A NEW FUZZY UNIT COMMITMENT MODEL AND SOLUTION

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***Abstract*- This paper presents a new fuzzy unit commitment problem (UCP) model. The model treats the uncertainties in the load demand and the spinning reserve constraints in a fuzzy logic (FL) frame. The simulated annealing (SA) method is used to solve the combinatorial part of the unit commitment problem, while the nonlinear part of the problem is solved via a quadratic programming routine. A polynomial time cooling schedule is used in the implementation of the SA algorithm. Numerical results show the superiority of the solutions obtained compared to methods with traditional UCP models.**

1. INTRODUCTION

A common trend in previous treatment of the unit commitment problem (UCP) is utilizing fixed values of load demand and strict level of spinning reserve requirements [1-18]. This may result in an overestimated solution and consequently higher operating costs. Since the load demand is only known through short-term load forecasting, errors always exist in the forecasted system loads. Moreover, the spinning reserve constraint practically is based on the probability of abnormal conditions that might result in insufficient generation capacity to cover the load demand; hence this constraint could be a soft, not a hard limit, constraint. Consequently, it is advisable to formulate the problem within the uncertainty frame.

Fuzzy Logic (FL), which may be viewed as an extension of classical logical systems, provides an effective conceptual framework for dealing with the problem of knowledge representation in an environment of uncertainty and imprecision [23-28]. The FL can be used to realize the expected error in the forecasted load demand and the soft limits of the spinning reserve requirements [25-28].

Simulated Annealing (SA), is a powerful technique for solving combinatorial optimization problems [9-10, 15-22]. It has the ability of escaping local minima by incorporating a probability function in accepting or rejecting new solutions. A main advantage of the SA method is that it does not need large computer memory.

In the proposed fuzzy UCP model, uncertainties in load demand are considered. The spinning reserve constraints are treated as soft limits in a FL frame. A penalty factor based on both fuzzy membership functions is determined to guide the solution in the optimization problem.

On the other hand an efficient solution algorithm based on the Simulated Annealing (SA) method has been developed to solve the optimization problem of the UCP.

The implementation of the SA part in the proposed algorithm is based on a polynomial-time cooling schedule, which uses statistics calculation during the search. In the FL implementation, different membership functions for input and output variables are used to determine the penalty factors that are added to the objective function to guide the search in the SA algorithm.

The main idea of the proposed algorithm is to guide the search by adding penalty terms to the objective function of the UCP. These penalty terms are related to the membership function of both the error in load demand and the violation of the reserve constraints. Using this technique, the optimum solution will take into consideration the fuzzy nature of the constraints in addition to achieving minimum operating cost.

Several examples are solved to test the proposed algorithm. A comparison of results with other methods in the literature [5,6,9] is presented.

In the next section, a mathematical formulation of the problem is introduced. In Section 3, the proposed SAFL algorithm is described. Sections 4 and 5 present the detailed implemented of the SA and FL components. In Section 6, the computational results along with a comparison to previously published work are presented. Section 7 outlines the conclusions.

2. PROBLEM STATEMENT

In the UCP under consideration, one is interested in a solution that minimizes the total operating cost of the generating units during the scheduling time horizon while several constraints are satisfied [1,8-11].

2.1 The Objective function

The overall objective function of the UCP of N generating units for a scheduling time horizon T, (e.g., 24 HRs), is:

$$F_T = \sum_{t=1}^{T}\sum_{i=1}^{N}(U_{it}F_{it}(P_{it}) + V_{it}S_{it})\ \$ \qquad (1)$$

Where

U_{it} : is status of unit i at hour t (ON=1, OFF=0).

V_{it} : is start-up/shut-down status of unit i at hour t.

P_{it} : is the output power from unit i at time t

The production cost, $F_{it}(P_{it})$, of a committed unit i, is conventionally taken in a quadratic form:

$$F_{it}(P_{it}) = A_i P^2{}_{it} + B_i P_{it} + C_i \ \text{\$/HR} \qquad (2)$$

Where, A_i, B_i, C_i : are the cost function parameters of unit i.

The start-up cost, S_{it}, is a function of the down time of unit i [6]:

$$S_{it} = So_i[1 - D_i \exp(-Toff_i / Tdown_i)] + E_i\ \$ \qquad (3)$$

Where, So_i : is unit i cold start-up cost, and

D_i, E_i : are start-up cost coefficients for unit i.

2.2 The Constraints

The constraints that have been taken into consideration in this work, may be classified into two main groups:

(i) System Constraints:

a- Load demand constraints:

$$\sum_{i=1}^{N} U_{it}P_{it} = PD_t\ ;\ \forall t \qquad (4)$$

Where PD_t : is the system peak demand at hour t (MW).

b- Spinning Reserve

Spinning reserve, R_t, is the total amount of generation capacity available from all units synchronized (spinning) on the system minus the present load demand.

$$\sum_{i=1}^{N} U_{it}Pmax_i \geq (PD_t + R_t)\ ;\ \forall t \qquad (5)$$

(ii) Unit constraints:

The constraints on the generating units are

a- Generation limits

$$U_{it}Pmin_i \leq P_{it} \leq Pmax_i U_{it}\ \ \forall i, t \qquad (6)$$

Where, $Pmin_i, Pmax_i$ is minimum and maximum generation limit (MW) of unit i, respectively.

b- Minimum up/down time

$$\begin{matrix} Toff_i \geq Tdown_i \\ Ton_i \geq Tup_i \end{matrix}\ ;\ \forall i \qquad (7)$$

Where $Tup_i, Tdown_i$ are unit i minimum up/down time.

$Ton_i, Toff_i$ are time periods during which unit i is continuously ON/OFF.

c- Unit initial status

d- Crew constraints

e- Unit availability; e.g. , must run, unavailable, available, or fixed output (MW).

f- Unit derating

3. THE PROPOSED ALGORITHM

3.1 Overview

In the proposed algorithm we consider the load demand uncertainties and the reserve constraints as soft limits in a FL frame. The fuzzy load demand is calculated based on the error statistics and load membership function [25]. The spinning reserve is calculated for each solution along with its member ship function. A penalty factor is then determined, as function of both the load demand and reserve membership functions to guide the search in the SA algorithm.

The major steps of the SAFL algorithm are summarized as follow:

Step (1) Apply FL rules to calculate the fuzzy load demand.

Step (2) Initialize the temperature of the SA cooling schedule algorithm, Cp^o.

Step (3) Generate randomly an initial feasible solution and let it be the current and best solutions. For the k th iteration apply the following steps:

Step (4) Calculate the new temperature for the SA algorithm $Cp^k = Cp^o(\beta)^k$, where $0 < \beta < 1$.

Step (5) Generate randomly a trial solution as a neighbor to the current solution.

Step (6) Calculate the objective function of the trial solution by solving the EDP.

Step (7) Use the FL approach to calculate the penalty factor to be added to the objective function as reflection to the amount of reserve in the trial solution as follow:

a. Calculate the amount of spinning reserve in the trial solution.

b. Apply FL rules to calculate the reserve membership function.

c. Estimate the value of the penalty factor according the output of the load and reserve membership functions.

Step (8) Apply the SA test to accept or reject the trial solution.

Step (9) If the trial solution is accepted, let it be the current solution and update the best solution if needed.

Step (10) If the specified chain length reached go Step (k), otherwise go to Step (e).

Step (11) Check for stopping criteria. If satisfied stop, otherwise go to Step (d).

3.2 Stopping Criteria

There are several possible stopping conditions for the search. In our implementation, we stop the search if one of the following two conditions is satisfied in the order given:

- The number of iterations performed since the best solution last changed is greater than a prespecified maximum number of iterations, or
- Maximum allowable number of iterations is reached.

4. SA IMPLEMENTATION IN THE SAFL ALGORITIHM

4.1 SA Test

Implementation steps of the SA test as applied in the kth iteration of the proposed algorithm are described as follow [9]:

Step (1): At the same calculated temperature, $c_p{}^k$, apply the following acceptance test for the new trial solution.

Step (2): Acceptance test: If $E_j \le E_i$, or if $\exp[(E_i - E_j)/Cp] \ge U(0,1)$, then accept the trial solution, set $X_i = X_j$ and $E_i = E_j$. Otherwise reject the trial solution. Where X_i, X_j, E_i, E_j are the SA current solution, the trial solution and their corresponding cost respectively.

Step (3): Go to the next step in the algorithm.

4.2 Cooling Schedule

A finite-time implementation of the SA algorithm can be realized by generating homogenous Markov chains of finite length for a finite sequence of descending values of the control parameter. To achieve this, one must specify a set of parameters that governs the convergence of the algorithm. These parameters form a cooling schedule. The parameters of the cooling schedules are: an initial value of the control parameter decrement function for decreasing the control parameter and a final value of the control parameter specified by the stopping criterion, and a finite length of each homogenous Markov chain. Details of the implemented cooling schedule are described in details in [9].

5. FL IMPLEMENTATION IN THE SAFL ALGORITHM

In general, a fuzzy logic system, that is widely used, maps crisp inputs into crisp outputs. It comprises four principal component *fuzzifie; rule base, inference engine,* and *defuzzifier* [23-24].

In the proposed algorithm FL is used to deal with the uncertainties in the forecasted load demand and the prespecified spinning reserve requirements. The implemented fuzzy logic system consists of two inputs: the load demand and the spinning reserve, and two outputs: a fuzzy load demand and a penalty factor.

5.1 Membership function for the load demand

The fuzzy set of input for the load demand is divided into six fuzzy values (LN, MN, HN, LP, MP, HP). The membership function for load forecast error is taken as follow [25]:

$$\mu_L = \begin{cases} \dfrac{1}{1+2.33(\frac{\Delta l}{M_+})^2}, & \Delta l \ge 0 \\ \dfrac{1}{1+2.33(\frac{\Delta l}{M_-})^2}, & \Delta l < 0 \end{cases} \tag{8}$$

where Δl = percentage error = $\dfrac{\Delta L}{L_{forecasted}} \times 100\%$

$$= \frac{L_{actual} - L_{forecasted}}{L_{forecasted}} \times 100\% \tag{9}$$

5.2 Membership function for spinning reserve

The fuzzy set of input for the spinning reserve demand is divided into five fuzzy values (VL, L, M, H, VH) as shown in Fig. (1). The membership function for the spinning reserve is taken as follow:

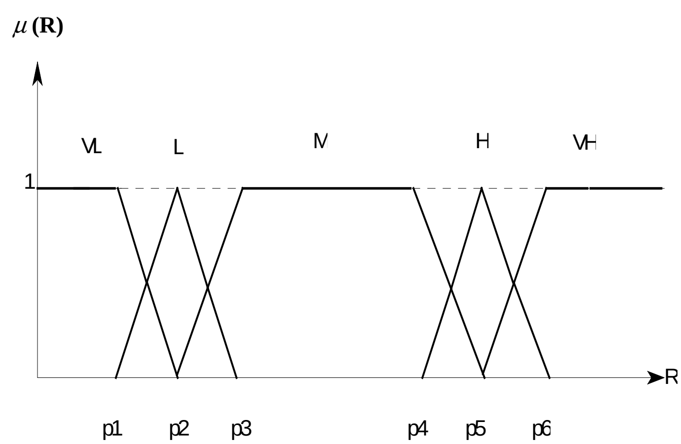

Fig. (1) Membership function for spinning reserve

where p1=RR-d1, p2=RR-d1/2, p3=RR, p4=RR+d2, p5=RR+(d2+d3)/2, and p6=RR+d3.
R: is the actual reserve in the schedule.
RR is the required reserve.
d1, d2, and d3 are selected percentage values of the spinning reserve.

5.3 Penalty factor calculation

The penalty factor for each hour is calculated based on fuzzy membership functions to guide the search for optimal solution as follow:

a) Calculate fuzzy membership function of loads (8), considered with six inputs.
b) Calculate fuzzy membership function of reserve (Fig. 1), with five inputs.
c) Calculate the membership function of penalty factor as a fuzzy output for the two input membership functions of load and reserve (calculated in (b)). The decision matrix contains 30 rules (6x5 inputs) with one output, which is the penalty factor.
d) The output membership function of the penalty factor is divided into seven values as: VVL, VL, L, M, H, VH, VVH) that is translated into a per unit value as: (0, 0.1, 0.3, 0.5, 0.7, 0.9, 1)
e) Having calculated the penalty factor for each hour, a term equal to the product of the penalty factor and the operating cost per hour is added to the objective function.

6. NUMERICAL EXAMPLES

In order to test the proposed hybrid algorithm (SAFL), two examples from the literature, solved by Lagrangian Relaxation (LR) and Integer Programming (IP) respectively [5,6], are considered. The two Examples include 10 generating units with a scheduling time horizon of 24 hours.

Different runs were carried out to evaluate the results obtained by the proposed algorithm (SAFL) and those obtained from the individual algorithms in [5,6,9]. Table (1) shows the results of this comparison for the two examples. The superiority of the SAFL algorithm is obvious. It is clear that the SAFL algorithm performs better than the SA as an individual algorithm and the LR and IP as well.

Table (1) presents the comparison of results obtained in the literature (LR,IP and SA) for the two Examples and the proposed SAFL algorithm.

Tables (2) and (3) show detailed results for Example 1, [5]. Table (2) shows the load sharing among the committed units in the 24 hours. Table (3) gives the hourly load demand, and the corresponding committed capacities, economic dispatch costs, start-up costs, and total operating cost.

Table (4) presents a comparison between the total required capacity, the committed capacity by the SA [9] and by the SAFL during the 24 hours. It's obvious that both solutions (SA [9] and SAFL) committed capacities more than required, which means solution is accepted. On the other hand, the SAFL achieved more saving in cost.

Table (1) Comparison with LR, IP and SA

	Example	LR [5]	IP [6]	SA [9]	SAFL
Total Cost ($)	1	540895	-	536622	536260
	2	-	60667	59385	59213
% Saving	1			0.79	0.856
	2			2.1	2.54

Table (2) Power Sharing (MW) of Example 1

HR	**Unit Number***						
	1	**2**	**5**	**7**	**8**	**9**	**10**
1	0	396.37	0	181.4	339.3	0	85.55
2	0	400	0	185.25	350.9	0	89.94
3	0	346.72	0	165.98	292.84	0	75
4	0	342.92	0	164.8	289.29	0	75
5	0	396.41	0	181.41	339.34	0	85.56
6	0	400	296.83	200	375	0	163.24
7	0	400	265.79	200	375	535.71	153.14
8	0	400	436.29	200	375	731.52	208.59
9	446.01	400	435.06	200	375	730.11	208.19
10	594.5	400	549.17	200	375	850	245.31
11	604.73	400	557.03	200	375	850	247.87
12	662.41	400	600	200	375	850	250
13	590.77	400	546.3	200	375	850	244.38
14	479.68	400	460.95	200	375	759.83	216.61
15	397.39	400	397.69	200	375	687.18	196.03
16	345.08	400	357.47	200	375	641	182.95
17	404.22	400	402.94	200	375	693.21	197.74
18	564.98	400	526.51	200	375	835.13	237.93
19	695.86	400	600	200	375	850	250
20	464.25	400	449.08	200	375	746.21	212.75
21	456.57	400	443.18	200	375	0	210.83
22	300	400	260.13	200	375	0	151.3
23	300	0	253.42	200	375	0	149.12
24	300	0	251.86	200	375	0	0

**Units 3,4 and 6 are OFF all hours.

Table (3) Load, Capacities (MW), and Hourly Costs ($) of Example 1

HR	Crisp Load	Fuzzy Load	Cap.	ED-Cost	ST-Cost	T-Cost
1	1025	1002.61	1225	9469.92	0.00	9469.92
2	1000	1026.08	1225	9679.75	0.00	9679.75
3	900	880.54	1225	8390.10	0.00	8390.10
4	850	872.01	1225	8315.39	0.00	8315.39
5	1025	1002.73	1225	9471.01	0.00	9471.01
6	1400	1435.06	1825	14038.60	2448.34	16487.00
7	1970	1929.65	2675	19109.50	2659.11	21768.60
8	2400	2351.39	2675	23235.90	0.00	23235.90
9	2850	2794.37	3675	28274.60	2597.56	30872.10
10	3150	3213.98	3675	32552.40	0.00	32552.40
11	3300	3234.62	3675	32766.60	0.00	32766.60
12	3400	3337.41	3675	33841.10	0.00	33841.10
13	3275	3206.45	3675	32474.30	0.00	32474.30
14	2950	2892.06	3675	29258.20	0.00	29258.20
15	2700	2653.29	3675	26867.10	0.00	26867.10
16	2550	2501.50	3675	25370.10	0.00	25370.10
17	2725	2673.12	3675	27064.00	0.00	27064.00
18	3200	3139.54	3675	31783.40	0.00	31783.40
19	3300	3370.87	3675	34194.20	0.00	34194.20
20	2900	2847.30	3675	28806.60	0.00	28806.60
21	2125	2085.57	2825	21122.10	0.00	21122.10
22	1650	1686.43	2825	17201.80	0.00	17201.80
23	1300	1277.54	2425	13399.70	0.00	13399.70
24	1150	1126.86	2175	11869.10	0.00	11869.10

Total operating cost = $536260.625

Table (4) Comparison of Required and Committed Capacities (MW) of Example 1

	Crisp Load	Fuzzy Load	Required Capacity	SA [9] Capacity	SAFL Capacity
Sum of 24 hours	53095	52541	57115	72330	67650
% Excess Reserve	0	0	0	26.64	18.45
Total Cost $	-	-	-	536622	536260
% Saving	-	-	-	0.79	0.856

7. CONCLUSIONS

In this paper we proposed a new hybrid algorithm for the UCP. The algorithm integrates the main features of two of the most commonly used artificial intelligence methods, SA and FL. The UCP is formulated in a FL frame to deal with the uncertainties in the load demand and the soft limit constraint of the spinning reserve. The SA algorithm is used to solve the combinatorial optimization part of the UCP while quadratic programming algorithm is used to solve the nonlinear programming part of the problem.

The SA algorithm is implemented via a simple cooling schedule to simplify and speed up the calculations [9].

Two examples from the literature were solved for comparison purposes with other methods. The obtained results are superior to those reported in [5,6] using LR and IP. Moreover the obtained results (using the proposed algorithm) are better than those obtained using the SA algorithm [9].

A basic advantage of the proposed algorithm is the high quality of solutions compared to those obtained by LR, IP and SA. Moreover, the algorithm is capable of handling practical issues such as the uncertainties in the UCP. Taking into account the fuzzy nature of the reserve has achieved an acceptable level of reserve with better-cost savings. Further work in this area may be in the application of parallel processing techniques, thus reducing the computation time or exploring wider solution space.

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