, the speed of convergence to the optimum solution is noticeably increased.**

***Index Terms*—Evolution theory, genetic algorithm, global-local search, hybrid methods, unit commitment.**

I. Introduction

In daily unit commitment the goal is to find an optimal schedule for turning the thermal units on and off (up and down), so that the total cost of operation in the study interval is minimized. This planning problem has to, in addition to satisfying demand and needed reserve margins, also satisfy the technical constraints in operating the thermal units [1]. In mathematical terms, daily operation planning is a nonlinear problem with both continuous and discrete variables and different linear and nonlinear, time invariant and time varying, and equality and inequality constraints. Because of the discrete variables representing the up and down states of the units, this optimization problem is nonconvex. Some of the methods used to solve this problem are, the priority list method, dynamic programming method, and the Lagrange relaxation method [2], [3].

Nowadays, Genetic Algorithms are being used as powerful tools in optimization problems, especially in the nonconvex problems [4]. Among the most important characteristics of these algorithms are their compatibility with nonlinear and/or discrete problems and parallel search in complicated spaces. These characteristics cause Genetic Algorithms to be powerful and important tools in solving the operational problems in power systems especially the new problems that have arisen due to the new competitive environment. Some of these new problems are; evaluation of bilateral contracts in competitive markets, market simulation, and solving more accurate models of daily unit commitments [5]–[7].

Experience in using GA has shown that, due to the fact that GA does not make optimum use of the available information, the process of reaching to the optimum solution is slow. This deficiency, resulting from GA's weakness in local search, can be remedied by using Hybrid Genetic Algorithms. The main idea in these methods is to use classical local optimization methods, or innovative other methods, to improve the local search phase of the optimization.

This paper proposes a new method for local optimization in the solution of the daily generation planning. This local optimizer, which tries to improve the fitness of one chromosome in the population, effectively uses the information generated in calculating the fitness. This local optimization method which from the evolution theory prospective, may be interpreted as the implementation of the Lamarckian evolutionary model, is applied probabilistically as a new genetic operator to the individuals of each generation. The new method is tested on a utility with 26 thermal generating units. The results clearly indicate the superiority of this hybrid algorithm over the pure GA.

II. Description of the Problem

An important daily problem all utilities face is the daily generation operation planning. System operator has to prepare an operation plan, complete with the start up and shot down schedule, for a proper set of generators to meet the next day's demand. This plan has to minimize the total operation cost of the system subject to a set of technical constraints for the generators. The total available and operable generation capacity should be sufficient to meet next day's demand plus an acceptable reserve margin. Considering a utility with N thermal units, the objective function, which has to be minimized in the time interval T, will be:

$$\mathrm{Min}\ J=\sum_{t=1}^{T}\sum_{i=1}^{N}C_i(P_i(t))u_i(t)+Sc_i(t)u_i(t)(1-u_i(t-l)) \tag{1}$$

where; $\mathrm{u}_i(\mathrm{t})$ is the state of unit i at hour t, $\mathrm{C}_i(\mathrm{P}_i(\mathrm{t}))$ is the fuel cost of unit i when generating power $\mathrm{P}_i(\mathrm{t})$, and $\mathrm{Sc}_i(\mathrm{t})$ is the start up cost of unit i at hour t. In the above minimization

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problem, the following constraints, imposed by the need to meet load demand and reserve margin, have to be satisfied:

$$\sum_{i=1}^{N} P_i(t)u_i(t) = D(t)\ t = 1, 2, \ldots, T \tag{2}$$

$$\sum_{i=1}^{N} P_{i\max}u_i(t) \geq D(t) + R(t)\ t = 1, 2, \ldots, T \tag{3}$$

where $\mathrm{D(t)}$ is the demand at hour t, $P_{i\max}$ is the maximum generation capacity for unit i, and $\mathrm{R(t)}$ is the needed reserve capacity in hour t. Moreover, the constraints regarding the minimum time the units can be on before they can be turned off and the minimum time they have to be off before they can be turned on, the minimum up and down times, and the minimum and maximum generation capacity limits for each unit has to be considered.

III. Optimal Daily Generation Plan Using Genetic Algorithm

Genetic Algorithms are an attractive class of computational methods being used for solving a variety of scientific and applied problems such as; optimization, modeling complex systems, estimation of dynamic system and so on [8]. These algorithms, which are known mostly as powerful tools in optimization, are essentially a mathematical implementation of Darwin's evolution theory. Similarly to Darwin's evolution model, these algorithms use the three operators of inheritance (to transfer the experiences from one generation to the next), coincidence (natural errors that occur in this transfer), and natural selection (those who are more compatible with the environment have a better chance of survival). Their most important characteristic, which separates them from the classical optimization methods, is that they work on a population of solution to the problem.

Genetic algorithm is essentially a method to generate a new population or generation from a given population. In this process the selection, crossover, and mutation operators are being used. Each member of the population, called a chromosome, is a possible solution for the problem under consideration, and is represented as a (usually binary) chain. Members of each generation are ranked according to a specific criterion called fitness. The choice operator gives those members with a higher fitness ranking a better chance of being present in the next generation. The crossover and mutation operators are applied to each chromosome with a specific probability and cause new chromosomes to be present in the new generation.

The basic Genetic Algorithm may be summarized as follows:

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Step 1: Generate a random initial popula-
tion with N individuals.
Step 2: Calculate the fitness functions of
all individuals in the population.
Step 3: Select two individuals from the
population with probability of selection
proportional to their fitness values.
Step 4: Apply the crossover and mutation
operators to these individuals with prob-
abilities equal to the crossover rate and
mutation rate respectively.
Step 5: Repeat steps 3 and 4 until N in-
dividuals are generated to form the next
generation.
Step 6: Go to step 2 and repeat the
process until a stopping criteria is met.
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TABLE I
Definition of the Generating Unit's Code.

Time	Up/Down-states of the units			
	U1	U2	U3	Un
1	1	1	0	0
2	1	1	0	1
...	.	.	.	.
T	1	0	1	1

To solve an optimization problem using GA, first the possible solutions of the problem have to be coded in chromosomes. Next a fitness function to compare the chromosomes has to be defined. In solving the daily generation planning, the main variables to be identified are the states, up and down, of the generating units. Therefore, a chromosome can be defined in the form of a matrix with binary elements as is seen in Table I. This matrix has T, the length of the planning period in hours (24), rows and N, number of units, columns.

Before calculating the fitness of each chromosome, its information is so modified to satisfy the minimum up/down time constraints of the units. That is tantamount to considering these constraints implicitly in coding [5], [9]. The modification procedure is very simple. As an example consider a generation schedule based on the information of an arbitrary chromosome such as Table I. Consider unit k and assume that the minimum up time for this unit is 3 hours. For the modification of the generation plan for this unit, after each transition from "0" to "1" in the code, that is, after each start up of unit k, the plan is modified in a way to have a sub-sequence "0111" in the code for this unit. This guarantees that once unit k is started, it will stay up for at least three hours. Similar modification is done in transition from "1" to "0".

The value of the fitness function is equal to the value of the cost function in (1), which has to be minimized. Therefore to calculate the fitness of a chromosome, the start up and fuel costs of the units have to be calculated using the information in the chromosome. Start up costs are directly calculated using the chromosome information. Fuel cost (operation cost) of the units are calculated using economic dispatch program. In this work, we have used Lagrangian Relaxation method to solve the Economic Dispatch problem. Economic dispatch is quadratic optimization problem and subsequently a convex one. Therefore Lagrangian Relaxation method is proper for its solution.

Constraints imposed by load demand and minimum and maximum generating capacity of the unit are considered and satisfied in the economic dispatch. If in a certain hour the inequality constraint regarding the reserve requirement is violated, the chromosome fitness is penalized. The value of penalty is composed of a fixed value and a variable value in proportion to the capacity shortage. As the assigned penalty is large enough, in these hours, there is no need to run the economic dispatch.

IV. A New Heuristic Method for Local Optimization in the Generation Planning

Genetic Algorithm is a global optimization algorithm. Arriving at a proper balance between the local and the global phases of the optimization is a precondition for successful global optimization. Experience in using GA has shown that, due to the fact that GA does not make optimum use of the available information, the process of reaching to the optimum solution is slow. This deficiency, resulting from GA's weakness in the local search can be remedied by using tools to improve the local search phase. It is essential in designing these algorithms that a compromise is reached between the speed of convergence to a solution and the reliability of the solution [10].

Hybrid Genetic Algorithms usually use new operators. These operators are very powerful in local search and are inspired by nature or classical optimization methods, such as gradient methods or quasi-Newtonian methods. Since local optimization methods try to improve the situation of one member of population, from the evolution theory prospective, they may be interpreted as the mathematical implementation of the Lamarckian evolutionary model. In this model, evolution is explained and modeled as the efforts exerted by, and variations undergone by, a member independently to be better compatible with its environment. Designing hybrid Genetic Algorithms based on the theories of Darwin and Lamarck essentially means considering the local and the global optimization simultaneously. Experience has shown that these algorithms have better computational efficiency than pure Genetic Algorithms [11].

Based on the above discussion, a question can be posed as how to improve the convergence speed of the Genetic Algorithm in solving the optimal daily generation planning problem. Because of the discrete variables representing the states of the units, the classical optimization methods such as the gradient method can not be used. Therefore heuristic methods have to be used in designing the local optimization algorithm.

The local optimization algorithm has to modify and improve any given plan for the operation of the thermal units such that the total cost of the plan is reduced. As was explained in Section III, for each hour of the operation plan, economic dispatch, based on the information of each chromosome, is run. One can use the information obtained from economic dispatch to improve the generation plan. The main idea is based on the notion that if economic dispatch is dispatching unit i near its maximum capacity during the hours it is on, it is probable that running the unit during the times that the plan calls for it to be off may be beneficial. Conversely, if a unit is dispatched near its minimum capacity during the time it is on, it may be beneficial to take it out during some of these hours.

TABLE II
Original Generation Plan for the Example Choromosome and $\mathrm{R_A}$ Values.

Units	Time horizon 1	2	3	Ra	P_{min} (MW)	P_{max} (MW)
U1	0	96	100	65%	25	100
U2	80	0	0	33%	20	80
U3	41	35	44	60%	12	66
U4	4	4	6	23%	4	20
Load	125	135	150			

Therefore, the total power generated by a unit during the plan may be used as an index to compare different units. Equation (4) is developed for this ranking.

$$Ra_i = \frac{\sum_{t=1}^{T} P_i(t)u_i(t)}{P_{i\,\max}T}. \tag{4}$$

In this equation, Ra_i is an index that ranks unit i and T is the duration of the planning horizon. Also $\mathrm{P}_i(\mathrm{t})$ and $\mathrm{u}_i(\mathrm{t})$ are the generated power and the state of unit i in hour t, respectively, and $P_{i\,\max}$ is the maximum generation capacity of this unit. The Ra_i index not only depends on the economic characteristics of the unit but also is closely related to the information in the chromosome under consideration. Therefore, if in a certain chromosome, a unit is off, or generates power near its minimum level, for most of the hours of the operation plan, according to this ranking, it will have a low ranking.

Therefore, depending on the information contained in the chromosome under study, units only get different rankings, so this method does not reduce the population diversity. Moreover, this method not only compares the performances of the units in their nominal capacities but also it is able to compare those units that are near their minimum capacity. An example will further clarify the method. It is assumed that number of units N is 4 and the duration of the plan, T is 3. Generation plan based on the information of a particular chromosome of the population, after optimal power flow is shown in Table II.

The last row in the table shows the load demand. It is seen that unit 1 is dispatched near its nominal capacity during the hours it is on but unit 4 is always dispatched at its minimum capacity. Therefore it seems beneficial to dispatch unit 1 in the first hour also. And it seems that taking unit 4 out may reduce the costs. The Ra values are calculated according to (4) and the results are shown in column four. Using these Ra values and considering the minimum time constraints, the generation planning problem is solved using a method similar to the priority list method. Table III shows the unit commitment plan for these units after this method is applied to the plan of the Table II.

The above ranking method will be implemented as a new genetic operator and just as mutation and crossover it is applied probabilistically to each chromosome.

TABLE III
UNIT COMMITMENT PLAN BASED ON THE HEURISTIC METHOD.

Units	Time horizon 1	2	3
U1	1	1	1
U2	0	0	0
U3	1	1	1
U4	0	0	0

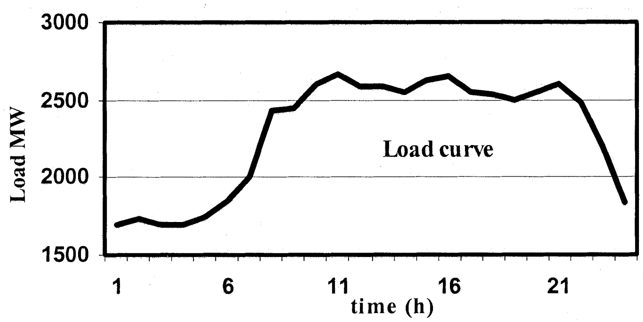

Fig. 1. The load curve of the study system.

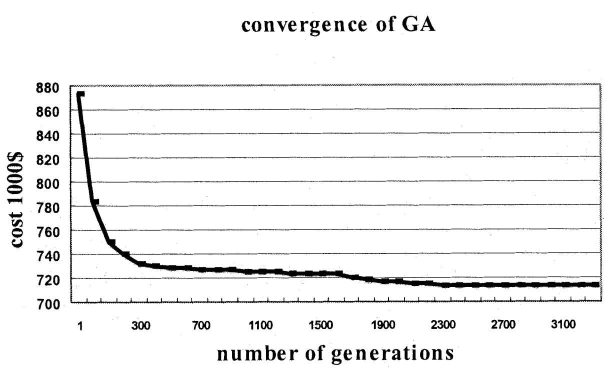

Fig. 2. Convergence of the fitness of best member to near optimal value.

V. AN EXAMPLE OF HYBRID GENETIC BASED SOLUTION OF THE DAILY GENERATION PLANNING PROBLEM

The system under study has 26 thermal units. Technical and economic data for the units, the initial states of the units at the beginning of the planning horizon and the load curve are as in [12]. For ease of reference this information is shown in the Appendix. This system has to satisfy the load curve shown in Fig. 1. Moreover a 10% reserve capacity has to be provided in each hour.

Due to the benefits of the tournament selection operator and its ease of implementation, it is used as the selection operator. Also a uniform crossover operator with probability of. 8 and probability of mutation of 0.002 is used. Analyzing the performance of the Genetic Algorithm with different number of population members shows that a population with 20 members has a relatively better performance.

Fig. 2 shows the variation of the fitness (operation cost in thousands of dollars) of the best member of the population with respect to the number of processed generations. It is seen that after approximately 2800 generations, a near optimal solution is obtained.

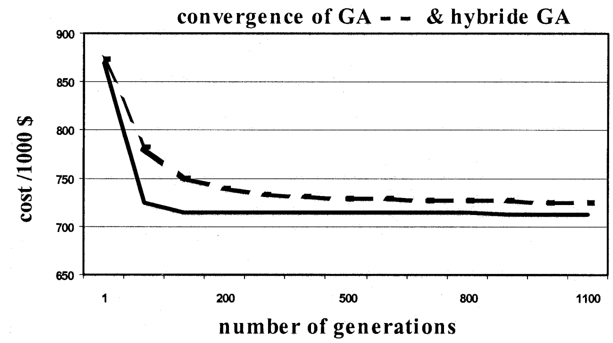

Fig. 3. Comparison of the convergence of the GA and the hybrid GA.

Now, to increase the speed of convergence of the Genetic Algorithm, the dynamic ranking method described in Section IV is used. This method is implemented as a new operator with probability of 0.05. That is, for a population of 20 individuals, the new operator is applied only to one chromosome. Of course, as for other operators, there is no guarantee that fitness will improve following the application of this operator. When this operator operates on a chromosome, first the units are ranked using their dispatched generation values based on the information contained in this chromosome. Next, based on this ranking and taking into consideration the minimum up/down time constraints for each unit, the plan presented by the chromosome is modified. In Fig. 3 convergence of the Genetic Algorithm and the hybrid Genetic Algorithm are compared. It is seen that the new operator has noticeably improved the speed of convergence. It is also seen that the hybrid GA has found an acceptable solution near the final solution (with 0.15% error) after only 200 generation. This new genetic operator, by using information more effectively improves the local search phase and therefore, takes the GA to the region of the optimal solution much more rapidly.

As the solution nears this region, the process is controlled more and more by the operators of the global search. That is in the final iterations, as the new genetic operator only considers the continuous generation costs, it does not exhibit good performance and it is possible that it would even increase the cost associated with the chromosome. The probability of operating this operator to a chromosome is tuned similarly to those of the crossover and mutation operators. When this probability is set at high values, the genetic search process is disturbed and the Genetic Algorithm is prevented from learning. Simulation results show that using this new operator with 0.05 probability leads to good results.

The convergence of the hybrid GA method is more accurately shown in Fig. 4. In this figure the solution obtained by using the Lagrange Relaxation method is also shown as a straight line.

It is seen that the hybrid GA is finding a slightly better optimal solution to the daily generation planning problem than the Lagrange Relaxation method. The GA method is solving the problem directly and therefore avoids the problem of duality gap and its solutions are always feasible, whereas, the Lagrange Relaxation method, due to the nonconvexity of the plan-

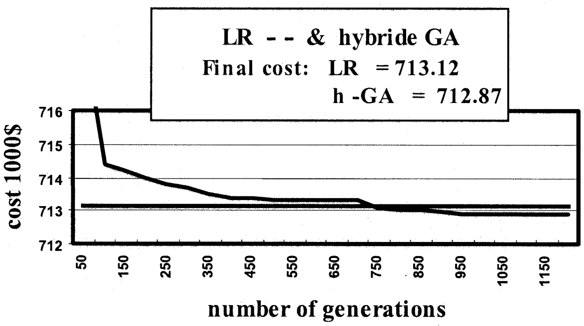

Fig. 4. Convergence of the hybrid GA and comparison of its final cost with that of Lagrange method.

ning problem has to face this problem. Processing time using a PC with Pentium Celeron 633 processor was 165 seconds. Employing better software techniques and hardware equipment can reduce this time by orders of magnitude.

VI. Conclusions

In this paper, in order to improve the convergence of the GA, a new local optimizer for the unit commitment problem based on Lamarck's theory in the evolution, has been proposed. This local optimizer, which tries to improve the fitness of one chromosome in the population, effectively uses the information generated in calculating the fitness. This heuristic local optimization method is implemented in the form of a new genetic operator which is then applied probabilistically to the individuals of each generation. As a result, decisions are made to increase or decrease the duration of the time units are up or down. Each unit that has more generation would be given a relative priority in the plan presented by the chromosome. This method is in fact a dynamic ranking method, as the ranking of the units is directly related to the information of the chromosomes. That is, for different chromosomes, different rankings would result which is important in maintaining the diversity of the population. Simulation results in scheduling of a system with 26 thermal units show using this local search method, the convergence behavior of the conventional Genetic Algorithm is noticeably improved. Also comparing the final solution with solution obtained by the Lagrange Relaxation method showed that the method is capable of finding the optimal solution. Due to its flexibility and its ability to operate on a population of solutions, this new hybrid algorithm can be employed to solve the new problems that have arisen in the new competitive environment of the electric energy industry and can be a good tool to improve and aid the decision process.

Appendix

The study system has 26 thermal units. Table IV provides the unit minimum up-time, minimum down-time, initial conditions, and various unit ramp limits. In this table the following notation is used;

UH_i : Ramp-up time of unit i (h)
DH_i : Ramp-down time of unit i (h)
UR_i : Ramp-up rate limit of unit i (MW/h)
DR_i : Ramp-down rate limit of unit i (MW/h)

TABLE IV
Generating Unit Operating Limits, Ramp Limits, and Initial Conditions.

Unit	Min Up (h)	Min Down (h)	Init. Cond. (h)	UH_i (h)	DH_i (h)	UR_i (MW/h)	DR_i (MW/h)
1-5	0	0	-1	0	0	48.0	60.0
6-9	0	0	-1	1	0	30.5	70.0
10-13	3	-2	3	2	1	38.5	80.0
14-16	4	-2	-3	2	2	51.0	74.0
17-20	5	-3	5	3	2	55.0	78.0
21-23	5	-4	-4	4	2	55.0	99.0
24	8	-5	10	5	3	70.0	120.0
25-26	8	-5	10	8	4	50.5	100.0

TABLE V
Generating Unit Capacity Limits and Fuel Cost Coefficients.

Unit	$\underline{P}_i$ (MW)	$\overline{P}_i$ (MW)	a_i (k$/MW^2)	b_i (k$/MW)	c_i (k$)
1	2.4	12.0	.02533	25.5472	24.3891
2	2.4	12.0	.02649	25.6753	24.4110
3	2.4	12.0	.02801	25.8027	24.6382
4	2.4	12.0	.02842	25.9318	24.7605
5	2.4	12.0	.02855	25.0611	24.8882
6	4.0	20.0	.01199	37.5510	117.7551
7	4.0	20.0	.01261	37.6637	118.1083
8	4.0	20.0	.01359	37.7770	118.4576
9	4.0	20.0	.01433	37.8896	118.8206
10	15.2	76.0	.00876	13.3272	81.1364
11	15.2	76.0	.00895	13.3538	81.2980
12	15.2	76.0	.00910	13.3805	81.4641
13	15.2	76.0	.00932	13.4073	81.6259
14	25.0	100.0	.00623	18.0000	217.8952
15	25.0	100.0	.00612	18.1000	218.3350
16	25.0	100.0	.00598	18.2000	218.7752
17	54.25	155.0	.00463	10.6940	142.7348
18	54.25	155.0	.00473	10.7154	143.0288
19	54.25	155.0	.00481	10.7367	143.3179
20	54.25	155.0	.00487	10.7583	143.5972
21	68.95	197.0	.00259	23.0000	260.1310
22	68.95	197.0	.00260	23.1000	259.6490
23	68.95	197.0	.00263	23.2000	260.1760
24	140.0	350.0	.00153	10.8616	177.0575
25	100.0	400.0	.00194	7.4921	310.0021
26	100.0	400.0	.00195	7.5031	311.9102

TABLE VI
Load Demand for the Study Period.

Hour	Load(MW)	Hour	Load(MW)	Hour	Load(MW)
1	1700	9	2540	17	2550
2	1730	10	2600	18	2530
3	1690	11	2670	19	2500
4	1700	12	2590	20	2550
5	1750	13	2590	21	2600
6	1850	14	2550	22	2480
7	2000	15	2620	23	2200
8	2430	16	2650	24	1840

The fuel cost of unit i is given by the relation;

$$C_i(P_i(t)) = a_i P_i(t)^2 + b_i P_i(t) + c_i.$$

The values of the parameters a_i, b_i, and c_i are given in Table V. Also in Table V, rated maximum and minimum power generation of each unit is given as $\overline{P_i}$ and $\underline{P_i}$, respectively. Finally, load curve for the system under study is given in Table VI.

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