A Fuzzy-Optimization Approach for Generation Scheduling With Wind and Solar Energy Systems

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***Abstract*—This paper presents a fuzzy-optimization approach for solving the generation scheduling problem with consideration of wind and solar energy systems. Wind and solar energy are being considered in the power system to schedule unit power output to minimize the total thermal unit fuel cost. When performing the generation scheduling problem in conventional methods, the hourly load, available water, wind speed, solar radiation must be forecasted to prevent errors. However, actually there are always errors in these forecasted values. A characteristic feature of the proposed fuzzy-optimization approach is that the forecast hourly load, available water, wind speed and solar radiation errors can be taken into account using fuzzy sets. Fuzzy set notations in the hourly load, available water, wind speed, solar radiation, spinning reserve and total fuel cost are developed to obtain the optimal generation schedule under an uncertain environment. To demonstrate the effectiveness of the proposed method, the generation scheduling problem is performed in a simplified generation system. The results show that a proper generating schedule for each unit can be reached using the proposed method.**

***Index Terms*—Fuzzy-optimization approach, fuzzy sets, generation scheduling, renewable energy.**

I. Introduction

RENEWABLE energy, such as solar energy and wind energy, has been actively researched and developed in advanced countries. This paper considers generating renewable energy connected to a power system to minimize the total thermal-unit fuel cost.

It is a typical optimization problem in which the total operating cost over the study period is minimized subject to the load and all system constraints. A survey of the literature on this problem reveals that various numerical optimization techniques [1]–[11] have been employed to solve the generation scheduling problem. Quite promising results in terms of fuel cost savings have been reached in most works. However, among these works, some uncertain factors were not involved in the generation scheduling problem and renewable energy systems were not considered.

A fuzzy-optimization approach is used in this paper to solve the generation scheduling problem considering wind and solar energy systems. To perform the generation scheduling problem using conventional methods, the hourly load for the power balance equations, available water for hydro units, wind speed for wind power generation, and solar radiation for photovoltaic (PV) generators must be forecasted to prevent errors. However, there are always errors in these forecasted values. A characteristic feature of the proposed fuzzy-optimization approach is that the errors in the forecast hourly load, available water, wind speed, and solar radiation can be taken into account using fuzzy sets. An approach based on fuzzy sets is proposed to reach the desired generation schedules based on uncertain load demand, available water, wind speed and solar radiation. This method has been successfully applied to other optimization problems such as integrated power system scheduling [12], dynamic economic dispatch [13], and so on. To reach an optimal generation schedule under a fuzzy environment, the total fuel cost, load demand, spinning reserve, available water, wind speed, and solar radiation are all expressed in fuzzy set notations. A genetic algorithm [14], [15] is then employed to reach the desired generation schedule.

The SO_2, NO_X, and CO_2 emission constraint will be considered in the generation scheduling problem for environmental protection. Power production from fossil burning and energy use may bring about significant adverse environmental effects through SO_2, NO_X, CO_2 emissions. This emission constraint will be considered in the generation scheduling problem. In general, these emissions can be expressed as a nonlinear function of power generation. Based on the air emission data from the Taiwan power system thermal units, the pollution models are built using pollution models in the generation scheduling problem.

The fuzzy-optimization approach is proposed to solve the generation scheduling problem considering wind and solar energy systems. The effectiveness and application of the proposed approach are demonstrated using a simplified generation system.

II. Problem Formulation

The generation system under study is shown in Fig. 1. It is comprised of thermal system, hydro system, wind and solar energy systems. The problem model does not consider system configuration and line impedances. The objective of the short-term generation scheduling problem considering wind and solar energy systems is to determine the optimal amounts of generation power for the hydro units, thermal units, wind, and solar energy systems over the study period so that the total thermal unit fuel cost is minimized subject to power balance equations, spinning reserve requirements and other constraints. To do this, the study

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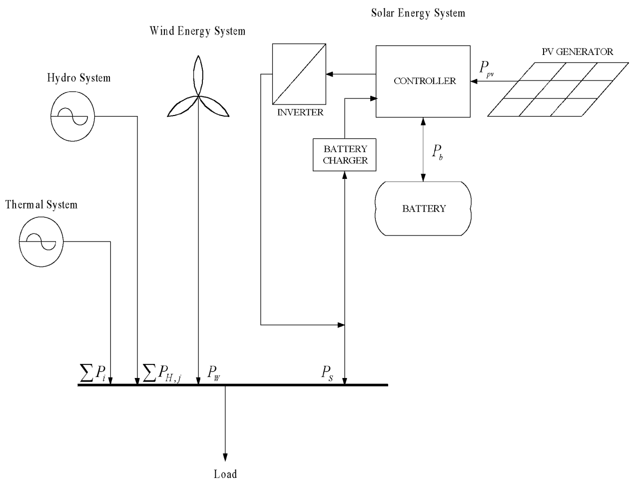

Fig. 1. Simplified generation system under study.

period is divided into T time intervals and the short-term generation scheduling problem can be formulated as follows:

$$\text{Minimize } TC = \sum_{t=1}^{T}\sum_{i=1}^{I} FC_i(P_{i,t}) \tag{1}$$

where

TC total fuel cost of thermal units over the study period;

FC_i fuel cost of the ith thermal unit can be expressed as a quadratic function of real power generation,

$$FC_i(P_i) = a_i + b_i P_i + c_i P_i^2$$

where a_i, b_i, and c_i are given.

$P_{i,t}$ power output of the ith thermal unit at hour t;

T number of considered time intervals under study;

I number of thermal units generated.

subject to the following.

a) Power balance equations

$$\sum_{i=1}^{I} P_{i,t} + \sum_{j=1}^{J} P_{H,j}(X_{j,t}) + P_{W,t} + P_{S,t} = L_t \quad t = 1, 2, \ldots, T \tag{2}$$

where

$P_{H,j}(\cdot)$ water-to-energy conversion function of the power plant associated with reservoir j;

$X_{j,t}$ volume of water released from jth reservoir for generation during hour t;

J number of reservoirs;

$P_{W,t}$ power output of wind energy system at hour t;

$P_{S,t}$ power output of solar energy system at hour t;

L_t forecast system load demand at hour t.

b) Spinning reserve constraints

$$\sum_{i=1}^{I} \min(P_i^{\max} - P_{i,t}, UR_i) + \sum_{j=1}^{J} (P_{H,j}^{\max} - P_{H,j}) \geq SR_t \quad t = 1, 2, \ldots, T \tag{3}$$

where

$P_i^{\max}$ maximum power output of the ith thermal unit;

$P_{H,j}^{\max}$ maximum power output of the jth hydro unit;

UR_i maximum increase in the output of the ith thermal unit over one time interval;

SR_t spinning reserve requirement at hour t.

c) Power output limits on thermal generating units—The problem model considers that the thermal generating units are on-line over the study period.

units without prohibited operating zones:

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \quad i \in I'; \quad t = 1, 2, \ldots, T \tag{4}$$

where

$P_i^{\min}$ minimize power output of the ith thermal unit;

I' set of thermal units without prohibited operating zones.

units with prohibited operating zones:

$$\begin{cases} P_i^{\min} \leq P_{i,t} \leq P_{i,1}^{L} \\ P_{i,k-1}^{U} \leq P_{i,t} \leq P_{i,k}^{L} \quad k = 2, 3, \ldots, l; \; i \in I''; \; t = 1, 2, \ldots, T \\ P_{i,l}^{U} \leq P_{i,t} \leq P_i^{\max} \end{cases} \tag{5}$$

where

I'' set of thermal units with prohibited operating zones.

d) Ramping response rate limits on thermal generating units

$$P_{i,t-1} - P_{i,t} \leq DR_i \quad i = 1, 2, \ldots, I; \; t = 1, 2, \ldots, T \tag{6}$$

$$P_{i,t} - P_{i,t-1} \leq UR_i \quad i = 1, 2, \ldots, I; \; t = 1, 2, \ldots, T \tag{7}$$

where

DR_i maximum decrease in the output of the ith thermal unit over one time interval.

e) Air emission limits on thermal generating units

$$\sum_{i=1}^{I}\sum_{t=1}^{T} [\mathrm{CO}_{2,i}(P_{i,t}) + \mathrm{NO}_{X,i}(P_{i,t}) + \mathrm{SO}_{2,i}(P_{i,t})] \leq E_{limit}^{total} \tag{8}$$

where

$CO_{2,i}$ equivalent CO_2 emission function of the ith thermal unit generating power which is given by a second-order polynomial

$$CO_{2,i}(P_i) = a_{c,i} + b_{c,i}P_i + c_{c,i}P_i^2$$

where $a_{c,i}$, $b_{c,i}$, and $c_{c,i}$ are given.

$NO_{X,i}$ equivalent NO_X emission function of the ith thermal unit generating power which is given by a first-order polynomial,

$$NO_{X,i}(P_i) = a_{n,i} + b_{n,i}P_i$$

where $a_{n,,i}$ and $b_{n,i}$ are given.

$SO_{2,i}$ equivalent SO_2 emission function of the ith thermal unit generating power which is given by a second-order polynomial,

$$SO_{2,i}(P_i) = a_{s,i} + b_{s,i}P_i + c_{s,i}P_i^2$$

where $a_{s,i}$, $b_{s,,i}$, and $c_{s,,i}$ are given.

E_{limit}^{total} total emission limit over the study period.

f) Available water from each reservoir in storage for generation

$$\sum_{t=1}^{T} X_{j,t} = X_j^{total} \quad j = 1, 2, \ldots, J \tag{9}$$

where

X_j^{total} forecast total available water for the jth reservoir over the study period.

g) Bounds on water release from each reservoir in storage

$$X_j^{\min} \le X_{j,t} \le X_j^{\max} \;\; j = 1, 2, \ldots, J; \;\; t = 1, 2, \ldots, T \tag{10}$$

where

$X_j^{\min}$ minimum volume of water released from the jth reservoir;

$X_j^{\max}$ maximum volume of water released from the jth reservoir.

h) Bounds on each reservoir in storage

$$Y_j^{\min} \le Y_{j,t} \le Y_j^{\max} \quad j = 1, 2, \ldots, J; \;\; t = 1, 2, \ldots, T \tag{11}$$

where

$Y_j^{\min}$ minimum water volume of the jth reservoir;

$Y_j^{\max}$ maximum water volume of the jth reservoir.

i) Power output limits on wind energy system

The power output function with respect to the wind speed is given by [8]

$$P_{W,t} = \begin{cases} 0 & v_{w,t} \le v_1 \text{ or } v_{w,t} \ge v_3 \\ \Psi(v_{w,t}) & v_1 \le v_{w,t} \le v_2 \\ P_{wn} & v_2 \le v_{w,t} \le v_3 \end{cases} \quad t = 1, 2, \ldots, T \tag{12}$$

where

$v_{w,t}$ forecast wind speed at hour t;

v_1 cut in wind turbine speed;

v_2 rated wind turbine speed;

v_3 cut out wind turbine speed;

$\Psi(v_{w,t})$ wind-to-energy conversion function for wind power generation;

P_{wn} equivalent rated power output for wind power generation.

j) Power output limits on solar energy system

$$P_{pv}(G_t) - P_{b,t} - P_{S,t} = 0 \quad t = 1, 2, \ldots, T \tag{13}$$

$$|P_{b,t}| \le P_b^{\max} \qquad t = 1, 2, \ldots, T \tag{14}$$

$$|P_{S,t}| \le P_S^{\max} \qquad t = 1, 2, \ldots, T \tag{15}$$

where

$P_{pv}(\cdot)$ solar radiation-to-energy conversion function of the PV generator given by [8]

$$P_{pv}(G_t) = \begin{cases} P_{sn}\frac{(G_t)^2}{G_{std}R_c} & 0 < G_t < R_c \\ P_{sn}\frac{G_t}{G_{std}} & G_t > R_c \end{cases} \quad t = 1, 2, \ldots, T \tag{16}$$

It is noted that PV cell temperature is neglected.

G_t forecast solar radiation at hour t;

G_{std} solar radiation in the standard environment set as $1000\ \mathrm{W/m^2}$;

R_c a certain radiation point set as $150\ \mathrm{W/m^2}$;

P_{sn} equivalent rated power output of the PV generator;

$P_{b,t}$ power charge/discharge to/from battery at hour t;

III. Generation Scheduling by Proposed Approach

The system load demand, total available water, wind speed and solar radiation shown in (2), (9), (12), and (16) must be known before the generation scheduling problem can be performed. These values can only be known through short-term forecasting. Since system load demand, total available water, wind speed and solar radiation depend on the social behavior of customers and weather variables, etc., there are always errors in these forecast values. In this paper these forecast errors are considered as uncertainties. A characteristic feature of the proposed fuzzy-optimization approach is that the forecast errors can be taken into account using fuzzy sets. Fuzzy set formulation is used because we want a good solution to a model that represents the uncertainties inherent in a practical optimization problem.

To solve generation scheduling using the proposed approach, membership functions for the total fuel cost, load demand, spinning reserve requirement, total available water, wind speed and solar radiation are first established [2], [16]. A genetic algorithm is then used to determine an optimal solution.

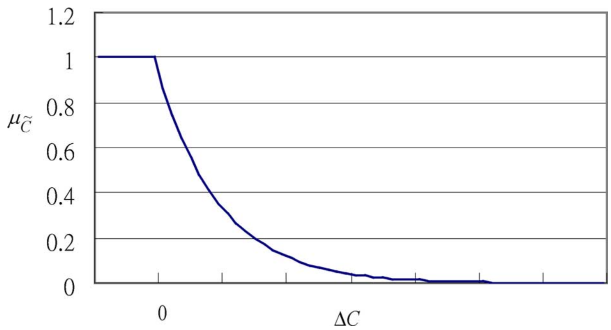

Fig. 2. Membership function $\mu_{\tilde{C}}$ for total fuel cost.

A. Construction Membership Functions

The membership functions are described as follows.

1) Membership Function for Total Fuel Cost: In the generation scheduling problem, the objective is to minimize the total fuel cost. We can define a membership function for the fuzzy set related to the total fuel cost so that a high cost is given a low membership value. By keeping the membership function as high as possible, a desirable solution with low generation cost can be obtained. Fig. 2 depicts the membership function $\mu_{\tilde{C}}$ for the fuzzy variable ΔC. In this figure, a membership or a satisfaction value of 1 is assigned to any ΔC that is less than zero. As ΔC becomes larger than zero, the degree of satisfaction will decrease to zero. The membership function $\mu_{\tilde{C}}$ is expressed as

$$\mu_{\tilde{C}} = \begin{cases} e^{-w\Delta C}, & \Delta C \geq 0 \\ 1, & \Delta C < 0 \end{cases} \tag{17}$$

where

$$\Delta C = \frac{TC - \sigma \cdot TC_{\max}}{\sigma \cdot TC_{\max}} \tag{18}$$

w weighting factor;

σ cost tolerance factor in which its value is less than one;

$TC_{\max}$ highest total fuel cost that include only thermal units to supply load.

2) Membership Function for Load Demand: It is noted from the power balance equations in (2) that the sum of the generation from thermal units, hydro units, wind and solar energy systems must be equal to the hourly load demand L_t. In the generation scheduling problem, L_t denotes the hourly load demands in the future. Therefore, L_t can only be obtained through load forecasting and there are always errors in the forecast hourly loads. A membership function $\mu_{\tilde{L}}$ as depicted in Fig. 3 is used. ΔL represents the percentage error in load forecasting. The membership value will be 1 for $\Delta L = 0$ where no forecast error is observed. For other ΔL values, the membership function decreases with increasing forecast error. The membership function $\mu_{\tilde{L}}$ can be written as

$$\mu_{\tilde{L}} = \begin{cases} \frac{1}{1+\eta_L\left(\frac{\Delta L}{L^+}\right)^2}, & \Delta L \geq 0 \\ \frac{1}{1+\eta_L\left(\frac{\Delta L}{L^-}\right)^2}, & \Delta L < 0 \end{cases} \tag{19}$$

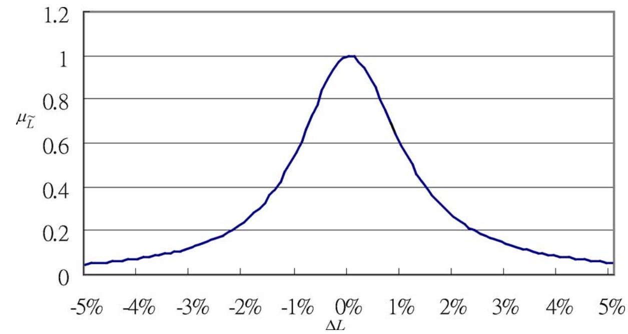

Fig. 3. Membership function $\mu_{\tilde{L}}$ for the load demand.

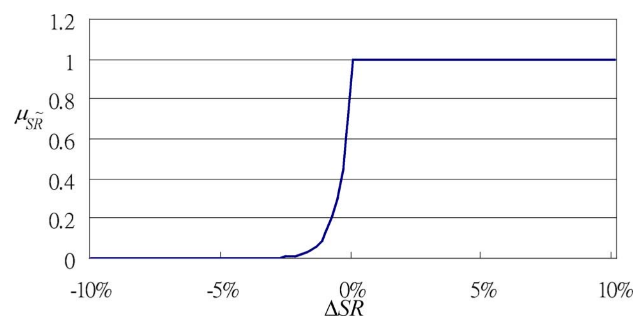

Fig. 4. Membership function $\mu_{\tilde{SR}}$ for spinning reserve requirement.

where

$$\Delta L = \frac{L_{actual} - L_{forecast}}{L_{forecast}} \times 100\% \tag{20}$$

L^+ average percentage error when the actual load is greater than the forecast load;

L^- average percentage error when the actual load is smaller than the forecast load;

η_L weighting factor.

3) Membership Function for Spinning Reserve Requirement: In general, utilities specify the required spinning reserve to ensure secure operations during outage events. A membership function $\mu_{\tilde{SR}}$ as shown in Fig. 4 is employed. The membership function $\mu_{\tilde{SR}}$ is expressed as

$$\mu_{\tilde{SR}} = \begin{cases} 1, & \text{if } SUM\_SR \geq SR \\ e^{r\Delta SR}, & \text{otherwise} \end{cases} \tag{21}$$

where

$$SUM\_SR = \sum_{i=1}^{I} \min(P_i^{\max} - P_i, UR_i) + \sum_{j=1}^{J} (P_{H,j}^{\max} - P_{H,j}) \tag{22}$$

$$\Delta SR = \frac{SUM\_SR - SR}{SR} \times 100\% \tag{23}$$

r weighting factor.

4) Membership Function for Available Water: Just as in the case of hourly load demands, there are also errors in the forecast

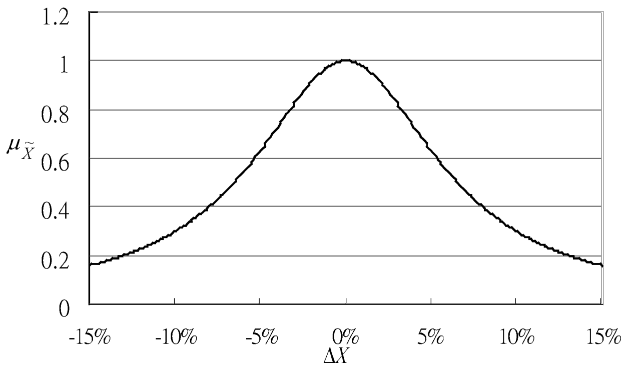

Fig. 5. Membership function $\mu_{\tilde{X}}$ for available water.

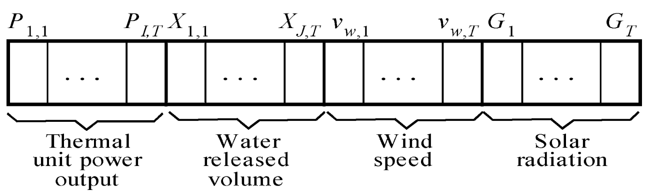

Fig. 6. GA chromosome structure.

available water. A membership function $\mu_{\tilde{X}}$ as depicted in Fig. 5 is employed. The membership function is expressed as follows.

$$\mu_{\tilde{X}} = \begin{cases} \frac{1}{1+\eta_X\left(\frac{\Delta X}{X+}\right)^2}, & \Delta X \geq 0 \\ \frac{1}{1+\eta_X\left(\frac{\Delta X}{X-}\right)^2}, & \Delta X < 0 \end{cases} \tag{24}$$

where

$$\Delta X = \frac{X_{actual}^{total} - X_{forecast}^{total}}{X_{forecast}^{total}} \times 100\% \tag{25}$$

X^+ average percentage error when the actual available water is greater than the forecast available water;

X^- average percentage error when the actual available water is smaller than the forecast available water;

η_X weighting factor.

5) Membership Function for Wind Speed: Just as in the case of hourly load demands, there are also errors in the forecast wind speed. A membership function $\mu_{\tilde{v}}$ that is similar to (19) is used. The membership function is formed as

$$\mu_{\tilde{v}} = \begin{cases} \frac{1}{1+\eta_v\left(\frac{\Delta v}{v+}\right)^2}, & \Delta v \geq 0 \\ \frac{1}{1+\eta_v\left(\frac{\Delta v}{v-}\right)^2}, & \Delta v < 0 \end{cases} \tag{26}$$

where

$$\Delta v = \frac{v_{actual} - v_{forecast}}{v_{forecast}} \times 100\% \tag{27}$$

v^+ average percentage error when the actual wind speed is greater than the forecast wind speed;

v^- average percentage error when the actual wind speed is smaller than the forecast wind speed;

η_v weighting factor.

6) Membership Function for Solar Radiation: Just as in the case of hourly load demands, there are also errors in the forecast solar radiation. A membership function $\mu_{\tilde{G}}$ that is similar to (19) is used. The membership function is formed as

$$\mu_{\tilde{G}} = \begin{cases} \frac{1}{1+\eta_G\left(\frac{\Delta G}{G+}\right)^2}, & \Delta G \geq 0 \\ \frac{1}{1+\eta_G\left(\frac{\Delta G}{G-}\right)^2}, & \Delta G < 0 \end{cases} \tag{28}$$

where

$$\Delta G = \frac{G_{actual} - G_{forecast}}{G_{forecast}} \times 100\% \tag{29}$$

G^+ average percentage error when the actual solar radiation is greater than the forecast solar radiation;

G^- average percentage error when the actual solar radiation is smaller than the forecast solar radiation;

η_G weighting factor.

B. Fuzzy-Optimization Solution

When the membership functions have been completed, an optimization method is then employed to solve the generation scheduling problem under uncertainties. A genetic algorithm (GA) [14], [15] is used on the optimization update procedure. GAs are general purpose optimization algorithms based on the mechanics of natural selection and genetics. GAs are an attractive alternative to other optimization approaches because of their robustness.

When applying GAs to solve the generation scheduling problem, the problem physical decision variables on a GA chromosome must be addressed first. The control variables of the generation scheduling problem involve each thermal unit power output, water released volume for hydro units, wind speed for wind power generator and solar radiation for PV generator in each hour. The chromosome to the problem variables is formed as shown in Fig. 6.

Here we use the following form to represent a chromosome in the GA search process

$$U_j = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,T} \\ \vdots & \vdots & \ddots & \vdots \\ P_{I,1} & P_{I,2} & \cdots & P_{I,T} \\ X_{1,1} & X_{1,2} & \cdots & X_{1,T} \\ \vdots & \vdots & \ddots & \vdots \\ X_{J,1} & X_{J,2} & \cdots & X_{J,T} \\ v_{w,1} & v_{w,2} & \cdots & v_{w,T} \\ G_1 & G_2 & \cdots & G_T \end{bmatrix} \quad j = 1, 2, \ldots, Q \tag{30}$$

where

U_j chromosome j;

Q number of GA chromosomes.

After deciding the control variables on a GA chromosome, we then define that the evaluation of the so-called fitness function to assign a quality value to every solution produced. Since we consider the forecast errors under uncertain environment and the membership values can be obtained from the membership functions described in (17), (19), (21), (24), (26), and (28) that represent the membership functions of total fuel cost, load demand, spinning reserve requirement, total available water, wind speed and solar radiation, respectively.

Given a candidate solution U_j to the problem, represented by a chromosome, the GA fitness function is computed as follows:

$$\mu_{\widetilde{L}^*} = \min(\mu_{\widetilde{L}_1}, \mu_{\widetilde{L}_2}, \ldots, \mu_{\widetilde{L}_T}) \tag{31}$$

$$\mu_{\widetilde{SR}^*} = \min(\mu_{\widetilde{SR}_1}, \mu_{\widetilde{SR}_2}, \ldots, \mu_{\widetilde{SR}_T}) \tag{32}$$

$$\mu_{\widetilde{X}^*} = \min(\mu_{\widetilde{X}_1}, \mu_{\widetilde{X}_2}, \ldots, \mu_{\widetilde{X}_J}) \tag{33}$$

$$\mu_{\widetilde{v}^*} = \min(\mu_{\widetilde{v}_1}, \mu_{\widetilde{v}_2}, \ldots, \mu_{\widetilde{v}_T}) \tag{34}$$

$$\mu_{\widetilde{G}^*} = \min(\mu_{\widetilde{G}_1}, \mu_{\widetilde{G}_2}, \ldots, \mu_{\widetilde{G}_T}) \tag{35}$$

and

$$\mu_{\widetilde{D}_j} = \min(\mu_{\widetilde{C}}, \mu_{\widetilde{L}^*}, \mu_{\widetilde{SR}^*}, \mu_{\widetilde{X}^*}, \mu_{\widetilde{v}^*}, \mu_{\widetilde{G}^*}) \tag{36}$$

where $\mu_{\widetilde{D}_j}$ is defined as fitness function associated with the solution U_j.

For all candidate solutions U_j, $j = 1, 2, \ldots, Q$, the higher the fitness value of function $\mu_{\widetilde{D}_j}$ represents the better the solution U_j. Mathematically

$$\mu_{\widetilde{D}^*} = \max(\mu_{\widetilde{D}_1}, \mu_{\widetilde{D}_2}, \ldots, \mu_{\widetilde{D}_Q}). \tag{37}$$

The formulated optimization problem can be solved according to the following steps.

Step 1: Initialize the control variables

Randomly generate an initial population of size Q, i.e., initialize the control variables of GA chromosomes in (30).

Step 2: Calculate the percentage errors for total available water, wind velocity, radiation and load demand; the spinning reserve and total fuel cost

With the solutions obtained from above step in hand, we can:

1) use (25), (27), and (29) to calculate the percentage errors ΔX, Δv, ΔG for total available water, wind velocity, and radiation, respectively.

2) calculate hydro unit power output $P_{H,j}$, wind energy system power output $P_{W,t}$ and solar energy system power output $P_{S,t}$ for all t .

3) use these all generating power output to obtain the load demand percentage errors ΔL in (20) and use (22) and (1) to calculate the spinning reserve and total fuel cost.

Step 3: Calculate the membership values

Use (17), (19), (21), (24), (26), and (28) to calculate the membership values of membership functions $\mu_{\widetilde{C}}$, $\mu_{\widetilde{L}}$, $\mu_{\widetilde{SR}}$, $\mu_{\widetilde{X}}$, $\mu_{\widetilde{v}}$, $\mu_{\widetilde{G}}$ for the total fuel cost, load demand, spinning reserve requirement, available water, wind speed and solar radiation, respectively.

Step 4: Calculate the fitness value

Use (31)–(36) to obtain $\mu_{\widetilde{D}_j}$ $(j = 1, 2, \ldots, Q)$. In this paper, $\mu_{\widetilde{D}_j}$ indicates the fitness function associated with the solution U_j. The fitness function is a measure of the quality of each candidate solution. The higher the fitness value of function $\mu_{\widetilde{D}_j}$ represents the better the solution U_j. Solutions with high fitness values have a high probability of contributing new offspring to the next generation.

Step 5: Create parent population

Create parent (new) population using the following replacement policy:

1) If all offspring outperform every existing chromosome in the old population, then all of the offspring replace all existing chromosomes in the new population.

2) If only some offspring fare better than the existing population, they replace an equal number of existing chromosomes which are lowest in order of performance in the old population.

Step 6 : Operate crossover and mutation

Two chromosomes are selected from the parent population based on their fitness value. The selection rule used in this paper is a simple roulette-wheel selection **[15]**. The chromosomes from the two parents selected are combined to form new chromosomes that inherit segments of information stored in parent chromosomes. The crossover operator is usually used with a high probability. The mutation operator is usually used with a small probability. In this paper, the probabilities for crossover and mutation are set as 0.95 and 0.01, respectively.

Step 7: Stop criterion

The fitness function evaluation and genetic evolution take part in an iterative procedure which stops when a maximum number of generations is reached. Otherwise the process returns to step 2.

IV. Testing Results

The study system shown in Fig. 1 comprises ten thermal units, seven hydro units (with one pumped storage unit), one equivalent wind energy system and one equivalent solar energy system. The cost function data for the ten thermal units are given in Table VII. A battery is connected to the solar energy system to store energy. The forecast hourly load demand is shown in Fig. 7. The forecast total available water for the hydro plants is shown in Table I. The Ta-Kuan II hydro plant is a pumped-storage plant. The forecast solar radiation and wind velocity data are shown in Table II. The spinning reserve requirement is set to 5% of the load demand. The fuzzy-optimization program was coded in Matlab and implemented on a PC-pentium IV computer.

Now, the population size Q of the GA is set as 60. We have three cases to simulate.

Case 1: Only the thermal generating system is used to supply load demands.

Case 2: Thermal, hydro, wind energy and solar energy generating systems are connected to supply load demands. However, the battery is not connected to the solar energy system.

Case 3: All generating systems, which include the battery, are connected to supply load demands.

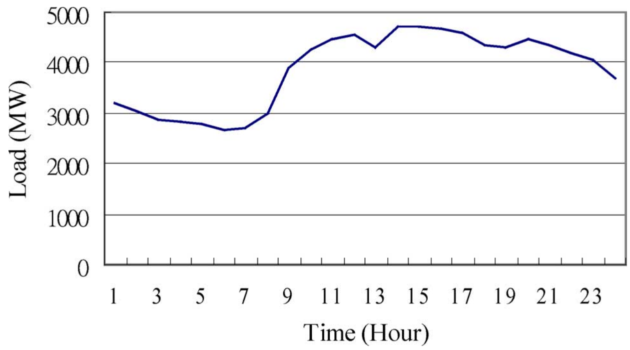

Fig. 7. Forecast hourly load.

TABLE I
FORECAST TOTAL AVAILABLE WATER FOR THE HYDRO PLANTS

Plant	X_j^{total} (1000 m^3)	Plant	X_j^{total} (1000 m^3)
Ta-Kuan II	133920	Chin-Shan	31536
Ta-Kuan I	22460	Ku-Kuan	40608
Chu-Kung	22460	Tien-Lun	40608
Te-Chi	31536		

TABLE II
FORECAST SOLAR RADIATION AND WIND VELOCITY

Time (Hour)	1	2	3	4	5	6
G_t (W/m^2)	0	0	0	0	0	0
$v_{w,t}$ (m/s)	3.5	3.6	1.5	1.4	0.1	1.8
Time (Hour)	7	8	9	10	11	12
G_t (W/m^2)	111	311	375	503	617	686
$v_{w,t}$ (m/s)	1.3	2.2	3.8	3.7	2.0	0.6
Time (Hour)	13	14	15	16	17	18
G_t (W/m^2)	703	736	586	425	291	86
$v_{w,t}$ (m/s)	0.4	8.4	9.9	10.1	9.7	9.2
Time (Hour)	19	20	21	22	23	24
G_t (W/m^2)	0	0	0	0	0	0
$v_{w,t}$ (m/s)	9.6	10.0	10.0	9.5	9.9	12.6

In case 1, only the thermal generating system (ten thermal units) is employed to supply load demands which are forecasted. There are always errors in these forecast loads. Therefore, we use the proposed fuzzy-optimization approach to solve the generation scheduling problem. The results include the decision membership value $\mu_{\widetilde{D}^*} = 0.9247$, the total fuel cost $TC = \text{NT\$}\,79.83 \times 10^6$, and the total emission equal to 96543 tons. Fig. 8 depicts the total thermal power output and forecast hourly load. It is observed from the results in Fig. 8 that the total thermal generation meets the load demands.

In case 2, the generation system that includes ten thermal units, seven hydro units, one equivalent wind energy system and one equivalent solar energy system (without battery) is used to supply the load demands. In this case the load demands, total available water for hydro units, wind velocity for wind turbine generator and solar radiation for PV generator are forecast. There are always errors in these forecast values. Therefore, the proposed method is used to solve the problem. The results include the decision membership value $\mu_{\widetilde{D}^*} = 0.9235$, the total

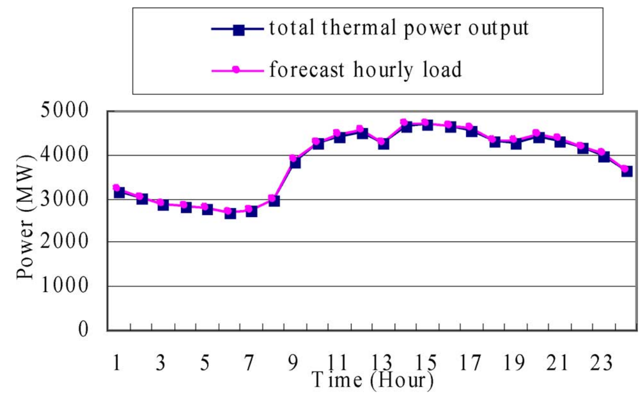

Fig. 8. Total thermal power output for case 1.

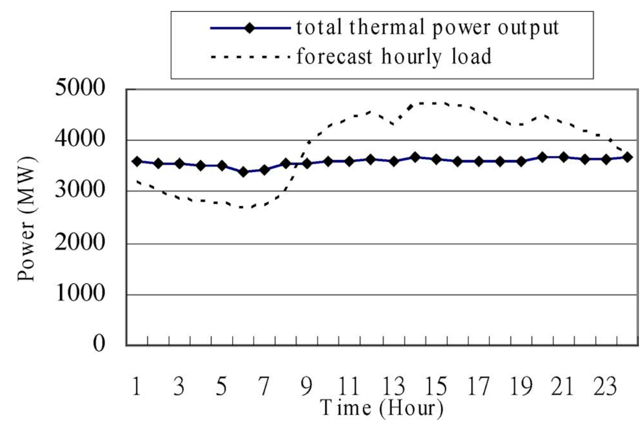

Fig. 9. Total thermal power output for case 2.

fuel cost $TC = \text{NT\$}\,74.23 \times 10^6$, and the total emissions equal to 89607 tons. Fig. 9 depicts the total thermal power output and forecast hourly load. The results in Fig. 9 show that the total thermal power output at the peak load period can be reduced by adding hydroelectric generation and renewable energy systems. The thermal power output at each hour is approximated. That is to say that the total fuel cost for the thermal generating units can be saved.

In case 3, the generation system that includes all generating units (with battery) is used to supply load demands. The proposed method is employed to solve the problem. We get the decision membership value $\mu_{\widetilde{D}^*} = 0.9106$, the total fuel cost $TC = \text{NT\$}\,73.87 \times 10^6$, and the total emission equals to 89404 tons. Fig. 10 depicts the total thermal power output and forecast hourly load. Fig. 11 illustrates the total hydro power output and wind energy system power output over the 24-h scheduling period. From Fig. 11 the hydro plants are operated to serve the peak load with hydro energy, which is usually referred to as the peak shaving operation. The negative hydro generating power outputs indicate the pumping operation for the Ta-Kuan II pumped-storage plant during the light load period. Fig. 12 depicts the individual generating curve for each hydro plant. Fig. 13 illustrates the solar energy system power output over the 24-h scheduling period. It is observed from Fig. 13 that the solar energy system is operated similar to the pumped-storage

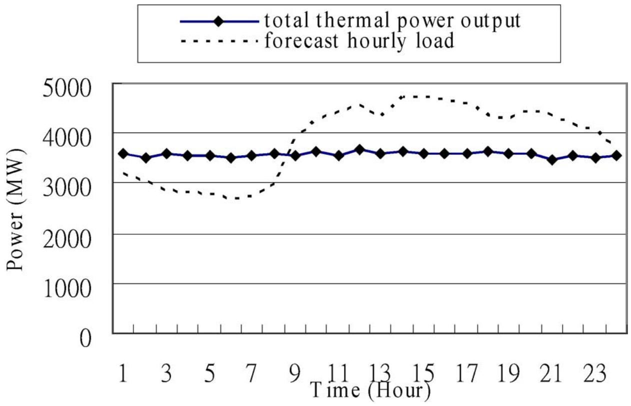

Fig. 10. Total thermal power output for case 3.

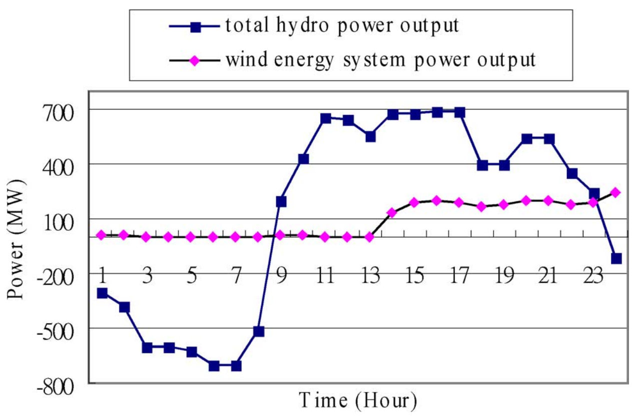

Fig. 11. Total hydro power output and wind energy system power output for case 3.

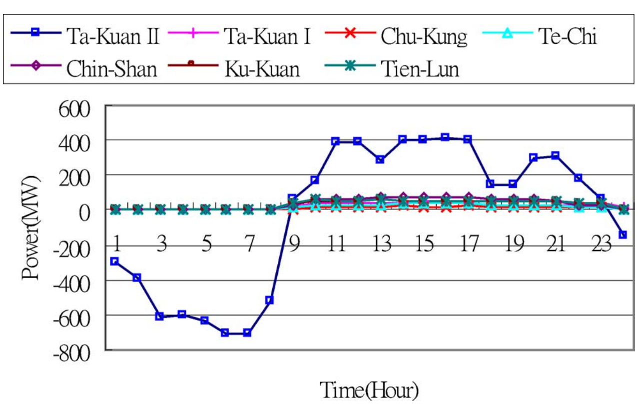

Fig. 12. Individual hydro generating power output for case 3.

hydro plant since the battery is involved. The negative solar energy system power outputs indicate the charging operation for the battery during the light load period.

The decision membership value $\mu_{\tilde{D}^*}$, total fuel cost and total emission obtained from above-mentioned three cases are compared in Table III. From the results in Table III, the following observations can be made:

1) Using case 1, only thermal generating system is used to supply the load demands. The total fuel cost is the most expensive and the total emissions are also the highest, i.e., the air pollution is the most serious.

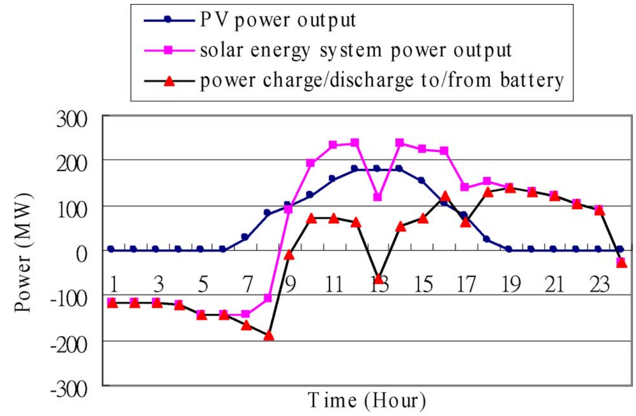

Fig. 13. Solar energy system power output for case 3.

TABLE III
SUMMARY OF DECISION MEMBERSHIP VALUE $\mu_{\tilde{D}^*}$, TOTAL FUEL COST, AND TOTAL EMISSION.

Case	$\mu_{\tilde{D}^*}$	Total fuel cost (NT$)	Total emission (tons)
1	0.9247	79.83×10^6	96543
2	0.9235	74.23×10^6	89607
3	0.9106	73.87×10^6	89404

TABLE IV
RESULTS FOR DIFFERENT GA POPULATION SIZES

Population size, Q	$\mu_{\tilde{D}^*}$	Total fuel cost (NT$)	Time (sec)
40	0.8885	74.06×10^6	21.59
60#	0.9106	73.87×10^6	33.25
80	0.9118	73.85×10^6	52.95
100	0.9118	73.85×10^6	81.73

# denotes the population size in our use.

2) Using case 2, the total fuel cost can be reduced by adding hydroelectric generation and renewable energy systems. The total fuel cost is saved about NT$ 5.6×10^6. The total emission from case 2 is smaller than that from case 1. The air pollution is also lower.
3) Using case 3, both the total fuel cost and the total emission are the lowest among the three cases. The fuel energy for the thermal generating units can be significantly saved, and the air pollution emissions from the thermal generating units can be meaningfully reduced.
4) Using the proposed method for the generation scheduling problems for these three cases, the obtained decision membership values were higher. That represents satisfactory solutions.

Now, we want to see the influence of different population sizes in the GA on the total fuel cost. Table IV shows the results from the decision membership value, total fuel cost and execution time for different population size from the proposed approach. Table IV shows that when the GA population size is increased, the total fuel cost will reduce. When it is increased to 100, the procedure will not find a better solution. However, the execution time will increase. In this paper the population size is set at 60. Because a population size of 60 results in a solution

TABLE V
RESULTS FOR DIFFERENT COST TOLERANCE FACTORS

Cost tolerance factor, σ	$\mu_{\tilde{D}^*}$	$\mu_{\tilde{C}}$	Total fuel cost (NT$)
0.93	0.9183	0.9989	74.39×10^6
0.92#	0.9106	0.9224	73.87×10^6
0.91	0.7726	0.7726	73.69×10^6

# denotes the value in our use.

TABLE VI
SUMMARY RESULTS OF 20 SIMULATION TESTS

	$\mu_{\tilde{D}^*}$	Total fuel cost (NT$)	Time (sec)
1	0.9052	73.95×10^6	32.94
2	0.9068	73.93×10^6	33.52
3	0.9046	73.96×10^6	35.05
4	0.9104	73.89×10^6	34.21
5	0.9095	73.91×10^6	32.86
6	0.9106	73.87×10^6	33.25
7	0.9104	73.90×10^6	35.15
8	0.9099	73.90×10^6	34.90
9	0.9023	73.92×10^6	35.21
10	0.9037	73.92×10^6	32.18
11	0.9056	73.94×10^6	33.32
12	0.9101	73.96×10^6	35.61
13	0.9087	73.91×10^6	34.26
14	0.9074	73.91×10^6	33.02
15	0.9093	73.92×10^6	33.11
16	0.9078	73.91×10^6	33.65
17	0.9042	73.94×10^6	34.25
18	0.9045	73.94×10^6	35.12
19	0.9096	73.89×10^6	32.89
20	0.9105	73.93×10^6	33.43
Average	-------	73.92×10^6	33.89

that is good and an execution time less than that from a population size of 80.

Since the cost tolerance factor σ described in (18) was selected somewhat arbitrarily, it is desirable to see how different σ values will affect the final result. The decision membership value and total fuel cost of the optimal generation schedules obtained using different σ values are compared in Table V. From Table V, when σ is reduced, the total fuel cost will decrease. However, a lower σ results in a decision membership value $\mu_{\tilde{D}*}$ that is too low. In practical applications, a decision membership value $\mu_{\tilde{D}*}$ that is too low is unacceptable because a small value implies that the load demand, total available water, wind velocity and solar radiation level used are far from the actual load, available water, wind velocity and solar radiation. Therefore the σ value should be appropriately chosen to find a proper solution. In our work the σ value was set to 0.92.

The initial solutions for the simulation tests were chosen somewhat arbitrarily. It is desirable to see how different initial solutions will affect the final results. We ran the proposed approach 20 times with different candidate solutions each time. Table VI shows the summary results from the 20 simulation tests using the proposed fuzzy-optimization approach. This result shows that the proposed approach has the ability to find a good solution. The cost difference between the highest and lowest total fuel cost was only NT$ 9000. In other words, the difference is just only 0.122%. This result shows that the stability of the proposed approach to reach the final solution is very good. Note that the crisp value for the total fuel cost, obtained using a conventional GA under a crisp environment, i.e., without taking the uncertainties into account was NT$ 74.41×10^6. The reduction in total fuel cost was achieved by taking advantage of the uncertainties in load, total available water, wind velocity, and solar radiation.

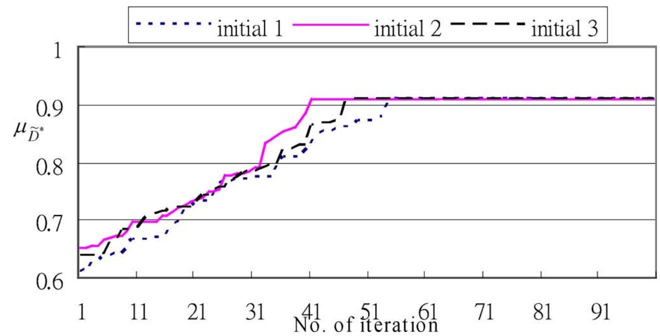

Fig. 14. Convergence curves of the proposed approach with three different initial solutions.

Fig. 14 shows the convergence characteristics from the proposed approach with three different initial solutions among the 20 simulation tests. From the results in Fig. 14, the proposed approach has good ability to find a good solution, although the initial solutions are different.

V. CONCLUSIONS

A fuzzy-optimization approach was presented for solving the generation scheduling problem considering wind and solar energy systems. The generation scheduling problem was converted into a numerical formulation. A fuzzy-optimization approach was then proposed to solve the generation scheduling. To take the errors in forecast hourly load, total available water, wind velocity and solar radiation into account, membership functions were derived for the total fuel cost, the load demand, the spinning reserve requirement, the total available water, the wind velocity and the solar radiation using fussy set notations. With these membership functions, an approach for a genetic algorithm was presented to reach the optimal generation schedule under a fuzzy environment. To demonstrate the effectiveness of the proposed fuzzy-optimization approach, a simplified system consisting of ten thermal units, seven hydro units (with one pumped storage unit), one equivalent wind energy system and one equivalent solar energy system was performed. The results revealed that the proposed fuzzy-optimization approach is very effective in reaching an optimal generation schedule when imprecision is considered. We believe that the proposed fuzzy-optimization approach has good performance and the ability to determine the optimal solution. Moreover, the renewable energy sources will be important in the future. To efficiently utilize renewable energy, the total fuel cost of thermal units can be reduced significantly and air pollution decreased.

APPENDIX

TABLE VII
COST FUNCTION DATA FOR THE TEN THERMAL UNITS

Unit	a_i (NT$/h)	b_i (NT$/MWh)	c_i (NT$/MW^{2}h)
1	31780	567.1	0.05401
2	31940	587.2	0.05382
3	31890	560.5	0.05373
4	31910	590.1	0.05317
5	31660	574.2	0.05318
6	31730	577.2	0.05391
7	51070	998.1	0.83580
8	43850	1033.0	0.00245
9	35450	1052.0	0.00342
10	47910	2758.0	3.31800

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