INTERNATIONAL JOURNAL
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IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

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Optimized Scheduling of Generating Unit for Economic Load Dispatch using Neuro-Fuzzy Expert Systems

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Abstract: It has remained a continuous effort of electrical engineers to minimize the operation cost per unit of electricity. With the advent of distributed power systems, an interconnection of power systems generating from different sources have come into consideration. However, all sources do not operate in the same manner and hence the generation cost for different sources varies significantly. Economic Load Dispatch (ELD) can be defined as a technique to schedule the power generator outputs with respect to the load demands, and to operate the power system in the most economical way.[7] This problem becomes challenging with system constraints and hence there is a need for effective optimization tolls for minimizing the cost to attain the condition of ELD. This paper proposes an expert neuro-fuzzy system for operation of power generation to attain the condition of economic load dispatch.
Keywords: Interconnected power systems, economic load dispatch, neural networks, fuzzy logic, neuro-fuzzy expert system.

I. INTRODUCTION

The present day power systems are increasing in size due to increasing demands of power. With such an increase in size, the following associated challenges are being faced:[1]

1) Reducing system operating cost,
2) Reducing the magnitude of pollution.
3) Reducing transmission loss.

Economic Load Dispatch (ELD) can be thought of as an optimization technique that tries to optimize the generation of different sources so as to minimize operation cost.

The mathematical condition for attaining ELD is:

$$\frac{\partial C1}{\partial P1} = \frac{\partial C2}{\partial P2} = \cdots \frac{\partial Cn}{\partial Pn} = \beta \qquad (1)$$

Here,
$\frac{\partial Ci}{\partial Pi}$ stands for the increment cost generation for the generator.
The above condition is also known as the criterion of β distribution or incremental cost-loading principle.[11]
The optimization problem can be solved in several ways. One of the most promising ways is the use of neuro-fuzzy expert system. The subsequent section explains the concept.

II. FUZZY LOGIC

Fuzzy systems exhibit the following characteristics to meet the challenge of complex optimization problems, which are:

A. Parallel processing architecture
B. Learning and adapting capability i.e. continuously learning from previous data to reduce subsequent errors
C. Capability to handle non-exact boundaries i.e. fuzziness**.**

Fuzzy Logic (FL) is a method of reasoning that resembles human reasoning. The approach of FL imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO. The conventional logic block that a computer can understand takes precise input and produces a definite output as TRUE or FALSE, which is equivalent to human's YES or NO.The inventor of fuzzy logic, Lotfi Zadeh, observed that unlike computers, the human decision making includes a range of possibilities between YES and NO, such as:-

1) Certainly Yes
2) Possibly Yes
3) Can Not Say
4) Possibly No
5) Certainly No

The fuzzy logic works on the levels of possibilities of input to achieve the definite output.

Fuzzy Logic Systems Architecture

It has four main parts as shown −

Fuzzification Module − It transforms the system inputs, which are crisp numbers, into fuzzy sets. It splits the input signal into five steps such as −

LP	x is Large Positive
MP	x is Medium Positive
S	x is Small
MN	x is Medium Negative
LN	x is Large Negative

Knowledge Base − It stores IF-THEN rules provided by experts.

Inference Engine − It simulates the human reasoning process by making fuzzy inference on the inputs and IF-THEN rules.

Defuzzification Module − It transforms the fuzzy set obtained by the inference engine into a crisp value.

Membership Function

Membership functions allow you to quantify linguistic term and represent a fuzzy set graphically. A membership function for a fuzzy *set A* on the universe of discourse X is defined as:

$$\mu_A : X \rightarrow [0,1] \qquad (2)$$

Here, each element of *X* is mapped to a value between 0 and 1. It is called membership value or degree of membership. It quantifies the degree of membership of the element in *X* to the fuzzy set *A*.

a) x axis represents the universe of discourse.

b) y axis represents the degrees of membership in the [0, 1] interval.

There can be multiple membership functions applicable to fuzzify a numerical value. Simple membership functions are used as use of complex functions does not add more precision in the output. –There can be several applications for the illustration of fuzzy systems. You can modify a FLS by just adding or deleting rules due to flexibility of fuzzy logic. A graphical illustration ensues wherein the membership functions are plotted against the voltage levels. All membership functions for LP, MP, S, MN, and LN are shown as below:-
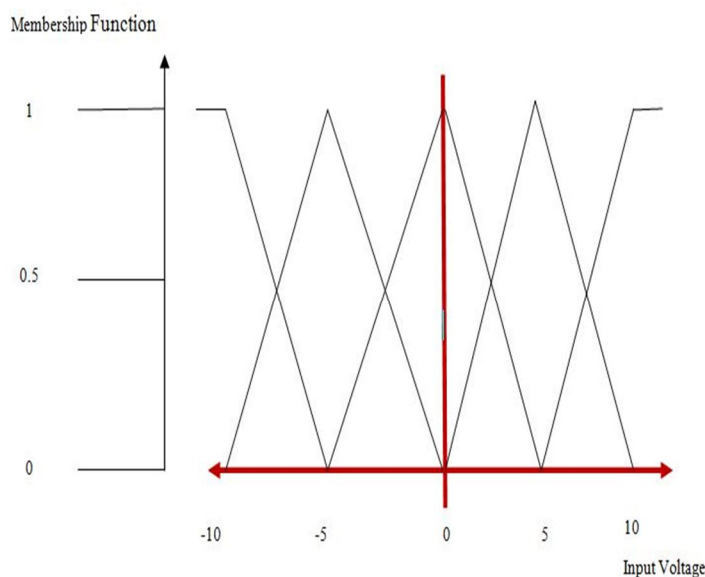

Fig. 1 Membership Function

III. NEURAL NETWORK

Artificial neural networks are a practical way of implementing artificial intelligence with an aim to solve fitting problems generally needing herculean efforts due to the data size and complexity. The artificial neural architecture tries to imitate the human thought process in the following ways:

A. Process data as a parallel stream independently

B. Identifying patterns and correlating them.

Evolving and updating the experiences (called weights) as per the changes in the data received. Neural networks work on training and testing mechanism. In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self organizing memory technique. The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self organizing learning ability. Mathematically, the neural network is governed by the following expression:

$$Y = \sum_{i=1}^{n} X_i \cdot W_i + \theta_i \tag{3}$$

Here,

X_i represents the parallel data streams

W_i represents the weights

θ represents the bias or decision logic

It is mandatory to choose a model that can perform time effective real time data analysis. So the precise identification of the solar models is immensely necessary for accurate solar forecasting. There exist certain models for the same which can help in this regard.

IV. NEURO-FUZZY EXPERT SYSTEMS

Neuro Fuzzy Systems are a combination of:

A. Neural Networks

B. Fuzzy Logic

Neuro Fuzzy Systems generally are based on expert view or fuzzy logic for deciding the thresholds or boundaries. Subsequently the data is fed to neural network for training. After training the system is tested for accuracy. The concept is illustrated subsequently: Consider a signal s_1 travelling through a path p_1 from dendrites with weight w_1 to the neuron. Then the value of signal reaching the neuron will be $s_1 . w_1$. If there are "n" such signals travelling through n different paths with weights ranging from w_1 to w_n and the neuron has an internal firing threshold value of θ_n, then the total activation function of the neuron is given by:

$$y = \sum_{i=1}^{n} X_i \cdot W_i + \theta_i \tag{4}$$

Where,

X_i represents the signals arriving through various paths,

W_i represents the weight corresponding to the various paths

and θ is the bias.

The entire mathematical model of the neuron or the neural network can be visualized pictorially or the pictorial model can be mathematically modelled. The design of the neural network can be modeled mathematically and the more complex the neural design more is the complexity of the tasks that can be accomplished by the neural network.
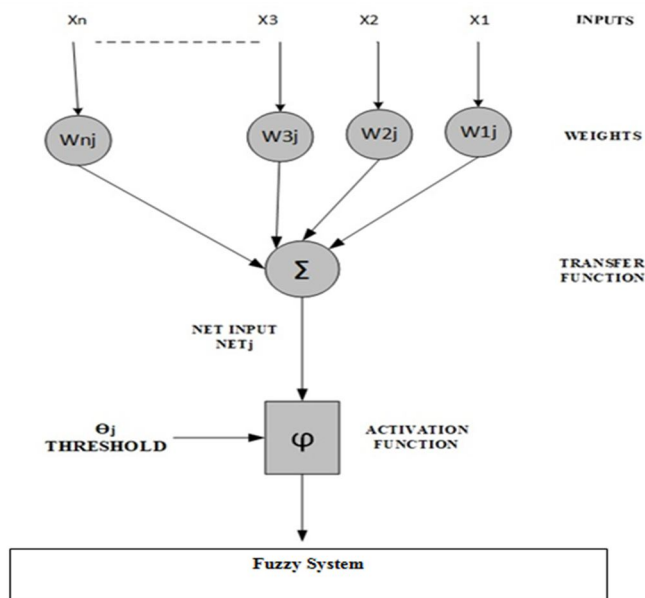
Fig.2 Block Diagram of a Neuro Fuzzy System

V.   RESULTS

In the section below the results obtained from the proposed algorithms in last section are shown and described. In first section results obtained from dynamic programing are presented which will follow with results from fuzzy logic algorithm. A total of 3 generating units are utilized in this work for solving unit commitment problem with both algorithms.

A.   Results Obtained by Dynamic Programming Method.

Certain initial conditions are assumed while solving problem with dynamic programming which are discussed below:
1) First two units are in operating condition
2) Last one is switched off from last 3 hours
3) Losses and reserve capacity are ignored initially

The load demand form next 24 hours starting from 12 midnight in the scale of 3 hours is available as shown below:

Table.1 Load Function

Unit no.	a_i (Rs/MW^{2}h)	b_i (Rs/MWh)	c_i (Rs/h)
1	0.00143	7.3	510
2	0.00195	7.86	310
3	0.00483	7.98	78

Hours	Load in MW
12 to 3	400
3 to 6	450
6 to 9	700
9 to 12	600
12 to 3	550
3 to 6	500
6 to 9	750
9 to 12	650

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 7 Issue II, Feb 2019- Available at www.ijraset.com

Table.2 Cost Functions

Load demand (MW)	Unit combinations	Dynamic approach
467.87	1 0 0	514.66
	1 1 0	504.56
	1 0 1	964.13
517.87	1 0 0	569.66
	1 1 0	557.44
	1 0 1	775.27
767.87	1 1 0	1397.14
667.87	1 1 0	716.08
617.87	1 1 0	663.22
	1 0 1	687.55
567.87	1 0 0	624.66
	1 1 0	610.33
	1 0 1	632.21
817.87	1 1 0	1506.97
717.87	1 1 0	2275.96

Table.3 Cost assimilated by Dynamic Approach (with constraints)

The same problem is solved again in this section bit now using fuzzy logic. The parameters chosen are also same with load demand, incremental cost as input to fuzzy model and power generation as output parameter. Here three generators are considered with each having a certain capacity as mentioned in below figures (PG1, PG2, PG3). All the parameters are normalized for better understanding of fuzzy set, that is crisp set is normalized to for fuzzy number then it is again converted to crisp output using de-fuzzifier. Based on the fuzzy sets, the membership functions are chosen for the fuzzy variables.

Load demand is taken from 400 MW to 800MW in this work with three functions Low(L), Normal(N) and high (H). Incremental cost is taken from 7 to 10 RsMWhr with three functions Low(L), Normal(N) and high (H) First generating station PG1 has a maximum capacity of 600 MW with three-member ship function (L M H). Second generating station PG2 has a maximum capacity of 400 MW with three-member ship function (L M H). Third generating station PG3 has a maximum capacity of 200 MW with three-member ship function (L M H).
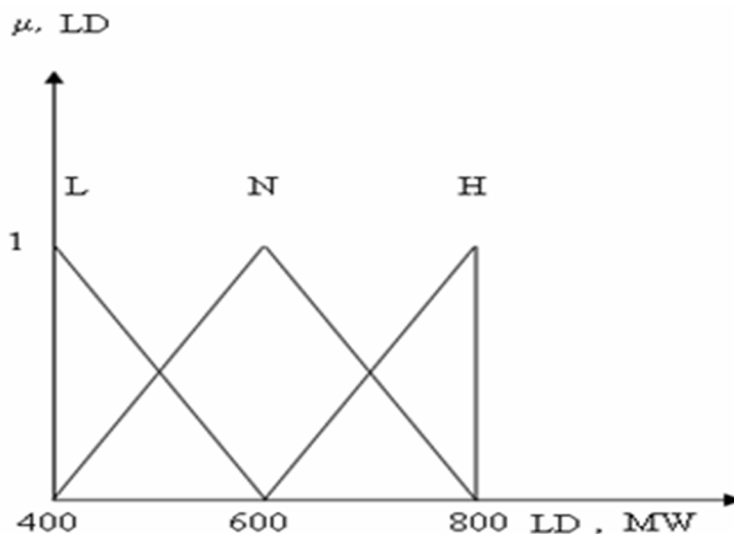

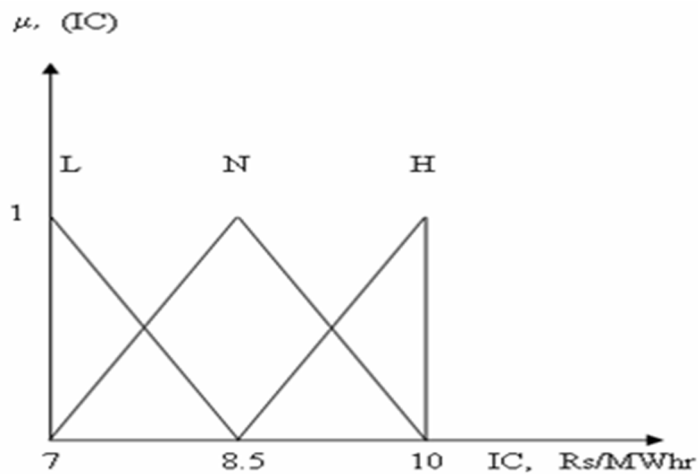Fig.3: Membership function of load demand variation

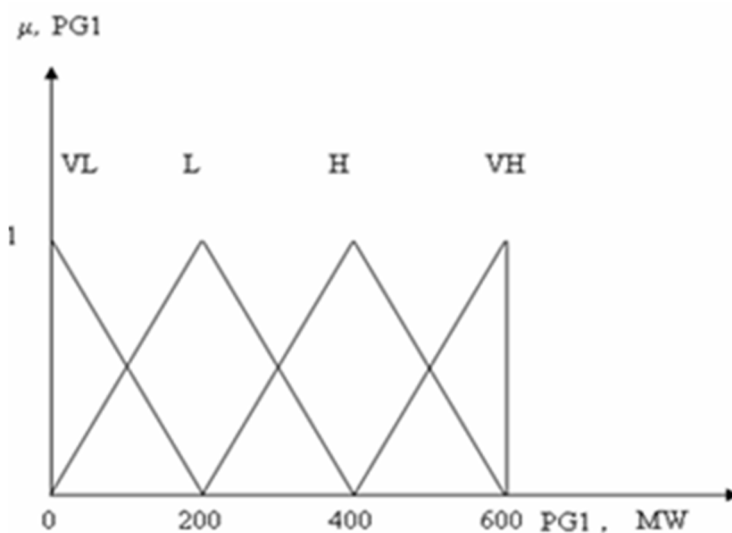Fig. 4: Membership function of Incremental cost variation
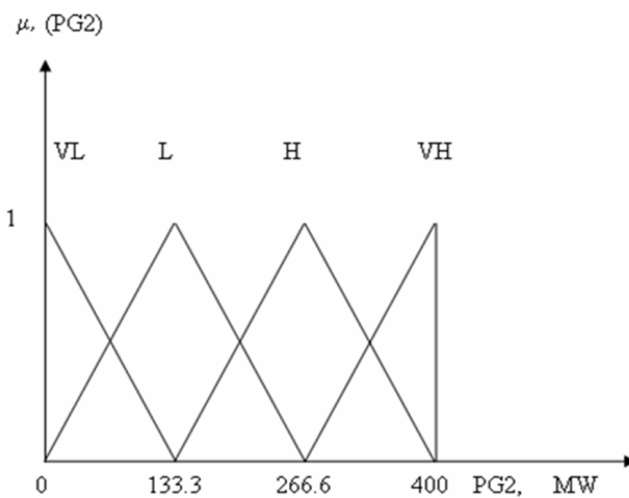
Fig. 5: Membership function of PG1
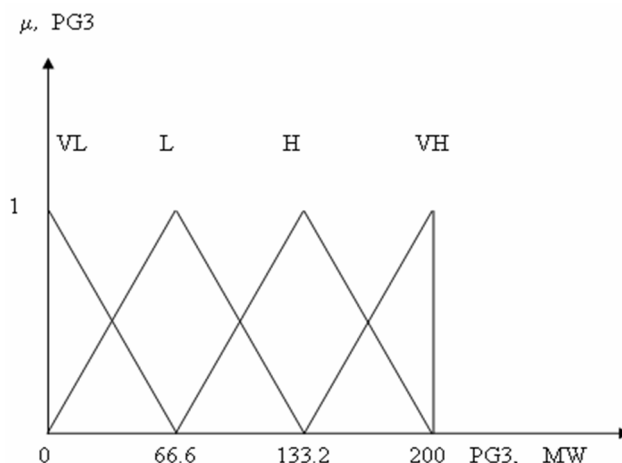
Fig. 6: Membership function of PG2

Fig. 7: Membership function of PG3

The results obtained using the fuzzy logic approach (considering all the three units committed).

VI. CONCLUSION

It can be concluded from the previous discussions, mathematical formulation and supporting results that the proposed system using neuro-fuzzy expert system is capable of achieving the condition of economic load dispatch. Three variants of load demand have been considered in the proposed work which is low, normal and high. The optimization considers incremental cost as a variable for the system performance metric.

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