Optimizing Unit Scheduling with Fuzzy Logic: A Strategic Approach for Efficient Power Network Operations

Sahbi Marrouchi
LaTICE Laboratory, National Higher Engineering School of Tunis, University of Tunis, Tunisia | Higher Institute of Technological Studies of Kef, Tunisia
sahbimarrouchi@yahoo.fr (corresponding author)

Moez ben Hessine
Higher Institute of Applied Sciences and Technologies of Gafsa, University of Gafsa, Tunisia
moezbenhessine@yahoo.com

Souad Chebbi
LaTICE Laboratory, National Higher Engineering School of Tunis, University of Tunis, Tunisia
chebbi.souad@gmail.com

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ABSTRACT

This study delves into addressing the challenge of resolving the Unit Commitment (UC) problem, which focuses on enhancing the efficiency of production units and devising their operational schedules to accommodate fluctuations in consumption spanning from a day to a month. Given the intricate, combinatorial, and nonlinear constraints associated with each production unit, this study advocates an optimization approach rooted in fuzzy logic. A Langrangian function was established to simplify the UCP and to transform the different inequality into a linear unconstrained problem. The choice of fuzzy inputs was established using the partial derivatives of a Lagrangian function as a function of the powers injected into each node of the electrical network. This combination of the Lagrangian function and the input of the fuzzy regulator made it possible to control the different constraints in the total production cost function and to improve the operating efficiency of the different production units. This method was effectively applied to a 14-bus IEEE power network encompassing 5 generating units, to address the UC problem by optimizing generator load capacity (LCG) and minimizing Incremental Losses (IL). The numerical processing of the fuzzy linguistic variables was implemented using Mamdani-type fuzzy rules. This strategy stands out for its robust exploratory capability, facilitating the identification of optimal solutions to reduce production costs while ensuring optimal planning of production units.

Keywords-unit commitment; optimization; fuzzy logic; production unit; energy management

I. INTRODUCTION

The production of electricity must be compatible with consumption since the electricity is not stored. Therefore, a power company must plan the generators to start and organize the moments to connect them to the network as well as their duration of operation. The Unit Commitment (UC) is the best solution in the field of modern power grid planning, enabling both the optimization of the day-to-day operational planning of the grids and the reduction of the total production cost through the improvement of units and respect of the schedules. The main objective is to program the production units to meet the consumption demand with the minimum cost. Generation scheduling includes the determination of commissioning and generation level for each unit during a given planning period. In addition, each unit has its own production limits and a minimum restart and shutdown time. It is therefore a complex, combinatorial, and non-linear optimization issue [1-6].

The UC problem is directly related to unit scheduling and economic dispatch, while knowing that the system is subjected to several constraints. Equilibrium offers demand and limitation of the minimum durations from top to bottom of the thermal production unit and ensures that the powers generated are within the allowable margins. However, this matter includes a multitude of difficulties, namely the large size of the network studied, the presence of coupling constraints, the presence of operational constraints, and the time constraint that must be small with regard to the size of the problem [5-6]. In this context, production unit operation planning should be established to select which of the production units to be available to supply the forecast load of the system over a future period. Many numerical optimization techniques have been proposed to address the UC problem, like dynamic programming [6-9], the Lagrangian relaxation method [10-13], mixed variable programming [14-15], and the branch-and-bound method [16]. The dynamic programming method is simple but has a rather long computation time to converge to the optimal solution. The branch-and-bound method adopts a linear function to represent fuel consumption and start-up costs as a function of time. The disadvantage of this method is that its required execution time increases rapidly for large-scale UC problems [17-18]. The method of programming in mixed variables uses linear programming to reach an optimal solution. This method has been applied to small UC problems and has required major assumptions that limit the margin of the solutions. On the other hand, the time factor has an advantage for the Lagrangian relaxation method, but the latter suffers from the quality of the optimal solutions obtained.

Several numerical techniques have been applied to the UC problem, such as fuzzy logic [19-22], artificial neural networks [23], simulated annealing [24-27], Tabu search [26, 28], and the genetic algorithm [29-30]. These methods can take into account more complex constraints and are claimed to have a better solution quality. In this context, several studies presented a genetic approach to determine the order of priority of production units [31-32]. These studies have examined the feasibility of using genetic algorithms to optimize production costs and presented effective simulation results. The use of genetic algorithms to solve the UC problem dynamically evaluates the priority of units, taking into account the parameters of the system, the operating constraints, and the load profile requested for a well-defined period. In [4], a hybrid optimization method was proposed to solve the UC problem. This method combined the Particle Swarm Optimization (PSO) method, the Sequential Quadratic Programming technique (SQP), and the Tabu-Search (TS) method. The combinatorial part of the UC problem was solved using the TS method. In [33], a method was utilized for an employee's recovery method to eliminate UC. This technique served to increase the likelihood of generating feasible solutions and significantly reduce the time elapsed for finding unrealizable solutions. In [34], a fuzzy logic approach was implemented to produce a logical and feasible solution for each period, considering the many uncertainties involved in the planning and operation of the electrical grid. The load request and the reserve margin were treated as fuzzy variables.

This study adopted a new strategy to solve the UC problem based on the fuzzy approach, which allows the optimization of the production cost (CP) while guaranteeing adequate planning of the production units using a good selection of the fuzzy inputs and fuzzy rules. The proposed approach relies on a Lagrangian function chosen as the objective function to determine the Load Capacity of the Generator (LCG) and the Incremental Losses (IL), which were chosen as fuzzy input variables. These parameters are essential to minimize the total CP, which was chosen as the fuzzy output variable.

II. PROBLEM FORMULATION

Many studies have been based on an analytical statement of the UC problem [5, 6, 35-36]. This study presents a mathematical model of the UC problem with limited security, which has been adapted in [36-37]. This model is mixed linear and constrained.

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

The objective of the UC problem is to establish the best production unit plan that will be available to minimize the total operating cost of the generating units and to supply the forecasted load over a period H [37-38]. ST_i is the starting cost of the i^{th} unit, defined by:

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

The minimization of the objective function is provided with the following constraints.

A. System Constraints

- Power balance constraint:

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

- Spinning reserve constraint:

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

B. Unit Constraints

- Generation limits:

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

- Minimum uptime constraint:

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

- Minimum downtime constraint:

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

Therefore, to simplify the UC problem and to transform the different inequality into a linear unconstrained problem, the following Lagrangian function was considered:

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

where λ_i is the Lagrangian coefficient.

III. METHODOLOGY OF RESOLUTION

Not only does fuzzy logic provide a meaningful and powerful representation for the measurement of uncertainties, but also a meaningful representation of the fuzzy notion expressed in normal language. Fuzzy logic is a mathematical theory that encompasses the idea of vagueness when defining a concept or a meaning. For example, there is uncertainty in expressions, such as "low" or "high", since these expressions are imprecise and relative. Thus, such variables are called "fuzzy" as opposed to "net". Fuzzy is simply a way to describe the uncertainty. Generally, solving such a problem via fuzzy logic is based on the following three steps [37, 39-41]:

- Fuzzification transforms numerical values of net input into fuzzy variables.
- Fuzzy inference consists of a set of fuzzy logic rules.
- Defuzzification allows the transformation of the fuzzy variables into net real output.

Such ideas can be easily applied to solve the UC problem. Fuzzy logic allows a qualitative description of the behavior of a certain system, its characteristics, and its response without the need for an exact mathematical formulation. This study applied a new optimization strategy based on the fuzzy approach, which allows for taking into account many uncertainties involved in the planning and operation of electrical networks.

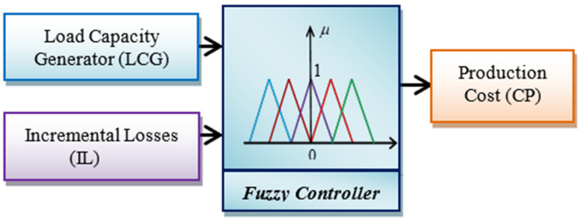

Fig. 1. Block diagram of the fuzzy controller.

Since the amount of expected power is inaccurate, it should be presented as a fuzzy quantity. In previous studies, the associated fuzzy variables for solving the UC problem were the load capacity of the generators, the cost of starting the units, and CP. However, this study considered the LCG and IL. The output variable is the CP. The following steps were taken to properly select the fuzzy variables that can lead to a minimal production cost. Starting from the condition that the partial derivatives of the Lagrange function (8) for each of the controllable variables are zero, the following equations were obtained:

$$\frac{\partial L}{\partial P_{ih}} = \frac{\partial[\varphi_i(P_{ih})]}{\partial P_{ih}} - \lambda\left(\frac{\partial P_{Lh}}{\partial P_{ih}} - U_{ih}\right) = 0 \quad (9)$$

The partial derivative of the Lagrange function for the controllable variable λ is as follows:

$$\frac{\partial L}{\partial \lambda} = P_{dh} - P_{Lh} - \sum_{i=1}^{N_g} P_i U_{ih} = \quad (10)$$

These conditions arise from the fact that to have a local or global minimum for such a linear function, these optimums correspond to the points where the partial derivative of the considered function is equal to zero. Equations (9) and (10) represent the optimality conditions necessary to solve (1) and (8) without resorting to inequality constraints (5), (6) and (7). Equation (9) can be written as follows:

$$\lambda = \frac{\frac{\partial[\varphi_i(P_{ih})]}{\partial P_{ih}}}{\frac{\partial P_{Lh}}{\partial P_{ih}} - U_{ih}};\ i = \{1, \ldots, N_G\};\ h = \{1, \ldots, H\} \quad (11)$$

The term $\frac{\partial[\varphi_i(P_{ih})]}{\partial P_{ih}}$ represents the incremental cost of each unit i, and $\frac{\partial P_{Lh}}{\partial P_{ih}}$ represents the incremental losses. To establish an effective strategy leading to the minimization of CP, it was necessary to take a better account of the losses already mentioned. The current expression of losses is translated as follows:

$$P_L = \begin{bmatrix} P_1 & P_2 & \ldots & P_{Nn} \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} & \ldots & B_{1Nn} \\ B_{21} & B_{22} & \ldots & B_{2Nn} \\ \ldots & \ldots & \ldots & \ldots \\ B_{Nn1} & B_{Nn2} & \ldots & B_{NnNn} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \ldots \\ P_{Nn} \end{bmatrix} + \begin{bmatrix} B_{10} & B_{20} & \ldots & B_{Nn0} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \ldots \\ P_{Nn} \end{bmatrix} + B_{00} \quad (12)$$

leading to:

$$P_L = \sum_{i=1}^{Nn} \sum_{j=1}^{Nn} P_i B_{ij} P_j + \sum_{i=1}^{Nn} B_{i0} P_i + B_{00} \quad (13)$$

where B_{ij} is the element (i, j) of the square matrix, B_{i0} is the element connected to the generator i, and B_{00} is the constant designating system losses if the power demand is equal to zero. These coefficients depend on the amplitude and the phase of the voltage and the reactive power injected into the electrical network at the bus i. The evaluation of (11) and (13) leads to the following equation of incremental losses:

$$IL_i = \frac{\partial P_{Lh}}{\partial P_{gi}} = 2\sum_{j=1}^{Nn} B_{ij} P_j + B_{i0} \quad (14)$$

Therefore the various variables (*LCG* and *IL*) can be established, forming the basis of the proposed strategy which can be used to reduce the total cost of production. These terms intervene as fuzzy variables associated with the UC problem-solving strategy. It should be noted that the strategy is based on the integration of a fuzzy controller to optimize CP while guaranteeing adequate planning of production units. In the current formulation, the fuzzy input variables associated with the UC problem are:

- *LCG*, which is based on the load to be served.
- *IL*, since losses can cause changes in the total CP and vary over the overall architecture of the power grid.
- The *CP* of the system is treated as a fuzzy variable because it is directly proportional to the hourly load demand.

The fuzzy sets defining these variables are selected and standardized between 0 and 1 [19-20]. The processing of the variables by a fuzzy controller requires three steps, namely a so-called fuzzification step, a second step named fuzzy inferences, and a last stage designated by defuzzification, consisting of transforming a fuzzy variable into a non-fuzzy variable. The process of processing variables using fuzzy logic is established as shown in Figure 2.

A. Membership Functions

The numerical processing of the linguistic variables of a fuzzy corrector requires the use of membership functions. These variables were characterized by fuzzy sets: Low (L), below average (BAV), average (AV), above average (AAV), and High (H). Several membership functions can be associated with these fuzzy sets. Based on the fuzzy sets cited, the membership functions are chosen for each fuzzy input and output variable as displayed in Figure 3. The fuzzy sets defining the input variables were adopted as follows: *LCG* and *IL* are indicated by the following fuzzy sets:

$$LCG = \{L, BAV, AV, AAV, H\}$$

$$IL = \{L, BAV, AV, AAV, H\}$$

The CP, taken as an objective function, is:

$$CP = \{L, BAV, AV, AAV, H\}$$

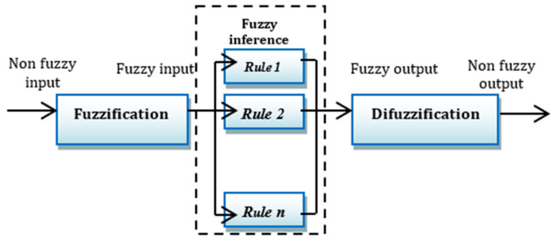

Fig. 2. Resolution process through fuzzy logic.

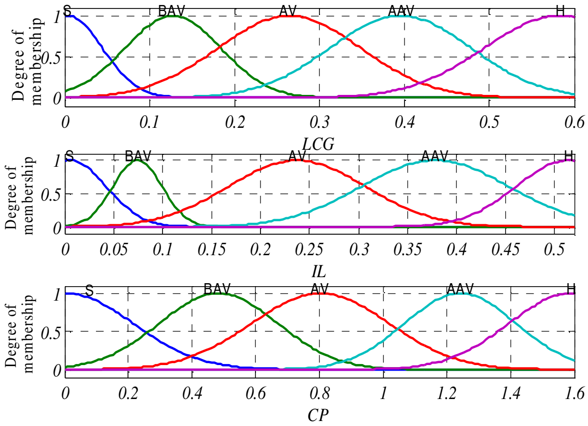

Fig. 3. Membership degrees of *LCG*, *IL*, and *CP*.

B. Fuzzification

Triangular and trapezoidal functions were used for the fuzzification of the input variables for two reasons: they do not require much calculation time in their evaluations, and they are easy to implement. Figure 4 shows the fuzzification of the input variable *IL* to assign a degree of belonging μ for this variable.

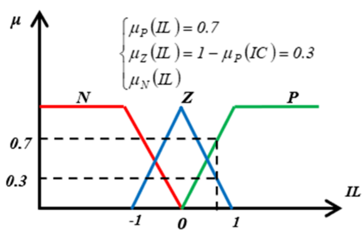

Fig. 4. Fuzzification of the input variable IL.

C. Fuzzy Inferences

Fuzzy deductions represent the set of conclusions to be drawn or the actions to be performed for each rule, following the determination of the membership functions and the input and output variables of a system already modeled. The decisions are taken at the level of the control vector of the fuzzy regulator, once the information on the inputs of the regulator is assembled. Based on the aforementioned fuzzy sets, the membership functions are chosen for each fuzzy input and output variable. For simplicity, a triangular shape is empoyed to illustrate the membership functions considered here. Once these sets are established, the input variables are then linked to the output variable by if-then rules, as illustrated in Figure 5.

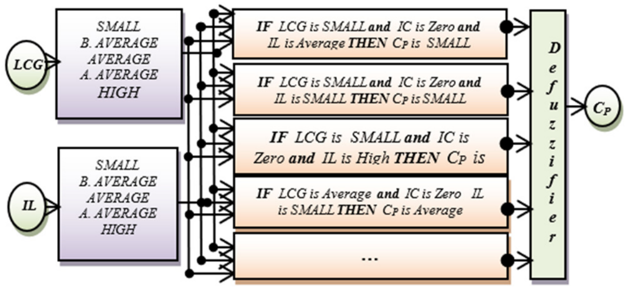

Fig. 5. Configuration of the strategy based on fuzzy logic.

D. Defuzzification

The inference step produced a control law expressed in terms of a membership function and, therefore, a fuzzy control law. Since the system to be controlled can only accept a defined command, this membership function must be translated into a non-fuzzy command. This process is known as defuzzification. Several methods of defuzzification exist in the literature: the best known is defuzzification by center of gravity. This method calculates the non-fuzzy control law U_C^* as an abscissa of the center of gravity of the membership function of the control law $\mu(U_C)$ μ(U_C). This study utilized Mamdani-type fuzzy rules to formulate conditional statements that include fuzzy logic. The proposed fuzzy rules are designed to optimize *CP* through a correct evaluation of the *LCG* and *IL* variables. In this respect, according to the fuzzy sets associated with each input variable, 25 fuzzy rules were established (5×5=25), as shown in Table I. Each rule represents the correspondence between the input and output spaces.

TABLE I. FUZZY RULES LINKING FUZZY INPUT/OUTPUT VARIABLES

Rule	LCG	IL	CP	Rules	LCG	IL	CP	Rules	LCG	IL	CP
1	S	S	S	10	BAV	H	AV	19	AAV	AAV	AAV
2	S	BAV	S	11	AV	S	BAV	20	AAV	H	BAV
3	S	AV	S	12	AV	BAV	BAV	21	H	S	AV
4	S	AAV	S	13	AV	AV	BAV	22	H	BAV	AAV
5	S	H	S	14	AV	AAV	AV	23	H	AV	AAV
6	BAV	S	S	15	AV	H	AV	24	H	AAV	H
7	BAV	BAV	BAV	16	AAV	S	AV	25	H	H	H
8	BAV	AV	BAV	17	AAV	BAV	AV				
9	BAV	AAV	BAV	18	AAV	AV	AAV				

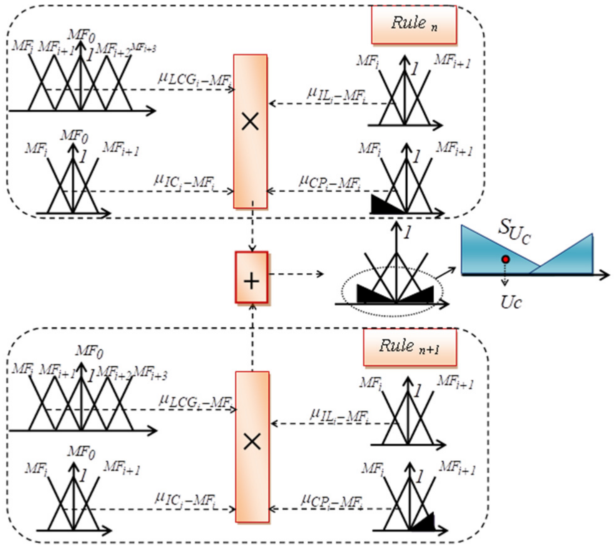

Fig. 6. Fuzzy deductions.

Once the fuzzy rules are defined, the results must be defuzzified to achieve exact values in the desired margins. The defuzzification method appied consists of determining the abscissa of the center of gravity of the surface swept by the fuzzy deductions given by the following equation:

$$C_P = \frac{\int_{-1}^{1} C_P.\mu(C_P).dC_P}{\int_{-1}^{1} \mu(C_P).dC_P} \tag{15}$$

where $\mu(U_C)$ is the degree of membership of the production cost vector. The rule surface shows the output value of *CP* for every combination of the inputs *LCG* and *IL*. The strategy to optimize the proposed UC problem was tested on the IEEE 14 bus test system.

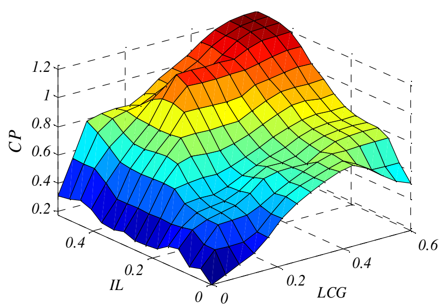

Fig. 7. Fuzzy controller rule surface.

IV. RESULTS AND DISCUSSIONS

The proposed mathematical modeling of the UC problem was simulated in Matlab. These simulations were applied on an IEEE electrical grid 14-bus test system with 5 generators [35-37, 42] over a 24-hour horizon. The strategy was started at time t = 40 s and the on-off states and the power quantity generated by each unit were taken every 3h. Tables II and III display the characteristics of the various production units and the expected load demand over a 24-hour horizon. The main successive periods were considered to establish the temporal evolution of the power demand.

TABLE II. CHARACTERISTICS OF PRODUCTION UNITS

U	Pmax (MW)	Pmin (MW)	c	b	a	MUT	MDT	Hot start-up cost ($)	Cold start-up cost ($)
1	582	110	379.2	30.36	0.0756	8	8	4500	9000
2	55	15	606.6	27.3	0.2274	3	3	170	340
3	53	10	454.8	22.74	0.2274	3	3	170	340
4	23	8	151.8	22.5	0.1518	1	1	30	60
5	23	8	303.6	22.74	0.1518	1	1	30	60

TABLE III. AMOUNT OF LOAD REQUIRED

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

The simulations aimed to verify the dynamics of the system and to predict whether the proposed strategy provides adequate planning of the production units to minimize *CP*. In addition, the proposed strategy aimed to reduce the time required to resolve the UC problem. Figure 8 depicts the temporal evolution of the powers generated by each production unit and the optimal power quantities estimated by the proposed method. It should be noted that the generated powers follow the optimal power quantities provided by the proposed optimization algorithm. This demonstrates the high performance of the control algorithms adopted for the supervision of the studied system and proves the efficiency of the regulation loops for the different production units. Furthermore, the proposed strategy aims to obtain sufficient and rapid planning in terms of convergence. The proposed strategy managed to optimize optimal solutions to reduce *CP*.

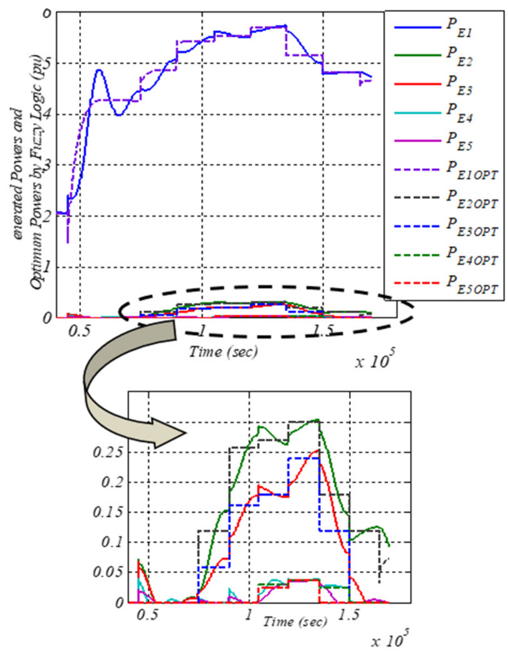

Fig. 8. Scheduling and amount of produced power based on the proposed fuzzy logic strategy.

Based on the results illustrated in Table IV, the proposed method solved the UC problem while addressing the planning of on-off states of the production units, which complied with the constraints of each unit (minimum start-up MUT_i and shut-down times MDT_i). Moreover, the power produced by the most powerful machine (615 MVA) remains unchanged throughout the 24 hours, while the other production units vary to produce the amount of power demanded by the network.

TABLE IV. RESULTS OF THE RESOLUTION OF THE UC PROBLEM BY FUZZY LOGIC STRATEGY

H	Power demand (MW)	Powers generated by each production (MW)					Total Production Cost ($)	Optimal scheduling
		615 MVA	60 MVA	60_Bis MVA	25 MVA	25_Bis MVA		
1	259	271.4	0	0	0	0	6820	10000
2	259	287.5	0	0	0	0	7148	10000
3	259	345.6	0	0	0	0	8361	10000
4	200	396.1	0	0	0	0	9457	10000
5	200	441.3	0	0	0	0	10470	10000
6	200	464.9	0	0	0	0	11012	10000
7	300	473.7	12.5	0	0	0	11561	11000
8	300	481.4	14.9	0	0	0	11808	11000
9	300	496.3	17.3	0	0	0	12226	11000
10	450	512.2	18.7	11.57	0	0	12936	11100
11	450	520.3	21.3	16.32	0	0	13342	11100
12	450	521.7	28.0	17.65	0	0	13608	11100
13	527	528.9	29.7	18.94	3.12	3	14011	11111
14	527	536	28.4	18.11	3.75	3.09	14137	11111
15	527	546.2	28.5	18.44	4.46	4.23	14413	11111
16	610	551.3	28.7	20.42	7.982	6.86	14786	11111
17	610	569.2	30.0	23.12	4.87	4.17	15208	11111
18	610	551.7	30.3	26.52	3.92	3.72	14870	11111
19	480	549.5	27.6	18.53	3.75	0	14384	11110
20	480	536.2	22.1	13.32	3.12	0	13732	11110
21	480	502.1	18.3	8.11	2.5	0	12648	11110
22	320	478.5	13.5	0	0	0	11702	11000
23	320	480.4	12.6	0	0	0	11721	11000
24	320	482.1	11.8	0	0	0	11739	11000
Total cost ($)							**2.9210 e+05**	
Total power demand (MW)							**12192**	
Time (s)							7.34	

The production costs established for solving the UC problem when compared with the algorithms in [43-44], demonstrate the high performance of the proposed strategy. Comparing the *CP* obtained through the proposed approach with that obtained via the genetic algorithm and gradient-PSO (Table V), indicated that the proposed approach was reliable and allowed a gain of 1% of the total *CP*. However, the strategy based on the use of the hybrid method gradient-genetic algorithm was the most efficient and revealed high performance at the *CP* level as well as the ability to converge towards the global optimum.

TABLE V. COMPARISON OF PERFORMANCE BETWEEN OPTIMIZATION METHODS

	Genetic Algorithm [24]	Fuzzy Logic	Gradient-PSO [35]
Production cost ($)	2.9457 e+05	2.9210 e+05	2.9125e+05
Execution time (sec)	10.21	7.34	8.653

By contrast, both genetic and gradient-genetic algorithm methods did not exhibit efficacy-time resolution, since each method requires enough time to reach the optimal solution. This is mainly due to the choice of the initial population. The proposed fuzzy logic strategy was more efficient than the other two algorithms in terms of execution time and convergence efficiency. This shows the relativity between execution time and the *CP* value of every production unit.

The proposed strategy had the shortest calculation time compared to other algorithms, such as the Artificial Bee Colony (ABC) and PSO [45]. The calculation time of the UC problem by ABC was about 40.74 s and by PSO 49.03 s [31], while the proposed strategy had a calculation time of 7.34 s. Table IV discloses that the proposed hybrid optimization method was able to organize the running and shutdown states of various production units. This is done by using an estimate of the amount of charge desired by the electrical network while taking into account the permissible constraints. However, fairly optimal planning allows us to benefit from a minimal *CP*. The superiority of the resolution through fuzzy logic theory is obvious. This strategy works better than other stochastic methods in terms of the planning of the on/off states of the various units and thus optimizes the total *CP*. Indeed, starting from the combination probability equation for such planning:

$$P_{Combination} = (2^n - 1)^m \tag{16}$$

where n is the number of units and m is the discretized time. For this case study, $P_{Combination}$ is worth about 6.2^{35} combinations. This number suggests the ability of the proposed method to choose a perfect plan that guarantees the balance between supply and demand and a fairly minimal CP. Considering the technical constraints specific to each production unit (power generation limit, minimum up-time constraint, minimum operating time before shutdown), the proposed strategy enables the planning of the on-off states of the various units while optimizing their produced power within the allowable margins. Solving the UC problem proves to be reliable for a problem involving identical production units, which is not the case for dynamic programming theory [46]. Figure 8 displays that the operational state planning based on fuzzy theory is promising, can be remarkable in the temporal evolution of the power produced by the most powerful machine (615 MVA), and suggests its resolution efficiency, especially when confronted with systems that are not difficult to model. This is only guaranteed with great consideration of the limitations taken for the amount of charge produced by each generator per hour and the permissible margins of the voltage levels for each node of the electrical network.

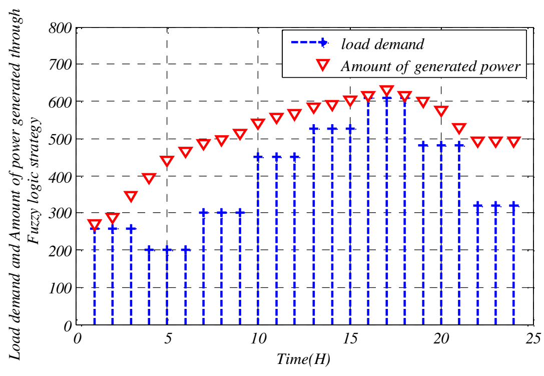

Fig. 9. Load demand and amount of power generated through the proposed strategy.

The improvement in *CP* of the proposed method depends on the number of fuzzy rules in the resolution. Optimization of *CP* by a genetic algorithm requires an adequate selection of parameters that vary from one system to another. The method using gradient-PSO [38] for the UC resolution suffers from convergence. In PSO, the swarm can prematurely converge, and the main cause of this problem is for the best global solution search. Furthermore, particles converge to a single point located between the best local and global solutions. This is not guaranteed for a local optimum. Another reason for this problem is the rapid rate of information transmitted between particles, leading to the creation of similar particles, and this results in a loss of diversity, which increases the possibility of falling into local optima. Therefore, it is difficult to reduce the calculation time and the *CP* for both of the methods cited. The proposed strategy proves to be the most promising since it has resulted in a better combination of the operating states of the production units, leading at an optimal cost and having a very competitive convergence time.

When integrating fuzzy logic into the UC problem, its resolution can be affected by several factors:

- Computational complexity: Fuzzy logic models can introduce additional computational complexity to the UC problem. The resolution of the problem can be affected by the efficiency of the algorithms used to solve the optimization model evoked by the objective function (8).
- Data quality: The quality of input data, including the amount of the consumed power at the h^{th} hour P_{dh} and unit parameters of each production unit, plays a crucial role in solving the UC problem with fuzzy logic. Inaccurate or unreliable data can lead to suboptimal solutions.
- Controller design: The choice of the fuzzy sets and the membership (triangular or trapezoidal) functions for input and output variables can influence the performance of the fuzzy logic model, improve the resolution of the UC problem, and reduce the computing time.

An integration with other metaheuristic algorithms or traditional optimization methods can affect the resolution of the problem.

V. CONCLUSION

This paper outlined the resolution of the UC problem by employing an optimization strategy based on fuzzy logic. The simulation results underscored the reliability of the proposed approach, with an execution time of 7.34 s and notable convergence efficiency. Emphasizing the crucial role of judiciously chosen controller input variables, the strategy facilitates effective planning of unit on-off states while optimizing power generation. The proposed approach was based on a Lagrangian function, chosen as an objective function to determine *LCG* and *IL*, which were chosen as fuzzy input variables according to partial derivatives for the different injected powers P_{ih} at each bus. These parameters are essential to minimize the total CP. The findings underscore the effectiveness of the strategy, qualifying it to address UC challenges in complex systems with a variable number of units. Future studies could extend this work to encompass a larger number of production units, focusing on data quality and intricate power system modeling. Additionally, ongoing efforts focus on refining *CP* reduction and minimizing computing time by integrating metaheuristic methods with fuzzy logic, aiming to further enhance the sought optimal solutions.

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