ELSEVIER

Electrical Power and Energy Systems 23 (2000) 827–836

ELECTRICAL POWER & ENERGY SYSTEMS

www.elsevier.com/locate/ijepes

Unit commitment using hybrid models: a comparative study for dynamic programming, expert system, fuzzy system and genetic algorithms

N.P. Padhy

Department of Electrical Engineering, University of Roorkee, Roorkee 247 667, India

Received 3 February 2000; revised 31 March 2000; accepted 30 October 2000

Abstract

Hybrid models for solving unit commitment problem have been proposed in this paper. To incorporate the changes due to the addition of new constraints automatically, an expert system (ES) has been proposed. The ES combines both schedules of units to be committed based on any classical or traditional algorithms and the knowledge of experienced power system operators. A solution database, i.e. information contained in the previous schedule is used to facilitate the current solution process. The proposed ES receives the input, i.e. the unit commitment solutions from a fuzzy-neural network. The unit commitment solutions from the artificial neural network cannot offer good performance if the load patterns are dissimilar to those of the trained data. Hence, the load demands, i.e. the input to the fuzzy-neural network is considered as fuzzy variables. To take into account the uncertainty in load demands, a fuzzy decision making approach has also been developed to solve the unit commitment problem and to train the artificial neural network. Due to the mathematical complexity of traditional techniques for solving unit commitment problem and also to facilitate comparison genetic algorithm, a non-traditional optimization technique has also been proposed. To demonstrate the effectiveness of the models proposed, extensive studies have been performed for different power systems consisting of 10, 26 and 34 generating units. The generation cost obtained and the computational time required by the proposed model has been compared with the existing traditional techniques such as dynamic programming (DP), ES, fuzzy system (FS) and genetic algorithms (GA).

Keywords: Unit commitment; Dynamic programming; Expert system; Fuzzy system; Neural network and genetic algorithms

1. Introduction

In most of the interconnected power systems, the power requirement is principally met by thermal power generation. Several operating strategies are possible to meet the required power demand, which varies from hour to hour over the day. It is preferable to use an optimum or sub-optimum operating strategy based on economic criteria. In other words, an important criterion in power system operation is to meet the power demand at minimum fuel cost using an optimal mix of different power plants. Moreover, in order to supply high quality electric power to customers in a secured and economic manner, thermal unit commitment is considered to be one of best available options (refer Appendix A). It is thus recognized that the optimal unit commitment of thermal systems results in a great saving for electric utilities.

E-mail address: nppeefee@rurkiu.ernet.in (N.P. Padhy).

1.1. Review of existing methods

For the past two and a half decades, research work is being carried out in the area of unit commitment problem [1,2]. Mostly numerical techniques have been used to solve the unit commitment problem. The major limitations of the numerical techniques are the problem dimensions, large computational time and complexity in programming. Exhaustive enumeration and mixed-integer programming methods for solving the unit commitment problems fail when the number of units increases because they require a large memory and suffer from great computational delay. Merlin [3] and Ahaw [4] proposed Lagrange relaxation approach to solve short-term unit commitment problems. It was found that the above method is very much suitable for middle order unit commitment problems, whereas mathematical complexity of the problem increases with an increasing number of units. Even though the Lagrange relaxation method is found to be best at present it can not incorporate the load forecasting errors. Lowery [5] and

0142-0615/01/$ - see front matter
PII: S0142-0615(00)00090-9

Nomenclature

AS_i	boiler cool-down coefficient at *i*th hour
BM_i	base maintenance cost at *i*th hour ($/h)
BS_i	boiler start-up energy at *i*th hour (MBTu)
D_i	number of hours down at *i*th hour
$FC_i(P_i)$	fuel cost at *i*th hour ($/h)
IM_i	incremental maintenance cost at *i*th hour ($/MWh)
K	proportional constant
MS_i	start-up maintenance cost at *i*th hour ($/h)
$MC_i(P_i)$	maintenance cost at *i*th hour ($/h)
P_i	power level at *i*th hour (MW)
∇Pi	power rate of generator i (MW/hr)
Load(H)	system load at hour H
$P(x)$	probability value of x
SD_i	start down cost at *i*th hour ($/h)
ST_i	start-up cost at *i*th hour ($/h)
T	the number of periods under study
Tiu	minimum up-time
Tid	minimum down-time
TS_i	turbines start-up energy at *i*th hour (MBTu)
a_i	cost coefficient of generator ($/MW * MW)
b_i	cost coefficient of generator ($/MW)
ci	cost coefficient of generator ($)
$d(A-B)$	distance between two fuzzy sets A and B
n	imprecisely defined load levels
$\mu(x)$	membership value of load x

Snyder [6] have described a new classical techniques based on modified dynamic programming (DP) methods for solving unit commitment problems. Unfortunately, when the system conditions and constraints are included, these methods also lead to more mathematical complexity and all these techniques require a large computational time for systems of a practical size.

An expert system (ES) model [7] was employed to reduce the solution time as it avoided the use of complex mathematical calculations. Expert system based methods fail, if the new load pattern is not similar to that of the stored load patterns in the dynamic database. Su [8] proposed a new approach using fuzzy DP in which, the errors in the forecasted hourly loads can be taken into account by using fuzzy set notation but still it suffers from mathematical complexity. Sasaki [9] used the modified Hopfield neural network for solving the unit commitment problem. Even though this method includes different constraints, the final solution in some cases is far away from the optimal solution due to its dependency on off-line training [10]. Ouyang [11] developed a hybrid dynamic-artificial neural network algorithm in which the DP is performed for off-line training. Fuzzy logic techniques [12] have been incorporated in a knowledge-based system to solve this multivariate problem involving multiple conflicting objectives. These methods are best suited for on-line applications due to reduction in computational time. But, these methods may lead to an unwanted solution in case of a sudden change in load demand. These methods are also not completely free from mathematical complexity.

Orero [13] presented a genetic algorithm based approach to the scheduling of generators in a power system. Sheble [14] used refined genetic based algorithm to economic dispatch problems. The algorithm utilizes the payoff information of respective solutions to evaluate optimality. Thus the constraints of classical techniques on units are eliminated. Dasgupta [15] discussed the application of genetic algorithms (GA) to determine the short-term commitment order of thermal units. They concluded that the main advantage of the GA [16] formulation is that fairly accurate results can be obtained within short time and constraints can be incorporated easily.

1.2. Objective of the paper

From the literature review, it has been observed that there exists a need for evolving simple and effective methods, for obtaining an optimal solution for the unit commitment problem. Hence, in this paper an attempt has been made to couple artificial intelligence (AI) based methods for meeting the requirements of the unit commitment problem, which eliminates the above mentioned difficulties.

The main objectives of this work are as follows:

- To develop hybrid models for solving the unit commitment problem with the help of AI based concepts of ES, fuzzy modelling and neural network.
- To develop ES, fuzzy decision system and GA based unit commitment models independently for comparison with hybrid models.

2. Hybrid model problem formulation

The structure of the proposed hybrid model mainly consists of the following:

(a) Fuzzified load profile.
(b) Off-line decision making for unit commitment scheduling.
(c) Pre-scheduling using fuzzy-neural network.
(d) Final scheduling through an adaptive ES.

Implementation of the hybrid model is discussed briefly in the following sections and the flow chart of the proposed hybrid model is shown in Fig. 1.

2.1. Load pattern representation

Linguistic values are used to represent the load demand patterns. A triangular membership function (Eq. (1)) has been used to assign values for the load demand profile [17]. The overlapping of the very low, low, medium, high