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A New Fuzzy Expert Decision Making Approach for Unit Commitment With Reliable Risk Reserve and Emission Constraints

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Abstract

In this paper a rule based possibilistic approach has been applied for analyzing the effect of load uncertainties on unit commitment problem rather than the probabilistic or classical approach. In the proposed fuzzy expert decision making approach a new strategy has been implemented to minimize the generation cost subject to reliable reserve margin, permissible emission and minimum up and down time constraints. The key factors such as load demand, reserve margin and emission are treated as fuzzy variables to emphasize the difference between randomness and fuzziness. The proposed approach determines the priority ordering of units and also selects the units to be ON or OFF based on fuzzy variables and expert opinions. An adaptive expert system is also used to manipulate the final schedule using rule base and also to support the user in decision making.

Nomenclature

VH	Very High
H	High
M	Medium
L	Low
VL	Very Low
E	Excellent
VG	Very Good
G	Good
AV	Average
F	Fair
VMH	Very Much High
MH	Much High
U	Usual
ML	Much Low
VML	Very Much Low
x	Linguistic Variable
X	Universal Set
$\mu A(x)$	Grade of membership function of x in A
$\cap$	Intersection
$\cup$	Union
P(x)	Probability of x
d(A-B)	Fuzzy distance between A and B
n	Number of System States
p(x)	Fuzzy probability of x
HV	Hurwicz fuzzy decision set
α	Optimism - Pessimism index
Hi	Highest grade of membership
Li	Lowest grade of membership

CLASS 1 Set of falling state transitions
CLASS 2 Set of rising state transitions

Definitions

Before the technique of fuzzy decision system is introduced, some important definitions of fuzzy sets are first described as follows:

Definition 1 Fuzzy Set

Let X be a collection of objects (X is the universal set). Then a fuzzy set A in X is defined to be a set of ordered pairs:

$$A = \{\{x, \mu A(x)), \mid x \in X\} \quad (1)$$

where $\mu A(x)$ is called the membership function of x in A

Definition 2 The Union of two fuzzy sets

Let A and B be the two fuzzy sets with membership functions $\mu A(x)$ and $\mu B(x)$ respectively. The membership function of the union $C = A \cup B$ is point wise defined by

$$\mu C(x) = \max(\mu A(x), \mu B(x)), x \in X\} \quad (2)$$

Definition 3 The intersection of two fuzzy sets

Let A and B be the two fuzzy sets with membership functions $\mu A(x)$ and $\mu B(x)$ respectively. The membership function of the intersection $C = A \cap B$ is point wise defined by

$$\mu C(x) = \min(\mu A(x), \mu B(x)), x \in X \quad (3)$$

Definition 4 The fuzzy distance between two fuzzy sets

Let A and B be the two fuzzy sets with membership functions $\mu A(x)$ and $\mu B(x)$ respectively. The fuzzy distance between two fuzzy sets A and B defined by

$$d\,(A\text{-}B) = (1/n) \sum_{i=1}^{n} \mid \mu A(x) - \mu B(x) \mid \quad (4)$$

n - number of system states.

Definition 5 The fuzzy probability

The fuzzy probability of changing from one state to the other is given by

$$p(A) = \sum_{i=1}^{n} \mid \mu A(x) - \mu B(x) \mid \quad (5)$$

Definition 6 The Hurwicz fuzzy decision set

The Hurwicz fuzzy decision set is defined by

$$HV = \alpha\, Hi + (1 - \alpha)\, Li \quad (6)$$

Definition 7 Fuzzy semantics

If y is defined as an atomic term, then very y can be defined as square of y

$$\text{Very } y = y^*y \quad (7)$$

Introduction

Planning and operation of complex power systems involve many uncertainties [1]. Most of the uncertainties in power system operations are treated in the probabilistic way. Probabilistic approach fails if the information is not known precisely [2]. In the unit commitment problem [3], the uncertainties are mainly in the forecasted load demand. Since it is not possible to predict the load demand accurately due to frequent and uncertain load changes, it can be expressed linguistically as low demand, high demand etc., where low and high are linguistic value [4]. This kind of uncertainty can well be modeled by using fuzzy sets. Hence, in this paper possibilistic approach has been applied to solve the unit commitment problem. The complexity of solving the unit commitment problem using mathematical approaches may thus be completely eliminated by the proposed approach [5-8].

A possibilistic approach to unit commitment problem

Generator experience frequents load changes. The load may vary from minimum load to a peak load in a day itself. A typical load curve is shown in Fig. 1. The Table 1 shows the variation in the load demand that may occur during a day and its linguistic representation. In the proposed approach [9-10], it is assumed that the reserve margin to vary with load instead of a constant reserve margin and emission also vary proportionally with generator loading [11].

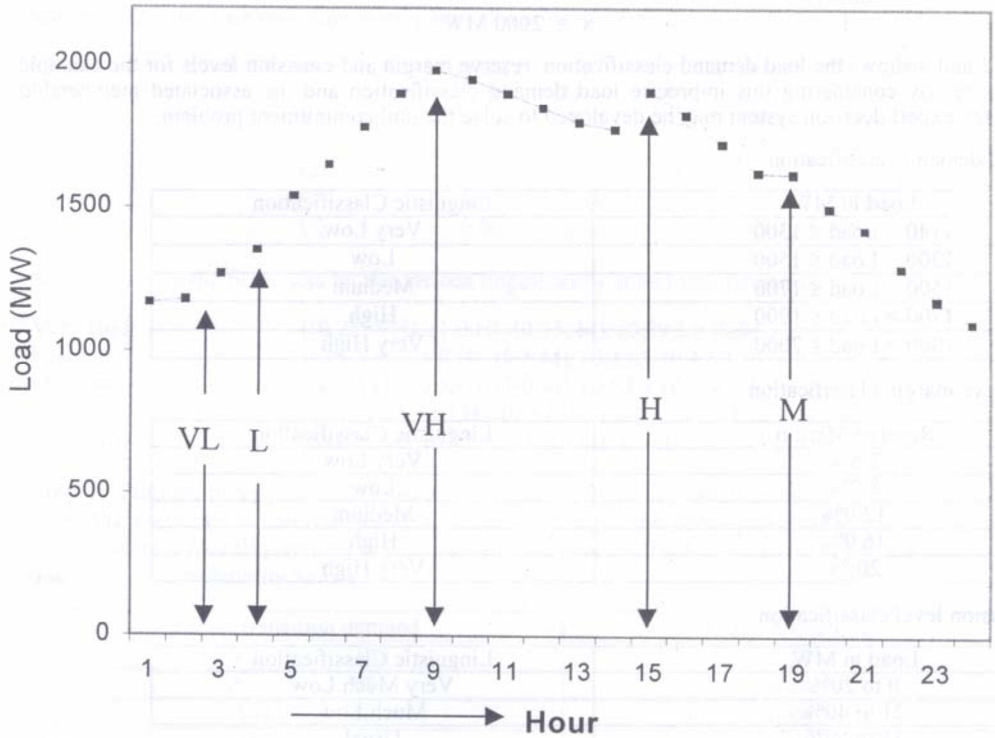

Fig. 1. Daily load curve (for 10-unit system)

The theory of fuzzy set [12] can be used to interpret such subjective terms in terms of linguistic values with membership functions. The assignment of the membership function of a fuzzy set is subjective in nature and in general reflects the context in which the problem is viewed. Although, the assignment of the membership function of fuzzy set is subjective, it cannot be assigned arbitrarily. The construction of a membership function may be accomplished with the help and assistance of experienced system managers for each specific application.

Table 1 Subjective representation of load demand

State	Subjective description of load demand	Representation
1	Very Low	VL
2	Low	L
3	Medium	M
4	High	H
5	Very High	VH

For example consider the sample 10 unit system problem. Let us assume that the load demand to vary approximately from 1140 MW to 2000 MW. Then, the membership function for the load pattern based on triangular function can be defined as follows:

$$\mu A(x) = \begin{cases} 0 & x \leq 1140\ \text{MW} \\ \dfrac{|x - 1140|}{860} & 1140 < x < 2000\ \text{MW} \\ 1 & x \geq 2000\ \text{MW} \end{cases}$$

The Table 2, 3 and 4 shows the load demand classification, reserve margin and emission levels for the example mentioned above. By considering this imprecise load demand classification and the associated membership function, a fuzzy expert decision system may be developed to solve the unit commitment problem.

Table 2 Load demand classification

Load in MW	Linguistic Classification
1140 > Load ≤ 1300	Very Low
1300 > Load ≤ 1500	Low
1500 > Load ≤ 1700	Medium
1700 > Load ≤ 1900	High
1900 > Load ≤ 2000	Very High

Table 3 Reserve margin classification

Reserve Margin	Linguistic Classification
2.5%	Very Low
8.0%	Low
12.0%	Medium
16.0%	High
20.%	Very High

Table 4 Emission level classification

Load in MW	Linguistic Classification
0 to 20%	Very Much Low
21 to 40%	Much Low
41 to 60%	Usual
61 to 80%	Much High
81 to 100%	Very Much High

The algorithm for the unit commitment problem based on the fuzzy decision approach is discussed in the next section considering the sample system having 10 units.

Algorithm for fuzzy decision system

A systematic fuzzy decision algorithm has been developed for scheduling the units of a 10 unit system. The step by step procedure is given below:

Step 1: Construct the state transition matrix for the load demand.

From the daily load demand curve shown in Fig.1, the following state transition matrix (the probability values of changing from one state to another) has been constructed.

$$[\text{Demand}] = \begin{array}{c} \\ VH \\ H \\ M \\ L \\ VL \end{array} \begin{array}{ccccc} VH & H & M & L & VL \\ 6/7 & 1/7 & 0 & 0 & 0 \\ 1/7 & 5/7 & 1/7 & 0 & 0 \\ 0\ 1/2 & 0 & 0 & 0 & \\ 0\ 0 & 1/3 & 1/3 & 0 & \\ 0\ 0 & 0 & 1/5 & 4/5 & \end{array} \qquad (8)$$

The probability values of changing from one state to another (i.e., from high Demand State to low Demand State and so on) are determined for a given system based on the load pattern.

Step 2: Find the state transition matrix after two units of time.

The possibility of all state transfers from one state to another after two units of time is given by:

$$[\text{Demand}]^2 = \begin{array}{c} \\ VH \\ H \\ M \\ L \\ VL \end{array} \begin{array}{ccccc} VH & H & M & L & VL \\ 0.75 & 0.22 & 0.02 & 0.00 & 0.00 \\ 0.22 & 0.60 & 0.10 & 0.07 & 0.00 \\ 0.07 & 0.35 & 0.23 & 0.16 & 0.16 \\ 0.00 & 0.16 & 0.11 & 0.34 & 0.37 \\ 0.00 & 0.00 & 0.06 & 0.22 & 0.70 \end{array} \qquad (9)$$

Step 3: Define the fuzzy sets for the various linguistically stated load demands

Very High = {(0.25, VH), (1.0,H), (0.25, M), (0.09,L), (0.01,VL)}
High = {(0.5,VH), (1.0,H), (0.5,M), (0.3,L), (0.1,VL)}
Medium = {(0.1,VH), (0.5,H), (1.0,M), (0.5,L), (0.1,VL)}
Low = {(0.1, VH), (0.3,H), (0.5,M), (1.0,L), (0.5,VL)}
Very Low = {(0.01,VH), (0.09,H), (0.25,M), (1.0,L), (0.25,VL)}

Step 4: Find the fuzzy probability values for changing from one state to another.
From the very high demand state, after two units of time, the fuzzy probability values (combining fuzziness with existing probability values) of various states are given in Table 5 based on definition 5.
Table 5 Fuzzy probability values

State transition demand	Fuzzy probability.
VL - M	0.24
M - VH	0.44
VH - H	0.60
H - L	0.32
L - VL	0.47

Step 5: Define the linguistic fuzzy probability values for state transitions and also for reserve margins accordingly.

From Table 5, it can be observed that the fuzzy probability value from very high to high demand state (CLASS 1), is very high (i.e., maximum among falling state transitions). Therefore, it is sufficient to have a very low reserve margin. Similarly, when the fuzzy value for the demand state transits from medium to very high demand (CLASS 2), is medium (i.e., maximum among rising state transitions), the reserve margin should be maintained at a very high level. Based on the analysis made the following rules [3] have been formed to decide the reserve margin level.

Rule 1: When the load demand decreases (CLASS 1) from one state to another i.e., very high to high, high to low and low to very low, arrange the corresponding state transition fuzzy probability value in descending order. Hence assign the linguistic reserve margins in ascending order (i.e., VL, L, M etc.,).

Rule 2: When the load demand increases (CLASS 2) from one state to another i.e., very low to medium and medium to very high, arrange the corresponding state transition fuzzy probability value in the descending order. Hence assign the linguistic reserve margins in descending order (i.e., ZVH, H etc.,).

Table 6 gives the linguistic representation of the required reserve margin based on state transition.

Table 6 Linguistic representation of reserve margin

State transition	Fuzzy probability	Linguistic representation of	
		Fuzzy probability	Reserve margin
VL - M	0.24	VL	H
M - VH	0.44	M	VH
VH - H	0.60	VH	VL
H - L	0.32	L	M
L - VL	0.47	H	L

The reserve margin, instead of being constant as in conventional methods, varies with respect to the load demand variation. The overall operating cost is thus reduced and at the same time the reliability is maintained.

Step 6: The generating capacity of each unit in the ten unit sample system has been shown linguistically in Table 7 to meet both load demand and reserve margin.

Table 7 Linguistic representation of units (Generation)

Demand+ Reserve	Generating units (generation)									
	1	2	3	4	5	6	7	8	9	10
VH	5	5	4	4	3	3	2	2	1	1
H	5	5	5	4	4	3	3	2	2	1
M	2	5	5	5	4	4	3	3	1	2
L	5	5	5	5	5	4	4	1	2	3
VL	5	5	5	5	5	4	3	2	2	1

The corresponding generating capacity fuzzy sets are:

State 1 - Excellent = {(10,1), (0.8,2), (0.2,3), (0.0,4), (0.0,5)}
State 2 - Very Good = {(0.8,1), (1.0,2), (0.8,3), (0.2,4), (0.0,5)}
State 3 - Good = {(0.9,1), (1.0,2), (0.9,3), (0.45,4), (0.0,5)}
State 4 - Average = {(0.0,1), (0.2,2), (0.4,3), (1.0,4), (0.6,5)}
State 5 - Fair = {(0.0,1), (0.0,2), (0.2,3), (0.6,4), (1.0,5)}

Step 7: The emission rate of generators in the ten unit sample system has been shown linguistically in Table 8 to meet both load demand and reserve margin.

Table 8 Linguistic representation of units (Emission)

Demand+ Reserve	Generating units (emission)									
	1	2	3	4	5	6	7	8	9	10
VH	4	5	5	4	4	3	3	2	2	1
H	4	5	4	4	3	3	2	2	3	3
M	3	3	5	4	4	3	3	2	1	2
L	5	4	3	2	1	1	2	3	3	3
VL	1	4	3	2	1	1	2	3	4	4

The corresponding emission rate of generators fuzzy sets is

State 1 - Very Much High = {(0.0,1), (0.2,2), (0.8,3), (1.0,4), (1.0,5)}
State 2 - Much High = {(0.0,1), (0.0,2), (0.2,3), (0.8,4), (1.0,5)}
State 3 - Usual = {(0.0,1), (0.0,2), (0.1,3), (0.55,4), (1.0,5)}
State 4 - Low = {(1.0,1), (0.8,2), (0.6,3), (0.0,4), (0.0,5)}
State 5 - Much Low = {(1.0,1), (1.0,2), (0.8,3), (0.4,4), (0.0,5)}

Step 8: Find the fuzzy distance d (L-G) between respective load demand and reserve (L) and generators generation capacity (G) using definition 4.

The fuzzy distance matrix, d (L-G) is given as

Table 9 Fuzzy distance matrix d (L-G)

Demand+ Reserve	Generating units (generation) 1	2	3	4	5	6	7	8	9	10
VH	0.56	0.56	0.54	0.54	0.33	0.33	0.24	0.24	0.22	0.22
H	0.6	0.6	0.6	0.46	0.46	0.21	0.21	0.16	0.16	0.28
M	0.36	0.3	0.3	0.4	0.4	0.31	0.31	0.31	0.54	0.36
L	0.32	0.32	0.32	0.32	0.32	0.08	0.08	0.64	0.6	0.59
VL	0.26	0.26	0.26	0.26	0.26	0.12	0.65	0.66	0.66	0.6

Step 9: Find the fuzzy distance d (L-E) between respective load demand and reserve (L) and generators emission capacity (E) using definition 4

The fuzzy distance matrix, d (L-E) is given as:

Table 10 Fuzzy distance matrix d (L-E)

Demand+ Reserve	Generating units (emission)									
	1	2	3	4	5	6	7	8	9	10
VH	0.24	0.32	0.32	0.24	0.24	0.57	0.57	0.6	0.6	0.7
H	0.2	0.2	0.24	0.24	0.61	0.61	0.64	0.64	0.61	0.61
M	0.49	0.49	0.36	0.49	0.49	0.49	0.49	0.52	0.4	0.52
L	0.66	0.6	0.35	0.26	0.2	0.2	0.26	0.35	0.35	0.35
VL	0.28	0.66	0.29	0.22	0.28	0.28	0.22	0.29	0.66	0.66

Step 10: Find the Hurwicz fuzzy decision set HV using definition 6, after normalizing both step 8 and step 9.

Table 11 Hurwicz fuzzy decision set matrix

Demand+ Reserve	Generating units (generation + emission)									
	1	2	3	4	5	6	7	8	9	10
VH	0.802	0.835	0.807	0.774	0.508	0.741	0.693	0.721	0.71	0.817
H	0.793	0.793	0.811	0.643	0.893	0.770	0.805	0.778	0.74	0.803
M	0.856	0.823	0.627	0.823	0.871	0.871	0.829	0.871	0.92	0.898
L	0.85	0.78	0.521	0.467	0.440	0.246	0.309	0.859	0.81	0.803
VL	0.411	0.817	0.418	0.372	0.411	0.348	0.785	0.829	1.00	0.97

Step 11: Commit the units depending upon the low fuzzy distance. If the distances are equal, the unit T that has lower generating capacity has to be committed. The ordering of units to be committed are as shown below.

Table 12 Priority ordering of units

Unit (Mw)/ Demand + Reserve = Generation available	1 60	2 80	3 100	4 120	5 150	6 280	7 320	8 445	9 520	10 550
	Priority listing of units (MW)									
VL + H = VL	7	10	8	6	1	5	2	4	3	9
M + VH = M	5	6	9	1	10	3	8	4	2	7
VH + VL = H	5	2	1	3	6	7	4	8	10	9
H + M = VH	9	6	5	4	3	1	2	10	8	7
L + L = L	3	7	5	2	4	1	6	8	10	9

Results and discussion

The fuzzy decision system approach for short-term unit commitment problem has been tested for 10, 26 and 34 unit systems. Tables 13 give the generated schedule using dynamic programming without constraints and Table 14 give the generated schedule using fuzzy decision system model with constraints respectively for load demand profile of 10 unit systems. Table 15 gives the comparison between generation costs obtained using both fuzzy decision system and dynamic programming technique for 10 unit systems. Table 16 gives the characteristic of generating units of 10 unit system.

Table 13 The unit commitment schedule generated using dynamic programming approach for 10 unit system without spinning reserve and emission constraints

Hour	Commitment Schedule (Unit to 10 →)	Generation Cost ($/h)
1	0000001111	3207.38
2	0000001111	2456.79
3	0000001111	2725.96
4	0000101111	3251.97
5	0000101111	3469.57
6	0001101111	3851.43
7	0001111111	4125.91
8	0001111111	4067.01
9	0001111111	4166.08
10	0001111111	4187.64
11	0001111111	4142.33
12	0001111111	4043.48
13	0001111111	3949.91
14	0000111111	3836.59
15	0010111111	4014.58
16	0011101111	3933.43
17	0011101111	3472.09
18	0001101111	3034.82
19	0001001111	2833.07
20	0000001111	2621.94
21	0000001111	2456.79
22	0000001111	2329.23
24	0000001111	2200.43
	Total generation cost ($/day)	80622.94

Table 14 The unit commitment schedule generated using fuzzy expert system approach for 10 unit system wit spinning reserve and emission constraints

Hour	Commitment Schedule (Unit to 10) →	Generation Cost ($/h)
1	1111111100	2868.61
2	1111111100	3019.57
3	0111111101	3434.30
4	1111111101	3659.52
5	1011111111	3695.83
6	1011111111	4391.38
7	1101010111	4342.80
8	1101010111	4211.21
9	1101010111	4306.50
10	1101010111	4331.09
11	1101010111	4282.05
12	1101010111	4188.05
13	1101010111	3341.70

14	1011111111	4888.75
15	1011111111	4504.06
16	1011111111	4391.37
17	1011111111	3403.83
18	1111111101	3662.07
19	0111111101	3035.03
20	0111111100	2778.48
21	1111111100	3184.20
22	1111111100	2925.41
23	1111111100	2868.61
24	1111111100	2841.97
	Total generation cost ($/day)	88556.97

Table 15 Comparison of scheduling results of the two models (dynamic programming and fuzzy expert decision system) for 10unit systems

Constraints	Generation cost (p.u.)/10 Unit System Dynamic	Fuzzy Expert	% Error
Nil	1.00	1.009	0.891
Min. Up and Down Time	1.00	1/-11	1.088
Min. Up and Down Time, Spinning and Emission	1.00	1.014	1.380

Table 16 Characteristic of generating units

Unit	Max. (MW)	Min. (MW)	Ai ($/MW^2)	Bi ($.MW)	Ci $
1	60	15	0.00510	2.2034	15
2	80	20	0.00396	1.9161	20
3	100	30	0.00393	1.8518	40
4	120	25	0.00382	1.6966	32
5	150	50	0.00212	1.8015	29
6	280	70	0.00261	1.5354	72
7	320	120	0.00289	1.2643	49
8	415	125	0.00148	1.2136	82
9	520	250	0.00127	1.1956	105
10	550	250	0.00138	1.1285	100

In the proposed model, a variable reserve margin has been employed instead of maintaining a constant percentage of reserve margin. It has been realized that it is sufficient to have low or high reserve levels if the load falls from a high level or increases to a high level respectively. Due to which, a generator can operate upto the level of maximum risk and becomes more reliable. the generation cost obtained using fuzzy decision system is approximately 3% higher than that due to the dynamic programming. Because the commitment schedule prescribed in this paper does not compel the generating units to run upto its maximum risk level. It has been observed that the overall generation operating the generating units upto their maximum risk level can stillreduce cost. The rules implemented and the heuristic information used in the proposed approach may vary from system to system.

Conclusion

The proposed fuzzy decision system model is faster and requires low core memory. The mathematical complexity in the dynamic programming approach and other heuristic approaches is completely eliminated and the proposed method does not suffer from problem of dimensionality. The fuzziness in the variation of the load demand has been incorporated. A systematic fuzzy decision algorithm using fuzzy distance approach has been given. The reserve margin is not fixed at a particular level. It is maintained at a satisfactory level corresponding to the possibilistic variation of load demand. The proposed algorithm provides a decision for a unit commitment problem which will satisfy the minimum cost, meet the required demand and maintain appropriate reserve margin level.

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