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ScienceDirect
Neurocomputing 70 (2006) 119–129
NEUROCOMPUTING
www.elsevier.com/locate/neucom

Neural computation using discrete and continuous Hopfield networks for power system economic dispatch and unit commitment

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Received 11 March 2005; received in revised form 13 October 2005; accepted 4 May 2006
Communicated by A. Zobaa
Available online 2 August 2006

Abstract

A new method using artificial neural networks for the solution of the unit commitment (UC) and economic dispatch (ED) using Hopfield neural network (HNN) is presented. Discrete and Continuous Hopfield Networks have been used earlier to solve UC and ED problems separately. But these two problems are completely interdependent. Due to their inseparable nature, both the problems must be solved simultaneously. The difficulty in combining these problems is that while the first one requires a discrete neuron model, the latter requires a continuous neuron model. The combined solution of these problems using HNN requires the interconnection of discrete and continuous neural network models and the formulation of a unified energy function, which is quite complicated. The important contribution of this work is the proposal of a new architecture for the discrete HNN for UC and the output of the UC module is used as input to the continuous HNN for ED. The associated advantage of using HNN for the combined solution of UC and ED is the decoupling of their interdependency, i.e., both the UC and ED are iteratively solved using respective HNN for the particular period. The implementation of the proposed method causes a considerable reduction in the HNN size and hence complexity and computation requirements, compared to earlier attempts. The method was successfully tested for different cases (3, 5, 6, 10 and 26 generator units), with varying load pattern of different durations (24 and 168 h) on Matlab on P-IV machine in windows enviroment. Each case study is done with an aim to bring out the important features of the proposed method. The results for the case studies are presented and important observations are discussed.

Keywords: Economic dispatch; Unit commitment; Hopfield neural networks; Discrete and continuous; Optimisation; Constraint satisfaction

1. Introduction

Operation scheduling in the electric power industry concerns operations scheduling of a utility's generating facilities. Usually in a power system, a variety of power plants like thermal, hydel, and nuclear units are connected to the grid to meet the load demand. These are switched ON and OFF to satisfy the generation load balance with reserve. Determination of the unit status of a plant for a particular load, so that the cost of operation is minimum, is defined as the problem of unit commitment (UC). Even after the commitment decision is made, one has to decide on the amount of generation of each unit, so that the fuel cost is minimum, without violating the unit's generation limits. This is called economic dispatch (ED). The main aim of ED is to minimise the total cost of generating real power in the plant while satisfying the load and spinning reserve [14]. The economic consequences of operations scheduling are very important. Since fuel cost is a major cost component, reducing the fuel cost by as little as 0.5% can result in savings of large amount of money per year for large utilities [1]. Since in the case of both ED and UC problems, it is attempted to minimise the operational cost of the power system such that the system operates in a most economical manner, these problems come under the class of constrained optimisation problems [1].

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doi:10.1016/j.neucom.2006.05.002

2. Artificial neural networks (ANN) for optimisation

Neural networks are composed of many massively connected neurons [3,4]. With their structures resembling more or less their biological counterparts, ANN are representational and computational models composed of interconnected simple processing elements called *artificial neurons*. In processing information, the processing elements in an ANN operate concurrently and collectively in a parallel and distributed fashion. Neural networks have very close ties with optimisation, and the ties are manifested mainly in two aspects. On one hand, many learning algorithms have been developed based on optimisation techniques to train neural networks to perform numerous modeling tasks. The popular back-propagation algorithm is based on gradient-descent method. On the other hand, neural networks have been developed for solving various optimisation problems [2]. Though a variety of ANN models are available, here Hopfield neural network (HNN) is being used for solving ED and UC problems.

2.1. HNN

HNN is a type of recurrent network that operates in an unsupervised manner. The HNNs have three major forms of parallel organisations found in neural systems, namely (i) parallel input channels, (ii) parallel output channels, and (iii) a large amount of interconnectivity between the neural processing elements. The architecture of HNN is as shown in Fig. 1.

The processing elements are modeled as amplifiers in conjunction with feedback circuits [17]. The amplifiers have sigmoidal monotonic input–output relations. For these symmetrically connected neurons, an energy function can be defined which is specific to a particular connection. The action of HNN is to minimize this energy function. If the cost function or performance index of an optimisation problem can be mapped on to this energy function, then the network will converge to an optimal solution. Basically there are two types of HNN—(i) the discrete type, and (ii) the continuous type, which are discussed below.

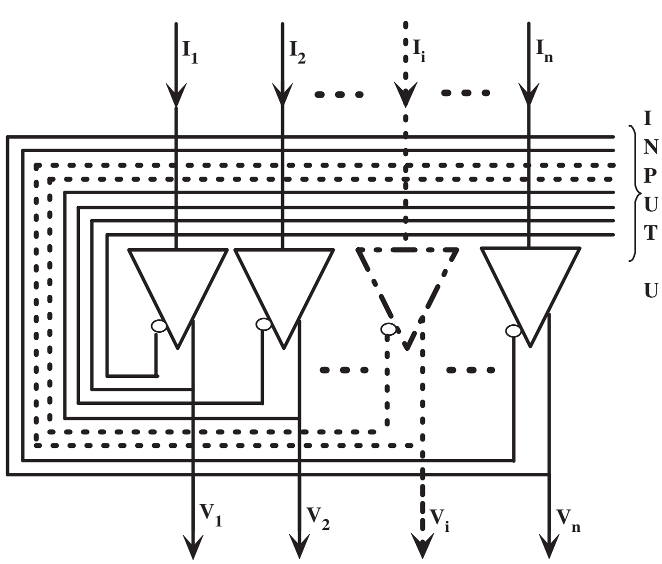

Fig. 1. Architecture of Hopfield neural network for optimisation.

2.1.1. Discrete HNN

The discrete HNN is a two-state (0,1) threshold *neuron*, which follows a stochastic algorithm [4],

$$U_i = \sum_j T_{i,j} V_j + I_i, \tag{1}$$

where each neuron i has two states, $V_i = 1$ and $V_i = 0$.The input of each neuron comes from two sources, external inputs I_i and inputs from other neurons V_j. The total input to the neuron i is given by

$$V_i = g_\mathrm{d}(U_i) = 0 \quad \text{if } U_i < 0. \tag{2}$$

The output of neuron i is given by

$$V_i = g_\mathrm{d}(U_i) = 1 \quad \text{if } U_i > 0. \tag{3}$$

The energy function of the discrete HNN is defined as

$$E = -\left(\frac{1}{2}\right) \sum_i \sum_j T_{i,j} V_i V_j - \sum_i I_i V_i. \tag{4}$$

The change ΔE in E due to change in the state of neuron i by ΔV_i is given as

$$\Delta E = -\left[\sum_j T_{i,j} V_j + I_i\right] \Delta V_i, \tag{5}$$

where U_i is the total input to neuron i, $T_{i,j}$ the synaptic interconnection strength from neuron j to neuron i, I_i the external input to neuron i, V_j the output of neuron j, $g_\mathrm{d}(U_i)$ the discrete transfer function as given in Eqs. (2) and (3), and ΔV_i the change in output of neuron i.

As can be seen ΔE is always negative. This means that a state change always leads to a decrease in energy. The modification of element activation continues till a stable state is reached, i.e., a minimum energy is reached. The transfer function $g_\mathrm{d}(U_i)$ for discrete HNN is as shown in Fig. 2.

2.1.2. Continuous Hopfield Neural Network

In the continuous model the output variable V_i for neuron i has the range $V_i^0 \leqslant V_i \leqslant V_i^1$ and the input output function is a continuous and monotonically increasing

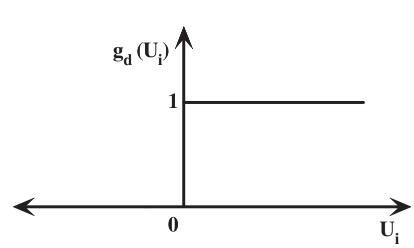

Fig. 2. Transfer function of discrete neurons.

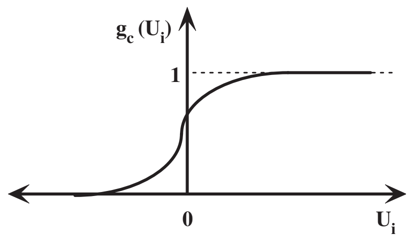

Fig. 3. Transfer function of continuous neurons.

function of the input U_i to the neuron i [2]. The typical input—output function $g_c(U_i)$ is a sigmoidal function as shown in Fig. 3.

The dynamics of the neuron is defined by

$$\mathrm{d}U_i/\mathrm{d}t = \sum_j T_{i,j} * V_j + I_i, \tag{6}$$

where output of neuron i is given by

$$V_i = g_c(U_i), \tag{7}$$

and

$$g_c(U_i) = 1/(1 + \exp(-U_i/u_0)). \tag{8}$$

Energy function of continuous HNN is defined as

$$E = -(1/2)\sum_i \sum_j T_{i,j} V_i V_j - \sum_i I_i V_i, \tag{9}$$

and

$$\mathrm{d}E/\mathrm{d}t = -\sum_i g_c'(U_i)(\mathrm{d}U_i/\mathrm{d}t)^2, \tag{10}$$

where $g_c(U_i)$ is the input–output function of neuron i, and u_0 a coefficient that determines the shape of the sigmoidal function. $\mathrm{d}E/\mathrm{d}t$ is always negative. As a result, the solution always seeks out a minimum of E and reaches the minimum-energy point.

3. ANN for UC

It has been recognised [17] that UC problem cannot be tackled accurately within the framework of conventional Hopfield network. This is due to the fact that both discrete and continuous terms must be considered to fully model the problem [12]. However with proper approximations, discrete HNN can be used to solve UC problem separately without taking ED into account. In this section, method of solving UC without doing ED is explained in detail. The UC schedule consists of only ones and zeroes, depending on whether the unit is ON or OFF. The output variable V_{ij}, giving the status of the ith generator in jth period, takes only values 1 or 0. As a result, this problem can be mapped on to a discrete HNN [10].

The following are the assumptions made in formulating the UC problem:

(1) power demand during each period is constant and is specified.
(2) transmission losses are neglected.
(3) spinning reserve is specified.

3.1. Mapping of the problem

The most important step in solving any optimisation problem using HNN is the mapping of the problem objectives and constraints onto the energy function of the network. The unit commitment problem consists of minimising the sum of the fuel cost and start-up cost [9]. In mapping the unit commitment on to neural network, it is assumed that the fuel cost of the generator can be expressed as a linear function of power generation. Here the fuel cost is taken as the average of maximum and minimum fuel cost, which is a constant. Start-up cost can either be an exponential function of the down time of the unit or a constant value and it is dependent on the status of the unit in the present and previous periods.

3.2. Objective function

The objective is to minimise the total cost, which is the sum of fuel cost and start-up cost given by

$$TC = \sum\sum(FC_i V_{i,j} + SC_i V_{i,j}(1 - V_{i,j-1})). \tag{11}$$

The energy function of the discrete HNN is given by

$$E = \sum_i \sum_j T_{i,j} V_i V_j - \sum_i I_i V_i. \tag{12}$$

Mapping Eqs. (11) and (12) would result in

$$I_i = -FC_i - SC_i(1 - V_{i,j-1}). \tag{13}$$

Since FC_i is assumed to be constant and $V_{i,j-1}$, the status of the unit in the previous hour is known, the weight coefficient corresponding to Eq. (12) is zero, i.e., $T_{ij} = 0$ for all i,j, or there is no feed back between neurons. This network is called '*variable network*' and has the number of neurons equal to the number of generators.

3.3. Constraints

The constraints are taken into account by using '*constraint networks*'. The output of the neurons is 0 if the constraint is satisfied and 1 if it is not satisfied. This is also implemented by discrete neurons.

Constraints used for mapping are:

(1) Power balance and reserve margin (constraints 1 and 2)
Constraint 1:

$$\sum_{i=1}^{N} \min P_i V_{i,j} - (PL_j + R_j) \leqslant 0. \tag{14}$$

Constraint 2:

$$\sum_{i=1}^{N} \max P_i V_{i,j} - (PL_j + R_j) \geqslant 0. \tag{15}$$

All the inequality constraints should be first changed into the form $h(V)\geqslant 0$, so that they are constrained from their lower limits. Then the coefficients of the constraints are directly used as the weights of the connections. Converting (14) into $h(V)\geqslant 0$ form,

$$-\sum_{i=1}^{N} \min P_i V_{i,j} + (PL_j + R_j) \geqslant 0. \tag{16}$$

Weights from variable network to constraint-1 network obtained on comparing Eqs. (16) and (1) is

$$W_{VC1i} = -\min P_i. \tag{17}$$

Weights from constraint-1 network to variable network is a modified form of Eq. (17), since the inputs to the variable network are in the normalised form and has to be incremented in small steps.

$$W_{C1Vi} = -K1\, n \min P_i, \quad 0 < K1 < 1, \tag{18}$$

where $n \min P_i$ is the normalised value of $\min P_i$ given by

$$n\,min\,P_i = \frac{\min P_i}{\max(\min P_i)}. \tag{19}$$

The bias current of the constraint-1 neuron, obtained from Eq. (16) is

$$I_{C1i} = PL_j + R_j. \tag{20}$$

Similarly for constraint-2,

$$W_{VC2i} = -\max P_i, \tag{21}$$

$$W_{C2Vi} = -K2\, PAV_i, \quad 0 < K2 < 1, \tag{22}$$

where PAV_i is given by

$$PAV_i = (\max P_i + \min P_i)/2, \tag{23}$$

$$I_{C2i} = -(PL_j + R_j). \tag{24}$$

The network consists of two neurons, one for constraint 1 and one for constraint 2.
Minimum up time and down time (Constraints 3 and 4).
Constraint 3:

$$T_i^{\mathrm{ON}} - MUT_i(V_{i,j-1} - V_{i,j}) > 0. \tag{25}$$

This equation is valid only when the unit status changes from 1 to 0.
Constraint 4:

$$T_i^{\mathrm{OFF}} - MDT_i(V_{i,j} - V_{i,j-1}) > 0. \tag{26}$$

This equation is valid only when the unit status changes from 0 to 1.
Weights from variable network to constraint-3 network obtained from Eq. (25) is

$$W_{VC3(i,k)} = MUT_i \quad \text{for } i = k, \tag{27}$$

$$W_{VC3(i,k)} = 0 \quad \text{for } i \neq k. \tag{28}$$

Weights from constraint-3 network to variable network is

$$W_{C3V(i,k)} = 2[ID], \tag{29}$$

where ID is the identity matrix of order N. W_{C3V} is chosen such that unit remains ON when MUT constraint is violated.
Biasing current of constraint-3 network is

$$I_{C3i} = T_i^{\mathrm{ON}} - MUT_i V_{i,j-1}. \tag{30}$$

Similarly for constraint-4 weights and bias current obtained from Eq. (26) is

$$W_{VC4(i,k)} = MDT_i \quad \text{for } i = k, \tag{31}$$

$$W_{VC4(i,k)} = 0 \quad \text{for } i \neq k, \tag{32}$$

$$W_{C4V(i,k)} = -2[ID], \tag{33}$$

$$I_{C4i} = T_i^{\mathrm{OFF}} + MDT_i V_{i,j-1}. \tag{34}$$

Both constraint-3 and 4 networks have N neurons each.
Switching OFF of excess units (Constraint 5).
Constraint 5:

$$-\sum_{i=1}^{N} \max P_i + PL_j + M \geqslant 0. \tag{35}$$

This constraint ensures that no excess number of units is turned ON. Here M is the minimum of the maximum limits among the units, which are ON.
Weights from variable network to constraint-5 network obtained from Eq. (35) is

$$W_{VC5i} = -\max P_i. \tag{36}$$

Weights from constraint-5 network to variable network is

$$W_{C5Vi} = -2, \tag{37}$$

if i correspond to the unit with minimum of maximum limits, else

$$W_{C5Vi} = 0. \tag{38}$$

The bias current of the constraint-5 neuron is

$$I_{C5i} = (PL_j + M). \tag{39}$$

4. Proposed architecture

The architecture proposed for solving UC problem is given in Fig. 4 can be divided into two blocks—the objective function block and the constraint block. The neurons in objective function block are called 'variable neurons'. The input to the 'variable neurons' is the 'biasing currents' and weighted feedback from constraint blocks. The constraint block can be further divided into smaller blocks consisting of 'constraint neurons'. Each of these sub–block handles one constraint of the problem under consideration. The input to the constraint neurons is weighted output of the variable-neurons and biasing currents. Firstly the network is initialised with biasing currents and some value is assumed for the variable-neuron output. With this output the constraint satisfaction is checked. Depending on the weight attached, there will be a feedback to the variable neurons. With this new set of input to the variable neuron, the updated output is found. This process is repeated till all the constraints are satisfied, at which instant all the feedback from constraint block becomes zero. The advantage of the formulation is that several constraints can be handled along with the objective function. Furthermore, multi-objective optimisation can also be included.

5. ANN for ED

ED is one of the most important optimisation problems in power system operation. The ED decision involves the allocation of the system demand and spinning reserve capacity among the operating units during each hour of operation [7]. The allocation has to be done in such a way as to minimise the total cost while meeting all the constraints [1,14]. It is proposed to use continuous HNN for solving ED. The complete solution is obtained when the discrete HNN for the UC is integrated with this network as is proposed in this paper.

In this paper continuous HNN is used for solving the economic dispatch problem. This is because the neuron output, which gives the generation schedule, is a continuous value, which varies between minimum and maximum generation limit of the units. The assumptions made here are:

(1) the cost function of the generator can be represented by a single quadratic function,
(2) the generation units are supplied with single type of fuel,
(3) ED is done on an hourly basis.

5.1. Mapping of the problem

The objective function is to minimise the total operating cost of the unit in a plant. The cost function of a generator is given as

$$FC_i = \sum_i (a_i + b_i P_i + c_i P_i^2). \tag{40}$$

Objective function is

$$\min\, FC_i = \min \sum_i (a_i + b_i P_i + c_i P_i^2), \tag{41}$$

which has to be minimised. This is done subjected to the power balance constraint and the generator limits. These constraints are given by the following equations:

$$\sum_{i=1}^{N} P_i = D \tag{42}$$

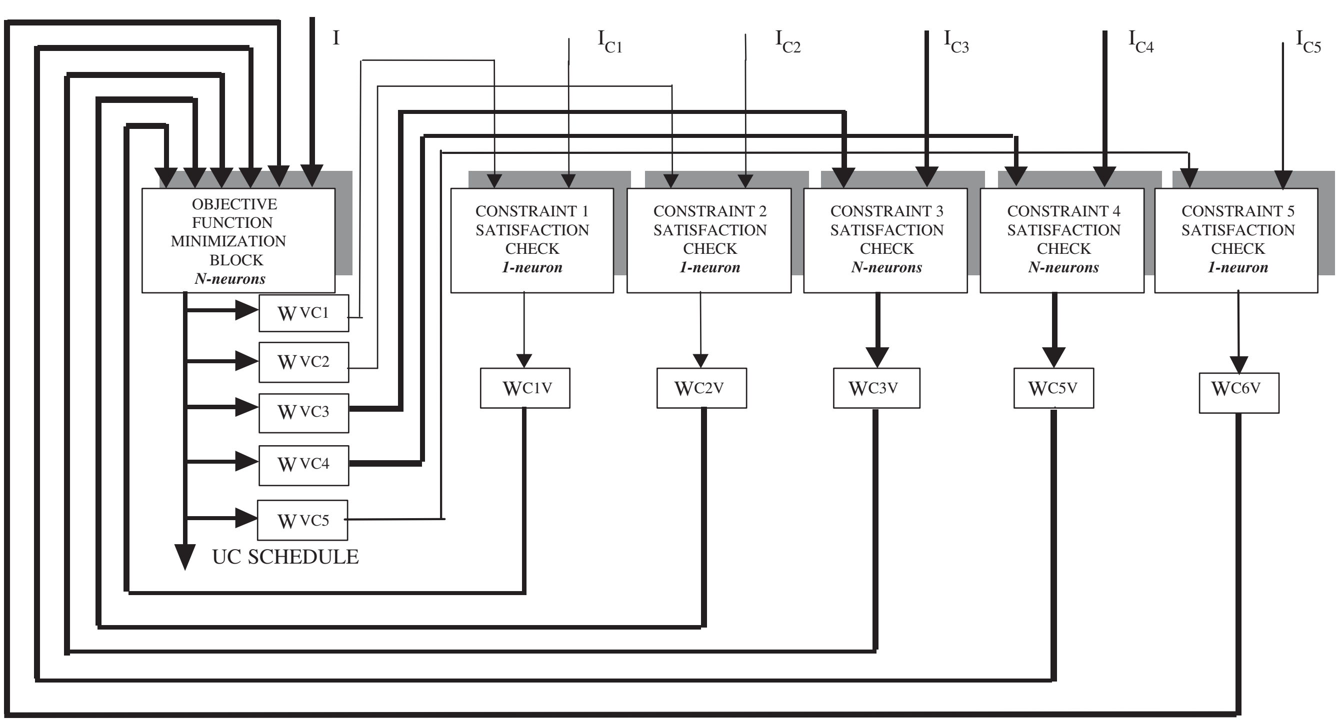

Fig. 4. Proposed architecture for UC.

$$\min P_i \leqslant P_i \leqslant \max P_i. \tag{43}$$

The power balance constraint is an equality constraint. The equality constraints are handled in optimisation problems using HNN by making it a part of the objective function. So in effect, the objective function for economic dispatch problem has two parts—(i) the fuel cost minimisation part, and (ii) the generation error minimisation part. The second constraint, i.e., generator limit constraint, is an inequality constraint. This constraint is taken into account by changing the continuous HNN transfer function [3–5] given in Eq. given in (44) to the form given in Eq. (45).

$$g_c(U_i) = 1/(1+\exp(-U_i/u_0)), \tag{44}$$

$$g_c(U_i) = \left[(\max P_i - \min P_i)/(1+\exp(-U_i/u_0))\right] + \min P_i. \tag{45}$$

5.1.1. Objective function

In order to solve the ED problem the following energy function is defined by combining the objective function Eq. (41) with constraint Eq. (42) by means of weight coefficients, which determines the weight given to each factor [2]:

$$E = (A/2)\left(D - \sum_i P_i\right)^2 + (B/2)\sum_i (a_i + b_i P_i + c_i P_i^2). \tag{46}$$

Here $A(\geqslant 0)$ and $B(\geqslant 0)$ are weighting factors. The energy function of HNN is

$$E = -(1/2)\sum_i \sum_j T_{i,j} V_i V_j - \sum_i I_i V_i. \tag{47}$$

Mapping Eq. (46) onto (47) would result in

$$T_{i,i} = -A - Bc_i, \tag{48}$$

$$T_{i,j} = -A, \tag{49}$$

$$I_{ED_i} = AD - Bb_i, \tag{50}$$

if the unit i is ON, else,

$$I_{ED_i} = 0. \tag{51}$$

5.1.2. Adaptive calculation of A and B

In the general Hopfield model for optimisation, the coefficients A and B are assigned a fixed value in the initial stage corresponding to each load power demand. These values are valid only for that particular load demand. In the case of a change in the load demand, these coefficients have to be computed such that

(1) the equality constraint relation is satisfied and
(2) the objective function is minimised.

In order to achieve these objectives, a method to vary the coefficients A and B is proposed in such a way that the coefficients adapt dynamically to varying load demand [11]. In the implementation aspect initial values are chosen for A and B. The relations given below then update these values.where

$$A = [IM + 0.5Bb_m]/P_G, \tag{52}$$

$$B = -[IM - AD]/[0.5b_m], \tag{53}$$

$$IM = (1/S)\sum_i I_{ED_i}, \tag{54}$$

$$b_m = (1/S)\sum_i b_m, \tag{55}$$

and

$$P_G = \sum_i P_i. \tag{56}$$

S denotes the number of units which are ON.

6. Proposed architecture

The architecture for the proposed scheme to solve ED is shown in Fig. 5. The main block is the objective function minimisation block, which consists of N neurons. The input to this block is the updated weights and biasing currents. The biasing currents are calculated from the power system data and UC schedule. The weight updating is done with the new values of A and B, which are calculated using adaptive relations.

In earlier efforts at solving ED using HNN, the weight coefficients A and B are calculated by trial and error each time the load changes. In the proposed method an adaptive calculation method is employed to the coefficients A and B. The solution to the problem is complete when ED is done among the units, which are committed. This is obtained by interconnecting the two networks, i.e., the one for Unit

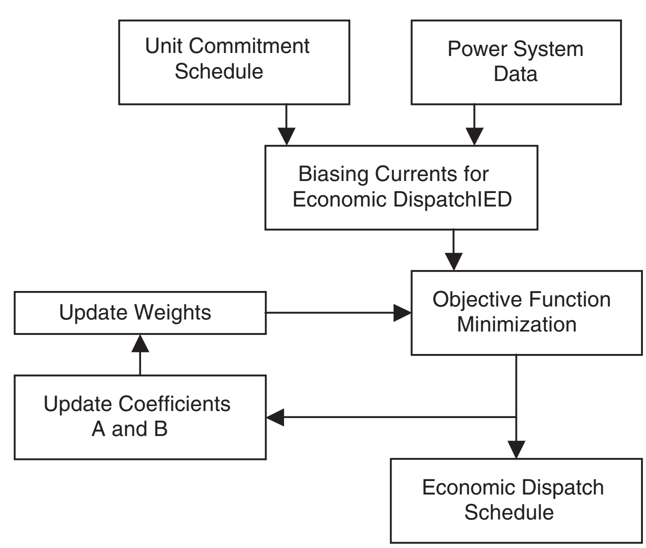

Fig. 5. Proposed architecture for ED.

Commitment and the one for ED. The inputs for this combined network are the power system data and forecasted load data for the entire period considered, on an hourly basis.

7. Proposed integrated architecture

The proposed architecture incorporating ED to UC is as shown in the Fig. 6. The architecture has two main parts–the UC part and the ED part. Given the input, the first network provides the UC schedule, for the hour under consideration, as the output, which is given as weighted input for ED. The output of the second network gives the generation schedule corresponding to the unit schedule for that particular hour.

This process is repeated for the entire duration under consideration. Given the input (system data and load demand), the first network provides the UC schedule, for the hour under consideration, as the output, which is given as weighted input for ED Block. The output of the second network gives the generation schedule corresponding to the unit schedule for that particular hour. This process is repeated for the entire duration under consideration. The details of each block in Fig. 4 are as follows: The UC block has a main block and a sub-block. The main block is the optimisation unit, which is made up of discrete Hopfield neurons. The sub-block, also made of discrete neurons, is the feedback loop that ensures that none of the constraints are violated. The output of this part is given as input to the ED unit. Here also there is a main block for optimisation and a sub-block for ensuring constraint satisfaction, both made of continuous Hopfield Neurons.

8. Implementation

The proposed method was tested for various test systems like 3, 10, 26 unit systems for 24 h load patterns and a 11-unit system for a 168 h load pattern. The program was developed in Matlab on P-IV machine in windows environment. The inputs required are the quadratic fuel cost coefficients of each unit, the minimum and maximum generation limit of each unit and the load pattern. The output from the proposed architecture is the unit commitment and ED schedules. The applicability of the method can be easily scaled up for large-scale systems [6,15].

The flow chart of the proposed algorithm is given in Fig. 7. Each period (hour) the UC schedule is first obtained by the UC Module, which consists of a main module and feedback loop. The ED Module, which is also made up of a main module and feedback loop, dispatches the load between the committed units in an economic fashion. This is repeated for every hour taking into consideration the minimum up time and minimum down time constraints.

8.1. 3-generator unit 24 h period

The UC and ED schedule for a 3-unit system for 24-h load pattern is given in the Table 1.

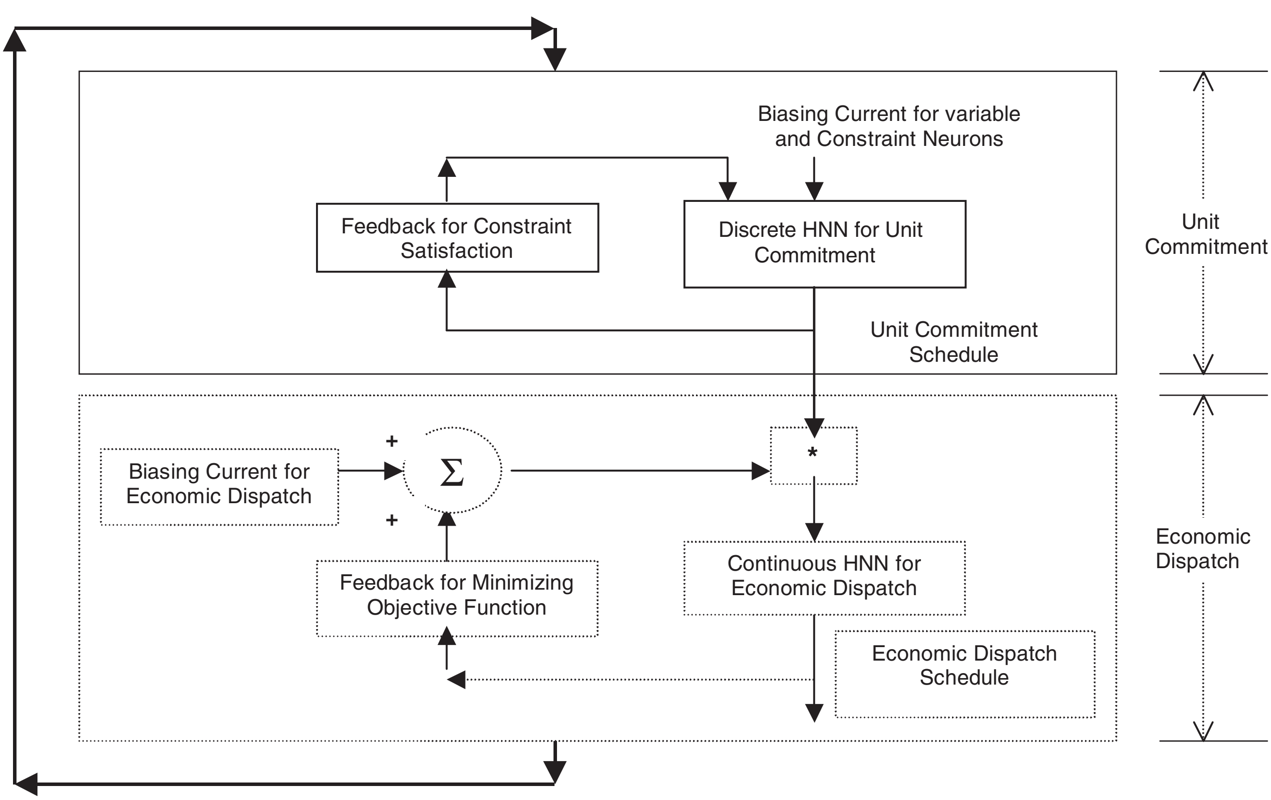

Fig. 6. Proposed architecture for ED and UC.

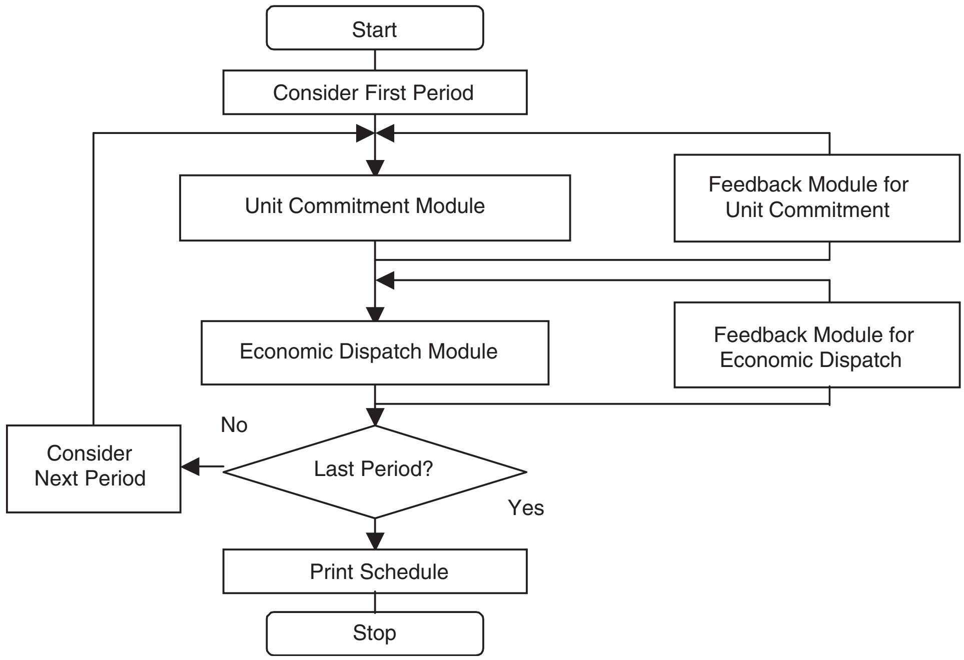

Fig. 7. Flow chart of the proposed scheme.

Table 1
UC and ED Schedule for **3**-generator unit 24-h period

Hour	UC schedule	Individual generation			Total generation (MW)	Load (MW)	Hourly FC ($)	Total FC ($)
		P1	P2	P3				
1	1 1 1	599.94	399.96	199.98	1199.88	1200	11,872.12	11,872.12
2	1 1 1	599.94	399.96	199.98	1199.88	1200	11,872.12	23,744.24
3	1 1 1	577.57	385.39	187.15	1150.11	1150	11,365.82	35,110.06
4	1 1 1	555.59	371.15	173.33	1100.07	1100	10,859.07	45,969.12
5	1 1 0	599.94	399.96	0	999.90	1000	9634.76	55,603.88
6	1 1 0	539.49	360.46	0	899.95	900	8680.04	64,283.92
7	1 1 0	479.04	320.89	0	799.93	800	7742.20	72,026.12
8	1 0 0	599.94	0	0	599.94	600	5874.73	77,900.86
9	1 0 0	549.95	0	0	549.95	550	5389.00	83,289.85
10	1 0 0	499.96	0	0	499.96	500	4911.15	88,201.01
11	1 0 0	499.97	0	0	499.97	500	4911.18	93,112.19
12	1 0 0	499.95	0	0	499.95	500	4911.06	98,023.25
13	1 0 0	499.96	0	0	499.96	500	4911.09	1,02,934.34
14	1 0 0	499.96	0	0	499.96	500	4911.14	1,07,845.47
15	1 0 0	599.94	0	0	599.94	600	5874.73	1,13,720.21
16	1 1 0	479.04	320.90	0	799.94	800	7742.26	1,21,462.47
17	1 1 0	509.32	340.75	0	850.06	850	8210.08	1,29,672.55
18	1 1 0	539.49	360.45	0	899.94	900	8679.95	1,38,352.50
19	1 1 0	569.85	380.24	0	950.09	950	9156.85	1,47,509.35
20	1 1 0	599.94	399.96	0	999.90	1000	9634.76	1,57,144.11
21	1 1 1	533.19	356.61	160.29	1050.09	1050	10,359.02	1,67,503.12
22	1 1 1	555.60	371.16	173.33	1100.09	1100	10,859.32	1,78,362.44
23	1 1 1	599.94	399.96	199.98	1199.88	1200	11,872.12	1,90,234.56
24	1 1 1	599.94	399.96	199.98	1199.88	1200	11,872.12	**2,02,106.68**

8.2. 10-generator unit 24 h period

Table 2 gives the UC schedule along with total generation and load in MW and hourly start up cost, total start up cost, hourly fuel cost and total fuel cost in $ for a 10-unit system.

Table 3 gives the ED schedule of the individual generation of all units in MW.

Table 2
UC schedule for 10-generator unit 24 h period

Hour	UC schedule										Total generation (MW)	Load (MW)	Hourly SC ($)	Total SC ($)	Hourly FC ($)	Total FC ($)
	1	2	3	4	5	6	7	8	9	10						
1	1	1	1	1	0	0	1	1	1	1	1517.12	1517	0	0	3325.38	3325.38
2	0	1	1	1	0	0	1	1	1	1	1426.10	1426	0	0	3131.65	6457.03
3	0	0	1	1	0	0	1	1	1	1	1368.12	1368	0	0	3012.27	9469.30
4	0	0	1	1	0	0	1	1	1	1	1328.11	1328	0	0	2914.77	12,384.06
5	0	0	1	1	0	0	1	1	1	1	1317.06	1317	0	0	2887.67	15,271.73
6	0	0	1	1	0	0	1	1	1	1	1351.09	1351	0	0	2970.79	18,242.53
7	0	0	1	1	0	0	1	1	1	1	1398.14	1398	0	0	3087.04	21,329.57
8	0	0	1	1	0	0	1	1	1	1	1351.11	1351	0	0	2970.87	24,300.44
9	0	0	1	1	0	0	1	1	1	1	1317.11	1317	0	0	2887.98	27,188.42
10	0	0	0	1	0	0	1	1	1	1	1293.12	1293	0	0	2859.91	30,048.33
11	0	0	0	1	0	0	1	1	1	1	1238.12	1238	0	0	2722.89	32,771.22
12	0	0	0	1	0	0	1	1	1	1	1226.07	1226	0	0	2693.15	35,464.36
13	0	0	0	1	0	0	1	1	1	1	1203.10	1203	0	0	2637.31	38,101.68
14	0	0	0	0	0	0	1	1	1	1	1180.11	1180	0	0	2622.69	40,724.37
15	0	0	0	0	0	0	1	1	1	1	1170.11	1170	0	0	2597.01	43,321.38
16	0	0	0	0	0	0	1	1	1	1	1136.11	1136	0	0	2510.37	45,831.75
17	0	0	0	0	0	0	1	1	1	1	1113.08	1113	0	0	2453.33	48,285.07
18	0	0	0	0	0	0	1	1	1	1	1079.07	1079	0	0	2369.69	50,654.76
19	0	0	0	0	0	0	1	0	1	1	1034.10	1034	0	0	2301.37	52,956.13
20	0	0	0	0	0	0	1	0	1	1	1022.10	1022	0	0	2269.07	55,225.20
21	0	0	0	0	0	0	1	0	1	1	1010.09	1010	0	0	2236.49	57,461.69
22	0	0	0	0	0	1	1	0	1	0	1058.09	1058	175.45	175.45	2411.82	59,873.50
23	0	0	0	0	1	1	1	0	1	0	1124.04	1124	159.80	335.25	2510.84	62,384.34
24	0	0	0	1	1	1	1	1	1	0	1517.14	1517	341.60	676.85	3421.05	**65,805.38**

Table 3
ED schedule for 10-generator unit 24 h period

Hour	Generation (MW)									
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	57.98	75.24	97.71	115.81	0	0	508.76	147.20	316.16	198.26
2	0	73.33	95.06	112.19	0	0	498.44	143.48	309.28	194.33
3	0	0	96.33	112.68	0	0	500.67	145.73	314.81	197.89
4	0	0	92.87	108.27	0	0	487.83	140.78	305.62	192.75
5	0	0	91.83	105.84	0	0	481.53	139.74	305.14	192.98
6	0	0	94.86	111.38	0	0	496.47	143.42	309.95	195.02
7	0	0	98.96	118.12	0	0	514.96	148.72	318.21	199.17
8	0	0	94.86	111.46	0	0	496.65	143.40	309.83	194.91
9	0	0	91.89	106.49	0	0	483.03	139.58	304.04	192.08
10	0	0	0	117.01	0	0	512.00	148.02	317.30	198.78
11	0	0	0	108.81	0	0	489.29	141.12	306.01	192.88
12	0	0	0	106.73	0	0	483.65	139.66	304.02	192.01
13	0	0	0	104.08	0	0	475.96	136.65	298.03	188.39
14	0	0	0	0	0	0	515.43	148.55	317.50	198.62
15	0	0	0	0	0	0	510.20	147.09	315.28	197.54
16	0	0	0	0	0	0	491.47	142.15	308.23	194.26
17	0	0	0	0	0	0	482.71	138.72	301.45	190.21
18	0	0	0	0	0	0	468.14	133.71	292.29	184.93
19	0	0	0	0	0	0	517.23	0	318.06	198.81
20	0	0	0	0	0	0	510.73	0	314.50	196.87
21	0	0	0	0	0	0	502.43	0	311.85	195.81
22	0	0	0	0	0	260.98	492.73	0	304.39	0
23	0	0	0	0	117.63	244.98	466.10	0	295.33	0
24	0	0	0	117.52	144.85	275.88	513.28	148.22	317.39	0

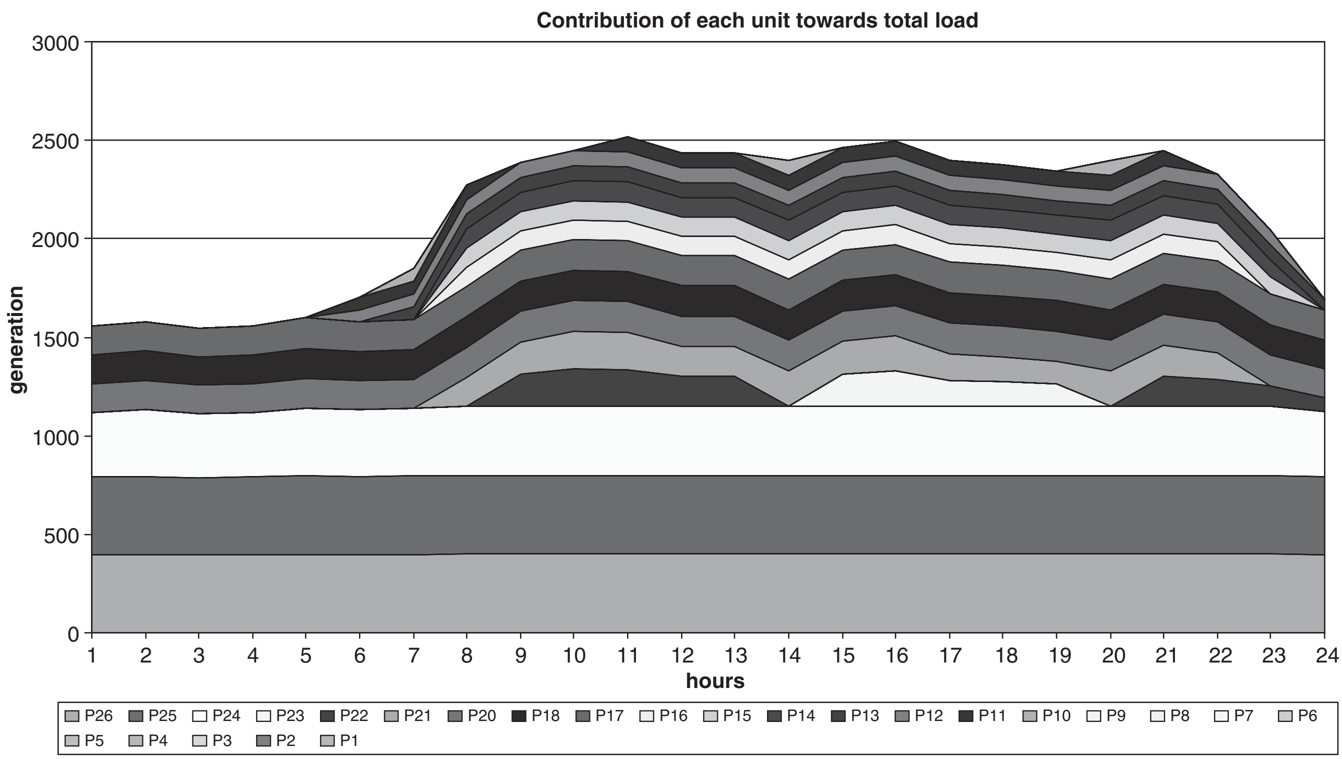

Fig. 8. Load distribution among units for 26-generator unit 24 h period.

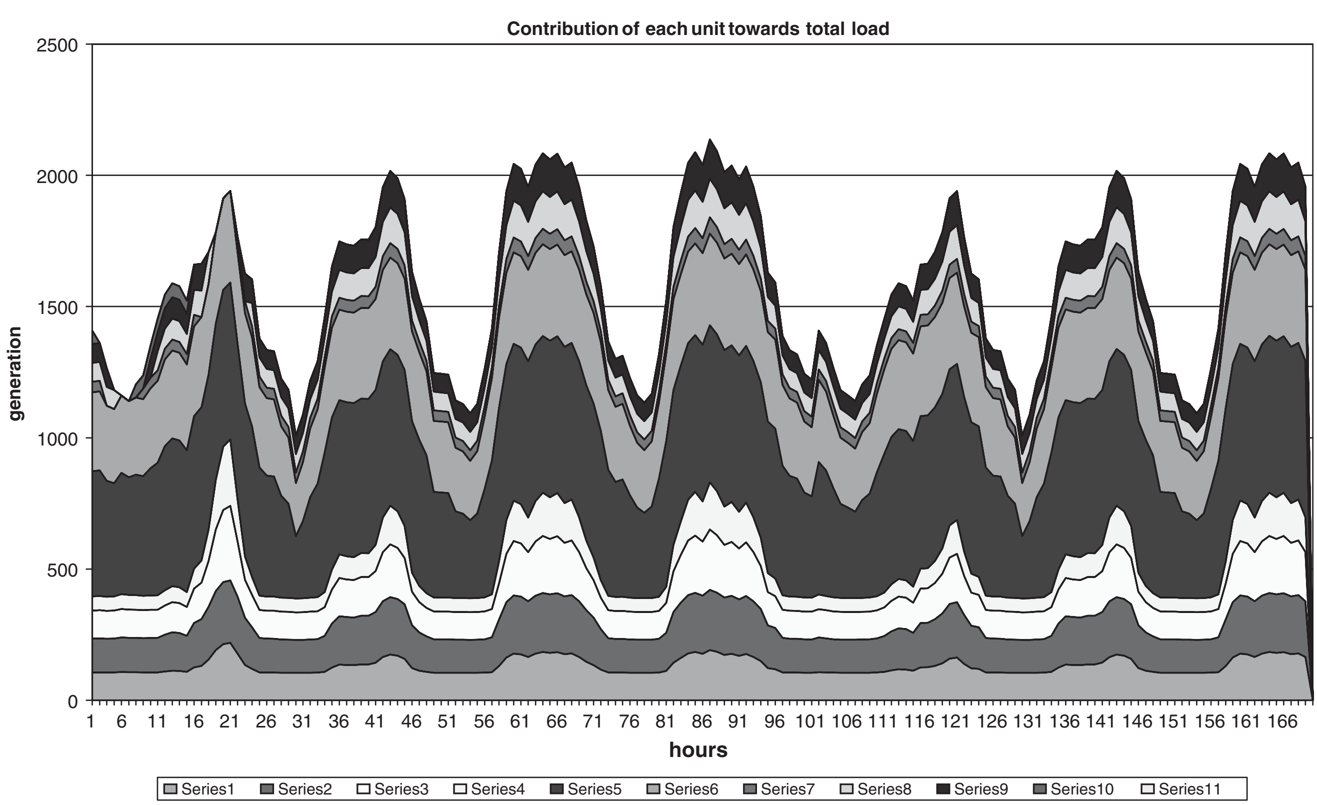

Fig. 9. Load distribution among units for 11-generator 168 h period.

8.3. 26-generator unit 24 h period

The results for a 26-unit system are represented in a graphical fashion in Fig. 8.The above results indicate that the proposed method works satisfactorily even if the number of units goes on increasing.

8.4. 11-generator unit 168 h period

The above case study is undertaken to show the effect of increasing the number of hours under consideration. The result for 11-unit system for a 168-h load pattern is given in Fig. 9. The total cost of operation is 1,743,686,344.53 $. The result supports the argument that the system works well independent of the time duration considered.

9. Conclusion

The paper proposes a solution methodology of UC using discrete HNN. Compared to some earlier attempts, there are some improvements incorporated in the proposed method. The objective function is modified to avoid the self-feedback of variable neurons. The dependence of architecture size on the number of hours under consideration is also avoided here. In the earlier method [8], as the hours under consideration increases, the dimension of the associated matrices increases, which makes the computations complex and extremely slow. Another major difference is the addition of the fifth constraint, which ensures that excess number of units is not switched ON, which helps in the optimum solution of UC. In the proposed method both UC and ED problems are solved simultaneously, but keeping them decoupled. This avoids the need for a complex unified energy function. It has been observed that the method works satisfactorily when either the number of units or the number of hours are increased. The dimension of the network is independent of the time duration under consideration. Additional constraints [13,16] can be easily incorporated into the neural network model, since the network offers no limit on the number of constraint blocks that can be added.

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