Fuzzy Based Generation Scheduling of Power System with Large Scale Wind Farms

H. Siahkali , *Student Member, IEEE,* M. Vakilian

Abstract-- **Wind power introduces a new challenge to system operators. Unlike conventional power generation sources, wind power generators supply intermittent power because of uncertainty in its resource. In a power system involved large-scale wind power generation scenario, wind intermittency could oblige the system operator to allocate a greater reserve power, in order to compensate the possible mismatch between predicted and the actual wind power output. This would increase the total operation cost.**

This paper presents a new approach in fuzzy based generation scheduling (GS) problem using mixed integer nonlinear programming (MINLP). While the reserve requirements, load-generation balance and wind power availability constraints are satisfied. Constraint modeling is an important issue in power system scheduling. Since the constraints are fuzzy in nature, crisp treatment of them may lead to over conservative solutions. In this paper, a fuzzy optimization-based method is developed to solve power system GS, considering fuzzy objective and constraints. This at first converted to a crisp optimization problem. Then, this problem has been solved using mixed integer nonlinear programming. The proposed approach is applied to a 12-unit test system (including 10 conventional units and two wind farms). The results are compared with the crisp problem solution. The general Algebraic Modeling System (GAMS) has been used to solve the minimization of this GS model using the BARON optimization program.

Index Terms**—Generation scheduling, fuzzy optimization, wind power availability**

NOMENCLATURE

a_g, b_g, c_g	The coefficients of fuel cost function of generating unit g
g	Index for thermal generator unit
N_G	Number of thermal generator units
N_W	Number of wind farms
$n(t)$	Number of hours at time t (e.g. 720 hr)
$OMFCT(g)$	Operation and maintenance fixed cost of thermal unit g, in \$/MW-yr
$OMFCW(w)$	Operation and maintenance fixed cost of wind farm w, in \$/MW-yr
$OMVCT(g)$	Operation and maintenance variable cost of thermal unit g, in \$/MWh
$OMVCW(w)$	Operation and maintenance variable cost of wind farm w, in \$/MWh
$P_d(t)$	System demand at time t, in MW
$P_{Gg,\min}$	Lower limit of thermal unit g, in MW
$P_{Gg,\max}$	Upper limit of thermal unit g, in MW
$P_{GD}(g,t)$	Load contribution of thermal unit g at time t, in MW
$P_R(t)$	A fraction of total system load for system reserve requirement (first part) at time t, in MW
$P_{GR}(g,t)$	Reserve contribution of thermal unit g at time t, in MW
$P_W(w,t)$	Generation of wind farm w at time t, in MW
$P_{W,\max}$	Maximum generation of wind farm w, in MW
$RESW$	A fraction of total wind power employed to compensate wind power prediction errors, in percent
t	Index for time
T	Number of periods under study (12 Months)
$U(g,t)$	Commitment state of unit g at time t (on = 1, off = 0)
$V(w,t)$	Commitment state of wind farm w at time t (on = 1, off = 0)
w	Index for wind farm
$W_{av}(w,t)$	Maximum available wind power of wind farm w at time t, in MW

H. Siahkali, is a PhD student in the Department of Electrical Engineering, Sharif University of Technology, Azadi Ave., P.O.Box: 11365-8639, Tehran, IRAN, (e-mail: siahkali@ee.sharif.edu)

M. Vakilian, is with the Department of Electrical Engineering, Sharif University of Technology, Azadi Ave., P.O.Box: 11365-8639, Tehran, IRAN, (e-mail: vakilian_m@yahoo.com)

I. INTRODUCTION

In power system operation, the term "operation planning" carries a wide range of meaning. For some utilities, operation planning denotes primarily short-term planning tasks (up to several days), such as load forecasting, unit commitment, hydro-thermal coordination, transaction pricing, fuel allocation, and security analysis while for other companies operational planning is interpreted in a wider context, and include mid-term planning activities (up to several months), such as maintenance planning, fuel budgeting, rate forecasting, network planning, relay coordination, etc [1]. The mid-term planning provides the link between the long-term and short-term planning programs. The duration of this planning may be one to two years which can be divided into monthly or weekly intervals.

So, the operational planning problem is usually decomposed into smaller problems in order to be solved in an easier way. In this way, the operational planning involves some main decision stages, usually separated using a hierarchical time based decomposition method as follows: the hydrothermal generations coordination problem, the unit

978-1-4244-2235-7/09/\$25.00 ©2009 IEEE

commitment problem, the maintenance scheduling problem and the economic load dispatch problem.

The generation scheduling (GS) problem is commonly a nonlinear, large-scale, mixed integer combinatorial problem. The exact solution of the GS problem can be obtained by complete enumeration of all feasible combinations of generating units, which is impossible for realistic power systems [2]. Due to the large economic advantage gained by the improvement in generation scheduling, considerable efforts have been devoted to develop robust solution methods. Various mathematical programming and heuristic based approaches are employed for solving the generation scheduling problem such as; dynamic programming [3], neural networks [4], simulated annealing [5], genetic algorithms [7–8], Lagrangian relaxation [9], bender's decomposition [10], ant colony optimization [11] and particle swarm optimization [12].

Using these methods, GS can be solved as a crisp problem, although part of GS is imprecise due to the related prediction errors. [13–18], have employed fuzzy modeling of these systems as effective alternatives for solving the GS problem. In most of these cases, fuzzy UC model is optimized by GA [13, 16], simulated annealing [17], particle swarm [18], while the degree of fuzzy membership is used as a selection criterion of an appropriate solution. Imprecise parameters that can be modeled with fuzzy logic can be better fed directly into an uncertainty-based optimization method.

In the past years, wind power has become one of the most important renewable energy sources in the electricity sector. However, some difficulties arise during integration of wind power into the electric power system operation and planning. As wind is not perfectly predictable, modeling of problem while the wind power is integrated to power system suffers the forecasting errors. In order to overcome the forecast errors, the conventional units in the power system have to operate in a more flexible manner to maintain the stability of the power system. Such changes in the operation of power plants can result in additional costs in the power system. These related effects become more important when wind power capacities increase.

In next section the problem formulation (both crisp and fuzzy) and the constraints of generation scheduling problem are discussed and the uncertain parameters were represented with fuzzy membership function. The solution methodology for fuzzy generation scheduling (GS) is presented in section III. In section IV, the wind turbine model is discussed. The 12-unit test system (containing; 10 conventional generating units and 2 wind farms) is employed as a sample problem, in section V, to solve this optimization problem by the proposed method in section III. Summary and conclusion are presented in section VI.

II. Problem Formulation

To clearly present the problem formulation, the crisp model will be introduced, and then followed by the fuzzy version. The time horizon of this problem is one year with monthly interval. In this formulation, the ramping and minimum up/down constraints will be ignored because of time scheduling of this problem.

A. Crisp Problem Formulation

The objective function of the GS problem is to minimize the cost of supplying the load while satisfying the reserve requirement, wind power availability and unit constraints. The objective function is defined as the total generation cost; including fuel cost, operation and maintenance costs. And its minimization equation is as follows:

$$\begin{aligned}\min J = &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{F\left(P_{GD}(g,t)\right)\cdot n(t)\right\}\cdot U(g,t) + \\ &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{(P_{GD}(g,t)+P_{GR}(g,t))\cdot OMVCT(g)\cdot n(t)\right\}\cdot U(g,t) + \\ &\sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{P_{Gg,\max}(g)\cdot OMFCT(g)\cdot n(t)/8760\right\} + \\ &\sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{P_W(w,t)\cdot OMVCW(w)\cdot n(t)\right\}\cdot V(w,t) + \\ &\sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{P_{W,\max}(w)\cdot OMFCW(w)\cdot n(t)/8760\right\}\end{aligned} \quad (1)$$

Where:

$$F(P_{GD}(g,t)) = a_g + b_g\cdot P_{GD}(g,t) + c_g\cdot\left(P_{GD}(g,t)\right)^2 \quad (2)$$

This objective function is subject to a number of system and unit constraints including the system demand, reserve requirement and generating units' constraints which will be satisfied as follows:

To satisfying system demand it is required to have the following satisfied equation:

$$\sum_{g=1}^{N_G} P_{GD}(g,t)\cdot U(g,t) + \sum_{w=1}^{N_W} P_W(w,t)\cdot V(w,t) = P_d(t) \qquad t = 1,2,\ldots,T \quad (3)$$

The reserve requirement should be satisfied. The operating reserve requirement has two parts; first part is a percentage of the total system load (e.g. 5% of load) and the second part is a surplus reserve which is chosen to compensate the mismatch between the forecasted wind power generation and its actual value. Thus, this reserve to compensate the errors in wind power generation forecast can be obtained through assessment of the recorded data on wind speed at a wind turbine site [19]. The second part of reserve is determined using a percentage of total wind power availability (RESW) in this paper. The reserve requirement (both parts) must be taken care of by the conventional units in a system.

$$\sum_{g=1}^{N_G} P_{GR}(g,t)\cdot U(g,t) \geq P_R(t) + RESW * \sum_{w=1}^{N_W} P_W(w,t)\cdot V(w,t) \qquad t = 1,2,\ldots,T \quad (4)$$

The generating unit constraints also should be satisfied. Therefore the wind power availability should be satisfied as follows:

$$P_W(w,t) = W_{av}(w,t) \qquad t = 1,2,\ldots,T \quad (5)$$

And the maximum and minimum generation of the generating unit limits should be satisfied as follows:

$$P_{Gg,\min} \leq P_{GD}(g,t) + P_{GR}(g,t) \leq P_{Gg,\max} \quad (6)$$

B. Fuzzy Problem Formulation

As mentioned, fuzzy set theory is a natural platform to model fuzzy or imprecise constraints and/or objectives. Given a collection of objects, Y, a fuzzy set $\widetilde{A}$ is defined as:

$$\widetilde{A} = \{(y, \mu_{\widetilde{A}}(y)) | y \in Y\}, \qquad 0 \le \mu_{\widetilde{A}}(y) \le 1 \tag{7}$$

Where $\mu_{\widetilde{A}}(y)$ the membership of y, representing the degree is that y belongs to $\widetilde{A}$ (ranging from zero to one for a normalized fuzzy set). If $\mu_{\widetilde{A}}(y)$ could only be 0 or 1, $\widetilde{A}$ degenerates to a crisp set. A fuzzy or inexact relation, such as "roughly greater than or equal to" or "slightly less than or equal to," is also associated with a membership function representing the degree of certainty of that relation. For example, load demand depends on weather variables, social behavior of customers, etc. The forecasted demand is imprecise, thus it can be described as a fuzzy quantity. Any variable associated with the system load will be considered as a fuzzy variable.

To obtain an optimal generation scheduling under the fuzzy environments: production cost, load demand equality constraint, reserve inequality relation constraint and wind power availability inequality relation constraint are all expressed in fuzzy set notations. On the other hand, the crisp quantities include; limits on thermal, and wind unit outputs constraints. Four membership functions will be defined for this formulation.

a. Load balance membership function

The predicted system load deviation is usually from ±2 to ±5% [20]. In this study, the maximum range of variation of the predicted demand (ΔP_d) is taken equal to±5%. The membership function of the fuzzy equality ($\cong$) can be described as (Fig. 1):

$$\mu_{P_d}(x) = \begin{cases} 1 & x = P_d \\ \dfrac{x - P_d + \Delta P_d}{\Delta P_d} & P_d - \Delta P_d \le x \le P_d \\ \dfrac{P_d + \Delta P_d - x}{\Delta P_d} & P_d \le x \le P_d + \Delta P_d \\ 0 & otherwise \end{cases} \tag{8}$$

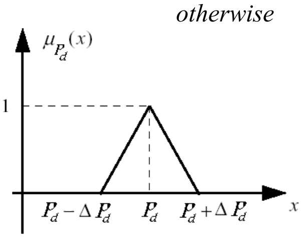

Fig. 1. Fuzzy Membership Function of Power System Load Equality

b. Reserve membership function

The reserve constraint can be described through a fuzzy inequality relation ($\gtrsim$), i.e., the total reserve contribution at time t should roughly be greater than or equal to the reserve requirement at that time. The membership function of the fuzzy inequality is described by:

$$\mu_{P_R}(x) = \begin{cases} 1 & x \ge P_R \\ \dfrac{x - P_R + \Delta P_R}{\Delta P_R} & P_R - \Delta P_R \le x \le P_R \\ 0 & x \le P_R - \Delta P_R \end{cases} \tag{9}$$

Where P_R is the normal reserve requirement at time t, and $P_R - \Delta P_R$ is the minimum reserve acceptable. In this study, the normal reserve requirement (P_R) is taken equal to 5% of the load demand and ΔP_R is assumed to be 5%. Figure 2 shows the membership function of reserve inequality.

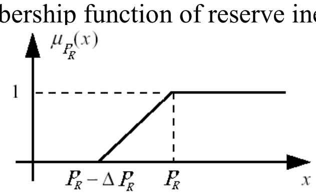

Fig. 2. Fuzzy Membership Function of Reserve Requirement Inequality

c. Wind power availability membership function

The wind power availability constraint can be described as fuzzy equality relation ($\cong$). Figure 3 shows the membership function of wind power availability equality. In this study, the maximum range of variation of the wind power availability (ΔW_{av}) is taken equal to 5%.

$$\mu_{W_{av}}(x) = \begin{cases} 1 & x = W_{av} \\ \dfrac{x - W_{av} + \Delta W_{av}}{\Delta W_{av}} & W_{av} - \Delta W_{av} \le x \le W_{av} \\ \dfrac{W_{av} + \Delta W_{av} - x}{\Delta W_{av}} & W_{av} \le x \le W_{av} + \Delta W_{av} \\ 0 & otherwise \end{cases} \tag{10}$$

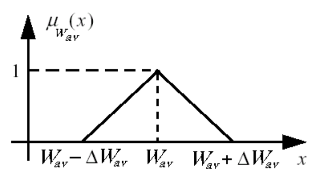

Fig. 3. Fuzzy Membership Function of Wind Power Availability Equality

d. Objective equation membership function

The objective function equation can be described as fuzzy inequality relation ($\lesssim$). Following above thinking, the total generation cost should be essentially smaller than or equal to some aspiration level J_0:

$$\min J \lesssim J_0, \tag{11}$$

The membership function for the fuzzy inequality in (10) is assumed to be (Fig. 4):

$$\mu_J(x) = \begin{cases} 1 & x \le J_0 \\ \dfrac{J_0 + \Delta J - x}{\Delta J} & J_0 \le x \le J_0 + \Delta J \\ 0 & x \ge J_0 + \Delta J \end{cases} \tag{12}$$

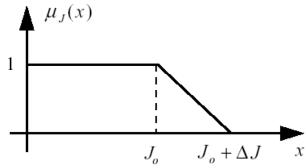

Fig. 4. Fuzzy Membership Function of Total Cost

The aspiration level J_0 represents the ideal generation cost. A schedule becomes less acceptable as the cost increases above J_0 as indicated by the reduced membership function. One possible candidate for the highest acceptable generation cost $J_0+\Delta J$ is the cost of the crisp scheduling problem with all normal reserve requirements satisfied. The value ΔJ can be determined based on experience, e.g., as a certain percentage of J_0 (in this study is assumed to %10). Selection of these parameters may be subjective and dependent on specific operational practice. The overall scheduling problem with fuzzy objective and constraints can thus be formulated as the satisfaction of (11) subject to (8) to (10), and individual unit constraints.

III. Solution Methodology

The key step of fuzzy optimization is to convert the fuzzy problem to a crisp one. Since all the fuzzy objective and constraints are desired to be satisfied simultaneously. The problem is then to maximize the degree to which all the constraints (including the objective function constraint) are satisfied. Defining z as the minimum degree of satisfaction among all fuzzy constraints, mathematically,

$$\max_{z\in[0,1]} z = \max_{z\in[0,1]}\left\{min\{\mu_J,\mu_{P_d(t)},\mu_{P_R(t)},\mu_{W_{av}(k,t)}\}\right\} \quad t=1,2,...,T \quad k=1,2,...,N_W \tag{13}$$

The above equation can be rewritten as:

$$\max z, \tag{14}$$

Subject to:

$$z \le \mu_J$$
$$z \le \mu_{P_d(t)} \quad ,t=1,2,...,T$$
$$z \le \mu_{P_R(t)} \quad ,t=1,2,...,T$$
$$z \le \mu_{W_{av}(k,t)} \quad ,t=1,2,...,T \quad , \quad k=1,2,...,N_W$$
$$0 \le z \le 1$$

and all original crisp constraints. Substituting the membership functions (8) to (12), the fuzzy scheduling problem can be converted to the following crisp optimization problem:

$$\max z, \tag{15}$$

Subject to:

$$(z-1)\cdot\Delta J - J_0 + J \le 0$$
$$(z-1)\cdot\Delta P_d - \sum_{g=1}^{G} P_{GD}(g,t)\cdot U(g,t) - \sum_{w=1}^{W} P_W(w,t)\cdot V(w,t) + P_d(t) \le 0$$
$$(z-1)\cdot\Delta P_d + \sum_{g=1}^{G} P_{GD}(g,t)\cdot U(g,t) + \sum_{w=1}^{W} P_W(w,t)\cdot V(w,t) - P_d(t) \le 0$$
$$(z-1)\cdot\Delta P_R - \sum_{g=1}^{G} P_{GR}(g,t)\cdot U(g,t) + RESW * \sum_{w=1}^{W} P_W(w,t)\cdot V(w,t) + P_R(t) \le 0$$
$$(z-1)\cdot\Delta W_{av}(w,t) - W_{av}(w,t) + P_W(w,t) \le 0$$
$$(z-1)\cdot\Delta W_{av}(w,t) + W_{av}(w,t) - P_W(w,t) \le 0$$
$$P_{Gg,\min} \le P_G(g,t) \le P_{Gg,\max}$$

Note that all the original crisp constraints still have to be satisfied and J must be substitute by equation (1). In the membership problem, the optimal membership variable *z* tends to decrease as the cost and reserve constraint violations become larger and the associated multipliers increase. The membership variable *z* may become less than one, implying that not all normal constraints can be satisfied.

IV. Wind Turbine Model

The generated power varies with the wind speed at the wind farm site. The power output of a wind turbine can be determined from its power curve, which is a plot of output power against wind speed. Fig. 5 shows a typical power curve of a wind turbine. A turbine is designed to start generating at the cut-in wind speed (*V*ci) and is shut down for safety reasons at the cut-out wind speed (*V*co). Rated power *P*r is generated when the wind speed is between the rated wind speed (*V*r) and the cut-out wind speed. There is a nonlinear relationship between the power output and the wind speed when the wind speed lies within the cut-in and the rated wind speed as shown in Fig. 5.

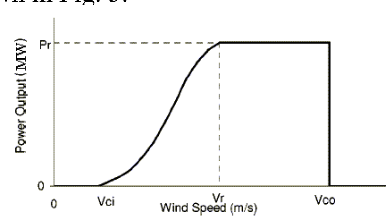

Fig. 5. Power curve of a wind turbine

Therefore, the power generated *Pi* corresponding to a given wind speed SW*i* can be obtained from:

$$P_i = \begin{cases} 0 & 0 \le SW_i < V_{ci} \\ P_r*(A+B*SW_i+C*SW_i^2) & V_{ci} \le SW_i < V_r \\ P_r & V_r \le SW_i \le V_{co} \\ 0 & SW_i > V_{co} \end{cases} \tag{16}$$

The constants *A, B*, and *C* are presented in [19]. The application of the common wind power generation model is illustrated in this paper by applying it to a wind turbine rated at 2 MW, and with cut-in, rated, and cut-out wind speeds of 2.5, 14, and 25 m/s, respectively.

V. Numerical Testing Results

The proposed optimization algorithm is applied to a model system to verify its effectiveness. This approach is applied to the test system, which has 12 generating units. The input data for 10 conventional units of test system are given in table I [21] and also, two wind farms is shown in this table (wind1 and wind2), too. The annual peak load is assumed 1500 MW for this test system. The load percentage in each time interval of operation period is shown in table II, and wind speed and wind power availability of the two wind farms are also given in this table. Each wind farms has 40 wind turbine units with 2 MW capacities. In this study, the RESW is assumed to 10% of total available wind power of each wind farms. For instance, reserve requirement of this test system is 59.1935 MW in third period that obtained by summation of the two parts; the first part is 56.25 MW (5% of total load) and the second part is 2.9435 MW (10% of available wind power).

TABLE I
Generator Characteristics and Cost Function Coefficients

Coeff.	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
$P_{G,\max}$ (MW)	455	455	130	130	162	80
$P_{G,\min}$ (MW)	150	150	20	20	25	20
Fixed O&M Cost ($/MW-yr)	5000	5000	7000	7000	7000	8500
Variable O&M Cost ($/MWh)	0.3	0.3	0.8	0.8	0.8	0.9
a ($/hr)	1000	970	700	680	450	370
b ($/MWh)	16.19	17.26	16.6	16.5	19.7	22.26
c ($\$/MW^2h$)	0.00048	0.00031	0.002	0.00211	0.00398	0.00712

Coeff.	Unit 7	Unit 8	Unit 9	Unit 10	Wind1	Wind2
$P_{G,\max}$ (MW)	85	55	55	55	80	80
$P_{G,\min}$ (MW)	25	10	10	10	0	0
Fixed O&M Cost ($/MW-yr)	10000	10000	10000	10000	0	0
Variable O&M Cost ($/MWh)	0.8	0.9	0.9	0.9	3.973	6.193
a ($/hr)	480	660	665	670	0	0
b ($/MWh)	27.74	25.92	27.27	27.79	0	0
c ($\$/MW^2h$)	0.00079	0.00413	0.00222	0.00173	0	0

TABLE II
Load Pattern, Reserve Requirement and Wind Power Availability

Period (Month)	Percentage of Annual Peak Load (%)	Reserve Requirement (MW)	Wind Speed (m/s)		Wind Power Availability (MW)	
			Wind1	Wind2	Wind1	Wind2
1	87.8	67.8683	5.788	8.284	3.576	16.607
2	88	67.7905	5.358	8.149	2.23	15.675
3	75	59.1935	5.829	9.446	3.717	25.718
4	83.7	66.0643	7.193	9.134	9.817	23.076
5	90	70.6211	7.989	8.284	14.604	16.607
6	89.6	69.3703	7.559	7.19	11.905	9.798
7	88	67.8043	7.25	6.826	10.13	7.913
8	80	63.8324	7.063	9.836	9.122	29.202
9	78	61.2626	7.591	8.127	12.097	15.529
10	88.1	68.1806	6.165	8.213	4.937	16.119
11	94	73.2722	6.414	8.966	6.007	21.715
12	100	79.1649	7.035	10.202	8.973	32.676

The crisp and fuzzy models described in this paper have been written in GAMS (General Algebraic Modeling System) language [22]. This program has been used to solve this optimization problem using the BARON optimization program (Branch and Reduce Optimization Navigator) based on Mixed Integer Non Linear Programming (MINLP).

Figures 6 and 7 present the results of GS problem of the test system for load and reserve units' contribution, respectively. In these figures, the amount of power generation of each unit in different time periods to supply load and reserve are shown. These results of optimal generation scheduling (GS) are obtained by MINLP in crisp formulation. In this study, the equality relation of load balance and wind power availability and inequality relation of reserve power have been used and satisfied. Total cost of test system in this annual scheduling is 243.18 million dollar per year and total wind power availability has been used in this scheduling.

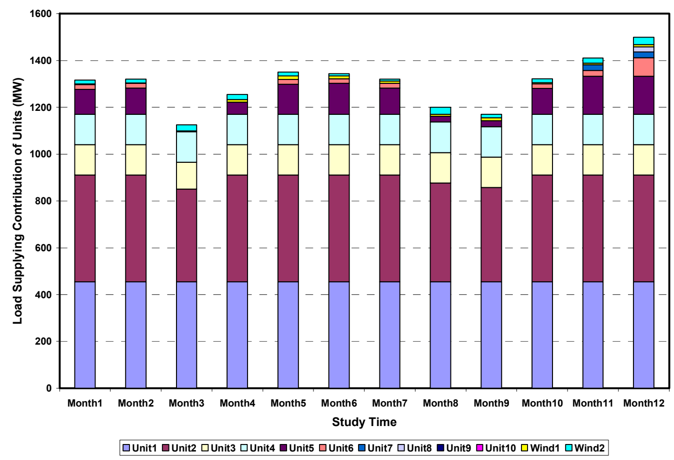

Fig. 6. Mid Term GS Results for Load Contribution (Crisp Solution)

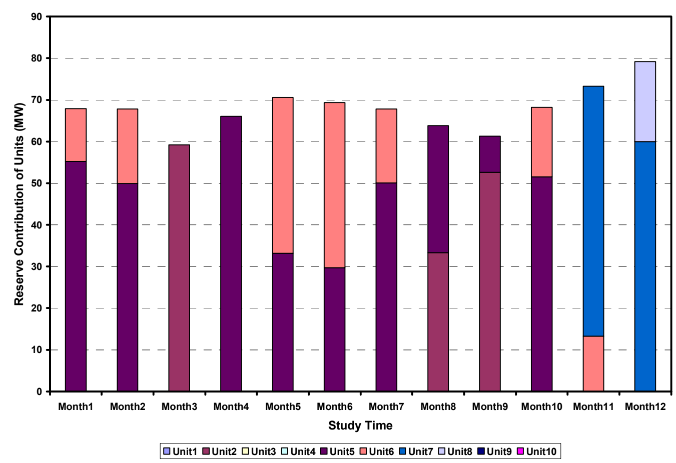

Fig. 7. Mid Term GS Results for Reserve Contribution (Crisp Solution)

The brief results of fuzzy optimization of GS problem have been shown in table III. These results are obtained in some runs for solving this problem with different quantities of J_0, and also ΔJ that is taken as 10% of J_0. The membership variable z and objective function J are presented in this table, too. These parameters are related by equation (17).

$$J = J_0 + \Delta J \cdot (1 - z) \qquad (17)$$

Also, this table shows the maximum ratio of total generation, total reserve allocation and total wind power generation between fuzzy and crisp solutions in each period of time. The minimum value of J has been obtained in #3-run of this problem. In this run, the differences between fuzzy and crisp solutions are -%0.8, -%0.6 and %0.8 for total generation, reserve and wind generation, respectively. Also, the total cost of this difference is -%0.73. It means the total cost and total wind power generation of fuzzy solution are lower than crisp solution but the total generations for load balance constraint and reserve power are grater than crisp solution.

The membership variable z in run #13 is one. This means that all normal constraints are 100% satisfied but the total cost of this scheduling has been obtained over crisp solution. Other runs of this problem indicate that when the membership variable z is lower than one, implying that some constraints are not satisfied. So, the operators have some options to select the best and suitable scheduling. This clearly indicates the trade-off between minimizing generation cost and satisfying constraints. In some runs of this problem (#1 to #4 and #6 to #9), it can be seen that the load balance, reserve and wind power constraints are below the normal requirement (a little bit), but the minimum allowable of this constraints have been satisfied (e.g. $P_R - \Delta P_R$).

TABLE III
MANY RUNS OF FUZZY OPTIMIZATION SOLUTION

Run	J_0 (M\$/yr)	z	J (M\$/yr)	Max. Ratio Between Fuzzy and Crisp Solutions (%)		
				Total generation	Reserve	Wind power
#1	236.16	0.764976	241.71	98.8	98.8	101.2
#2	236.88	0.76172	242.52	98.8	109.6	101.2
#3	237.6	0.839437	241.41	99.2	99.4	100.8
#4	238.32	0.860218	241.65	99.3	99.3	100.7
#5	239.04	0.793193	243.98	99	99	101
#6	239.76	0.901007	242.13	99.5	132.3	100.5
#7	240.48	0.92611	242.26	99.6	99.6	100.4
#8	241.2	0.918879	243.16	99.6	99.6	100.4
#9	241.92	0.972768	242.58	99.9	99.9	100.15
#10	242.64	0.969187	243.39	99.8	99.8	100.16
#11	243.36	0.901007	245.77	100.5	222.5	100.5
#12	244.08	0.979230	244.59	99.9	99.9	100.1
#13	244.8	1.0	244.8	100	100	100
#14	245.52	0.973885	246.16	99.9	166.2	100.13
#15	246.24	0.973885	246.88	99.9	146.8	100.13

It is clearly, the #9-run of this problem has the best result with respect to crisp solution (-0.1%, -0.1% and 0.15%) and z=0.972768 that is obtained by J_0 equals to 241.92 million dollar per year. Also, the total cost of the fuzzy solution with respect to the crisp solution is 99.48% with a difference of -0.52%.

The generation scheduling of the test system has been carried out by fuzzy formulation with parameters in the solution run #9 of the test system in table III is shown in figures 8 and 9. These figures present the results of fuzzy GS of the test system for load and reserve units' contribution, respectively. In this scheduling, annual cost of test system is 242.58 million dollar per year and all normal reserve requirements are 100% satisfied. So, total cost of fuzzy solution with minimum differences of crisp formulation is less than crisp solution. Also, the schedulers can be selected the generation scheduling of system using fuzzy formulation that is obtained by tradeoff between cost and satisfying constraints.

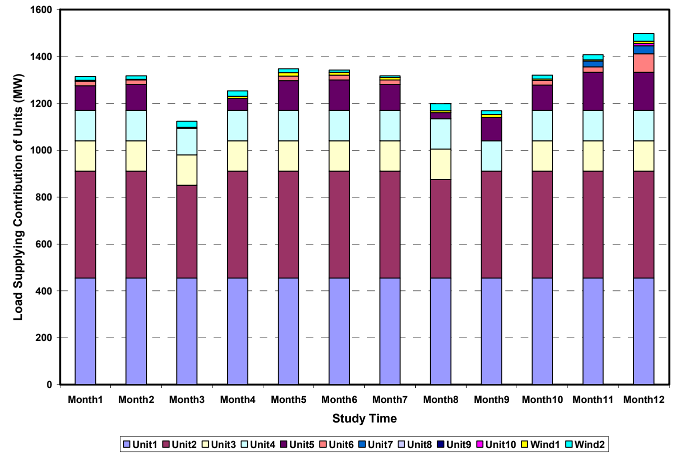

Fig. 8. Mid Term GS Results for Load Contribution (Fuzzy Solution #9-Run)

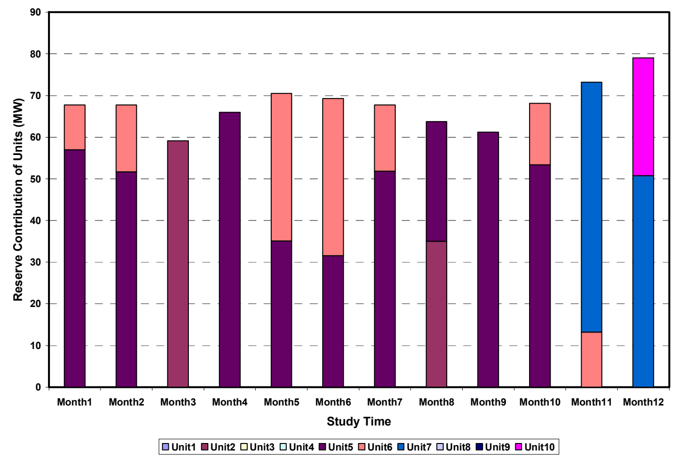

Fig. 9. Mid Term GS Results for Reserve Contribution (Fuzzy Solution #9-Run)

These two solutions (crisp and fuzzy formulations) have nearly same patterns of unit scheduling and the cost obtained in fuzzy formulation is approximately similar to those obtained by the crisp algorithm for the same reserve requirements. Therefore, near optimal schedules are obtained.

Table IV shows some changes in the range of variation in the main parameters of this optimization such as predicted demand, reserve requirement and wind power availability. The run #1 in table IV is fuzzy solution and run #5 of this table is crisp solution and other runs are between these two solutions. Also, when the variation of each parameter omitted, the total cost of solution will be greater than pure fuzzy solution. On the other hand, crisp nature in constraints lead to extra cost. The results of runs #2, #3 and #4 show this concept.

TABLE IV
MANY RUNS OF FUZZY OPTIMIZATION SOLUTION (#9-RUN IN TABLE III)

Run	ΔP_d (%)	ΔP_R (%)	ΔW_{av} (%)	z	J (M\$/yr)	Max. Ratio Between Fuzzy and Crisp Solutions (%)		
						Load	Reserve	Wind
#1	5	5	5	0.972768	242.58	99.9	99.9	100.15
#2	0	5	5	0.914753	243.98	100	99.57	100.43
#3	5	0	5	0.920578	243.84	99.6	100	100.4
#4	5	5	0	0.965396	242.76	99.8	99.8	100
#5	0	0	0	0.948113	243.18	100	100	100

VI. Summary and Conclusions

A fuzzy optimization-based method is developed to solve power system generation scheduling problem with fuzzy reserve requirements and wind power availability constraints. The problem is first converted to a crisp optimization problem, and then efficiently solved by using the Mixed Integer Non Linear Programming (MINLP) method. Numerical testing results clearly show the trade-off between minimizing cost and satisfying constraints. For a given desired cost, the fuzzy optimization-based method can generate a near optimal scheduling and provide information for generation scheduler to provide the "best" trade-off between the cost and constraints uncertainties. On the other words, the membership value of decision variable (z) shows the deviation from mean value of parameters. So, the risk is increased when the value of this membership of decision is decreased. The system operator must compromise between this value and total cost to obtain the best results.

VII. References

[1] D. Hayward, et al, "Current issues in operational planning", *IEEE Trans. Power Systems*, Vol. 7, No. 3, Aug. 1992.

[2] A. J. Wood and B. F. Wollenberg, Power system generation, operation and control, 2nd ed., New York: John Wiley, 1996.

[3] Z. Ouyang and S. M. Shahidehpour, "An intelligent dynamic programming for unit commitment application," *IEEE Trans. Power Systems*, vol. 6, no. 3, pp. 1203–1209, Aug. 1991.

[4] F. Liu and F. E. Villaseca, "Neural networks for generation scheduling in power systems," *International Joint Conference on Neural Networks IJCNN*, vol. 2, pp. 233–238, June 1992.

[5] K. P. Wong and Y. W. Wong, "Hybrid genetic/simulated annealing approach to short term multiple fuel constrained generation scheduling," *IEEE Trans. Power Systems*, Vol. 12, no. 2, pp. 776–784, May 1997.

[6] G. Demartini, et al, "Dual programming methods for large-scale thermal generation scheduling," *IEEE Trans. Power Systems*, Vol. 13, no. 3, pp. 857–863, Aug. 1998.

[7] S. O. Orero and M. R. Irving, "A genetic algorithm modeling framework and solution technique for short term optimal hydrothermal scheduling," *IEEE Trans. Power Systems*, vol. 13, pp. 501–514, May 1998.

[8] E. Gil, J. Bustos and H. Rudnick, "Short-term hydrothermal generation scheduling model using a genetic algorithm," *IEEE Trans. Power Systems*, vol. 18, no. 4, pp. 1256–1264, Nov. 2003.

[9] D. K. S. M. G. I. S. J. Wang, S.M. Shahidehpour, "Short-term generation scheduling with transmission and environmental constraints using an augmented lagrangian relaxation," *IEEE Trans. Power Systems*, vol. 10, no. 3, pp. 1294–1301, Aug. 1995.

[10] M. S. H. Yamin, S. Al-Agtash, "Security-constrained optimal generation scheduling for gencos," *IEEE Trans. Power Systems*, vol. 19, no. 3, pp. 1365–1372, Aug. 2004.

[11] Y. S. In-Keun Yu, C.S. Chou, "Application of the ant colony search algorithm to short-term generation scheduling problem of thermal units," *Inter. Conf. on Power System Technology*, POWERCON '98, vol. 1, pp. 552–556, Aug. 1998.

[12] T. O. Ting, M. V. C. Rao and C. K. Loo, "A novel approach for unit commitment problem via an effective hybrid particle swarm optimization," *IEEE Trans. Power Systems*, vol. 21, no. 1, pp. 411–418, Feb. 2006.

[13] K. P. Wong and Y. W. Wong, "Combined genetic algorithm/simulated annealing/fuzzy set approach to short-term generation scheduling with take-or-pay contract," *IEEE Trans. Power Systems*, vol. 11, pp. 128–136, Feb. 1996.

[14] H. Y. Yamin, "Fuzzy self-scheduling for GenCos," *IEEE Trans. Power Systems*, vol. 20, no. 1, pp. 503–505, Feb. 2005.

[15] R. H. Liang and J. H. Liao, "A Fuzzy optimization approach for generation scheduling with wind and solar energy systems," *IEEE Trans. Power Systems*, vol. 22, no. 4, pp. 1665–1674, Nov. 2007.

[16] A. H. Mantawy, "A genetic algorithm solution to a new fuzzy unit commitment model," *Elect. Power Syst. Res.*, vol. 72, pp. 171–178, 2004.

[17] A. Y. Saber, et al., "Fuzzy unit commitment scheduling using absolutely stochastic simulated annealing," *IEEE Trans. Power Systems*, vol. 21, no. 2, pp. 955–964, May 2006.

[18] A. Y. Saber, et al, "Unit commitment computation - A novel fuzzy adaptive particle swarm optimization approach," *IEEE Power Systems Conf.*, pp. 1820–1828, 2006.

[19] P. Giorsetto and K. F. Utsurogi, "Development of a new procedure for reliability modeling of wind turbine generators," *IEEE Trans. Power App. Syst.*, vol. 102, no. 1, pp. 134–143, Jan. 1983.

[20] P. Attaviriyanupap, et al., "A new profit based unit commitment considering power and reserve generating," *IEEE Power Eng. Society Winter Meeting*, vol. 2, pp. 1311-1316, 2002.

[21] C. P. Cheng, C. W. Liu, and C. C. Liu, "Unit commitment by Lagrangian relaxation and genetic algorithms," *IEEE Trans. Power Systems*, vol. 15, no. 2, pp. 707–714, May 2000.

[22] GAMS Release 2.50, "A user's guide," GAMS Development Corporation, 1999 available: www.gams.com.

VIII. Biogtaphies

Hassan Siahkali (S'06) received the B.Sc. degree in Electronic Engineering from the Tabriz University Tehran, Iran and M.Sc. degree in Power System Engineering from the Amir Kabir University of Technology, Department of Electrical Engineering, Tehran, Iran in 1993 and 1997, respectively. He worked as a project manager at the Niroo Research Institute (N.R.I.) from 1999 to 2005. He is currently pursuing the PhD degree from department of electrical engineering, Sharif University of Technology, Tehran, Iran. His main research interests are in the areas of electric power systems planning and operation and restructuring of power system.

M. Vakilian received his B.Sc. in electrical engineering (1978) and M.Sc (1986) in electric power engineering from Sharif University of Technology in Tehran and PhD in electric power engineering from Rensselaer Polytechnic Institute, Troy, NY, USA in 1993. From 1986 he joined the Faculty of Department of Electrical Engineering of Sharif University of Technology As Instructor. From 1993 he continued his work as Assistant Professor in electric power engineering; from 1997 to 2001 he was also Director of Electric Power Group. From 2001 to 2003 he was Associate Professor and also Chairman of the Department. He is now working as Professor in this department and he is also director of a committee in charge of restructuring the under graduate program in this department. His research interests are transient modeling of power system equipments and power system, optimum design of high voltage equipments insulation, insulation monitoring, and some aspects of power system management.