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Research paper

New Strategy Based on Combined Use of Genetic Algorithm and Gradient to Solve the UC Problem: Theoretical Investigation and Comparative Study

Sahbi. Marrouchi[1]*, Moez Ben Hessine[1], Souad Chebbi[1]

[1]*Laboratory Technologies of Information and Communication and Electrical Engineering (LaTICE), National Superior School of Engineers of Tunis (ENSIT), University of Tunis, 5 Street Taha Hussein Montfleurie, 1008 Tunis, Tunisia.*
**Corresponding author E-mail: sahbimarrouchi@yahoo.fr*

Abstract

This paper presents a comparative study between a new strategy based on hybrid Gradient-Genetic Algorithm method and metaheuristic methods for solving Unit Commitment problem. Strategies have been applied on the IEEE electrical network 14 bus test system for a variable load profile during a discretized margin of time (24-hour time requirement). The right choice of the initial population and the best knowledge of the technical constraints specific to each generator (power balance constraints, Spinning reserve constraints, minimum up time, minimum down time) suggests the possibility of obtaining improvements in the time execution. The adopted strategy has presented high performance both for minimizing the production cost and for the rapidity of convergence to optimal solutions and is promising compared to Genetic algorithm.

Keywords: *Unit commitment ; Optimization ; Scheduling ; Genetic Algorithm ; Gradient method*

1. Introduction

In Unit Commitment Problem, each unit has its own production limits and minimum time to reboot and shutdown. It is, therefore, a mixed complex optimization problem [1,2], combinatorial and nonlinear [3,4,5,6]. It is difficult to determine a planning economic operation for this reason; the researchers observed that the stochastic models are more efficient than deterministic models in uncertainty. However, stochastic search algorithms are able to overcome the shortcomings of conventional optimization techniques [7, 8, 9, 10]. These methods can handle complex nonlinear constraints and provide high quality solutions.
However, PG Lowery et al [11] established a strategy based on dynamic programming (DP) to solve the UC problem. The strategy was effective in reducing the production cost and computation time but it presents a combinatorial complexity while the number of generators increases which makes the time to slower calculation. For this purpose, Pang et al. [12] proposed two algorithms: combinatorial sequential dynamic programming (MHPD) and combinatorial truncation dynamic programming (DPTC) to solve the combinatorial complexity and calibrate the resolution of the Unit Commitment problem by dynamic programming. The results show that MHPD offers better solutions compared to DP and DPTC and is effective at reducing the total cost of production and in execution time. However, Merlin et al. [13] proposed a new approach to develop a flexible algorithm for simultaneous management of pumping units and probabilistic determination of the reserve to guarantee through the Lagrangian relaxation method. The method was validated with the power company de France (EDF). The method was promising except that the running time of the program increases only linearly with the size of the system and that it is applied only for electrical networks including power plants. As for Ongsakul et al. [14], they proposed an adaptive improvement on Lagrangian relaxation which aims to eliminate the drawbacks mentioned by LR Aoki and merlin. This improvement is to adapt a heuristic search to adjust the program if any of the consumption of forecast errors and employ adaptive Lagrangian relaxation to find the best possible planning. The results show that this improvement provides a final solution at a lower cost compared to conventional LR and DP, but the degree of optimality (percentage of optimal solution) decreases when the units of the numbers increase and classical LR remains fast computing time that this technique. Furthermore, Kavatza et al. [15] suggested a new simulated annealing approach combined with the method of dynamic load to ensure the scheduling of production units, while load balancing procedure was applied by integrating the constraints of the ramp rate in solving the Unit Commitment problem in order to determine the output power of each generator. Compared to methods LR, GA and SA, the simulated annealing method is effective in minimizing the cost of production but it has quite a long time. Sheble et al. [16] presented a new approach based on genetic algorithm (GA) for the planning of production units. The results show that this method provides good quality solutions at lower total cost of production but requires a lot of computation because it manipulates several solutions simultaneously. The success of the development requires several tries so it takes a huge time. However, Rudolf et al. [17] proposed an approach to two levels of programming to solve the problem of engagement of the units. The first level uses the algorithm that was developed by the states to decide Sheble units on / off. The second uses a formulation of the nonlinear programming by the LR method to perform load balancing within the constraints of the system. This technique has been applied to a hydrothermal system at real scale. The simulation results show that the implementation of this strategy is easy

and allows convergence to the optimal solution but it is very slow compared to the Al. Mori et al. [18] have improved their approach based on taboo search method through the integration of the priority list method in the tabu search method. The resolution of the load balancing problem is by Lambda iterations of method but the determination of states on / off generators is determined by the method of seeking taboo. The results were promising in terms of convergence speed and at lower total cost of production but the strategy does not solve the problem of computing time that remains very slow. Thus, in order to inquire into the performance and benefits of solving the genetic algorithm and the gradient method, we thought a new strategy based on the combination of these two stochastic and deterministic methods for solving the Unit Commitment problem.
The paper is organized as follows; Section 2 is reserved to formulate the Unit Commitment Problem. In section 3, we have presented the methodology of resolution through Gradient-genetic algorithm methods. Next, section 4 deals with the discussion of simulation results and the main improvements of adopted strategies are highlighted. Finally, section 5 resumes the main conclusions followed by references.

2. Problem Formulation

The resolution of the Unit Commitment problem is available through the On/Off status scheduling and the optimization of the generated power over an H planning horizon time and among N_g units in order to minimize the total operating cost. The objective function is expressed [1,7,18, 19], as given in (1):

$$Min \left[F_T(P_{ih},U_{ih}) = \sum_{i=1}^{N_g}\sum_{h=1}^{H}[a_i P_{ih}^2 + b_i P_{ih} + c_i + ST_i(1-U_{i(h-1)})]U_{ih} \right] \quad (1)$$

Where;
$F_T(P_{ih},U_{ih})$: The operating cost,
ST_i: The starting cost of the i^{th} unit defined by:

$$ST_i = \begin{cases} HSC_i \text{ if } MDT_i \le \tau_i^{OFF} \le MDT_i + SC_i \\ CSC_i \text{ if } \tau_i^{OFF} \succ MDT_i + SC_i \end{cases} \quad (2)$$

a_i ,b_i and c_i : Coefficients of the production cost,
P_{ih} : Active power generated by the i^{th} unit during h^{th} hours, $i = 1,2,3,....,N_g$ and $h = 1,2,3,....,H$
U_{ih} : On/Off status of the i^{th} production unit at the h^{th} hour, $U_{ih} = 0$ for the off state of one generating unit and $U_{ih} = 1$ for the operating status of one generating unit,
HSC_i : Hot start-up cost of the i^{th} unit,
CSC_i : Cold start-up cost of the i^{th} unit,
MDT_i : Minimum down-time of the unit i ,
τ_i^{OFF} : Continuously off-time of unit i ,
SC_i : Cold start time of unit i .
N_g : Number of generating units,
H : Time horizon for UC (h).
The problem is usually subjected to the following constraints [7, 19]:

- **Power balance constraints**

$$\sum_{i=1}^{N_g} P_{ih}U_{ih} = P_{dh} \quad (3)$$

- **Spinning reserve constraints**

$$P_{dh} + P_{rh} - \sum_{i=1}^{N_g} U_{ih}P_{ih} \le 0 \quad (4)$$

- **Generation limits**

$$P_i^{min}.U_i \le P_{ih}.U_i \le P_i^{max}.U_i \quad (5)$$

- **Minimum up-time constraint**

$$U_{ih} = 1 \quad for \sum_{t=h-up_i}^{h-1} U_{ih} \le MUT_i \quad (6)$$

- **Minimum down-time constraint**

$$U_{ih} = 0 \quad for \sum_{t=h-down_i}^{h-1} U_{ih} \le MDT_i \quad (7)$$

With:
P_{rh} : System spinning reserve at the h^{th} hour,
P_{dh} : Amount of the consumed power at the h^{th} hour,
P_{Lh} : Total active losses at the h^{th} hour,
P_i^{min} , P_i^{max} : Minimum and maximum power produced by a generator,
MUT_i, MDT_i : Continuously up and down-time of unit i .
Therefore, in order to simplify the UCP and to transform the different inequality to transform a linear unconstrained problem, we have considered the following Lagrangian function:

$$L(P_{ih},U_i,\lambda_i) = \sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{ih}) + ST_i(1-U_{i(h-1)})]U_{ih} + \lambda_i.(P_d - \sum_{i=1}^{N_g} P_i U_{ih}) \quad (8)$$

Where, λ_i is the Lagrangian coefficient.

3. Methodology of Resolution

3.1. Fitness Function

The aim of this paper is to evaluate the effectiveness of the model of the model. In order to arrive at an adequate planning of the units of production, we have combined two methods; The genetic algorithm and the gradient method. However, the genetic algorithm is very slow because of the complexity of the problem and its constraints. On the other hand, gradient method is fast, whereas its major disadvantage is that it can converge towards solutions that are far from optimal. Thus, we think of establishing a new strategy combining the advantages of these two solutions and trying to reduce their disadvantages. In this strategy, we integrate the Lagrangian function which defines the cost of generating energy from the set of equality and inequality constraints in the fitness function. In this evaluation function, the Lagrange coefficient (λ) plays the role of a corrective coefficient trying to establish the balance of the power consumption energy balance and thanks to this coefficient of an equality constraint. According to the fundamental principle of Genetic algorithm in one individual's population, only the strongest or the best suited to the natural environment is able to survive and give offspring [10, 16]. At each genetic algorithm operation, chromosomes use the data structures given by the study state of electrical network and try the search a new global optimum among the local optimum. This search procedure is very related to constraints given both for the electrical network and for production unit. In order to develop our optimization strategy, we have considered the integration of the Lagrangian function which defines the cost of energy production from the set of equality and inequality constraints in the fitness function. A strategy for which we have opted to minimize the objective function by maximizing the evaluation function.

$$F(U,P)=\left(1+K\left(\frac{Max\left(\dfrac{1}{\sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{ih})+ST_i\,(1-U_{i(h-1)})]U_{ih}+\lambda_i.(P_d-\sum_{i=1}^{N_g}P_iU_{ih})+\sum_{h=1}^{H}\beta_h.L}\right)}{\dfrac{1}{\sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{ih})+ST_i\,(1-U_{i(h-1)})]U_{ih}+\lambda_i.(P_d-\sum_{i=1}^{N_g}P_iU_{ih})+\sum_{h=1}^{H}\beta_h.L}}-1\right)\right)^{-1} \quad (9)$$

With:

L : Penalty coefficient,

K : Scaling coefficient,

β_h : Constant defined as follows: $\begin{cases}\beta_h=1 \;\; if \;\; C(P_{ih},U)\neq 0\\ \beta_h=0 \;\; if \;\; C(P_{ih},U)=0\end{cases}$

3.2. Coding Process

After passing through the genetic operators (selection, crossing and mutation) and in order to proceed with the conversion of each binary solution, two steps are presented:

- The first consists in transforming the corresponding binary values into decimal values obeying the following equati

$$\hat{y}_i=\sum_{i=1}^{ls}(S_i).2^{(ls-i)} \quad (10)$$

- The second step consists of a scaling technique so as to attribute to the previously found value a corresponding real value in the appropriate search space as shown by the following equation:

$$y_i=y_{min,i}+\hat{y}_i.\frac{y_{max,i}-y_{min,i}}{2^{ls}-1} \quad (11)$$

Herein, we have proceeded by encoding in a 12-bit string since the simulation model used contains 5 generators. This leads to a resolution of 2^{12} = 4096 discrete considered power values in the range of supplied power $\left(P_i^{min},P_i^{max}\right)$ generated by each production unit.

3.3. Selection

Several selection method are used in genetic algorithm [7,10,16], the most popular one is the biased roulette wheel method which corresponds on the selection of the best chromosomes according to their best performances $perf(c_i)$ obeying to the following equation:

$$perf(c_i)=\frac{f(c_i)}{\sum_{i=1}^{l}f(c_i)} \quad (12)$$

Once the best chromosomes have been selected, the crossover operation takes place to produce the descending chromosomes.

3.4. Crossover and Mutation

We have adopted the principle of binary crossing (the crossing performed on sequences) and for this purpose the crossing point falls between the bits of two parameters. In this case, the offspring receives some of its parameters from one parent and the others from the other parent. If the crossover point is between the bits of a parameter, the part of the binary code to the left of the crossover point corresponds to the most significant bits and the right part to the least significant bits. So the offspring receive a larger part of one parent and a less significant part of the other parent. The offspring may therefore be considered as a disturbance of the first parent, where the amplitude of the disturbance is determined by the difference between the least significant bits of the parents. If the crossover is between bits k and $k+1$, the disturbance is similar to changing the bits $k+1$ to N_{bits} of one of the parents (for an n-bit coded sequence). The probability of crossover C_r is given by the following expression [7,10,16]:

$$C_r=K_1.\left[\frac{Max(\dfrac{1}{1+K(\frac{F_{max}}{Fr}-1)})-F_{CROSS}}{Max(\dfrac{1}{1+K(\frac{F_{max}}{Fr}-1)})-\overline{F}}\right] \quad (13)$$

Where; F_{CROSS} presents the larger of the fitness values of the solutions to be crossed, $\overline{F}$ is the average of the fitness function and K_1 is the constant of proportionality.

In a binary coding and especially when there is a mutation, the bits are changed from 0 to 1 or from 1 to 0. When a bit undergoes a mutation, it can be perceived as a perturbation of the actual parameter. The amplitude of the perturbation depends on the bit that is modified and the expression of the probability of mutation M_P is given as follows:

$$M_P=K_2.\left[\frac{Max(\dfrac{1}{1+K(\frac{F_{max}}{Fr}-1)})-\dfrac{1}{1+K(\frac{F_{max}}{Fr}-1)}}{Max(\dfrac{1}{1+K(\frac{F_{max}}{Fr}-1)})-\overline{F}}\right] \quad (14)$$

Where, K_2 is the constant of proportionality.

4. Resolution Process

In order to guarantee the optimization of the production energy rate and the arrangement of the operating states of the production units, we have opted for the strategy so that it merges the operating state (On / Off) as well as the optimum amount of active power to be supplied by each unit i so that if the production unit must be in the ON state for one given time t and the amount of active power optimized by the genetic algorithm will be indicated by a single value representing the desired amount of power P_{hi}. In the opposite case, this variable takes the value 0. Thus, in the matrix encompassing the set of solutions, each column of the solution matrix representing the planning of the states of operations of the production units indicates the set of switching states as well as than the rate of production in active power. The column vector of length l_s in the matrix of the solutions is converted to its similar in equivalent decimal number. These solutions will be introduced into the evaluation function in order to distinguish those leading to a minimal production cost. The best solutions are saved in a V_{best}

vector. Once the criterion for stopping the first research phase is reached (the number of generations reaches its maximum number N_{Gen}^{Max}), the process based on the gradient method will take place in order to refine the search for solutions and get closer to of the overall optimum leading to a satisfactory cost.

The process of this strategy is carried out by searching for the direction of descent of the greatest slope corresponding to the minimum cost of production possible. Indeed, this approach emphasizes the search for a vector γ_k that contains the possible combinations of on /off states of the production units U_{ih}, the values of the power $P_{gi,h}$ produced in a specific time interval and the values λ_i leading to the minimization of the individual objective function of each production unit. This vector will be determined in an iterative manner obeying the following relation:

$$\gamma_{k+1} = \gamma_k + d_k.\xi_k \tag{15}$$

Vectors γ_{k+1}, d_k, ξ_k are defined by the following equation system:

$$\xi_k = \begin{bmatrix} \dfrac{\partial\left(\sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{gi,h}) + ST_i(1-U_{i(h-1)})]U_{ih} + \lambda_i.(P_d - \sum_{i=1}^{N_g} P_{gi,h}U_{ih})\right)}{\partial P_{gi,h}} \\ \dfrac{\partial\left(\sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{gi,h}) + ST_i(1-U_{i(h-1)})]U_{ih} + \lambda_i.(P_d - \sum_{i=1}^{N_g} P_{gi,h}U_{ih})\right)}{\partial U_{ih}} \\ \dfrac{\partial\left(\sum_{i=1}^{N_g}\sum_{h=1}^{H}[\phi_i(P_{gi,h}) + ST_i(1-U_{i(h-1)})]U_{ih} + \lambda_i.(P_d - \sum_{i=1}^{N_g} P_{gi,h}U_{ih})\right)}{\partial \lambda_i} \end{bmatrix}; \quad \gamma_{k+1} = \begin{bmatrix} P_{gi,h} \\ U_{ih} \\ \lambda_i \end{bmatrix}; \quad d_k = \frac{\xi_k^{\,t}.\xi_k}{\xi_k.\left(\left(\nabla^2 L(P_{gi,h}, U_i, \lambda_i)\right).\xi_k\right)} \tag{16}$$

Where, the Hessian matrix A is defined as:

$$A = \begin{bmatrix} \dfrac{\partial^2 L}{\partial P_{ih}\partial P_{jh}} & \dfrac{\partial^2 L}{\partial P_{ih}\partial U_{jh}} & \dfrac{\partial^2 L}{\partial P_{ih}\partial \lambda_j} \\ \dfrac{\partial^2 L}{\partial U_{ih}\partial P_{jh}} & \dfrac{\partial^2 L}{\partial U_{ih}\partial U_{jh}} & \dfrac{\partial^2 L}{\partial U_{ih}\partial \lambda_j} \\ \dfrac{\partial^2 L}{\partial \lambda_i\partial P_{jh}} & \dfrac{\partial^2 L}{\partial \lambda_i\partial U_{jh}} & \dfrac{\partial^2 L}{\partial \lambda_i\partial \lambda_j} \end{bmatrix}; i = \{1 \dots N_G\}; j = \{1 \dots N_G\} \tag{17}$$

ξ_k Presents the gradient vector indicating the descent direction to the global minimum d_k presents the calculation step and A presents the Hessian matrix defined by the partial derivatives of the production function relative to the generated powers and to the various on / off states of each production unit. The process of solving the Unit Commitment problem using the gradient-genetic algorithm is carried out according to the calculation flowchart given by the figure1.

5. Simulations and Results

In a perspective to test the performance of the optimization proposed method; the strategy has been applied to an IEEE electrical network 14 buses, having 5 generators, over a period of 24 hours [4,7]. The strategies are occurring at t = 40 sec. In this paper, we have considered 24 successive periods in order to establish the temporal evolution of the power demand given in Table 2. The characteristics of the different production units are given in Table 1. We have took as population size = 40, crossover probability = 0.6, mutation probability = 0.02 and the maximum generation number = 300 [10,16].

8 successive periods has been considered in order to establish the temporal evolution of the power demand. The amount of the power demand is established according to table3.

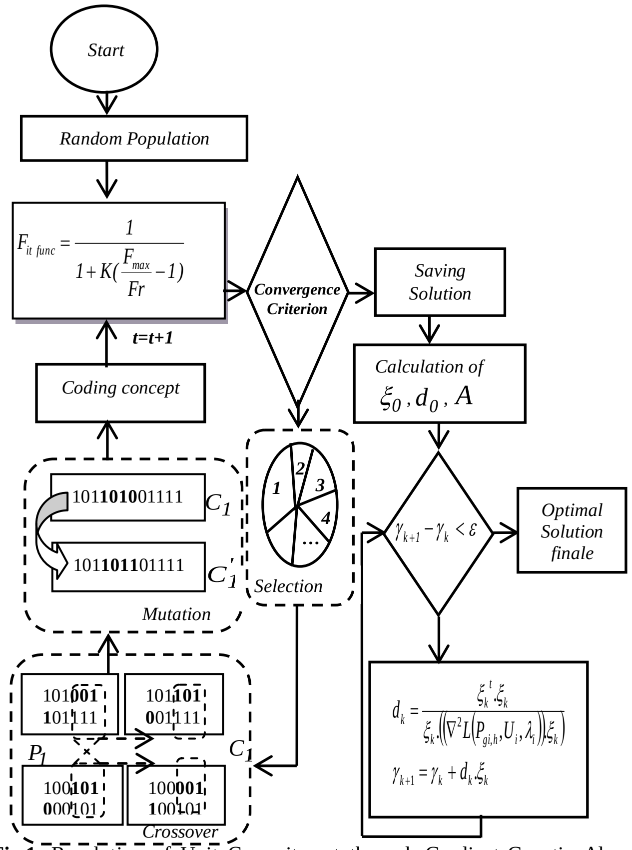

Fig.1. Resolution of Unit Commitment through Gradient-Genetic Algorithm

Table 1. Characteristics of production units

U	P_{max}	P_{min}	a	b	c	Up	Down	Hot start cost ($)	Cold start cost ($)	Cold start (h)
1	**582**	**110**	**379.2**	**30.36**	**0.0756**	**8**	**8**	**4500**	**9000**	**6**
2	**55**	**15**	**606.6**	**27.3**	**0.2274**	**3**	**3**	**170**	**340**	**2**
3	**53**	**10**	**454.8**	**22.74**	**0.2274**	**3**	**3**	**170**	**340**	**2**
4	**23**	**8**	**151.8**	**22.5**	**0.1518**	**1**	**1**	**30**	**60**	**0**
5	**23**	**8**	**303.6**	**22.74**	**0.1518**	**1**	**1**	**30**	**60**	**0**

Table 2. Amount of the power demand

Hour	3	6	9	12	15	18	21	24
Demand (MW)	259	200	300	450	527	610	480	320

The results of planning and distribution of the production cost based on the genetic algorithm and the Gradient-Genetic Algorithm approach we adopted for each hour are detailed in Table 3. It should be noted that thanks to the hybrid optimization method, it has been possible to organize the start and stop conditions of the various production units, and this is done by estimating the amount of charge desired by the electrical network, while taking into account allowable constraints. However, a fairly optimal planning allows a profit of the cost of production. The superiority of the Gradient-Genetic Algorithm method is obvious. This method works better than the individual algorithms in terms of planning the on / off states of the various units and thus optimizing the total cost of production. In addition, it is interesting to note that through the gradient algorithm-genetic algorithm, we were able to reduce the quantities of power produced by each unit while approaching the quantity demanded with a consideration of a guaranteed power. for reserve constraints. This profit in power quantities provided proved the effectiveness of the gradient-genetic algorithm strategy compared to that based on the genetic algorithm. However, on the execution time plan, our strategy requires only 12.57 seconds, a time close to that required by the approach based on the genetic algorithm which is equal to 10.21 seconds.

Table 3. Results of Unit Commitment Problem by the Gradient-Genetic Algorithm Strategy

H	Power demand (MW)	Generated power by each unit (MW)					production cost ($)	Optimal planning
		615 MVA	60 MVA	60_Bis MVA	25 MVA	25_Bis MVA		
1	259	274.6	0	0	0	0	6885	10000
2	259	325.8	0	0	0	0	7942	10000
3	259	361.2	0	0	0	0	8695	10000
4	200	376.3	0	0	0	0	9022	10000
5	200	390.3	0	0	0	0	9329	10000
6	200	417.3	0	0	0	0	9928	10000
7	300	416.3	6.2	3.4	0	0	10156	11100
8	300	417.2	10.3	7.4	0	0	10391	11100
9	300	444.6	19.13	10.2	0	0	11333	11100
10	450	490.8	25	15	0	0	12757	11100
11	450	497.4	29.9	20.25	0	0	13166	11100
12	450	507.7	34.8	21.88	0	0	13605	11100
13	527	519.9	36.59	23.66	3.2	4.6	14189	11111
14	527	522.3	34.63	22.5	3.8	4.688	14416	11111
15	527	522.3	33.01	22.05	3.7	4.7	14102	11111
16	610	535.9	37.58	28.11	4.9	0	14432	11110
17	610	535	36.58	28.89	4.6	0	14658	11110
18	610	539	38	31.34	4.6	0	14886	11110
19	480	482	29.78	23.03	4.1	0	12986	11110
20	480	453	25.1	17.29	3.2	0	11975	11110
21	480	430.1	20.6	12.71	3.6	0	11399	11110
22	320	375.7	12.03	0	0	0	9342	11000
23	320	347.5	14.35	0	0	0	8799	11000
24	320	335.4	16.08	0	0	0	8590	11000
Total Cost($)								2.7750e+005
Total generated power (MW)								9438
Time (sec)								12.57

In order to validate our mathematical modeling and our hierarchical structure strategy, we present in the temporal evolutions the powers generated by each unit of production as well as the quantities of optimal powers estimated by the proposed optimization process (Gradient-Genetic Algorithm) in figure 2. We find that the generated powers follow in full the optimal power quantities provided by the two algorithms (Genetic Algorithm and Gradient-Genetic Algorithm), which shows the high performance of the control algorithms adopted for the supervision of the studied system.

In addition, the strategy adopted made it possible to obtain adequate and rapid planning in terms of convergence. The scheduling of the production units by the genetic algorithm and by the strategy based on the hybridization of the gradient method and the genetic algorithm prove that each unit has complied with have obeyed the time constraints mentioned (minimum up and down times). It is interesting to note that through the proposed strategy, we have managed to reduce the number of switching machines and this in order to minimize the total cost of production. Based on table 4, we note that we arrived through the hybridization of the GA and the gradient method to reduce the total production cost which proves the effectiveness of the adopted strategy.

Moreover, compared to works [20, 21] which have used simulated annealing and genetic algorithm methods to establish a better UC scheduling, we note that the adopted strategy presents high performances since it has reduced the production cost through a better optimization of the ON/OFF states (Fig. 3) of the various production units.

Table 4. Comparison between the optimization methods

	Genetic algorithm [20]	Gradient-GA
Production cost ($)	**2.9452e+005**	**2.7750e+005**
Execution time (sec)	***10.21***	***12.57***

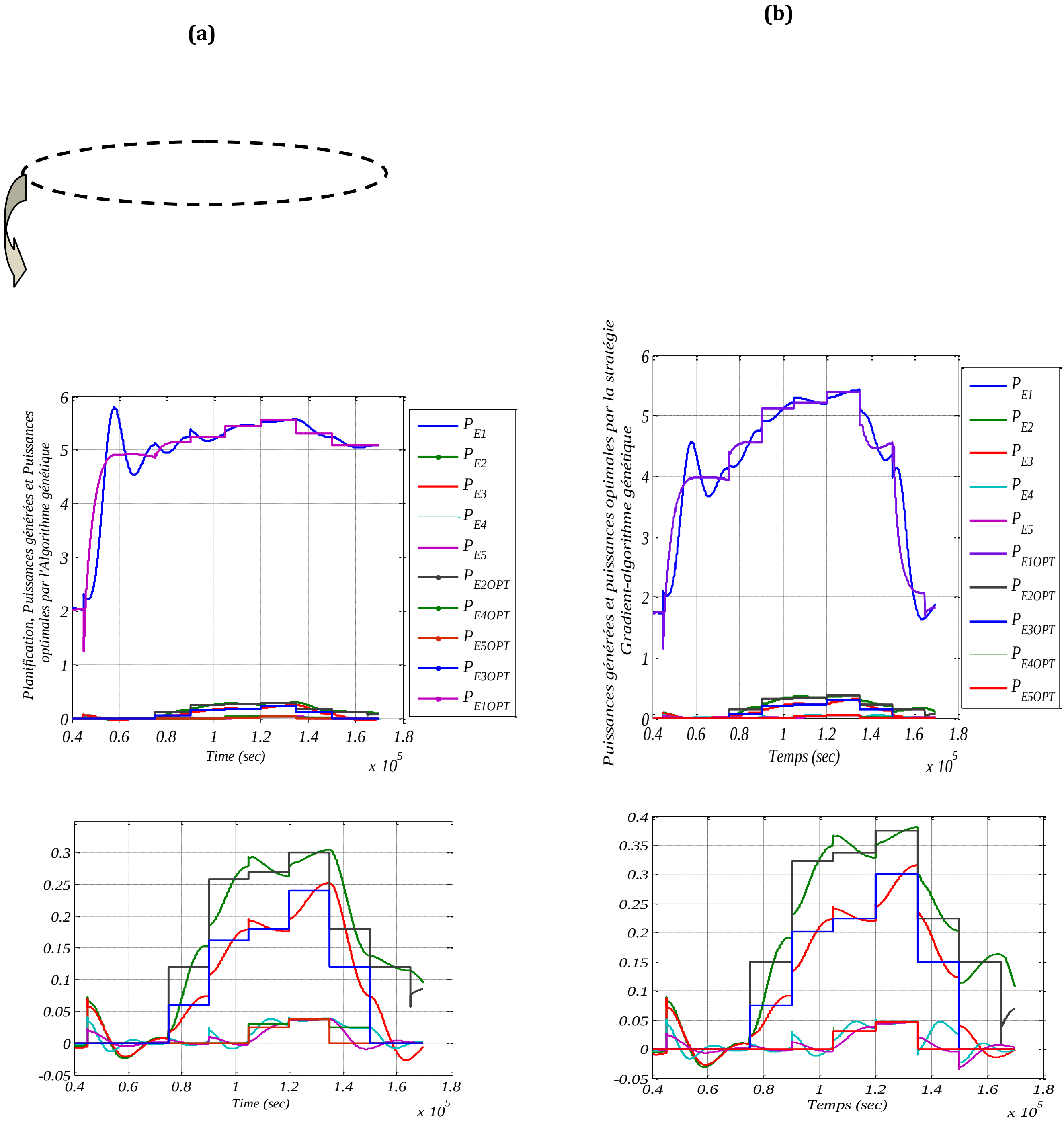

Fig.2. Scheduling and produced powers by production units using the genetic algorithm (a) and gradient genetic algorithm (b)

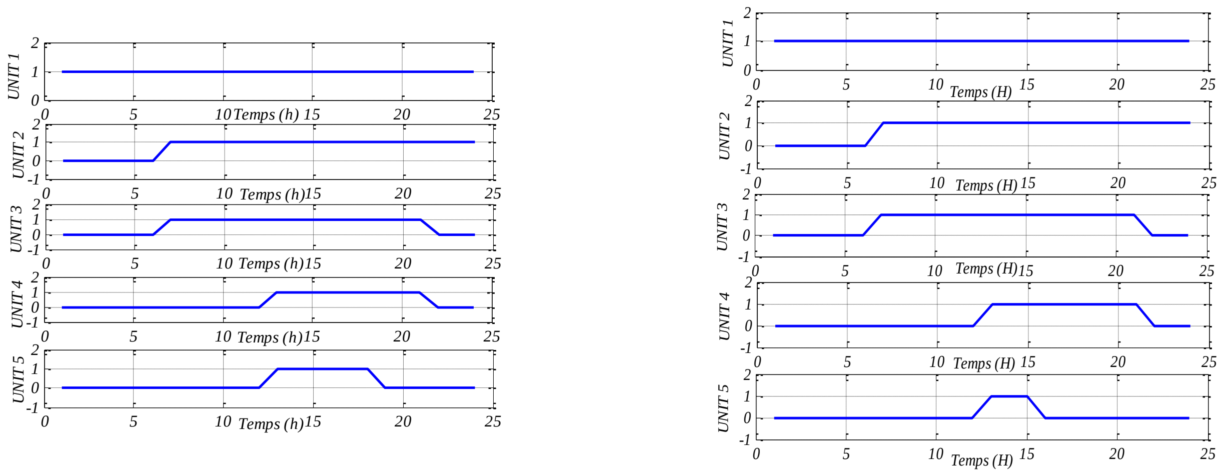

Fig.3. Scheduling of th production units using the GA (a) and gradient-GA (b)

6. Conclusion

The proposed strategy based on solving the Unit commitment problem by a hybrid approach combining gradient method and genetic algorithm presented high performance both for minimizing the production cost and for the rapidity of convergence to optimal solutions. However, the right choice of the initial population suggests the possibility of achieving improvements in execution time of the proposed strategy. Minimization was ensured through proper planning that takes into account the equilibrium constraints and unconstraints for each production unit. Compared to other stochastic methods as simulated annealing and genetic algorithm, it appears that our hybrid strategy was the most promising. The effectiveness of the proposed strategy suggests the possibility of applying it on a real network with a great number of buses.

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