



A NEW APPROACH BASED ON HOPFIELD NEURAL NETWORK TO ECONOMIC LOAD DISPATCH

Naser Mahdavi TABATABAEI¹, Ahmet NAYIR^{*2}, Gholam AHMADI³

¹ Electrical Engineering Department, Azarbaijan University of Tarbiat Moallem, Tabriz-IRAN

² Institute of Energy, Istanbul Technical University, Ayazağa Kampüsü, Maslak-ISTANBUL

³ Electrical Engineering Department, University of Tabriz, Tabriz-IRAN

Geliş/Received: 20.04.2004 Kabul/Accepted: 02.02.2005

ABSTRACT

The Economic Load Dispatch (ELD) problem is how to real power output of each controlled generating unit in an area is selected to meet a given load and to minimize the total operating cost in the area. This is one of the important problems in a power system. The Hopfield Neural Network (HNN) has a good capability to solve optimization problems. Recently, the economic load dispatch problem solved by using the Hopfield neural network approach and good result has obtained. This paper presents a new approach for solving ELD problem considering the returning cost using HNN model. In this approach two energy functions are introduced. The first energy function consist of mismatch power, total fuel cost and transmission line losses. Each term of this function is multiplied by a weighting factor which represents the relative importance of those terms. The other energy function composed of total fuel cost and losses power cost. Our purpose is to minimize these two function and the results shows that solving ELD problem with this approach yield more saving cost.

Keywords: HNN, ELD, Power system, Lagrangian method, Transmission line losses.

EKONOMİK YÜK RAPORUNDA HOPFIELD SINİR AĞINA DAYALI YENİ BİR YAKLAŞIM

ÖZET

Ekonomik yük raporu (ELD) problemi bu alandaki toplam en düşük işletim maliyeti ve verilen bir yük ile karşıldığında bir alanda kontrol edilen her bir üretim biriminin gerçek güç çıkışıdır. Bu güç sistemindeki önemli bir problemdir. Hopfield sinir ağı (HNN) en iyi kullanım problemlerinin çözümünde iyi bir kapasiteye sahiptir. Son zamanlardaki ekonomik yük raporu problemi Hopfield sinir ağı yaklaşımı kullanılarak çözülmüş ve iyi sonuç elde edilmiştir. Bu makale, HNN modeli kullanılarak geriletilen maliyet göz önüne alınarak ELD probleminin çözümünde yeni bir yaklaşımı arz etmektedir. Bu yaklaşımda iki enerji fonksiyonu arz edilmektedir. İlk enerji fonksiyonu, toplam yakıt maliyeti ve taşıma hattı kaybı olan, mismatch gücünden ibarettir. Bu fonksiyonun her bir terimi bu terimlerin birbirine göre önemini arz eden bir faktörle çarpılır. Öteki enerji fonksiyonu toplam yakıt maliyetinden ve güç maliyeti kaybından ibarettir. Amacımız bu iki fonksiyonu minimize etmektir ve sonuçlar maliyetin daha çok korunduğu bu yaklaşım verimiyle ELD probleminin çözüldüğünü göstermiştir.

Anahtar Sözcükler: HNN, ELD, Güç sistemi, Lagrangian metodu, İletim hattı kaybı.

* Sorumlu Yazar/Corresponding Author; e-posta: ahmetnayir@hotmail.com, tel: (0212) 285 67 98

1. INTRODUCTION

Economic load dispatch is one of the most important problems in a power system. The goal of solving this problem is obtaining optimum generating power for generation units in an electric power system to meet a given load and to minimize the total operating cost. For solving this problem, many approaches have presented. One of them is Lagrangian method. In this method a Lagrangian augmented function is first formulated [1-3].

The optimal conditions are obtained by partial derivation of this function. Calculation of the penalty factors and incremental losses is always the key points in the solution algorithm. Incremental losses and thus the penalty factors are determined by the B-coefficient method which states that the transmission losses can be expressed in quadratic forms of the generation powers. Recently, the ELD problem has been solved by using the Hopfield Neural Network and genetic algorithm. The HNN has a good capability to solve optimization problems. In this method the objective function of ELD problem is transformed in to a Hopfield energy function and numerical iteration are applied to minimize the energy function.

Gee and Prager introduced methods to improve the HNN approach by introducing slack variables for handling inequality constraints [4]. J.H. Park et. al have proposed a method to use the HNN to solve the ELD problem with a piecewise quadratic cost functions [5].

HNN converges very slowly which in the advantage methods have been used to update the slopes or bias of the network to speed the convergence. The piecewise quadratic cost functions in ELD are used to represent multiple fuels which are available to each generation unit. In these units it may be more economical to burn a certain fuel for some MW outputs and another kind of fuel for other outputs [6].

Reducing of transmission line losses is another parameter which must be taken into account in this problem, because transmission losses are the energies that the customers don't pay directly their costs. In this paper a new approach and mapping technique is presented for solving ELD problem in a power system, considering the cost that customer pay it, by using HNN. The proposed method has also achieved efficient and accurate solutions for different sizes of power systems.

2. ECONOMIC LOAD DISPATCH MODEL

The ELD problem is to find the optimal solution of power generation that minimizes the total cost while satisfying the system constraints. Mathematically, this problem can be expressed as [1]:

$$\sum_i C_i = \sum_i (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

where

P_i : The power output of i th generator

a_i, b_i, c_i : Cost coefficients of i th generator

C_i : The generation cost of the i th plant

Subject to satisfying the following constraints:

(a) The active power balance equation:

$$\sum_i P_i = P_L + P_D \tag{2}$$

where

$$P_L = \sum_i \sum_j P_i B_{ij} P_j \tag{3}$$

P_D : Total demand load

A New Approach Based on Hopfield Neural...

P_L : Transmission loss

B_{ij} : Transmission loss coefficients

(b) Maximum and minimum limit of power:

$$P_{i, \min} = P_i = P_{i, \max} \quad (4)$$

where

$P_{i, \min}$: The minimum generation limit of unit i

$P_{i, \max}$: The maximum generation limit of unit i

The well known solution method to this problem using the coordination equation is

$$PF_1 \frac{dF_1(P_1)}{dP_1} = \dots = PF_k \frac{dF_k(P_k)}{dP_k} = \dots = PF_i \frac{dF_i(P_i)}{dP_i} \quad (5)$$

where PF_k is the penalty factor of unit k given by

$$PF_k = \frac{1}{1 - \partial P_L / \partial P_k}, \quad (6)$$

$$k = 1, 2, \dots, i$$

and $\partial P_L / \partial P_k$ is the incremental loss of unit k . The penalty factors can be computed from losses formula (3).

3. THE STANDARD HOPFIELD NEURAL NETWORK

The Hopfield neural network consists of a set of neurons and a corresponding set of unit delays, forming a multiple loop feedback system. The number of feedback loops is equal to the number of neurons. The input of neuron i is supplied by two different sources, e.g., the output of other neurons and the external input.

The input-output relation is described generally by a sigmoid function given below [2]:

$$V_i = g_i(U_i) \quad (7)$$

V_i is a continuous variable in the interval 0 to 1, and $g_i(U_i)$ is a increasing function which constraints V_i to this interval.

$$g_i(U_i) = \frac{1}{1 + \exp(-\frac{2U_i}{u_0})} \quad (8)$$

where

U_i : The total input of neuron i

V_i : The output of neuron i

u_0 : The shape constant of sigmoid function

The dynamic characteristic equation of the system can be described by:

$$\frac{dU_i}{dt} = \sum_j T_{ij} V_j + I_i \quad (9)$$

where

I_i : The input bias current to neuron i

T_{ij} : Interconnection conductance from the output of neuron j to the input of neuron i

T_{ii} : Self connection conductance of neuron i

The energy function of the Hopfield neural network is defined as [4]:

$$E = -(1/2) \sum_i \sum_j T_{ij} V_i V_j - \sum_i I_i V_i \quad (10)$$

The time derivative of the energy function can be proven to be negative:

$$dE / dt < 0 \quad (11)$$

So the model state always moves in such a way that the energy function gradually reduces and converges to a minimum.

4. TRANSFORM OBJECTIVE FUNCTION INTO HOPFIELD ENERGY FUNCTION

To solve the ELD problem using the Hopfield method with considering returning cost, two energy functions are defined as follows [3]:

$$E_1 = (A/2)[(P_D + P_L) - \sum_i P_i]^2 + (B/2) \sum_i (a_i + b_i P_i + c_i P_i^2) + (C/2)P \quad (12)$$

and

$$E_2 = \sum_i (a_i + b_i P_i + c_i P_i^2) + 90P_L \quad (13)$$

The first energy function, E_1 , is composed of power mismatch, total fuel cost and transmission line losses. The positive weighting factors A , B and C introduce the relative importance for their respective associated terms and they are determined by trial and error. The other energy function, E_2 , is consist of total generating cost and transmission losses cost which the cost doesn't return to the system and our goal is to reduce that [5, 6].

Considering \$0.09 for each KWh energy (\$90 for each MWh), the cost of transmission losses will be $90P_L$ which taken into account in E_2 . If the generation output of unit i changes from P_{i0} to P_i then the transmission losses will change from P_{L0} to P_L , which may be expressed as

$$P_L \cong P_{L0} + \sum_i I_{Li0}(P_i - P_{i0}) \quad (14)$$

where I_{Li0} is the incremental loss of unit i at power generation of P_{i0} . Substituting (14) into (9) yields

$$E_1 = (A/2)[(P_D + P_L) - \sum_i P_i]^2 + (B/2) \sum_i (a_i + b_i P_i + c_i P_i^2) + (C/2)(P_{L0} + \sum_i I_{Li0}(P_i - P_{i0}))$$

so

$$E_1 \cong (A/2)(P_D + P_{L0})^2 + (B/2) \sum_i a_i + (C/2)(P_{L0} - \sum_i I_{Li0} P_{i0}) -$$

$$\sum_i [A(P_D + P_{L0}) - (Bb_i/2) - (C/2)I_{Li0}]P_i + \sum_i (A + Bc_i)P_i^2/2 + \sum_i \sum_{j \neq i} AP_i P_j/2$$

then

$$E_1 \cong H - \sum_i [A(P_D + P_{L0}) - (Bb_i/2) - (C/2)I_{Li0}]P_i + \sum_i (A + Bc_i)P_i^2/2 + \sum_i \sum_{j \neq i} (AP_i P_j/2) \quad (15)$$

Where H is a constant and is equal

A New Approach Based on Hopfield Neural...

$$H = (A/2)(P_D + P_{L0})^2 + (B/2)\sum_i a_i + (C/2)(P_{L0} - \sum_i I_{Li0}P_{i0}) \quad (16)$$

and

$$E_2 = \sum_i (a_i + b_i P_i + c_i P_i^2) + 90 \sum_i \sum_j P_i B_{ij} P_j = G + \sum_i (b_i) P_i + \sum_i (c_i + 90 B_{ij}) P_i^2 + 90 \sum_i \sum_{j \neq i} B_{ij} P_j P_i \quad (17)$$

Where G is a constant and

$$G = \sum_i a_i \quad (18)$$

The power output value, P_i , in Hopfield model can be expressed as follows:

$$P_i = g_i(U_i) = (P_{i,\max} - P_{i,\min}) / (1 + \exp(-2U_i / u_0)) + P_{i,\min} \quad (19)$$

By comparing (10) with (12) the weight parameters and external input of neuron in the network are given

$$\begin{aligned} T_{ii} &= -A - Bc_i \\ T_{ij} &= -A \\ I_i &= A(P_D + P_{L0}) - Bb_i / 2 - CI_{Li0} / 2 \end{aligned} \quad (20)$$

By using (9) and (20) we have

$$\Delta U_i = \{A(P_D + P_{L0} - \sum_j P_j) - (B/2)(b_i + 2c_i P_i) - CI_{Li0} / 2\} \Delta t, \quad (21)$$

$$P_i = g_i(U_i)$$

For computing energy function, E_2 , by comparing (10) and (13) the following equation are given

$$\begin{aligned} T_{ii} &= -(c_i + 90B_{ii}) / 2 \\ T_{ij} &= -90B_{ij} \\ I_i &= -b_i / 2 \end{aligned} \quad (22)$$

By using equations (9) and (22) we have

$$\Delta U_i = \{((-90B_{ij}) / 2) \sum_j V_j - (c_i / 2) V_i - b_i / 2\} \Delta t, \quad (23)$$

$$P_i = g_i(U_i)$$

Using iteration methods, equations (21) and (23) can be solved separately. In each iteration, the output of each neuron must be updated until the solution converges gradually to their feasible local minimum.

5. SIMULATION RESULTS

To illustrate the application of the proposed method, an example system is employed. The example system has 20 generating units to supply a total load demand of 2500 MW [3, 6]. Table 1 gives fuel cost coefficient and generation limits for each unit. Weighting factors A , B and C are obtained from trial and error. The computation results which are obtained by using iteration method and proposed approach are given in Table 2. According to Table 2 we find that the generating value for each unit, which are obtained from proposed method, has a little difference with its value, which are obtained from iteration method, while transmission losses is smaller in the proposed method.

Figure 1 shows the little difference between two methods. The cost that consume for generating power and transmission losses, related to two methods is calculated as follows:

$$C_1 = 62456.639 + 91.967 \times 90 = 70733.669 \text{ \$/h}$$

and

$$C_2 = 62462 + 91.807 \times 90 = 70724.63 \text{ \$/h}$$

C_1 is the cost in λ method and C_2 is this cost in the proposed method.

From the values of C_1 and C_2 it is obvious that the consumed cost in the proposed method is small and the difference is equal

$$C_1 - C_2 = 9.039 \text{ \$/h} = 9.039 \times 8760 \text{ \$/year}$$

In the other words, if we use the proposed method that is presented in this paper, more cost will be saved in one year.

6. CONCLUSIONS

This paper presents a new method based on Hopfield model for solving economic load dispatch problem. The proposed method essentially obeys the equal-incremental-cost criterion followed by conventional economic dispatch methods. The Hopfield neural network has a nonhierarchical structure and its connective conductances and external input can be determined by employing the system data. Thus, the proposed model unlike other neural networks requires no training. Using the Hopfield neural network for solving economic load dispatch decreases computation time.

Table 1. The coefficient of total fuel cost function and generating power limit units of test system

Unit <i>i</i>	a_i (\\$/h)	b_i (\\$/MWh)	c_i (\\$/MWh)	$P_{i, \min}$ (MW)	$P_{i, \max}$ (MW)
1	1000	18.19	0.00068	150	600
2	970	19.26	0.00071	50	200
3	600	19.80	0.00650	50	200
4	700	19.10	0.00500	50	200
5	420	18.10	0.00738	50	160
6	360	19.26	0.00612	20	100
7	490	17.14	0.00790	25	125
8	660	18.92	0.00813	50	150
9	765	18.27	0.00522	50	200
10	770	18.92	0.00573	30	150
11	800	16.69	0.00480	100	300
12	970	16.76	0.00310	150	500
13	900	17.36	0.00850	40	160
14	700	18.70	0.00511	20	130
15	450	18.70	0.00398	25	185
16	370	14.26	0.0712	20	80
17	480	19.14	0.00890	30	85
18	680	18.92	0.00713	30	120
19	700	18.47	0.00622	40	120
20	850	19.79	0.00773	30	100

Table 2. Computation results of two methods in the test system

Unit Generation (MW)	λ Iteration Method	The Proposed Method
P_1	512.7805	522.56
P_2	169.1033	153.92
P_3	126.8898	132.75
P_4	102.8657	94.711
P_5	113.6836	112.22
P_6	73.5710	74.921
P_7	115.2878	116.09
P_8	116.3994	113.66
P_9	100.4062	109.29
P_{10}	106.0267	106.02
P_{11}	150.2394	155.95
P_{12}	292.7648	274.41
P_{13}	119.1154	123.54
P_{14}	30.8340	39.449
P_{15}	115.8057	110.76
P_{16}	36.2545	36.22
P_{17}	66.8590	64.333
P_{18}	89.9720	89.553
P_{19}	100.8033	101.09
P_{20}	54.3050	60.37
P_{LOSS}	91.967	91.807

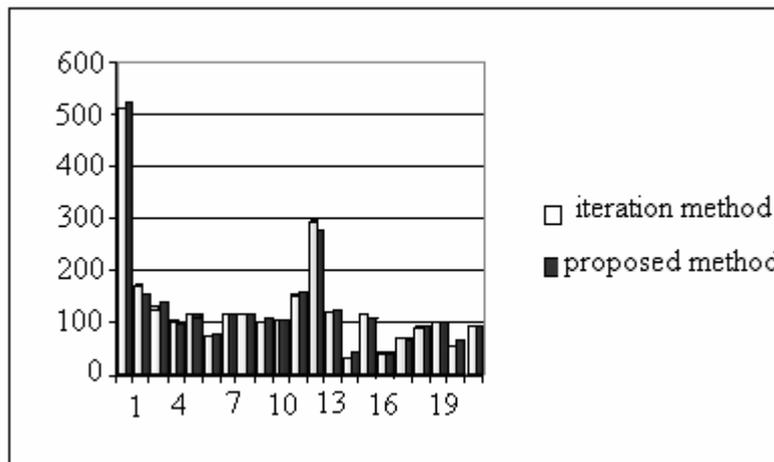


Figure 1. The λ iteration method values and the proposed method values for the test system

REFERENCES

- [1] Happ H.H., "Optimal Power Dispatch," IEEE Transactions PAS, vol. PAS-93, pp. 820-830, 1974.
- [2] Lin C.E., Chen S.T. and Huang C.L., "A Direct Newton-Rophson Economic Dispatch," IEEE Transactions on Power System, vol. 7, no. 3, pp. 1149-1154, 1992.
- [3] Su C.T. and Chiou G.J., "A Fast Computation Hopfield Method to Economic Dispatch of Power System," IEEE Transactions on Power Systems, vol. 12, no. 4, pp. 1756-1764, 1997.
- [4] Gee A.H. and Prager R.W., "Polyhedral Combinatorics and Neural Networks," Neural Computing, vol. 6, pp. 161-180, 1994.
- [5] Park J.H., Kim Y.S., Eom I. K. and Lee K. Y., "Economic Load Dispatch for Piecewise Quadratic Cost Function Using Hopfield Neural Network," IEEE Transactions on Power System, vol. 8, no. 3, pp. 1030-1038, 1993.
- [6] Lee K.Y., Sode-Yome A. and Park J.H., "Adaptive Hopfield Neural Networks for Economic Load Dispatch", IEEE Tansactions on Power Systems, vol. 13, no. 2, pp. 519-526, May 1998.