A FUZZY-GENETIC ALGORITHM BASED METHOD FOR SHORT-TERM MULTI- OBJECTIVE UNIT COMMITMENT IN LARGE-SCALE POWER SYSTEMS

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ABSTRACT: The short-term multi objective unit commitment problem in power systems containing a large number of thermal units is considered in this paper. The large dimensionality is handled by means of genetic algorithm where multiple objectives and flexible constraints are modeled by fuzzy optimization techniques. Results obtained show that there is no sever restriction for the number of thermal units to be committed by this method.

Keywords: unit commitment, fuzzy-genetic algorithm, flexible constraints.

1 INTRODUCTION

In most of the power systems, the power requirement is principally met by thermal power generation [1, 2], and the short-term unit commitment problem is mainly to scheduling thermal power plants to minimize the total production (fuel) cost in the programming period. On the other hand, due to the increasing public awareness of environmental protection, minimizing the total pollutant gases, produced by thermal power plants is also intensively attended in optimal generation scheduling of power systems [3]. Thus, optimizing multi competing objectives of economy, security, emission, reliability and etc. would be considered simultaneously for short and long-term unit commitment in real large-scale power systems.

The Pareto-optimal solution of the multi-objective problems, which is the solution where it is not possible to reduce one of the objective functions without increasing at least one of the other objective functions, would be successfully obtained by using the fuzzy optimal search technique [4]. Su and Hsu proposed a new dynamic programming method to solve the unit commitment problem [5], with considering the effect of errors in forecasted hourly loads and made it a superior approach to the conventional dynamic programming method. In [6], fuzzy modeling and fuzzy optimization were used to solve the multi-criteria load dispatch problem with flexible constraints.

High dimensionality is one of the most important difficulties in many conventional and new methods of solution to unit commitment problem in real power systems. Genetic algorithm (GA) is a kind of evolutionary programming where evolution is performed by selection, crossover and mutation operations on selected individuals. Like natural evolution, individuals with favorable traits are retained while others are discarded [7]. Many attempts have been made to solve the unit commitment problem by GA. Some genetic strategies are introduced in [8] for multi-criteria optimization where a new fuzzy evaluation technique is incorporated to replace the fitness function for constitution an optimal fuzzy model for multi-criterion function optimization.

In this paper, a fuzzy-genetic algorithm based method is proposed to solve the multi-criteria unit commitment problem in large-scale power systems. The unit commitment problem formulation is firstly discussed in section 2. Then, the proposed fuzzy-genetic algorithm based method is discussed in section 3. The multi-criteria optimal share of the committed units is evaluated at each hour of the programming period considering flexible constraints of unit permissible range of generation and uncertainties in the forecasted hourly load of the system by a fuzzy linear programming method that is investigated in section 4. Case studies and investigation of results obtained are discussed in section 5. Due to the time consuming nature of the problem, it is necessary to perform sensitivity analyses about the effect of problem data changes on obtained optimal parameters of the genetic algorithm. This concept is also discussed in this section. Conclusions are presented in the last section.

2 PROBLEM FORMULATION

In this section, objectives of the total fuel cost and the total produced emission as well as various generating units and system constraints are formulated and prepared to be used in the following sections for the fuzzy-genetic algorithm approach.

2.1 THE TOTAL FUEL COST

The objective function of the conventional short-term unit commitment problem in a thermal power system is to minimize the total generation fuel cost plus the start up costs of thermal units during the programming period. This objective function can be written as follows.

$$F_1 = \sum_{t=1}^{T} . \sum_{i=1}^{N} [\, U_{it} \,.C_{it}\,(P_{it}) + T_{it} \,.\, SC_{it} \,] \qquad (1)$$

Where:

U_{it}: Status of unit i in hour t (“1” = on, “0” = off).

T_{it}: Status change of unit i from t-1 to t. (“1” for change from OFF to ON and “0” for otherwise)

C_{it} (P_{it}): Production (fuel) cost of unit i in time t for P_{it} output power.

Usually:

$$C_{it}\,(P_{it}) = A_i\, P_{it}^2 + B_i\, P_{it} + C_i \qquad \$ / HR \qquad (2)$$

A_i, B_i and C_i are unit i fuel cost parameters.

SC_{it}: Start up cost of unit i in hour “t” where:

$$SC_{it} = C_{oi}\, [\, 1- \exp\, (-T_{off\, i} / T_{down\, i}) \,] + DCi \qquad (3)$$

$T_{off\, i}$: number of hours that unit i has been off.
$T_{down\, i}$: Minimum down time of unit i
C_{oi}: cold start up cost of unit i.
DC_i: constant start up cost of unit i.

2.2 THE TOTAL PRODUCED EMISSION

The total produced emission objective function of UC problem for N generating units for a scheduling time of T hours can be presented as follows:

$$F_2 = \sum_{t=1}^{T} . \sum_{i=1}^{N} [\, U_{it}\; E_{it}\,(P_{it}) + T_{it} \,.\, SE_{it} \,] \qquad (4)$$

Where:
U_{it} and P_{it} are the same as defined in (1)
E_{it} (P_{it}): produced emission by unit i at time t that can be evaluated by:

$$E_{it}\,(P_{it}) = X_i\, P_{it}^2 + Y_i\, P_{it} + Z_i \qquad \$ / HR \qquad (5)$$

Where, X_i, Y_i & Z_i: are the emission function parameters of unit i.
SE_{it}: start up emission of unit i in hour “t” where:

$$SE_{it} = E_{oi}\, [\, 1- \exp\, (-T_{off\, i} / T_{down\, i}) \,] + DEi \qquad (6)$$

E_{oi}: cold start up emission of unit i.
DE_i: constant start up emission of unit i.

2.3 DEMAND CONSTRAINTS

$$\sum_{i=1}^{N} U_{it}\, P_{it} = PD_t \qquad \text{for all } t=1,2,...,T \qquad (7)$$

Where:

PD_t is the forecasted load for hour “t”.

2.4 UNIT GENERATION LIMIT CONSTRAINTS

$$U_{it}\, P_i^{min} \leq P_{it} \leq U_{it}\, P_i^{max} \qquad (8)$$

P_i^{min} , P_i^{max} : minimum and maximum generation limits of unit i.

2.5 MINIMUM UP/DOWN TIME CONSTRAINTS

$$T_{off\, i} \;\geq\; T_{down\, i}$$
$$T_{on\, i} \;\geq\; T_{up\, i} \qquad (9)$$

Where:

$T_{up\, i}$ and $T_{down\, i}$: minimum up and down time of unit i.

$T_{on\, i}$, $T_{off\, i}$: Number of time intervals in which unit i has been continuously on, off.

2.6 SPINNING RESERVE CONSTRAINTS

$$\sum_{i=1}^{N} U_{it}\, P_i^{max} \;\geq\; (\, PD_t \;+\; R_t \,) \qquad \text{for all } t=1,2,...,T \qquad (10)$$

R_t: Spinning reserve requirement at time t.

3 THE FUZZY-GENETIC ALGORITHM BASED SOLUTION

In this section the proposed method based on multi-criteria fuzzy optimization used to evaluate the fitness function of chromosomes in genetic algorithm method and determine the Pareto-optimal solution of the unit commitment problem will be described.

3-1 SOLUTION ENCODING

In this paper, a chromosome of the genetic algorithm is a feasible solution of the UC problem that is randomly generated by a string of N*T bits where N is the number of generating units and T is the number of hours of programming period. The state of a unit at a given time is represented by a corresponding bit of this chromosome (1 for ON and 0 for OFF). Various modifications take place to a chromosome such that all units and system constraints satisfied.

3-2 THE INITIAL POPULATION

An initial population of randomly generated solutions is usually used to start the genetic algorithm solution.

3-3 FUZZY FITNESS FUNCTION BASED ON MULTIPLE CRITERIA

To solve the UC problem with a single objective function of the total cost, the fitness function shows the satisfaction degree of a solution and is related to the reciprocal of its total cost. Maximizing this fitness function is the main target achieved by the genetic algorithm progress.

For UC problem with multiple objective functions, the fitness function value of a chromosome should be determined with respect to all objective functions simultaneously. In this paper, for an existing population, a "fuzzy compromise fitness set" with membership function of μ_D, as the intersection of two fuzzy individual fitness sets for cost and emission, is defined as follows:

$$\mu_D\,(s^v) = \min \{\, \mu_{f_1}\,(s^v) \,,\, \mu_{f_2}\,(s^v) \,\} \qquad (11)$$

Where μ_{f_1} and μ_{f_2} are the membership functions of fuzzy individual fitness sets of cost and emission shown in Fig. 1 and defined as:

$$\mu_{f_1}(s^v) = \begin{cases} 1 \ldots\ldots \text{for } F_1(s^v) \leq f_1^{\min}(s^v) \\ \dfrac{\left(f_1^{\max}(s^v) - F_1(s^v)\right)}{f_1^{\max}(s^v) - f_1^{\min}(s^v)} \ldots\ldots \text{for } f_1^{\min}(s^v) \leq F_1(s^v) \leq f_1^{\max}(s^v) \\ 0 \ldots\ldots \text{for } F_1(s^v) \geq f_1^{\max}(s^v) \end{cases} \qquad (12)$$

$$\mu_{f_2}(s^v) = \begin{cases} 1 \ldots\ldots \text{for } F_2(s^v) \leq f_2^{\min}(s^v) \\ \dfrac{\left(f_2^{\max} - F_2(s^v)\right)}{f_2^{\max} - f_2^{\min}} \ldots\ldots \text{for } f_2^{\min}(s^v) \leq F_2(s^v) \leq f_2^{\max}(s^v) \\ 0 \ldots\ldots \text{for } F_2(s^v) \geq f_2^{\max}(s^v) \end{cases} \qquad (13)$$

Where:

s^v : a solution s in population v

$f_1^{\max}(s^v)$: the maximum value of total cost determined in population v

$f_1^{\min}(s^v)$: the minimum value of total cost determined in population v

$F_1(s^v)$: the value of total cost determined for solution s in population v

$f_2^{\max}, f_2^{\min}, F_2(s^v)$: similar functions determined for total emission

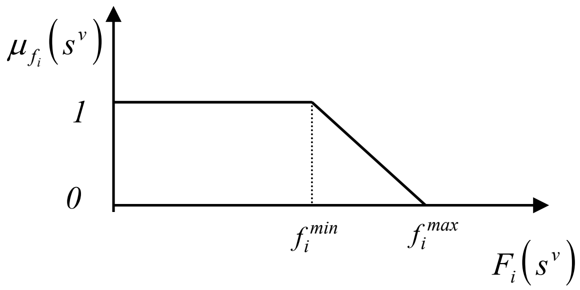

Fig. 1: membership function of fuzzy set assigned to each objective function

$\mu_D(s^v)$ is the membership function of the fuzzy fitness function set that shows the overall satisfaction degree of chromosome s in the population v according to multiple objective functions of cost and

3-4 ALGORITHM OVERVIEW

To start with the proposed algorithm, an initial population of a known size as a set of feasible solutions to the UC problem is randomly generated. Then, for each individual of population the membership function of the fuzzy fitness function set $\mu_D(s^v)$ is calculated by (11) and used as the compromise fitness function in the genetic algorithm procedure. On this basis, selected chromosomes by the roulette wheel rule are subject to genetic operators of crossover and mutation to produce children and a part of the parents having the better fitness function value are directly transferred to the new population to maintain its superiority and convergence of the algorithm.

4 MULTI CRITERIA LOAD DISPATCH WITH FLEXIBLE CONSTRAINTS AND UNCERTAIN FORCASTED LOAD

When the genetic algorithm converges to the Pareto-optimal solution of the UC problem and the optimal generating schedule is found, the optimal share of the thermal generating units should also be determined according to the multiple criteria considered in the overall problem. This is done by employing the fuzzy linear programming method as discussed in [6]. By this method, at each programming hour, a fuzzy decision making set is defined that its membership function λ shows the compromise satisfaction degree of multiple objective functions and is maximized by solving the following classic linear programming problem.

Maximize: λ

Subject To:

$$\lambda \leq \mu_{f_1}(P) \qquad (14)$$

$$\lambda \leq \mu_{f_2}(P)$$

Other constraints

In 14, membership functions of $\mu_{f_1}(P)$ and $\mu_{f_2}(P)$, similar to $\mu_{f_1}(s^v)$ and $\mu_{f_2}(s^v)$ in 12 and 13, are defined as approximate linear functions of total cost and total emission produced by ON units committed by the fuzzy-genetic algorithm for time interval t under consideration. P is the multi-objective optimal share of these units that can be found by solving the LP problem defined in 14. It is possible to consider unit permissible range of generation defined by 8 within not sharp, but flexible boundaries. On the other hand, the main equality constraint in the optimal load dispatch problem is the total generated power of ON units should meet the hourly forecasted load at each programming period of time. There are usually some error and uncertainties in the forecasted hourly demand due to unknown and unpredictable variables. These flexibilities and uncertainties are properly modeled and added to 14 by means of fuzzy constraints. This concept is more comprehensively discussed in [6].

5 TEST RESULTS

To evaluate the proposed algorithm, a test power system containing 100 thermal generating units is selected and the results obtained are investigated in this section. Tables 1 and 2 show a sample of generating unit's cost and emission data defined in (2), (3), (5) and (6). To run the proposed algorithm three cases were firstly defined where in:

Case 1: the single objective function of the total cost,

Case 2: the single objective function of the total emission,

Case 3: multiple objectives of the total cost and the total emission, is / are to be minimized.

Due to the time consuming nature of the problem, it is necessary to perform sensitivity analyses about the effect of problem data changes on obtained optimal parameters of the genetic algorithm. This concept has been considered through a large number of case studies and proper values for genetic algorithm parameters are found. In all case studies the proper number of iterations is chosen equal to1000, and the size of populations is 100. The crossover rate of 0.9 is found to be convenient and the mutation rate is dynamically set to 0.002, 0.003 and 0.005 due to algorithm rate of convergence.

A sample of the Pareto-optimal solution obtained in Case 3 for the generating power of 10 first units is shown in Table 4 and the final results of the total cost and total emission obtained for the optimal solution in cases 1, 2 and 3 are shown in Table 5.

Figures (2) and (3) show the variation and convergence of two objective functions versus the number of genetic algorithm iterations for three mentioned cases. As it is seen in both figures, the value of an objective function is improved and converged to its optimal value when it is chosen as the single objective function in the UC problem. In Case 3, results obtained for an objective function lays between values obtained for that objective function considered and discarded as the single objective function of the problem, in Cases 1 and 2, that is the Pareto-optimal solution to the multi-objective unit commitment problem.

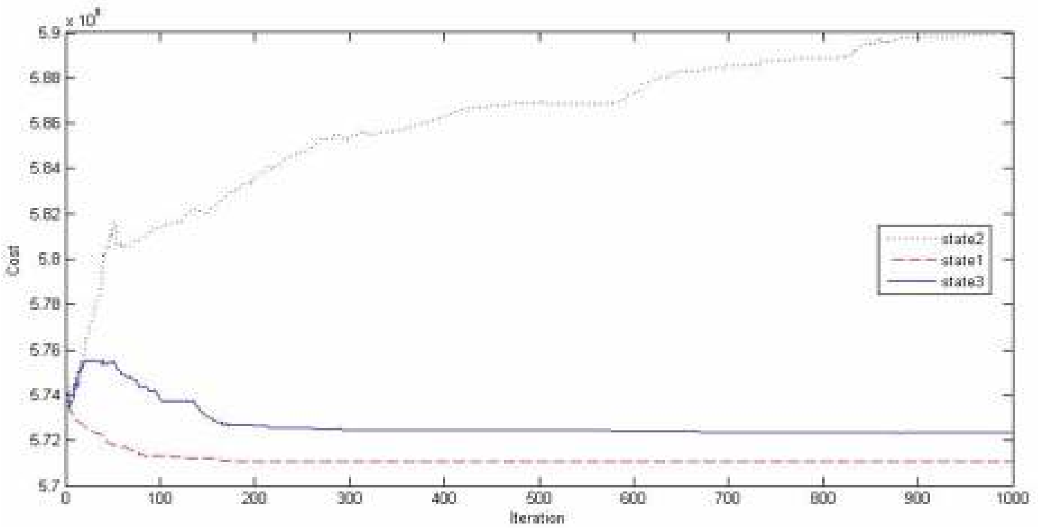

Fig. 2: The total cost variations versus genetic algorithm iterations for various cases

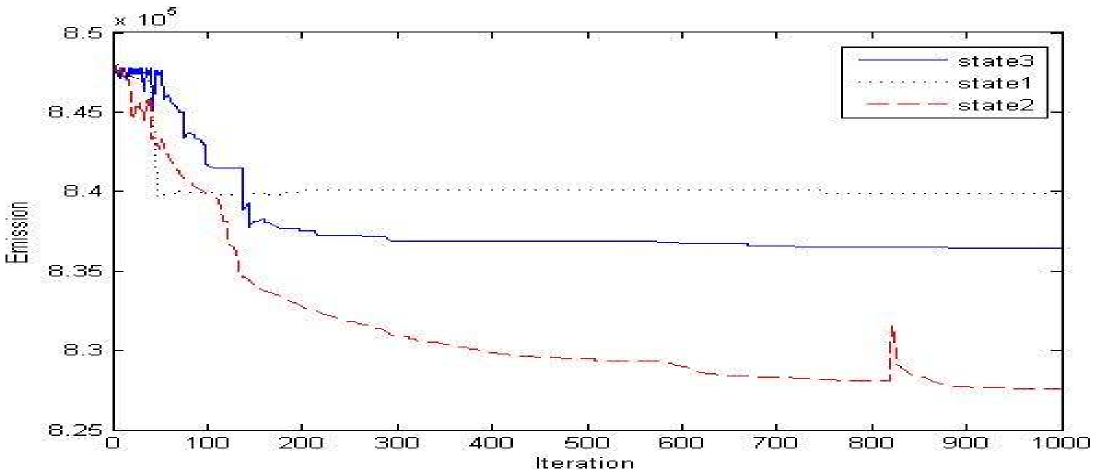

Fig. 3: The total emission variations versus genetic algorithm iterations for various cases

6 CONCLUSIONS

In this paper, the short-term multi-objective generation scheduling problem in power systems containing a large number of thermal units was considered and solved based on a fuzzy- genetic algorithm method. By the proposed algorithm, multi competing objectives of economy, security, emission, reliability and etc. would be considered simultaneously. The large dimensionality of the problem is handled by the use of genetic algorithm (GA), and multi-criteria optimization is considered by evaluating and maximizing the membership function of a fuzzy fitness function set (FFFS) defined for the genetic algorithm populations. The higher value for the membership function of FFFS denotes a better satisfaction degree for the corresponding chromosome and plays the role of fitness function in the GA.

When the genetic algorithm converges to the Pareto-optimal solution of the UC problem and the optimal generating schedule is found, the optimal share of the thermal generating units should also be determined according to the multiple criteria considered in the overall problem. This is done by employing the fuzzy linear programming method, where, at each programming hour, a fuzzy decision making set is defined that its membership function shows the compromise satisfaction degree of multiple objective functions and is maximized by solving a classic linear programming problem. Flexible constraints and uncertainties in the hourly forecasted loads are properly encountered in the problem at this stage.

The proposed algorithm is used and investigated for solving a multi-criteria unit commitment problem to minimize the total cost and the total produced emission in a test power system containing 100 thermal generating units. Results obtained show the capability of the proposed method to deal with the high dimensionality of this multi-criteria unit commitment problem and its effectiveness in finding the Pareto-optimal solution.

REFERENCES

[1] Wood A. J., Wollenberg B. F. (1996): "Power Generation, Operation, and Control, 2nd Edition", *John Wiley & Sons, 1996.*

[2] Padhy N. P. (2004): "Unit Commitment – A Bibliographical Survey" *IEEE Transaction on Power Systems, vol. 19, No. 2, pp 1196-1205, May 2004.*

[3] Elkeib A., Ma H. and Hart J. L. (1990): " Economic Dispatch in View of the Clean-Air Act of 1990", *IEEE Transaction on Power Systems, vol. 9, , pp 972-978, May, 1994.*

[4] Srinivasan D., Chang C. S. and A. C. Liew (1994): "Multi objective generating scheduling using fuzzy optimal search technique", *IEE Proc. Generation, Transmission and Distribution, vol. 141, No. 3, May 1994.*

[5] Su C.C., Hsu Y. Y. (1991): "Fuzzy dynamic programming: an application to unit commitment", *IEEE Transaction on Power System, vol. 6 pp. 1231-1237, Aug. 1991.*

[6] Ebrahimi A., Ehsan M. and Tahani V. (1994): "Multi-criteria Load Dispatch with Fuzzy Constraints", *Journal of Intelligent & Fuzzy Systems, vol. 2, No. 4, pp 315-323, 1994.*

[7] Goldberg D. E., "Genetic Algorithm in Search, Optimization, and Machine Learning", *Addison Wesley, 1989.*

[8] Yan L., Jumin H., and Zhuoshang J., "Genetic algorithm based on fuzzy evolution for multi-criterion

Table 1: a sample of units cost data

Unit	$P_i^{\min}$	$P_i^{\max}$	D C i	A_i	B_i	C_i
1	150	445	13500	0.00048	16.19	1000
2	150	445	15000	0.00031	17.26	970
3	20	130	1650	0.002	16.6	700
4	20	130	1680	0.00211	16.5	680
5	25	162	2700	0.00398	19.7	450
6	20	80	510	0.00712	22.26	370
7	25	85	780	0.00079	27.74	480
8	10	55	90	0.00413	25.92	660
9	10	55	90	0.00222	27.27	665
10	10	55	90	0.00173	27.79	670

Table 2: a sample of units emission data

Unit	x_i	y_i	z_i	DEi	T_i^{on}	T_i^{off}
1	0.000173	1.619	67	9	8	8
2	0.000222	1.729	66.5	9	8	8
3	0.000413	1.660	66	9	5	5
4	0.000079	1.65	48	78	5	5
5	0.000712	1.97	37	51	6	6
6	0.000398	2.226	45	270	3	3
7	0.000211	2.774	68	168	3	3
8	0.0002	2.592	70	1650	1	1
9	0.000031	2.727	97	1500	1	1
10	0.000048	2.779	100	1350	1	1

Table 3: The load demand for a 24 hrs time period

hour	load	hour	load	hour	load	hour	load
1	700	7	1150	13	1400	19	1200
2	750	8	1200	14	1300	20	1400
3	850	9	1300	15	1200	21	1300
4	950	10	1400	16	1050	22	1100
5	1000	11	1450	17	1000	23	900
6	1100	12	1500	18	1100	24	800

Table 4: A sample of the Pareto-optimal solution showing the generating Mw power of 10 first units

Unit \ Hour	1	2	3	4	5	6
1	445	445	445	445	445	445
2	0	0	445	445	445	445
3	130	130	130	130	0	0
4	0	0	0	0	130	130
5	25	109.2	162	162	0	0
6	0	0	0	80	80	80
7	0	0	0	0	85	25.59
8	0	0	0	0	55	0
9	0	0	0	0	55	0
10	0	0	33.02	10	49.54	0

Unit \ Hour	7	8	9	10	11	12
1	445	445	445	445	445	445
2	445	371.25	423.49	445	445	445
3	0	0	0	130	130	130
4	130	130	130	130	130	130
5	0	0	0	0	162	162
6	0	0	0	0	0	80
7	25	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0

Table 5: The total cost and total emission obtained for the optimal solution in cases 1, 2 and 3

Case	Total cost	Total emission
1	5170800	827590
2	5900000	839900
3	5723400	836460