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Fuzzy Logic Unit Commitment based on Load Forecasting using ANN and Hybrid Method

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Abstract— In this study, unit commitment (UC) problem for four-unit Tuncbilek thermal plant which is in Kutahya region in Turkey, is solved for an optimum schedule of generating units based on the load data forecasted by using the conventional Artificial Neural Network (ANN) and an improved hybrid method, ANN model with Weighted Frequency Bin Blocks (WFBB). Fuzzy Logic (FL) method is used for solving the UC problem. Since under forecasting results in the requirement of purchasing power from spot market or over forecasting brings about an unnecessary commitment of generating units, an accurate load forecasting is the first step to solve the UC problem. Total costs calculated for both actual and forecasting load data are compared. The data used in the analysis was taken from Turkish Electric Power Company and Electricity Generation Company. All the analyses are implemented using MATLAB.

Keywords -fuzzy logic, unit commitment, load forecasting, artificial neural network, weighted frequency bin blocks.

I. INTRODUCTION

Load forecasting is important in power system planning and operation. The main problem of the planning is the demand knowledge in the future. Basic operating functions such as thermal and hydrothermal UC, economic dispatch, fuel scheduling and unit maintenance can be performed efficiently with an accurate forecast [1]. There are many methods which have been developed for the short term load forecasting. The major methods are regression based methods [2], time-series approach [3], expert system techniques [4], ANN models [5-6], fuzzy logic [7], wavelet transform [8] and ANN Model with Weighted Frequency Bin Blocks [9].

UC problem is an important subject in power system optimization. The problem is a complex optimization problem with both integer and continuous variables. The exact solution for the UC problem can be obtained by a complete enumeration of all feasible combinations of generating, which could be very huge in number [10]. There have been various methods for solving the UC problem. They are based on mathematical programming and heuristic based approaches such as dynamic programming [11], heuristic UC [12], simulated annealing [13], evolutionary programming [14], constraint logic programming [15], genetic algorithms [16], and Lagrangiane relaxation [17].

FL approach is used for solving the UC problem in this paper. FL was brought forward by Zadeh in 1965 [18]. FL appeared as a result of the studies of this researcher on control systems; the interference of non-linear equations in the process for obtaining the control he desired, hence confusion in the method and difficulty in reaching a conclusion [19-20].

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FL is a mathematical approach to problem solving. It excels in producing exact results from imprecise data, and is especially useful in computers and electronic applications. The use of FL has received increasing attention in recent years because of its usefulness in problem solving. In FL applications, output values become better in case of giving the appropriate values for the input.

Since UC solves for an optimum schedule of generating units based on load forecasting data, an accurate load forecasting is very important for the operational planning in power systems. Under forecasting or over forecasting may improperly schedule the generating units, which will result in the requirement of purchasing power from spot market or an unnecessary commitment of generating units. Therefore, the improvement of load forecasting is first step to enhance the UC solution [21].

In this paper, our purpose is to solve UC problem for four-unit Tuncbilek thermal plant which is in Kutahya region in Turkey, by using FL approach based on the load data forecasted by the conventional ANN and the improved ANN model with WFBB. The rest of this paper is arranged as follows: next day load forecasting is presented and ANN with WFBB model is discussed giving the sample block diagram in Section 2. In Section 3, the FL approach for UC problem is explained briefly. Applications and simulations for next day load forecasting and solving UC problem are given in Section 4. At last, conclusion is drawn in Section 5.

II. NEXT DAY LOAD FORECASTING

The next day load forecasting is basically aimed at predicting system load with a leading time of one hour to day, which is necessary for adequate scheduling and operation of power systems. The next day load forecasting traditionally has been an essential component of energy management systems as it provides the input data for load flow and contingency analysis. ANN-based methods are a good choice to study the next day load forecasting problem, as these techniques are characterized by not requiring explicit models to represent the complex relationship between the load and the factors that determine it [22-23].

The conventional ANN and the hybrid method (ANN with WFBB) are used for predicting the next day load values based on the previous two-day load values, respectively.

The hybrid method of ANN model with WFBB is divided five steps:

1) The Fast Fourier Transform (FFT) algorithm is applied to all given data.
2) All data found from step 1 is arranged according to the magnitude of frequency values.
3) The results of step 2 are multiplied by appropriate weighted values. Higher frequency values of the FFT signal are multiplied lower weighted values.
4) Inverse FFT algorithm is applied to the results of step 3.
5) The results of the inverse FFT algorithm are used for the input of the ANN Structure.

The sample diagram of ANN model with WFBB is given in Figure 1.

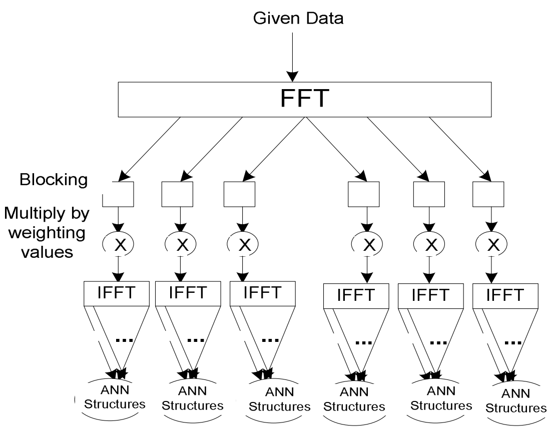

Fig. 1. Sample diagram of the ANN models with WFBB

III. FL APPROACH FOR UC

UC is an operating scheduling function, which is sometimes called pre-dispatch. UC schedules the on and off times of the generating units, and calculates the minimum cost hourly generation schedule while ensuring that start-up rates is considered. The function sometimes includes deciding the practicality of interregional power exchanges, and meeting daily or weekly quotas for consumption of fixed-batch energies, such as nuclear, restricted natural gas contracts, and other fuels that may be in short supply. The objective function and associated constraints of the thermal UC problem are given as follows [24]: The objective function can be represented mathematically as:

$$MinC = Min\sum_{t=1}^{T}\sum_{i=1}^{N}[u_i(t)OC_i[P_{it}(t)] + SC_i(1-u_i(t-1))] \quad (1)$$

The constraint models for the UC optimization problem are as follows: Load Balance:

$$\sum_{i=1}^{N} u_i(t)P_i(t) = P_d(t) \quad (2)$$

Spinning Reserve: There are various classifications for reserve and these include units on spinning reserve and units on colds reserve under the conditions of banked boiler or cold start. Unit constraints are generation output limits.

$$P_d^{\,t} + P_r^{\,t} - \sum_{i=1}^{N} P_{i,\max} u_i^{\,t} \le 0 \quad (3)$$

FL approach is appropriate other than complex mathematical methods for solving the UC problem, which is important for power system analysis because of large economic benefits. FL is a superset of conventional logic that has been extended to handle the concept of partial truth-truth values between "completely true" and "completely false". As its name suggests, it is the logic underlying modes of reasoning which are approximate rather than exact. The importance of FL derives from the fact that most modes of human reasoning and especially common sense reasoning are approximate in nature. A fuzzy set is a set whose elements have degrees of membership. That is, a member of a set can be full member (%100 membership status) or a partial member (eg. less than %100 membership and greater than %0 membership). To fully understand fuzzy sets, one must first understand traditional sets [25].

A membership function is a mathematical function which defines the degree of an element's membership in a fuzzy set. Various types of membership functions are used such as triangular, trapezoidal, generalized bell shaped, and Gaussian.

$$A = \{(x, \mu_A(x)) \;|\, x \in X\} \quad (4)$$

The basic configuration of a FL system is shown in Fig. 2. The components of FL system are fuzzification, fuzzy rule base, fuzzy output engine and defuzzification. Moreover, input and output data can be added. The input data in FL contains the input variables which the event to studied exposed and every data concerning them.

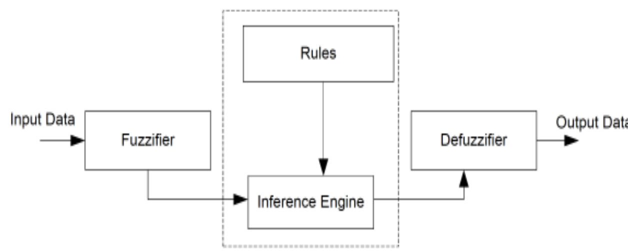

Fig. 2. Block diagram of FL system

The transmission network is equivalent to single plant bus to which all generators and all loads are connected, and total plant output equals the total system load. The 24-h day is subdivided into discrete intervals or stages, as exemplified in Fig. 3.

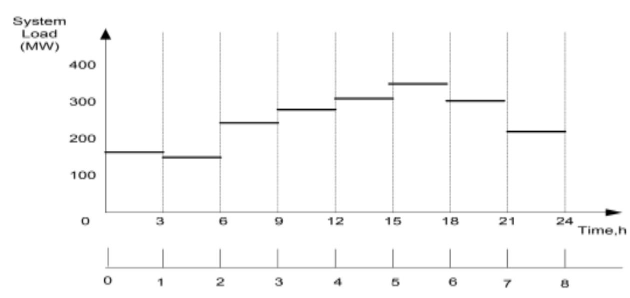

Fig. 3. Discrete levels of system load for an example daily load cycle

Fuzzy variables associated with UC are generator load capacity, start-up cost, incremental cost, load varying, and production cost. After defining the variables, the fuzzy sets are selected and normalized between 0 and 1. This normalized value can be multiplied by a selected scale vector to accommodate any desired variable. Since generator load capacity, start-up cost, and incremental cost for the units are among different values, the variables can be defined with fuzzy sets. Similarly, load variation and production cost values are also defined with fuzzy sets given below:

Generator Load Capacity (GLC) {Low (L), Below Average (BA), Average (A), Above Average (AAV), High (H)}

Start-up Cost (SC) = {Low (L), Medium (M), High (H)}

Incremental Cost (IC) = {Zero (Z), Small (S), Large (LG)}

Load Varying (LV) = {Base (B), Medium (M), High (H)}

Production cost is defined as an objective function given below:

Production Cost (PRC) = {Low (L), Below Average (BA), Average (A), Above Average (AAV), High (H)}

After defining the fuzzy sets If-Then rules that connect the inputs in the data base to output variables, are composed. “If” condition is an antecedent to the “Then” consequence of each rule. Generator load capacity, start-up cost, incremental cost and load varying are considered as the input variables and production cost is treated as the output variable. Input and output relation is given as:

PRC = {GLC} and {SC} and {IC}and {LV}

This expression is written as fuzzy set notation:

PRC = GLC ∩ SUP ∩ IC ∩ LV

The membership function of the production cost µPRC is computed as follows:

µPRC = µGLC∩ µSUP ∩ µIC ∩ µLV

µPRC = min { µGLC, µSUP, µIC, µLV }

where µGLC, µSUP, µIC are µLV memberships of generator load capacity, start up cost and incremental cost, respectively.

Fuzzy rule table is formed based on input and output variables by using the experiences. The number of total rules is determined as 135 considering the membership functions. The relationship of some rules is given in Fig. 4.

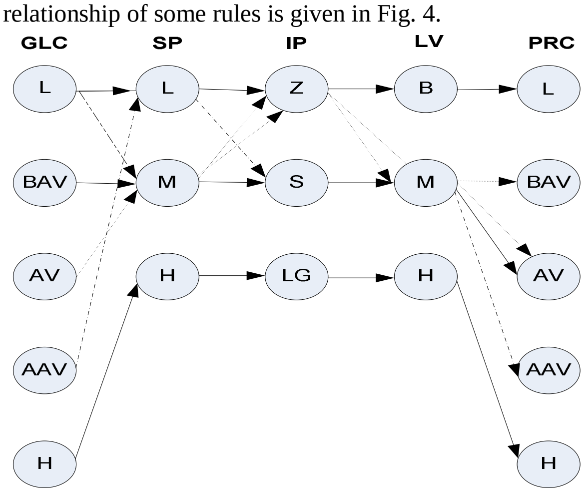

Fig. 4. Relationships for some of the rules

These rules are composed in the following manner:

If GLC is (.) and SC (.) and IC (.) and LV (.) Then PRC (.)

Some of these rules are as follows:

Rule 1: If GLC is L and SC is L and C is 0 and LV is L then PRC is L.

Rule 2: If GLC is BA and SC is M and IC is S and LV is M Then PRC is BA.

Rule 3: If GLC is AV and SC is M and IC is Z and LV is M Then PRC is AV.

Rule 4: If GLC is AAV and SC is L and IC is S and LVis H Then PRC is AAV.

Rule 5: If GLC is H and SC is H and IC is H and LV is H, then PRC is H.

Defuzzification is used for finding the crisp values after determining the input and output values and forming the rule table. Centroid method which is one of the defuzzifications is used for obtaining the PRC.

$$PRC = \frac{\sum_{i=1}^{n} \mu(PRC)_i \, xPRC_i}{\sum_{i=1}^{n} \mu(PRC)_i} \qquad (5)$$

where μPRC_i is the membership value of the clipped output, PRC_i is the quantitive value of the clipped output, and n is the number of points corresponding to quantative value of the output.

IV. APPLICATIONS AND SIMULATIONS

Next Day Load Forecasting: In this paper, the performances of the conventional ANN structure and the improved ANN model with WFBB are tested separately. Feed forward back propagation is used in both ANN structure and the hybrid model. The daily data composed some periodicities which are similar from one day to the other. But some unexpected events such as holidays, failures on power plants, and weather condition changing effect the load values. In this model based on the parametric methods, it is assumed that the data sequence is stationary. The hourly load values for January is given in Fig. 5.

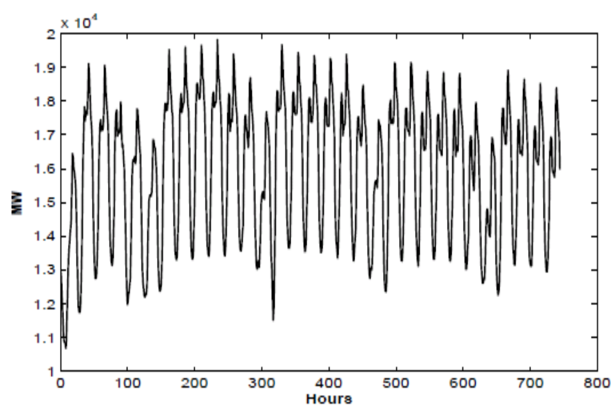

Fig. 5. The hourly load values for January

The conventional ANN and the hybrid method are used for predicting the next day load values based on the previous two-day load values, respectively. The conventional ANN structure has 2 layers. First layer and output layer are composed of 48 and of 24 neurons, respectively. The size of the input and output vector are 48x10 and 24x10 in this structure, respectively. ANN is trained 15 epochs.

The FFT algorithm is applied to all given data for the hybrid method. The FFT structure of this data is given in Fig. 6. Frequency response of the training set is also given in Fig. 7.

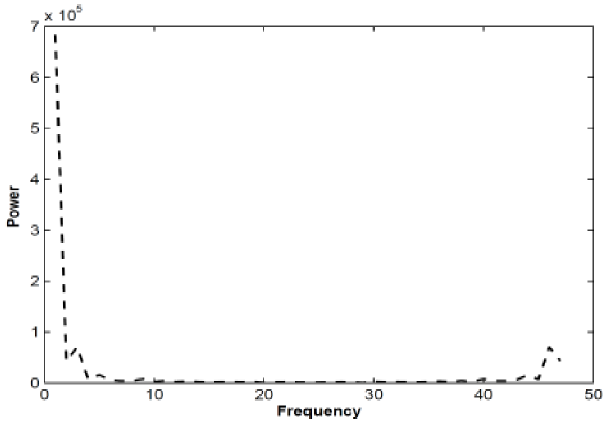

Fig. 6. FFT structures of the data

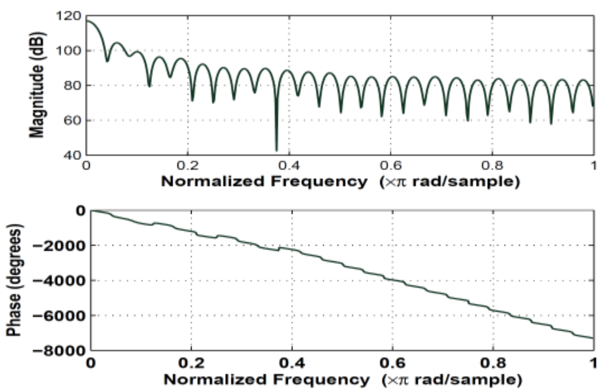

Fig. 7. Frequency response for the training data.

The results of the IFFT algorithm are used for the input of the ANN structure, this structure has 2 layers. First layer and output layer are composed of 48 and 24 neurons, respectively. In this cases, the sizes of the input and output vectors are 48x10 and 24x10 in this structure, respectively. ANN training is finished at the end of 16 epochs [9].

FL UC: The UC problem for 4-unit Tuncbilek thermal plant is solved by using the FL structure. The data used in the analysis is taken from Turkish Electric Power Company and Electricity Generation Company. The characteristics of four units are given in Table 1.

TABLE I: UNIT CHARACTERISTICS

Unit No	GLC (MW)		SC ($)	IC ($/MWh)
	Min	Max		
1	8	32	60	33.73
2	17	65	240	28.952
3	35	150	550	27.005
4	30	150	550	27.659

The membership functions of describing GLC, SC, IC and LV are shown in Fig. 8. The ranges of each subset are chosen in a subjective manner. For example, given that SC that can be served by the largest SC is between "$60" and "$550". The subset "low SC" may be chosen between "$60" and "$210" also high SC can be chosen with a range "$380-$550". Similarly the subsets for other variables can be also linguistically defined.

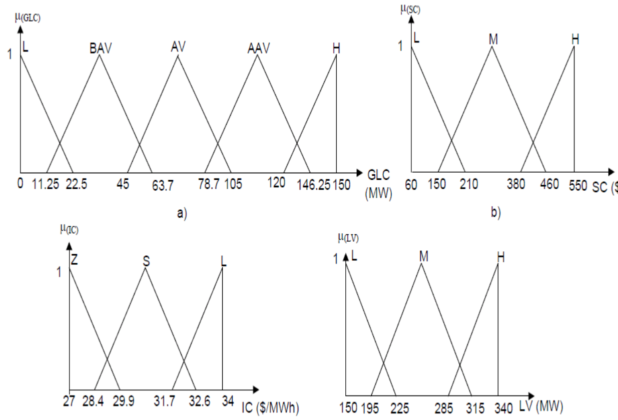

Fig. 8. Membership functions of a) GLC, b) SP, c) IC, and d) LV

The membership function of PRC is shown in Fig. 9. The fuzzy sets corresponding to the range of values of the production cost are described as follows: A "low cost" is defined as being in the range of $320 - $1250. Similarly a "high cost" may be described as lying in the range $3670-$4700. Similar expression can be given to describe the other subsets of production cost. The rules are written to relate the fuzzy input variables. Units are committed from their lowest incremental cost to highest one. Mamdani min-max rule is used as the inference engine in this analysis.

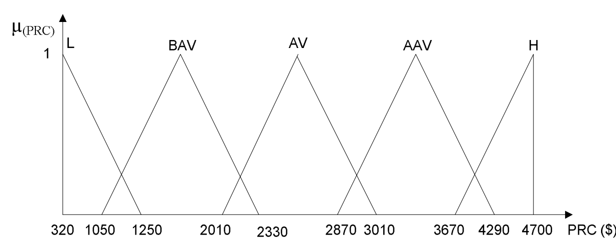

Fig. 9. Membership function of production cost

In this study, the 24-h day is subdivided into 8 discrete stages. The actual load demands for these stages are given in Table 2 and the range of predicted load variation is taken equal to ± 5%.

TABLE II: LOAD DATA (MW)

Stage	Load	Stage	Load
1	154.74	5	186.55
2	145.66	6	182.31
3	160.35	7	186.78
4	191.74	8	192.65

Forecasting load values for each stage found by using the conventional ANN method and the ANN with WFBB are given in Table 3 and 4, respectively.

TABLE III:FORECASTING LOAD VALUES FOR CONVENTIONAL ANN METHOD (MW)

Stage	Load	Stage	Load

1	157.96	5	188.67
2	148.81	6	185.33
3	163.98	7	189.83
4	194.58	8	196.24

TABLE IV:FORECASTING LOAD VALUES FOR ANN WITH WFBB (MW)

Stage	Load	Stage	Load
1	153.91	5	185.91
2	144.91	6	181.74
3	159.67	7	185.97
4	190.85	8	192.01

UC schedule for Tuncbilek thermal plant for actual and forecasting load values is given in Table 5.

TABLE V: UC SCHEDULE OF TUNCBILEK THERMAL PLANTS FOR LOAD VALUES AND FORECASTING LOAD VALUES

	Feasible UC (ANN model with WFBB)	Feasible UC (Load Values)	Feasible UC (ANN)
1	0 0 1 1	0 0 1 1	0 1 1 1
2	0 0 1 1	0 0 1 1	0 1 1 1
3	0 0 1 1	0 0 1 1	0 1 1 1
4	0 1 1 1	0 1 1 1	1 1 1 1
5	0 0 1 1	0 0 1 1	1 1 1 1
6	0 0 1 1	0 0 1 1	0 1 1 1
7	0 0 1 1	0 1 1 1	1 1 1 1
8	0 1 1 1	0 1 1 1	1 1 1 1
TC	$37385	$37142	$38129

It is clear that accurate load forecasting is very important for the UC solution. The total cost of the forecasting load values for ANN method is more than that of actual load values by $987. Additionally, the total cost of the forecasting load values for ANN with WFBB is less than that of actual load values by $234.

V. CONCLUSION

In this study, unit commitment (UC) problem for four-unit Tuncbilek thermal plant which is in Kutahya region in Turkey, is solved for an optimum schedule of generating units based on the load data forecasted by using the conventional Artificial Neural Network (ANN) and an improved ANN model with Weighted Frequency Bin Blocks (WFBB). Fuzzy Logic (FL) method is used for solving the UC problem. Comparing to the total costs shows that load forecasting is important for unit commitment. Furthermore, it is clear that the UC solution with the ANN with WFBB model forecasting load is better than ANN one in terms of total cost.

VI. REFERENCES

[1] K Kim, H. S. Youn, and Y. C. Kang, "Short-Term Load Forecasting for Special Days in Anomalous Load Conditions Using Neural Networks and Fuzzy Inference Method," *IEEE Trans. Power Syst*, vol. 15, pp. 559-565, 2000.

[2] A. D. Papalexopoulos and T. C. Hesterberg, "A regression based approach to short-term system load forecasting, " Proceedings of PICA Conference, 414-423, 1989.

[3] T. Hill, M. OConnor, and W. Remus, "Neural Networks Models for Time Series Forecasts, " *Management Sciences*, pp.1082-1092, 1996.

[4] K J. Hwang, G. H. Kim and S. H. Kim, "Development of a weekly load forecasting expert system ", *Trum. KIEE*,vol. 48A, no. 4, pp. 365-370, 1999.

[5] H. Mori and A. Yuihara, "Deterministic Annealing Clustering For Annbased Short-Term Load Forecasting," *IEEE Transactions on Power Systems*, vol. 16, no. 3, pp. 545-551, 2001.

[6] T. Senjyu, H. Takara, and T. Funabashi, "One-Hour-Ahead Load Forecasting Using Neural Network", *IEEE Transactions on Power Systems*, vol. 17, pp. 113-118, 2002.

[7] K. B. Song, Y. S. Baek, D. H Hong., and G. S. Jang, "Short-Term Load Forecasting for The Holidays Using Fuzzy Linear Regression Method, " *IEEE Transactions on Power Systems*, vol. 20, (2005) 96-101.

[8] I-K Yu, C. I. Kim,, and Y. H. Song,, "A Novel Short-Term Load Forecasting Technique Using Wavelet Transform Analysis, " *Electrical Machines and Power Systems*, vol. 1, pp. 537-549, 2000.

[9] M.Kurban, and Ü Başaran Filik, "A New Approach for Next Day Load Forecasting Integrating Artificial Neural Network Model with Weighted Frequency Bin Blocks", LNCS Springer, vol. 4985, 703-712, 2008.

[10] J.A. Momoh :Electric Power System Application and Optimization, 2001.

[11] C.L Chen,. N. Chen, "Strategies to Improve the Dynamic Programming for Unit Commitment Application", *Trans. Chin. Inst. Eng*., vol.9, 2002.

[12] R. Nayak, J.D. , "Hybrid Neural Network and Simulated Annealing Approach to the Unit Commitment Problem", *Comput. Elect. Eng*., vol. 26, 2000.

[13] R.C. Asir,. M.R. Mohan, K. Manivannan, "Refined Simulated Annealing Method for Solving Unit Commitment Problem", *Proc. Int. Joint Conf. Neural Netw*., vol. 1, 2002.

[14] K.A. Juste, E. Tanaka, J. Haegawa, "An Evolutionary Programming Solution to the Unit Commitment Problem", *IEEE Trans. Power Syst.*, vol. 14, no.4, 1999.

[15] K.Y. Huang, H.T. Yang, C.L. Yang, "A New Thermal Unit Commitment Approach Using Constraint Logic Programming", *IEEE Trans. Power Syst.*, vol. 13, no.3, 1998.

[16] T. Senjyu, et al., "A Unit Commitment Problem by Using Genetic Algorithm Based on Characteristic Classification", *Proc. IEEE Power Eng. Soc. Trans. Distr. Conf.*, vol.1, 2002.

[17] P.C. Chuan, W.L. Chih, C.L.Chun , "Unit Commitment by Lagrangiane Relaxation and Genetic Algorithms", *IEEE Trans. Power Syst*., vol.15, no. 2, 2000.

[18] LA. Zadeh: Fuzzy sets. Inform Control ,8, 338-353, 1965.

[19] SV.Kartalopoulos, "Understanding Neural Networks and FL Basic Concepts and Applications", New York: IEEE Press, 1996.

[20] Z. Sen, "Fuzzy Algorithm for Estimation of Solar Irradiation from Sunshine Duration", *Sol Energy*, vol. 63, 39-49, 1998.

[21] T. Saksornchai, W.J. Lee, K. Methaprayoon, J. Liao, J.R Richard, "Improve the Unit Commitment Scheduling by Using the Neural-Network-Based Short-Term Load Forecasting", *IEEE Trans. on Industry applications*, vol. 41, 169-179, 2005.

[22] A. D. Papalexopoulos, S. Hao, and T. M Peng., "An Implementation of a Neural Network Based Load Forecasting Model for the EMS," *IEEE Trans. Power Syst.*, vol. 9, 1994, 1956-1962.

[23] H. Chen, "A Practical On-line Predicting System for Short-Term Load", *East China Electric Power*, 24,1996.

[24] M.M. El-Saadawi, A.Tantawi, E.Tawfik, "A Fuzzy Optimisation-Based Approach to Large Scale Thermal Unit Commitment", *Electric Power Systems Research*, Elsevier, vol. 72, 245-252 ,2004.

[25] S.C. Pandian, K. Duraiswamy, "Fuzzy logic implementation for solving the unit commitment problem", *Power System Technology, PowerCon International Conference*,1, 413-418, 2004,

VII. BIBLIOGRAPHIES

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