Application of Neural Based Fuzzy to Unit Commitment

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Abstract

A new approach using Neural Based Fuzzy (NBF) is proposed for the unit commitment of a power system. The objective of the paper is to find the generator scheduling such that the total operating cost can be minimized, when subject to a variety of constraints. This method allows a qualitative description of the behavior of a system, the system's characteristics, and response without the need for exact mathematical formulations. It is demonstrated through numerical example that a Neural based fuzzy approach achieves a logical and feasible economical cost of operation of the power system, which is the major objective of Unit Commitment (UC). The Neural Network is a powerful tool for optimization problems that has been successfully applied to a number of combinatorial optimization problems. It has the ability to avoid entrapment in local minima by employing a flexible memory system. Fuzzy logic is having the capability of qualitative representative of results in terms of input variables. The solution of Unit Commitment is a two stage process and it uses the advantage of both approaches. In the first stage the generator schedule is produced using Neural Network and in the second stage the production cost is calculated using fuzzy logic model. By doing so, it gives the optimum solution rapidly and efficiently. The Neyveli Thermal Power Station (NTPS) unit II in India has been considered as a case study and extensive studies have also been performed for different power systems consisting of 10, 20, and 26 generating units. Numerical results obtained by NBF are compared with conventional methods like DP and Lagrangian Relaxation (LR) to reach proper unit commitment.

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1. Introduction

In all power stations, investment is quite expensive and the resources needed to operate them are rapidly becoming more sparse. As a result, the focus today is on optimizing the operating cost of power stations. In the present world, meeting the power demand as well as optimizing generation has become a necessity. Unit Commitment in power systems refers to the optimization problem for determining the on/off status of generating units that minimise the operating cost subject to a variety of constraints for a given time horizon [1]. The solution of the Unit Commitment Problem (UCP) is complex optimization problem. The exact solution of the UCP can be obtained by complete enumeration of all feasible combinations of generating units, which could be huge number. The unit commitment is commonly formulated as a nonlinear, large scale, mixed-integer combinational optimization problem.

Review of UCP may be found in reference [2]. The DP method [3-4] based on priority list is flexible, but the computational time suffers from dimensionality. Lagrangian Relaxation (LR) for UCP [5-6] was superior to DP due to its higher solution quality and faster computational time. However, numerical convergence and solution quality of LR are not satisfactory when identical units exist [7]. With the advent of heuristic approaches, Genetic Algorithm (GA) [8], Evolutionary Programming (EP) [9], Simulated Annealing (SA) [10], and Tabu Search (TS) [11] have been proposed to solve the UC problems. The results obtained by GA, EP, TS and SA required a considerable amount of computational time especially for large system size.

Considering the characteristics of the daily Unit Commitment, one can find that the load demand profile usually follow some basic patterns. If the previous scheduling information is effectively utilised, a significant amount of calculation for DP and LR method will be saved. In this respect alternate method for UC has been presented by the authors who employ Artificial Neural Network (ANN) as the global optimization support.

The use of fuzzy logic has received increased attention in recent years because of its usefulness in reducing the need for complex mathematical models in problem solving. Rather, fuzzy logic employs linguistic terms, which deal with the causal relationship between input and output variables. For this reason, Fuzzy logic approach makes it easier to manipulate and solve many problems, particularly where the mathematical model is not explicitly known, or is difficult to solve. Furthermore, fuzzy logic is a technique, which approximates reasoning, while allowing decisions to be made efficiently.

The proposed NBF is a two stage process which consists of ANN and Fuzzy programming approach for the short term UC problem. The proposed intelligent system retrieves a pre-schedule by ANN, which is trained by existing scheduling information for various load profile, and passes the pre-schedule to Fuzzy programming approach to obtain proper commitment schedule and allocate the system demand among the committed units.

The effectiveness of the proposed technique has been demonstrated by unit commitment on Neyveli Thermal Power Station in India, which consists of 7 thermal units. The proposed ANN is a typical three layer network, with back-propagation learning scheme. Under Fuzzy environment generation cost and load demand are all expressed in Fuzzy set notation. Integrating ANN and Fuzzy shows the potential applicability and advantage in terms of reducing execution time and preserving the solution feasibility without trading off the solution quality.

2. Unit Commitment Problem

The unit commitment problem can be mathematically described as follows

$$Min\, F_i(P_i^t) = \sum_t \sum_i [(a_i + b_i P_i^t + c_i (P_i^t)^2) + ST_{i,t}(1-U_{i,t-1})]U_{i,t} \quad (1)$$

where $F_i(P_i^t)$ is generator fuel cost function in quadratic form, a_i, b_i and c_i are coefficients of unit i, and P_i^t is the power generation of unit i at time t.

Subject to the constraints

(a) Power balance constraint

$$\sum_i P_i^t U_{i,t} = P_D^t + P_L^t \quad (2)$$

where P_D^t is total load demand at time t and P_L^t is power loss at time t.

(b) Spinning reserve constraint

$$P_D^t + R^t - \sum_{i=1}^{N} P_{i,max} U_{i,t} \leq 0 \quad (3)$$

where R^t is spinning reserve constraint at time t and N is the total number of generator units.

(c) Generation limit constraint

$$P_{i,\min} \le P_i^t \le P_{i,\max} \quad (4)$$

where $P_{i,min}$ is the minimum generation limit and $P_{i,max}$ is the maximum generation limit of unit i.

Minimum up and down time constraint

$$U_{i,t} = \begin{Bmatrix} 1 & if\ T_{i,on} < T_{i,up} \\ 0 & if\ T_{i,off} < T_{i,down} \\ 0\ or\ 1, & otherwise \end{Bmatrix} \quad (5)$$

where $T_{i,up}$ is minimum up time, $T_{i,down}$ is minimum down time, $T_{i,on}$ is continuously on time and $T_{i,off}$ is continuously off time of unit i.

(e) Startup cost

$$ST_{i,t} = S_{oi}[1 - D_i\, e^{(-Toff_i/Tdown_i)}] + E_i \quad (6)$$

Where S_{oi} is cold start-up cost, D_i and E_i are start-up cost coefficients for unit i

3. Artificial Neural Network Computing

In recent years, ANN computing has become an important branch of the artificial intelligence. The ANN is the functional imitation of a human brain which simulates the human intuition. In this study, ANN is applied to the short term unit commitment.

As shown in figure 1 a three layer (input, hidden and output layer) model is used for this application. The input layer of the ANN is configured to adapt to a load demand profile, which consists of M neurons, with M being the total hours in the schedule span. For the daily scheduling, there are 24 neurons in the input layer to represent the forecasted load demand for the next 24 hours.

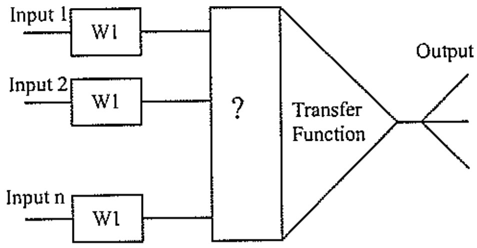

Figure 1 Structure of artificial neuron

The neurons in the output layer form the output schedule, which is NxM matrix, and N corresponds to the number of units to be scheduled. A commitment schedule contains on/off states of each unit every hour within the scheduling time span. The state variable can only take 1 or 0 values. When the training is completed, ANN will produce the corresponding schedule pattern for any input load profile. However, if the input load profile is not exactly the same as any of the profiles used in the training, some of the output neurons will take values between 0 and 1.

4. Fuzzy-logic computing

Fuzzy logic provides not only a meaningful and powerful representation for measurement of uncertainties but also a meaningful representation of vague concept expressed in natural language. Fuzzy logic is a mathematical theory, which encompasses the idea of vagueness when defining a concept or a meaning. For example, there is uncertainty or fuzziness in expressions like 'large' or 'small', since these expressions are imprecise and relative. Variables considered thus are termed 'fuzzy' as opposed to 'crisp'. Fuzziness is simply one means of describing uncertainty. Such ideas are readily applicable to the unit commitment problem.

4.1 Fuzzy UCP model

The objective of every electric utility is to operate at minimal cost while meeting the load demand and spinning reserve requirements. In the present formulation, the fuzzy variables associated with the UCP are

1. Load capacity of generator (LCG)
2. Incremental fuel cost (IC)
3. Start-up cost (SUC)
4. Production cost (PRC)

The Load capacity of generator is considered to be fuzzy, as it is based upon the load to be served. Incremental fuel cost is taken to be fuzzy, because the cost of fuel may change over the period of time, and because the cost of fuel for each unit may be different. Further, the start-up costs of the units are assumed to be fuzzy, because some units take more time than others to be placed on line. The start-up cost of each unit depends upon the recent unit temperature history; for cold starts, the cost will be higher than for hot starts. The maintenance costs and crew expenses of the units are also included in the start-up cost, as are some repair costs. Finally, production cost (which includes no-load cost) of the system is treated as a fuzzy variable since it is directly proportional to the hourly load. Certain other variables, such as minimum up and minimum down times, spinning reserve and generator limitations, are considered to be crisp variables in the unit commitment problem.

4.2 Fuzzy set associated with Unit Commitment

After identifying the fuzzy variables associated with unit commitment, the fuzzy sets defining these variables are selected and normalized between 0 and 1. This normalized value can be multiplied by a selected scale factor to accommodate any desired variable. The sets defining the load capacity of the generator are as follows:

LCG (MW) = {Low, Below Average, Average, Above Average, High}

The incremental cost is stated by the following sets:

IC (Rs) = {Zero, Small, Large}

The sets representing the start-up cost are shown below:

SUC (Rs) = {Low, Medium, High}

The production cost, chosen as the objective function, is given by:

PRC ($) = {Low, Below Average, Average, Above Average, High}

Based on the aforementioned fuzzy sets, the membership functions are chosen for each fuzzy input and output variable.

For convenience, a triangular shape is used to illustrate the membership functions considered here. Once these sets are established, the input variables are then related to the output variable by *If-then* rules as described in the next section.

4.3 Fuzzy If-Then Rules

If fuzzy logic based approach decisions are made by forming a series of rules that relate the input variables to the output variable using *If-then* statements. The *If* (condition) is an antecedent to the *then* (consequence) of each rule. Each rule in general can be represented in the following manner:

If (antecedent) ... *then* (consequence)

Load capacity of generator, incremental fuel cost, and start-up cost are considered as input variables and production cost is treated as the output variable. This relation between the input variables and the output variable is given as:

Production cost = {Load capacity of generator} and {Incremental fuel cost} and {Start-up cost}

In fuzzy set notation this is written as,

PRC = LCG)" IC)" SUC

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

$\mu PRC = \mu LCG)" \mu IC)" \mu SUC$ or

$\mu PRC = \min\{\mu LCG, \mu IC, \mu SUC\}$

where μLCG, μIC and μSUC are memberships value of load capacity of generator, incremental fuel cost, and start-up cost respectively.

Using the above notation, fuzzy rules are written to associate fuzzy input variables with the fuzzy output variable. Based upon these relationships, a total of 45 rules can be composed since there are 5 sub sets for load capacity of generator, 3 subsets for incremental cost and 3 subsets for start-up cost (5*3*3=45).

For example, rule 1 for the load capacity of the generator can be written as follows:

Rule 1:

If Load capacity of generator is low and
Incremental fuel cost is small and
Start up cost is low,
then Production cost is low.

After relating the input variable to the output variable, the fuzzy results must be defuzzified through what is called a defuzzification process to achieve crisp numerical values.

4.4 Defuzzification process

One of the most commonly used methods of defuzzification is the centroid or center-of-gravity method. Using this method, the production cost is obtained as follows

$$\Pr oduction\cos t = \frac{\sum_{i=1}^{n} \mu(PRC)_i * PRC_i}{\sum_{i=1}^{n} \mu(PRC)_i} \qquad (7)$$

where $\mu(PRC)_i$ is the membership value of the clipped output, PRC_i is the quantitative value of the clipped output and n is the number of the points corresponding to quantitative value of the output.

5. Neuro-Fuzzy Implementation

The solution process consists of two steps. In the first step the forecasted load demand profile is given as input to the trained ANN. The ANN is trained with input/ pattern data for most of the typical commitment schedules. Therefore the output represents a schedule for the given load profile with a degree of uncertainty. This output is denoted as a pre-schedule.

The second step consists of removing uncertainty in the schedule, allocating the system demand among operating units and calculating total production cost for the period of 24 hours.

In the proposed method, each hour represents a stage, and according to the content of the pre-schedule at this hour, a stage belongs to determined stage or undetermined stage. The determined stage represents an hour in the pre-schedule when all the units have certain states. Undetermined stage represents an hour in the pre-schedule when some units have uncertain states.

Obviously, in order to obtain a complete commitment schedule, undermined stages need to be processed further. Uncertain states are presented by their probabilities (valued between 0 and 1) in the ANN. A higher probability indicates that the unit is more likely to be committed at the current hour. This motivates us to arrange all the uncertain units according to their probability values computed by the ANN.

Certain uncertain states are made to certain state based on minimum uptime and minimum down time. If at hour j unit i has uncertain state, but at hours j-1 and j+1, it has the certain state of 1, and its minimum down time is greater than one hour, then unit i is a must-on unit at hour j. . If at hour j unit i has uncertain state, but at hours j-1 and j+1, it has the certain state of 0, and its minimum up time is greater than one hour, then unit i is a must-off unit at hour j.

Based on minimum up/down time and full load average production cost a generator schedule is arrived. The economic dispatch is simultaneously solved via a quadratic programming routine. The production cost of each unit at each hour is calculated based on its membership value.

Figure 2 shows the flow chart of the proposed NBF algorithm.

The major steps of the algorithm are summarized as follows.

1. Input the load and generator data
2. Identify fuzzy input and output variables.
3. Trained Neural Network generates a pre-schedule.
4. All the uncertain state in the pre-schedule is made certain state.
5. Generate units schedule.
6. Conduct economic dispatch
7. Defuzzify the output variable (Production cost) from its membership value.

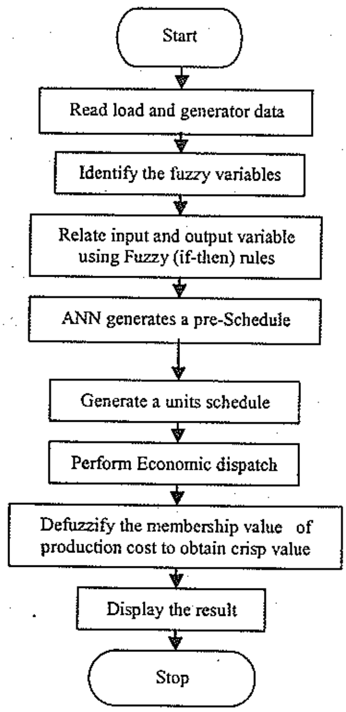

Figure 2 Neuro-Fuzzy Programming algorithm

6. Numerical Results

A total of 25 training patterns are used in this study which is generated by the Lagrangian relaxation method. The training of each load pattern takes approximately two to three minutes. To minimise the dimensions of ANN, the base units with high minimum up/down time units are not included in the output layer because their schedules are already determined. Figure 3 shows that the proposed ANN takes 380 epochs to make the sum squared error to zero during training.

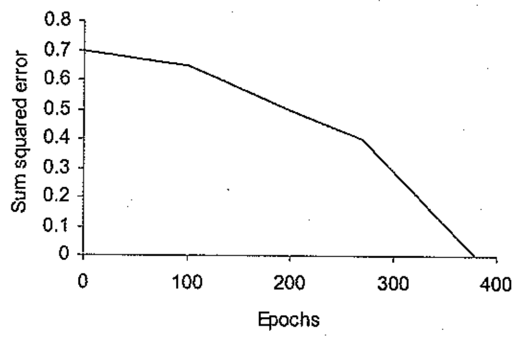

Figure 3 Sum squared error and epochs required

6.1 Case Study

A NTPS in India with seven generating units has been considered as case study. A time period of 24 hours is considered and the UC problem is solved for these seven units and also compared with 10, 20 and 26 generating unit power systems. The cost coefficient and maximum real power generation of each unit of NTPS are given in Table 1 and load demand for 24 hours is given in Table 2.

The UC schedule generated by the proposed ANN is supplied as input to the Fuzzy programming approach, which calculates the cost of real power generation. Using production cost as the output variable, and the load capacity of generator, incremental fuel cost and start-up cost as input variables, the fuzzy sets describing LCG, IC, SUC, and PRC are illustrated in

Table 1 Cost coefficient of NTPS 7 unit system

Unit	P_{min} (MW)	P_{max} (MW)	Running cost			Start-up cost			Min. up time (S)	Min. down time (S)
			c_i Rs	b_i Rs/Wh	a_i Rs/Wh^2	So_i Rs	D_i Rs	E_i Rs		
1	15	60	750	70	0.255	4250	29.5	10	3	3
2	20	80	1250	75	0.198	5050	29.5	10	3	3
3	30	100	2000	70	0.198	5700	28.5	10	3	3
4	25	120	1600	70	0.191	4700	32.5	9	3	3
5	50	150	1450	75	0.106	5650	32	9	5	5
6	50	150	4950	65	0.0675	14100	37.5	4.5	5	5
7	75	200	4100	60	0.074	11350	32	5.5	6	6

Table 2 Load hour data for 24 hour

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	840	5	770	9	770	13	545	17	449	21	460
2	757	6	778	10	764	14	538	18	439	22	434
3	775	7	757	11	598	15	535	19	466	23	530
4	773	8	778	12	595	16	466	20	463	24	840

figures 4, 5, 6 and 7. It is to be noted that the ranges of each subset are chosen in a subjective manner. For example, if the load range that can be served by the largest generator is between 0-200 MW, then high LCG could be chosen within a range of 170-200 MW. This allows a relative comparison of the linguistic definitions with the numerical values. Similarly, the subsets for other variables can be linguistically defined.

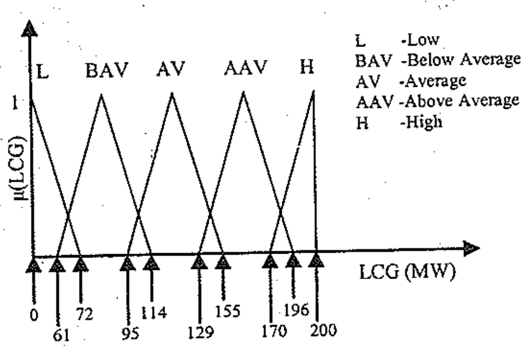

Figure 4 Assigned membership function of load capacity of generator

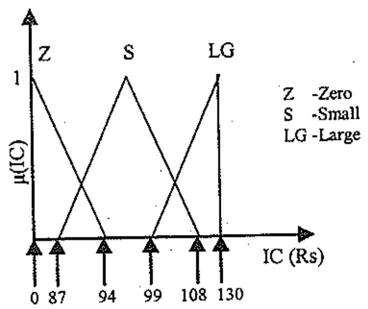

Figure 5 Assigned membership function of Incremental fuel cost

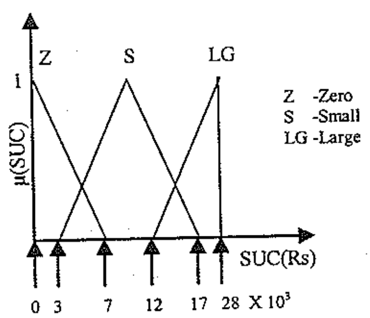

Figure 6 Assigned membership function of start-up cost

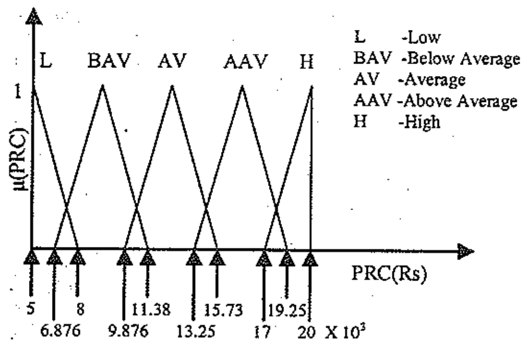

Figure 7 Assigned membership function of Production cost

Calculations are shown below for one period in which all seven units are on line and supplying a total load of 840 MW (Period 1 in Table 3). These units are committed according to their incremental fuel costs from lowest to highest. The production cost for unit 1 which supplies 60 MW is arrived at using rules 1 and 2.

Rule 1:

If Load capacity of generator is low and
Incremental fuel cost is small and
Start up cost is low,
then Production cost is low.

$\mu(PRC) = Min[\mu(LCG), \mu(IC), \mu(SUC)]$

$\mu(PRC) = Min[0.6,0.5,1]$ '! 0.5

Rule 2:

If Load capacity of generator is low and
Incremental fuel cost is large and
Start up cost is low,
then Production cost is low.

$\mu(PRC) = Min[\mu(LCG), \mu(IC), \mu(SUC)]$

$\mu(PRC) = Min[0.6,0.2,1]$ '! 0.2

Since the output of the above rule is in the low region of the Production Cost, these output values are combined using the max operation

$\mu(PRC) = Max[0.5,0.2]$ '! 0.5

The next step is to defuzzify the fuzzy output by the centroid method using Equation (7). Therefore, the crisp value of the production cost of unit 1 is calculated as follows:

$$PRC = \frac{0.5(5000+6100+7200)}{(3*0.5)}$$
$$= Rs.6100$$

The same method is used to find the production cost of other units. From the above procedure, the total cost for period one can be calculated as

Total Cost = 6100+9130+9820+10500
+15300+15400+18800
= Rs. 85050

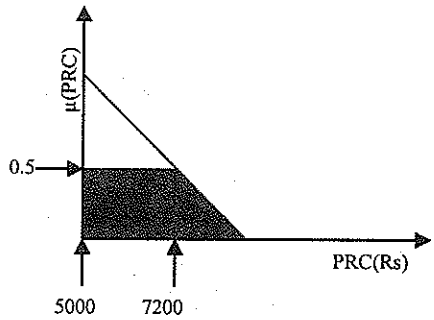

Figure 8 Crisp value of production cost of unit 1

A graphical representation of the above defuzzification is depicted in figure 8. A PC-based code was developed to compute the values of the output using MATLAB. It calculates the crisp values of outputs for given inputs. The complete set of results of this approach for a given load pattern is shown in Table 3. In Table 3, zero indicates that the unit is off and real power generation shows that the unit is on. A comparison of results shown in Table 4 indicates that the NBF outcomes are comparable to those of conventional methods like dynamic programming and lagrangian relaxation. The dynamic programming and lagrangian relaxation have been implemented using C language and Neural Network method has been implemented in MATLAB for comparison.

The CPU times shown in table 4 of NBF, DP and LR are obtained from a Pentium IV, 2.9GHz and 256 MB RAM personal computer. However the CPU times of NBF are smaller than those of other methods. Moreover the CPU time of NBF increases linearly with system size which is favorable for large scale implementation.

Table 3 Generator schedule and power generation of Neyveli Thermal Power Station 7 unit system

Hour	Load (MW)	Generation of units (MW)						
		1	2	3	4	5	6	7
1	840	60	80	98.2	101.8	150	150	200
2	757	60	0	96.73	100.27	150	150	200
3	775	60	0	100	115	150	150	200
4	773	60	0	100	113	150	150	200
5	770	60	0	100	110	150	150	200
6	778	60	0	100	118	150	150	200
7	757	60	0	96.73	100.27	150	150	200
8	778	60	0	100	118	150	150	200
9	770	60	0	100	110	150	150	200
10	764	60	0	100	104	150	150	200
11	598	0	0	0	98	150	150	200
12	595	0	0	0	95.86	149.14	150	200
13	545	46.11	0	0	61.56	87.33	150	200
14	538	44.63	0	0	59.59	83.78	150	200
15	535	44.00	0	0	58.74	82.26	150	200
16	466	0	0	0	116	150	0	200
17	449	0	0	0	99	150	0	200
18	439	0	0	0	93.72	145.28	0	200
19	466	0	0	0	116	150	0	200
20	463	0	0	0	113	150	0	200
21	460	0	0	0	110	150	0	200
22	434	0	0	0	91.93	142.07	0	200
23	530	60	0	0	120	150	0	200
24	840	60	80	98.2	101.8	150	150	200

Total operating cost Rs. 15,63,830

Table 4 Comparison of cost and CPU time

System	Methods	Total Cost PU	CPU time (Sec)
NTPS 7 units	DP	1	180
	NN	0.98089	20
	LR	0.97913	169
	NBF	0.97837	5
10 Units	DP	1	246
	NN	0.96521	27
	LR	0.94430	230
	NBF	0.94301	8
20 Units	DP	1	502
	NN	0.97531	32
	LR	095484	485
	NBF	0.94357	11
26 Units	DP	1	1849
	NN	0.98437	43
	LR	0.95724	1838
	NBF	0.94132	17

Conclusion

A new technique using Neuro Fuzzy programming has been developed for UC of a power system. As the size of the system grows and more complicated constraints are imposed, it is often insufficient to rely on human intuition to achieve the optimal solution. Hence more rigorous programming like NBF is implemented for solving the UC problem. The existing methods such DP and LR provide effective alternative for evaluating commitment plans. However, they demand a vast amount of calculating power.

The redundancy involved in the mathematical programming is effectively avoided and depending on the similarity between the given load profile and its matched set inside the Neural Network, various saving in execution time can be achieved.

The developed algorithm is applied to the UCP of NTPS in India and 10, 20 and 26 unit systems. Results from the present study reveal that the proposed NBF is very effective in reaching an optimal commitment schedule. It is demonstrated by the case study that the hybrid algorithm preserves the optimization accuracy by the Lagrangian Relaxation procedure and overcomes unnecessary calculations for similar load profiles. Accordingly, NBF is suitable for UC due to the substantial production cost saving and fast computing time.

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Author's Biography

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