CHAPTER 4

A HYBRID FUZZY-NEURAL NETWORK EXPERT SYSTEM MODEL

4.1 INTRODUCTION

The aim of this chapter is to develop a hybrid model to overcome the limitations of expert system and fuzzy decision system approaches, while determining the unit commitment schedule of generating units. It is proposed to determine the unit commitment schedule in two steps. The first step, involves in applying the non-linear fuzzy membership values of the load demand profile to the input layer of the neural network, so that it can accept fuzzy inputs. Then an adaptive expert system is used to manipulate the schedules by using rule-base and inference mechanism. The proposed hybrid model yields a promising approach to solve short-term unit commitment problem which will offer good performance and overcome the above mentioned difficulties experienced using the previous methods. The flow chart for the proposed hybrid model is shown in Figure 4.1.

4.2 FUZZY-NEURAL NETWORK DESIGN

4.2.1 Input Layer Representation

Linguistic values are used to represent the load demands. A triangular membership function shown in Figure 4.2 has been used to assign values for the input load demand profile with overlapping regions for very low, low, medium, high and very high values.
READ LOAD DEMAND PROFILE

DIVIDE THE LOAD DEMAND INTO FIVE DIFFERENT LEVELS AND ASSIGN FUZZY VALUES PRECISELY

INITIALIZE AND EXECUTE FUZZY-NEURAL NETWORK

EXECUTE EXPERT SYSTEM

IF $i \geq 24$

START

$l = 0$

Yes

STOP

FIGURE 4.1 FLOW CHART FOR THE HYBRID MODEL
Let the input vector to the neural network be \( X = (x_1, x_2, \ldots, x_n) \). The fuzzy neurons associated with \( X \) are defined by \( \mu(x_1), \mu(x_2), \ldots, \mu(x_n) \), where \( \mu(x_i) \) denotes the grade of membership of \( x_i \) in this set.

The schematic representation of a fuzzy neuron for the load demand profile is shown in Figure 4.3.

### 4.2.2 Fuzzy-Neural Network Configuration

In the proposed method, a three layer ANN model is used. The input layer of the ANN is made to adopt a fuzzy classified load demand profile which consists of \( N \) neurons, where \( N \) represents the total hours in the schedule period. Since the load demand is forecasted at one hour interval for the short-term unit commitment problem, the value of \( N \) is considered as equal to 24. Similarly the neurons in the output layer from the output schedule is of size \( N \times M \), where \( M \) represents the number of units to be scheduled. The output schedule has values of 1 and 0 to represent respectively the ON and OFF state of the units. The schematic representation of the fuzzy-neural network is shown in Figure 4.4.

For training purpose, a set of load profiles and their corresponding commitment schedules are prepared using fuzzy decision approach. The fuzzy-neural network is then trained with the input (load variables) and the output (commitment schedule) available from the fuzzy decision approach. Presently, the number of input neurons are considered to be 24 and output neurons to be 240 \((24 \times 10)\) with 50 hidden neurons for 10 unit system. During the training, the input parameters to the back propagation neural (BPN) network comprise different features of demands. This input pattern is used for producing twenty-four hour ahead unit commitment scheduling. The BPN algorithm has been used to train the fuzzy-neural network to obtain initial scheduling. Supervised learning is used to assign membership function values to the input nodes and for each training vector.
FIGURE 4.2 TRIANGULAR MEMBERSHIP FUNCTION FOR LOAD DEMANDS

FIGURE 4.3 SCHEMATIC REPRESENTATION OF FUZZY NEURONS
Fuzzy input layer
(Load demand)

FIGURE 4.4 SCHEMATIC REPRESENTATION OF FUZZY-NEURAL NETWORK

FIGURE 4.4 SCHEMATIC REPRESENTATION OF FUZZY-NEURAL NETWORK
The error is computed with respect to each such desired output. After a number of iterations, the neural network converges to a minimum error solution. Finally, the proposed fuzzy-neural network is capable of presenting an initial commitment schedule successfully. This trained fuzzy-neural network will produce the initial schedule pattern for any input fuzzy load profile.

4.3 AN ADAPTIVE EXPERT SYSTEM

To implement the final scheduling process quickly and most efficiently, it is desirable and necessary to reduce the amount of calculations as required by traditional approaches. This is achieved by introducing an adaptive expert system. The schematic representation of an adaptive expert system is shown in Figure 4.5. The minimum up-time and down-time constraints impose the most challenging task for optimal scheduling. The units with larger minimum up-time and down-time will have a greater impact over the overall scheduling strategy. However, from a practical point of view, units that have larger minimum up-time and down-time are the least probable to be committed and decimated in the short-term scheduling. Depending upon the demand, different type of units are brought to the system for scheduling.

The rule base consists of a set of production rules. The production rules are expressed in terms of

\[ \text{IF (premise) THEN (conclusion)} \]

For example:

\[ \text{IF the Load Demand} \leq \text{Medium Demand} \]
\[ \text{THEN go for Thermal Units} \]
FIGURE 4.5 SCHEMATIC REPRESENTATION OF AN ADAPTIVE EXPERT SYSTEM
The performance of the present model can be improved to satisfy different constraints by adding more number of production rules. In many emergency conditions, as in case of short term unit commitment problem, sub-optimal solution using expert system can be obtained for real-time operation instead of mathematical optimization techniques that require longer time for computation.

The important aspects of the proposed hybrid fuzzy-neural network expert system are

- Fuzzyfied input load profile
- Pre-scheduling from fuzzy-neural network
- Final scheduling through an adaptive expert system.

The block diagram representation of the proposed hybrid model is shown in Figure 4.6.

4.4 RESULTS AND DISCUSSION

To demonstrate the effectiveness of the proposed model, load demand profile with unit data presented in appendices 1-4 have been considered. Once the ANN is initiated, membership functions representing the load demand profile are inserted into the input layer. The ANN yields a pre-schedule at the output layer. This result has been analysed again by sending the output to the adaptive expert system to have a real-time commitment schedules which are shown in Table 4.1, 4.2 and 4.3 respectively for 10, 26 and 34 unit systems. The comparison of the cost of generation using the hybrid model and dynamic programming is given in Table 4.4.

The results show that the proposed hybrid model is able to provide an accurate solution i.e., error within 0.338%, 0.792% and 0.849% respectively for 10, 26 and 34 unit systems compared to dynamic
FIGURE 4.6 BLOCK DIAGRAM REPRESENTATION OF THE HYBRID FUZZY-NEURAL NETWORK EXPERT SYSTEM FOR UNIT COMMITMENT PROBLEM
TABLE 4.1  THE UNIT COMMITMENT SCHEDULE GENERATED USING HYBRID MODEL FOR 10 UNIT SYSTEM

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<th>Commitment Schedule</th>
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</thead>
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<td>2</td>
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Total generation cost ($/day) 80895.66
### TABLE 4.2 THE UNIT COMMITMENT SCHEDULE GENERATED USING HYBRID MODEL FOR 26 UNIT SYSTEM

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<td>(Unit 1 to 26) →</td>
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Total generation cost ($/day) 666848.66
**TABLE 4.3 THE UNIT COMMITMENT SCHEDULE GENERATED USING HYBRID MODEL FOR 34 UNIT SYSTEM**

<table>
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<tr>
<th>Hour</th>
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<td>51418.37</td>
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<td>2</td>
<td>0000000 1111111 0000000 1111111111111</td>
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</tr>
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**Total generation cost ($/day):** 1229729.66
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<th>System</th>
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<th>% Error</th>
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<td>34 unit</td>
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TABLE 4.4 COMPARISON OF SCHEDULING RESULTS OF THE TWO MODELS (DYNAMIC PROGRAMMING AND HYBRID) FOR 10, 26 AND 34 UNIT SYSTEMS
programming approach. The error due to generation cost and solution time have still reduced compared to expert system and fuzzy decision system. The proposed hybrid model is also free from the limitations faced by the expert system and fuzzy decision system. The hybrid model can accept linguistically defined load patterns and can meet the defined constraints within two seconds. The error due to generation cost also improved compared to solutions obtained using expert system and fuzzy decision system approaches.

The non-linear load model proposed in this chapter, which need not classify the training pattern into weekday and special day as the conventional artificial neural network model do. As a result the proposed hybrid model yield a promising approach to unit commitment problem which offers good performance. To achieve better performance, the hybrid model should still employ more rules and knowledge for very special load patterns.

4.5 SUMMARY

A hybrid fuzzy-neural network expert system is developed for calculating one day ahead schedule for short-term unit commitment problem. In this method, the neural network is implemented in such a way that it can accept fuzzy values in the input layer. An expert system is used to manipulate the initial commitment schedule for real-time operation. The rules are developed to meet constraints successfully. The results obtained from the above model are highly impressive and encouraging for real-time implementation in any power systems.