A GENETIC BASED ALGORITHM FOR SHORT-TERM THERMAL GENERATING UNIT COMMITMENT

خوارزم جينى لجدولة وحدات التوليد الحرارية على المدى القصير

M. E. El-Said

Electrical Power &Machines Dept., Faculty of Eng., Mansoura University.

ملخص البحث:

تعتبر مشكلة جدولة وحدات التوليد من المشاكل الصعبة والمعقدة بنظم القوى الكهربية نظرا لكبر حجم المشكلة والقيود العديدة المفروضة على تشغيل هذه الوحدات. تهدف جدولة وحدات التوليد إلى تحديد الوحدات التي يجب أن تعمل خلال فترة زمنية معينة بأقل تكلفة ممكنة لتلبية القدرة الكهربية اللازمة للأحمال مع توافر الأحتياطى السريع المطلوب وتحقيق قيود التشغيل للوحدات. تم صياغة المشكلة رياضيا بتقليل دالـــة الهـــدف المكونة من تكلفة الوقود وتكلفة البدء للوحدات التي يتم إدخالها للتشغيل، حيث تخضع هـــذه الوحـــدات عنـــد تشغيلها إلى مجموعة من القيود منها، حدود التوليد للوحدات، الأحتياطى السريع المطلوب لمواجهة اى حالـــة طارئة، الحد الأدنى الفوقي لزمن تشغيل الوحدات ووقت الراحة الأدنى عند فصل الوحدات، وكذلك معدل تغير القدرة المنتجة لهذه الوحدات. تم اقتراح خوارزم جينى لحل مشكلة جدولة وحدات التوليد الحرارية على المدى القصير مع أخذ كل جوانب المشكلة في الاعتبار، وتم تطبيق الخوارزم المقترح على نظامين، الأول مكون من ١٠ وحدات توليد، بينما الثاني مكون من ٢٦ وحدة توليد، وبمقارنة النتائج التي تم الحصول عليها مع نتـــائج برنامج البرمجة الديناميكية، تبين مدى قدرة الخوارزم المقترح على حل مشكلة جدولة وحدات التوليد الحرارية بالدقة الكافية مع تميزه بزمن تشغيل أقل بكثير.

ABSTRACT:

Unit Commitment is one of the most complex and difficult optimization problem in power systems. The objective of the optimal commitment is to determine the on/off states of the units in the system to meet the load demand and spinning reserve requirements at each time period, such that the overall cost of generation is minimized, while satisfying the various operational constraints. This paper presents the application of an improved genetic algorithm (GA) with crossover, mutation, and advanced operators such as repair and swap mutation to determine the commitment order of the thermal units in power generation. The proposed GA has been successfully applied to 10 and 26 generating-unit systems. Robustness of the proposed GA is demonstrated by comparison to the dynamic programming algorithm. The comparison results show the effectiveness of the proposed GA in solving the unit commitment problem with sufficient accuracy and low computational time.

Accepted June 30, 2005.

1. INTRODUCTION

The short-term thermal Unit Commitment Problem (UCP) is to find a units to be committed in every subperiod (typically 1 hour) of a given planning period (typically 1 day or 1 week) so that the customer demand is supplied at minimum cost while satisfying a set of operational constraints. The production cost includes fuel, startup, shutdown, and no-load costs. Constraints include capacity limits, spinning reserve, minimum up/down time, and ramp rates of generating units.

The UCP of thermal generating units is large-scale, combinatorial, mixed-integer, and nonlinear programming problem. Many techniques [1] have been used to solve the UCP such as integer programming, branch and bound, Bender's decomposition, Lagrangian relaxation, and dynamic programming [2].The main limitations of the numerical techniques are the problem of dimensions, large computation time, and complexity in programming. Expert system models [3] were employed to reduce the solution time, as they avoid the use of complex mathematical calculations. A fuzzy dynamic programming approach [4] was introduced to reduce the errors in the forecasted hourly loads, but this approach is not free from mathematical complexity. The modified Hopfield neural network [5] has also been used for solving the UCP. In [6], a unit decommitment method was developed as a post-processing tool to improve the solution quality of the existing UCP. Recently, modern heuristic approaches [7] have been used to solve the UCP such as simulated annealing, tabu search, and genetic algorithms (GAs). Several sequential GAs applied to the UCP can be found in the technical literature [8-11].

The UCP is a complex combinatorial optimization problem. GAs have been recently applied to solve various power system problems due to their capability in determining global or near global solution with low computational burden. The main objective of this paper is to utilize an improved GA to determine the optimal schedule of thermal generating units to meet the load demand while satisfying operational constraints with minimum operational cost. The paper is organized as follows. Section 2 contains the mathematical formulation of the UCP, Section 3 includes a description of the proposed GA and the solution procedure, Section 4 shows the results of case studies, and finally Section 5 provides conclusions.

2. UNIT COMMITMENT PROBLEM FORMULATION

The objective of the UCP is to minimize the sum of two cost terms. The first term is the cost of power produced by the generating units, which depends on the amount of fuel consumed. The second term is the start-up cost of the generating units, which for thermal units, depends on the prevailing temperature of the boilers.

2.1 Fuel Cost

The fuel cost $F_i(P)$ of producing P units of power by generating unit i is given by:

$$F_i(P)=a_i+b_iP+c_iP^2 \tag{1}$$

where a_i, b_i and c_i are the cost coefficients of unit i.

2.2 Start –up Cost

The start-up costs relate to turning a unit on. If thermal unit has been off for a long period, a cold start-up cost will be incurred. If the unit has been recently turned off, a hot start-up cost is applied. Two functions are commonly used to model start-up costs as a function of the temperature, two-step and exponential functions [12]. In this paper we use the two-step function method to model the start-up cost to be able to compare the obtained results with those obtained from dynamic programming technique. This cost can be calculated as:

$$S_i(t)=\begin{cases} S_{c_i} & if -x_i(t)\le t_{cs} \\ S_{h_i} & otherwise \end{cases} \qquad (2)$$

where S_{ci} and S_{hi} are the start-up costs for a cold and hot start of unit i, respectively, t_{cs} is the number of hours that it takes for the boiler to cool down; and $x_i(t)$ is the time that unit i has been up (+) or down (-) at time t. For instance, $x_2(10)$ equal to -5 that at hour 10 unit 2 has been down for 5 hours. Start-up costs $SC_i(t)$ are considered only when a transition from state off to on occurs, which can be expressed as follows:

$$SC_i(t)=S_i(t).U_i(t).(1-U_i(t-1)) \qquad (3)$$

where $U_i(t)$ is a status of unit i at time t (on=1, off=0).

2.3 Objective Function

The objective function of the UCP for N generating units and T hours can be written as follows:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N}[F_i(P_i(t)).U_i(t)+SC_i(t)] \qquad (4)$$

where $P_i(t)$ is the power output of unit i at time t.

2.4 System Constraints

The constraints that have been taken into consideration are as follows:

2.4.1 Load demand

$$\sum_{i=1}^{N}U_i(t).P_i(t)=D(t) \qquad (5)$$

where $D(t)$ is the system power demand at time t.

2.4.2 Capacity limits

$$U_i(t).P_{i,min}\le P_i(t)\le U_i(t).P_{i,max} \qquad (6)$$

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum capacity limits of unit i.

2.4.3 Minimum up/down time

The minimum uptime constraints arise from physical considerations associated with thermal stress on the units and are designed to prevent equipment failure. On the other hand, the minimum downtime constraints, are based on economic consideration to prevent excessive maintenance and repair costs due to frequent unit cycling [12]. The minimum up/down time constraints state that a unit that is running must be up for at least t_{up} hours and a unit that is down must stay down for at least t_d hours. The minimum up/down time constraints can be written as:

$$\begin{aligned} T_{on,i} &\ge t_{up,i} \\ T_{off,i} &\ge t_{d,i} \end{aligned} \qquad (7)$$

where $t_{up,i}$, $t_{d,i}$ are unit i minimum up/down time, and $T_{on,i}$, $T_{off,i}$ are time periods during which unit i is continuously on/off.

2.4.4 Spinning reserve

The total amount of power available at each hour must be greater than the load demand. The reserve power available $R(t)$, is used when a unit fails or an increase in load occurs. The spinning reserve constraint can then be written as:

$$\sum_{i=1}^{N}U_i(t).P_{i,max}\ge D(t)+R(t) \qquad (8)$$

2.4.5 Ramp rates of generating units

The ramp constraints are accounted for the fact that units can not change their output too rapidly. The ramp constraints can be written as:

$$P_i(t) \le P_i(t-1) + \Delta_{i,inc}$$
$$P_i(t) \ge P_i(t-1) - \Delta_{i,dec} \qquad (9)$$

where $\Delta_{i,inc}$ and $\Delta_{i,dec}$ are the maximum ramp rates (MW/h) for increasing and decreasing power output from unit i, respectively.

3. GENETIC BASED ALGORITHM FOR UNIT COMMITMENT

3.1 Genetic Algorithm

A genetic algorithm is a random search procedure, which is based on the survival of the fitness theory [13]. Their basic principle is the maintenance of a population of size p of solutions to a problem in the form of encoded individuals that evolve in time. GAs manipulate strings of binary digits (1 and 0) called chromosomes, which represent multiple points in the search space. Each bit in a string is called an allele. They carry out simulated evolution on populations of chromosomes. Like nature, GAs solve the problem of finding good chromosomes by manipulating the material in the chromosomes blindly without any knowledge about the type of problem that they are solving. The only information they are given is an evaluation of each chromosome they produce. This evaluation is used to bias the selection of chromosomes so that those with the best evaluations tend to reproduce more often than those with bad evaluations. A GA, which yields good results in many practical problems, is composed of three operators:

a- Selection: In the first stage, the selection operator is applied as many times as there are individuals in the population. In this stage each individual is replicated with a probability proportional to its relative fitness in the population.

b- Crossover: The main operator working on the parents is crossover, the crossover operator is applied with a probability P_c independent of the individuals to which it is applied. Two individuals (parents) are chosen and combined to produce two new individuals (offspring).

c- Mutation: Although first two operators produce many new strings, they do not introduce any new information into the population at the bit level. As a source of new bits, mutation operator is introduced and is applied with a low probability P_m.

These three operators are applied repeatedly until the offsprings take over the entire population. When new solutions of strings are produced, they are considered as a new generation and they totally replace the parents in order for the evolution to proceed. It is necessary to provide many generations for the population converging to the near optimal or an optimum solutions, the number increasing according to the problem complexity. The algorithm terminates after a fixed number of iterations and the best individual generated during the run is taken as the final solution.

3.2 Implementation of GA to Unit Commitment Problem

3.2.1 Encoding

For the UCP, every solution is determined by a 0/1 matrix ($U_i(t)$) of the units at each time t and the power $P_i(t)$ generated by each unit every time t. The matrix $U_i(t)$ consists from many columns as the number of planning period and as many rows as the number of available thermal units. If element (i,t) is 1, unit i is committed in period t ($U_i(t)$=1), otherwise it is not ($U_i(t)$=0). The values of $U_i(t)$ are generated by GA, while the optimum values of $P_i(t)$ are calculated through an economic dispatch algorithm. The 0/1 matrix of the units is stored as an integer-matrix U and the power generated as a real-power matrix P with dimension NxT. Figure 1 illustrates an example of encoding an 0/1 U matrix.

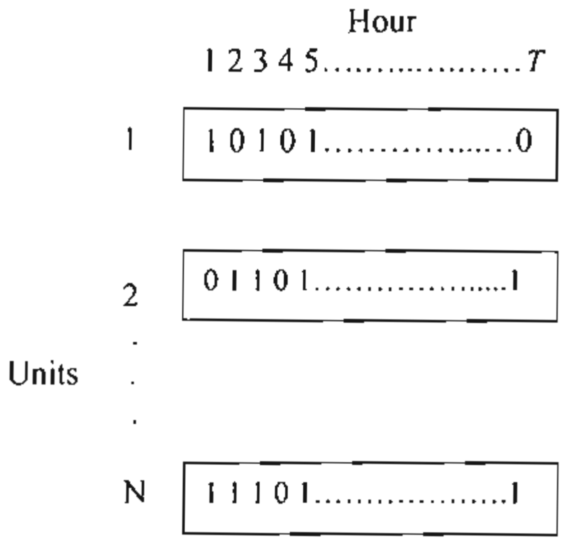

Figure1 Encoding on/off schedule matrix U.

3.2.2 Fitness function and constraints treatment

The fitness of a solution U is evaluated as the total production cost plus a penalty of those constraints that are violated:

$$Fit(U)=TotalCost(U) + TotalStartup\,Cost(U)+Penalty(U) \quad (10)$$

To evaluate the total fuel cost of a given solution U, the optimal value of P needs to be determined by solving T economic dispatch sub-problems (one at each hour) taking into account the constraints of load and ramp rates of each generating unit. The economic dispatch sub-problem consists of dispatching those units whose entries in U are equal to 1. The Lambda-iteration method [14] is used to solve this sub-problem. Once the optimal values of $P_i(t)$ are found, the total fuel cost is computed by adding the fuel cost of all generating units over the time period T. The total start-up cost is calculated by adding the start-up costs of those units that change their states from '0' to '1'. The fitness function also includes penalty values for violated constraints. The highest penalty is assigned to schedules that do not meet the load demand. The penalty due to unmet load demand is computed by penalizing the unmet load and power reserve requirements with a factor of high value. Other penalties apply to schedules that do not satisfy minimum up/down time constraints. The penalty due to unmet minimum up/down time constraints is a dynamic penalty that is minimum at early stages of evolution and grows with each generation. This allows solutions that satisfy the load requirements and do not meet the minimum up/down time constraints to evolve into feasible solutions. This penalty term is calculated as follows [11]:

$$Min\ up/down\ time\ penalty = n_v\sqrt{K} \quad (11)$$

where n_v is the total number of minimum up/down time constraints violated and K is the number of GA generations. The best fitness is therefore assigned to solutions with lowest value of cost and penalties.

3.2.3 Crossover operator

At first we use the standard two-point crossover to obtain deficient results and then a window crossover operator was devised to obtain offspring from two parents.

3.2.4 Mutation

According to a prespecefied mutation probability, an individual in each generation is randomly selected. A random element from 0/1 U matrix is flipped from 0 to 1 or vice versa.

3.3 Improving the Response of GA

3.3.1 Repair operator

To improve the response of GA to solve the UCP, a repair operator [10] is added. This operator repairs solutions that are infeasible regarding the minimum up/down constraints. The process of fixing a solution is done by evaluating the state of each unit, $x_i(t)$. The state of a unit is evaluated starting from hour 0. If at a given hour t the minimum up or down time constraint is violated, the state (on/off) of the unit at that hour is reversed and $x_i(t)$ is updated. The process continues until the last hour has been reached.

3.3.2 Swap mutation operator

Another operator called a swap operator is used to commit the generating units in a predetermined order. The swap operator uses the full load average cost (FLC) of the generating units to perform a swap of unit states. The FLC of a unit is defined as the cost per unit of power ($/MW) when the generating unit is at its full capacity. When the fuel cost is given by (1), FLC can be defined by [12]:

$$FLC = \frac{a}{P_{max}} + b + c.P_{max} \quad (12)$$

The generating units are ranked by their FLC in ascending order. Units with lower FLC should have higher priority to be dispatched. At a given hour, the operator probability swaps the states of two units i and j only if the unit i is ranked better than unit j $(i < j)$ and the state of the units are 'off' and 'on', respectively.

3.4 Proposed Solution Algorithm

The major steps of proposed GA to solve the short-term thermal UCP are as follows:

Step 1. Set the population size p, the probability of crossover P_c, the probability of mutation P_m, probability of repair operator P_r, probability of swap operator P_s, and the maximum number of generations K_{max}.

Step 2. Randomly generate a population of p chromosomes, each consisting of N strings of length T of bits '0' and '1' (integer matrix U), and then compute the real matrix P using the economic dispatch.

Step 3. Compute the objective function and constraints and then compute the fitness value (objective function +weighted penalty constraints) of each individual. Set $K = 0$.

Step 4. Set $K = K + 1$

Step 5. Generate p_1 from p by applying the selection operator.

Step 6. Transform p_1 to p_2 using crossover operator.

Step 7. Transform p_2 to p_3 by applying the mutation operator

Step 8. Transform p_3 to p_4 and p_4 to p_5 by applying the repair and swap operators.

Step 9. Set $p = p_5$ and evaluate the fitness value of each individual

Step 10. If $K < K_{max}$ go to step 4.

Step 11. Designate the best solution generated as the final solution and stop.

4. CASE STUDIES

In order to test the proposed GA to solve the UCP, two systems from literature, solved by dynamic programming are considered. The first system [8] consists of 10 units and a time horizon of 24 hours. The data of this system is given in Tables 1-3 respectively. The function used to compute the start-up costs of the units is the two-step function method.

Table 1 System data 1 for 10-unit system

Unit #	P_{max} 'MW'	P_{min} 'MW'	t_{up} 'hr'	t_d 'hr'	S_h (\$)	S_c (\$)	t_{cs} 'hr'	Initial state $x(0)$
1	455	150	8	8	4500	9000	5	8
2	455	150	8	8	5000	10000	5	8
3	130	20	4	4	550	1100	4	-5
4	130	20	4	4	560	1120	4	-5
5	162	25	6	6	900	1800	4	-6
6	80	20	3	3	170	340	2	-3
7	85	25	3	3	260	520	2	-3
8	55	10	1	1	30	60	0	-1
9	55	10	1	1	30	60	0	-1
10	55	10	1	1	30	60	0	-1

Table 2 System data 2 for 10-unit system

Unit #	a '\$'	b '\$/MW'	c '\$/MW^2'	Δ_{inc} 'MW/hr'	Δ_{dec} 'MW/hr'
1	1000	16.19	0.00048	80	80
2	970	17.26	0.00031	80	80
3	700	16.60	0.00200	20	20
4	680	16.50	0.00211	20	20
5	450	19.70	0.00398	25	25
6	370	22.26	0.00712	15	15
7	480	27.74	0.00079	20	20
8	660	25.92	0.00413	10	10
9	665	27.27	0.00222	10	10
10	670	27.79	0.00173	10	10

Table 3 Load pattern and spinning reserve for 10-unit system

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

The tuning parameters of GA for the two test systems are as follows:

Population size: $p = 50$

Probability of crossover: P_c =0.8

Probability of mutation: P_m = 0.05

Probability of repair operator: P_r = 0.7

Probability of swap operator: P_s = 0.3

Maximum no. of generations: K_{max} =400

Table 4 gives the generation schedule of the units at each hour and the total production cost during the time duration. Also, the proposed GA was successfully applied to a second system consists from 26 units. The system load pattern and the spinning reserve at each hour are given in table 5, while the remaining system data is found in [11]. The generation schedule at each hour and the total production cost are given in table 6. Table 7 presents a comparison of production cost and the solution time using the proposed GA against dynamic programming (DP) for 10 and 26-unit systems. The results obtained from the proposed GA are very encouraging, because the production cost error obtained is much less than of classical optimization techniques, and the solution time is also reduced. It is expected that for larger unit-systems, the computation time will be significantly much reduced.

Table 4 Unit commitment schedule generated for 10-unit system

Unit #	**Hour**																								**Production cost ($/day)**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	
1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	565863.58
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
3	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
8	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	
9	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	
10	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	

Table 5 Load pattern and spinning reserve for 26-unit system

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Load (MW)	1820	1800	1720	1700	1750	1910	2050	2400
Reserve (MW)	185	180	170	170	175	190	200	240
Hour	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Load (MW)	2600	2600	2620	2580	2590	2570	2500	2350
Reserve (MW)	260	260	260	260	260	260	250	235
Hour	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Load (MW)	2390	2480	2580	2620	2600	2480	2150	1900
Reserve (MW)	240	250	260	260	260	250	215	190

Table 6 Unit commitment schedule generation for 26-unit system

Hour	Commitment schedule																									
	Unit number																									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1
2	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1
3	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1
4	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1
5	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
6	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
7	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
8	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
10	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	0	0	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	0	0	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
24	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1
Total Production cost ($/day) = 666554.34																										

Table 7 Comparison results of the proposed GA against DP

System	Production cost (p.u)		Solution time (Seconds)	
	DP	GA	DP	GA
10-unit	1.0	1.0032	192	34
26-unit	1.0	1.0078	1830	72

5. CONCLUSION

The genetic algorithm is general optimization technique suitable for solving multi-constraints, and combinatorial optimization problems. Since, the UCP is a complex decision making process due to multiple constraints, therefore GA is suitable to model and handle the complex mathematics of this problem more efficiently. This paper presents a genetic algorithm-based approach to solve the short-term thermal generating unit commitment problem. Problem formulation and solution procedure considering the minimization of the total production cost and system operating constraints are provided. The production cost includes fuel cost of operating units and the start-up cost, while the operational constraints include capacity limits, spinning reserve, minimum up/down time, and the ramp rates of each generating unit. The response of proposed GA is improved by adding a repair and swap mutation operators. The algorithm has been successfully applied to 10 and 26 generating-unit systems to find the optimal schedule of the units to meet the requirements of system load demand during a time duration of 24 hours. Also, the obtained results are compared with those obtained from dynamic programming algorithm. The results show the effectiveness of the proposed GA to obtain the optimal schedule with a sufficient accuracy and low computation time. It is expected that for larger unit- systems, the computation time will be much significantly reduced. The work in progress is to obtain the optimal unit commitment schedule by considering transmission constraints and system losses.

REFERENCES

1. Sheble, G. B. and Fahd G. N., "Unit Commitment Literature Synopsis", IEEE Trans. on Power Systems, Vol. 9, No.1, 1994, pp. 128-135.
2. Lowery, P. G., "Generating Unit Commitment by Dynamic Programming", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-85, No.5, 1996, pp. 422-426.
3. Ouyang, Z. and Shahidehpour, S. M., "Short Term Unit Commitment Expert System", Electric Power System Research, No.20, 1990, pp. 1-13.
4. Su, C. C. and Hsu, Y. Y., "Fuzzy Dynamic Programming: An Application to Unit Commitment", IEEE Trans. on Power Systems, Vol. 6, No. 3, 1991, pp. 1231-1237.
5. Sasaki, H., Watanable, M.. Kubokawa, J. and Yorino, N., "A Solution Method of Unit Commitment by Artificial Neural Networks", IEEE Trans. on Power Systems, Vol. 7, No.3, 1992, pp. 974-981.
6. Tseng, C. L., Oren, S. S., Svoboda, A. J. and Johnson, R. B., "A Unit Decommitment Method in Power System Scheduling", Electrical Power & Energy Systems, Vol. 19, No.6, 1997, pp. 357-365.
7. Mantawy, A. H., Abdel-Magid, Y. L. and Selim, S. Z., "Integrating Genetic Algorithms, Tabu Search, and Simulated annealing for the Unit Commitment Problem", IEEE Trans. on Power Systems, Vol. 14, No.3, 1999, pp. 829-836.
8. Kazarlis, S. A., Bakirtzis, A. G. and Petridis, V., "A Genetic Algorithm Solution to the Unit Commitment Problem" IEEE Trans. on Power Systems, Vol.11, No.1, 1996, pp. 83-90.
9. Cheng, C. L., Chih-Wen, L. and Chun-Chang, "Unit Commitment by Lagrangian Relaxation and Genetic Algorithms", IEEE Trans. on Power Systems, Vol. 15, No. 2, 2000.
10. Arroyo, J. M., and Conejo, J. A., "A Parallel Repair Genetic Algorithm to Solve the Unit Commitment Problem", IEEE Trans. on Power Systems, Vol.17, N0.4, 2002, pp. 1216-1224.
11. Padhy, N. P., "Genetic Algorithm-Based Machine Learning Classifier System Model for Short-Term Unit Commitment Problem", International Journal of Power & Energy Systems, Vol. 23, No.1, 2003, pp. 49-60.
12. Lu, B. and Shahidehpour, M., "Short-term Scheduling of Combined Cycle Units", IEEE Trans. on Power Systems, Vol. 19, No.3, 2004, pp. 1616-1625.
13. Gen, M. and Cheng, R., 'Genetic Algorithms & Engineering Design', John Wiley& Sons, Inc., 1997.
14. Wood, A. J. and Wollenberg, B. F., 'Power Generation, Operation and Control', John Wiley & Sons, New York, 1984.