ECONOMIC LOAD DISPATCH FOR PIECEWISE QUADRATIC COST FUNCTION USING HOPFIELD NEURAL NETWORK

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Abstract - This paper presents a new method to solve the problem of economic power dispatch with piecewise quadratic cost function using the Hopfield neural network. Traditionally one convex cost function for each generator is assumed. However, it is more realistic to represent the cost function as a piecewise quadratic function rather than one convex function. In this study, multiple intersecting cost functions are used for each unit. Through case studies, we have shown the possibility of the application of the Hopfield neural network to the ELD problem with general nonconvex cost functions. The proposed approach is much simpler and the results are very close to those of the numerical method.

Key words - Neural network, Economic Load Dispatch, Energy Function, Piecewise Quadratic Cost Function, Valve Point Loading, Multiple Fuel.

1. INTRODUCTION

There has been a growing interest in neural network models with massively parallel structures, which purport to resemble the human brain. Owing to the powerful capabilities of neural networks such as learning, optimization and fault-tolerance, neural networks have been applied to the various fields of complex, non-linear and large-scale power systems[1-6].

The Hopfield neural network has been applied to various fields since Hopfield proposed the model in 1982[7] and 1984[8]. In the problem of optimization, the Hopfield neural network has a well demonstrated capability of finding solutions to difficult optimization problems. The TSP(traveling salesman problem), typical problems of NP(nondeterministic polynomial)-complete class, A/D conversion, linear programming and job-shopping schedule are good examples[9-12] which the Hopfield network provides with solutions. In the field of power systems, the Hopfield network has been applied to optimal power flow and economic load dispatch problems[13-15].

In the conventional Hopfield model, the neuron potential has arbitrary numbers during the intermediate stages but at the final stage the neuron potential converges to the limit values (0,1) or (-1,1) and thus, provides a solution. Sometimes it converges to the interior values of a hypercube instead of its vertices[16]. This is regarded as undesirable and calls for improvement. In general an optimization problem frequently needs a large numerical value as its solution. Thus far the counting method or the binary number representation[17] of various schemes has been used to represent real numbers. These methods, however, employ a large number of neurons to represent a correspondingly large numerical value. Therefore it is proposed to represent a large value by using a single neuron.

The economic load dispatch(ELD) problem is one of the important optimization problems in a power system. Traditionally, in the ELD problem, the cost function for each generator has been approximately represented by a single quadratic function. It is more realistic, however, to represent the generation cost function for fossil fired plants as a segmented piecewise quadratic function, as in the case of valve point loading. Some generation units, especially those units which are supplied with multiple fuel sources(gas and oil), are faced with the problem of determining which is the most economical fuel to burn[18].

As fossil fuel costs increase, it becomes even more important to have a good model for the production cost of each generator. Therefore a more accurate formulation is obtained for the ELD problem by expressing the generation cost function as a piecewise quadratic function. This approach can be applied to generators supplied with various fuels as well as valve point loading problems.

In this paper, a method of the Hopfield neural network to solve the ELD problem has been proposed. The proposed method has been successful in solving ELD problem with piecewise quadratic cost function. Compared with the hierarchical approach[19], the proposed method is much simpler to implement and the results are very close to those of the hierarchical method.

2. HOPFIELD NEURAL NETWORK

The Hopfield network which is useful for associative memory and optimization is a nonhierarchical structure. The structure of the network is shown in Fig. 1.

2.1. Binary Neuron Model

The original model of Hopfield neural network[7] used a two-state threshold "neuron" that followed a stochastic algorithm. Each neuron, or processing element, i had two states with values V_i^0 or V_i^1(which may often be taken as 0 and 1, respectively). The input of each neuron came from two sources, external inputs I_i and inputs from other neurons V_j. The total input to neuron i is given by

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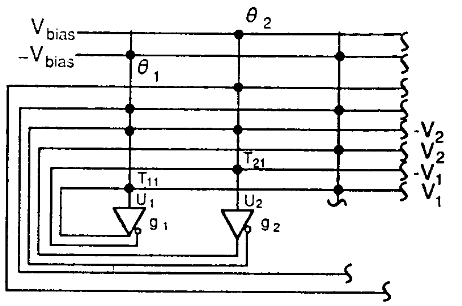

Fig.1. The structure of the Hopfield network.

$$U_i = \sum_{j \neq i} T_{ij} V_j + I_i, \quad (1)$$

where

U_i : the total input to neuron i
T_{ij} : 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.

Each neuron samples its input at random times. It changes the value of its ouput or leaves it fixed according to a threshold rule with thresholds θ_i:

$$V_i = V_i^0 \text{ if } U_i < \theta_i$$
$$V_i = V_i^1 \text{ if } U_i > \theta_i, \quad (2)$$

where

θ_i : threshold of neuron i.

The energy function of the Hopfield network is defined as

$$E = -1/2 \sum_{i \neq j} \sum T_{ij} V_i V_j - \sum_i I_i V_i + \sum_i \theta_i V_i. \quad (3)$$

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

$$\Delta E = -[\sum_{j \neq i} T_{ij} V_j + I_i - \theta_i] \Delta V_i. \quad (4)$$

where ΔV_i is the change in the output of neuron i.

Suppose that the input U_i of neuron i is greater than the threshold. This will cause the term in brackets in eq.(4) to be positive and, from eq.(1) and eq.(2), the output of neuron i changes in the positive direction. This means that ΔV_i is positive, and ΔE negative; hence the network energy decreases. Similarly, when the U_i is less than the threshold, it can be seen that ΔE is also negative.

The dynamics of the system state follows this simple rule and is asynchronous. An element, chosen at random, looks at its inputs, and changes state, depending on whether or not the sum of its input is above or below threshold. It can be seen from the form of the energy term that a state change leads to a decrease in energy. Therefore, the updating rule is an energy minimizing rule. Modifications of element activities continue until a stable state is reached, that is, a minimum energy is reached.

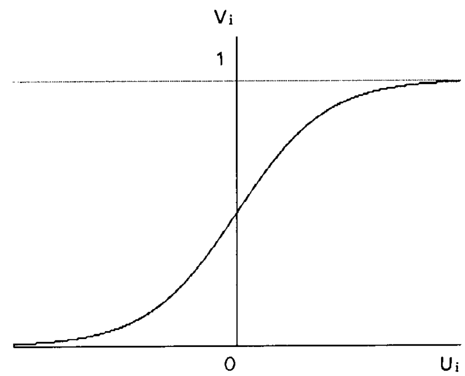

Fig.2. A sigmoidal function.

2.2. Continuous Neuron Model

The continuous and deterministic model of the Hopfield neural network[8] is based on continuous variables and responses but retains all of the significant behaviors of the original model. The output variable V_i for neuron i has the range $V_i^0 \leq V_i \leq V_i^1$ and the input-output function is a continuous and monotonically increasing function of the input U_i to neuron i. The typical input-output function $g_i(U_i)$ is a sigmoidal function as shown in Fig. 2.

The dynamics of the neurons is defined by

$$dU_i/dt = \sum_j T_{ij} V_j + I_i, \quad (5)$$

where

$V_i = g_i(U_i)$: the output value of the neuron i
$g_i(U_i) = 1/(1 + \exp(-U_i/u_0))$
g_i : the input-output function of the neuron i (shown in Fig. 2)
u_0 : a coefficient that determines the shape of the sigmoidal function.

The energy function of the continuous Hopfield network is similarily defined as

$$E = -1/2 \sum_i \sum_j T_{ij} V_i V_j - \sum_i I_i V_i, \quad (6)$$

and its time derivative is given by

$$\begin{aligned} dE/dt &= -1/2 \sum_i \sum_j T_{ij}[V_j(dV_i/dt) + V_i(dV_j/dt)] - \sum_i I_i(dV_i/dt) \\ &= -1/2 \sum_i (dV_i/dt)[\sum_j (T_{ij}V_j + T_{ji}V_j) + 2I_i] \\ &= -1/2 \sum_i (dV_i/dt)(2\sum_j T_{ij}V_j + 2I_i) \quad (7) \\ &= -\sum_i (dV_i/dt)(\sum_j T_{ij}V_j + I_i) \\ &= -\sum_i (dV_i/dt)(dU_i/dt) \\ &= -\sum_i g_i'(U_i)(dU_i/dt)^2 \end{aligned}$$

From this, we can see that dE/dt is always less than zero because g_i is a monotonic increasing function. Therefore the network solution moves in the same direction as the decrease in energy. The solution seeks out a minimum of E and comes to a stop at such point.

3. MAPPING OF THE ELD INTO THE HOPFIELD NETWORK

3.1.The Economic Load Dispatch Problem

The ELD problem is to find the optimal combination of power generation which minimizes the total cost while satisfying the total required demand. In this paper, the cost function is as follows :

$$C = \sum_i (a_i + b_i P_i + c_i P_i^2), \tag{8}$$

where
C : total cost
a_i, b_i, c_i : cost coefficients of generator i
P_i : the generated power of generator i.

In minimizing total cost, the following constraints should be satisfied.

a) Power balance

$$D + L = \sum_i P_i \tag{9}$$

where
D : total load.
L : transmission loss.
The transmission loss can be represented as

$$L = \sum_i \sum_j \alpha_{ij} P_i P_j. \tag{10}$$

where
α_{ij} : transmission loss coefficient.

b) Maximum and minimum limits of power

The generation power of each generator should be laid between maximum limit and minimum limit. That is,

$$\underline{P}_i \le P_i \le \overline{P}_i \tag{11}$$

where
$\underline{P}_i$: the minimum generation power
$\overline{P}_i$: the maximum generation power.

3.2. Mapping of the ELD into the Hopfield network

In order to solve the ELD problem, the following energy function is defined by combining the objective function eq.(8) with the constraint eq.(9):

$$E = A(D+L-\sum_i P_i)^2/2 + B\sum_i (a_i + b_i P_i + c_i P_i^2)/2, \tag{12}$$

where $A(\ge 0)$ and $B(\ge 0)$are weighting factors.

The synaptic strength and the external input are obtained by mapping the above energy function, eq.(12), into the Hopfield energy function, eq.(6). First by assuming that the loss L is constant, the eq.(12) is expanded and compared to eq.(6) in which V_i and V_j correspond to P_i and P_j, respectively:

$$\begin{aligned} E &= A[(D+L)^2 - 2(D+L)(\sum_i P_i) + (\sum_i P_i)^2]/2 \\ &\quad + B\sum_i (a_i + b_i P_i + c_i P_i^2)/2 \qquad (13) \\ &= A(D+L)^2/2 - \sum_i [A(D+L) + Bb_i/2]P_i \\ &\quad + \sum_i \sum_i (A+Bc_i)P_i P_i/2 + \sum_{i \ne j}\sum AP_i P_j/2 + B\sum_i a_i/2. \end{aligned}$$

Thus by comparing eq.(6) with eq.(13), the synaptic strength and external input of neuron i in the Hopfield network are given by

$$\begin{aligned} T_{ii} &= -A - Bc_i \\ T_{ij} &= -A \\ I_i &= A(D+L) - Bb_i/2. \end{aligned} \tag{14}$$

The differential synchronous transition mode[13] used in computation for this Hofield neural network is as follows:

$$\begin{aligned} U_i(k) - U_i(k-1) &= \sum_j T_{ij} V_j(k) + I_i \\ V_i(k+1) &= g_i[U_i(k)]. \end{aligned} \tag{15}$$

We then find the output value P_i by this Hopfield network and calculate the transmission loss by the loss formula, eq.(10). Again the calculated loss is assumed as a constant, thereafter the above process is repeated.

In representing a large value with the neural network, the binary number representation requires a large number of neurons which is a disadvantage. Therefore in this paper, we use a modified sigmoidal function:

$$V_i = g_i(U_i) = (\overline{P}_i - \underline{P}_i)(1/(1+\exp(-U_i/u_0)) + \underline{P}_i. \tag{16}$$

4. HIERARCHICAL STRUCTURE APPROACH

In the hierarchical structure approach[19], the hybrid cost function and hybrid incremental cost function of unit j in subsystem i are shown in Fig. 3. These functions are defined as

$$COST(P_{ij}) = \begin{cases} a_{ij1} + b_{ij1} \times P_{ij} + c_{ij1} \times P^2_{ij}, \text{ fuel 1} \\ \qquad \underline{P}_{ij} \le P_{ij} \le P_1 \\ a_{ij2} + b_{ij2} \times P_{ij} + c_{ij2} \times P^2_{ij}, \text{ fuel 2} \\ \quad \vdots \qquad P_1 \le P_{ij} \le P_2 \qquad \vdots \\ a_{ijk} + b_{ijk} \times P_{ij} + c_{ijk} \times P^2_{ij}, \text{ fuel k} \\ \qquad P_{k-1} \le P_{ij} \le \overline{P}_{ij} \end{cases} \tag{17}$$

where a_{ijk}, b_{ijk}, c_{ijk} are cost coefficients of fuel type k. Subscript j indicates units, and subscript k indicates fuel type. The hybrid cost functions give rise to an additional variable, f, which describes the available fuels. The Lagrangian with the transmission loss term neglected is written as

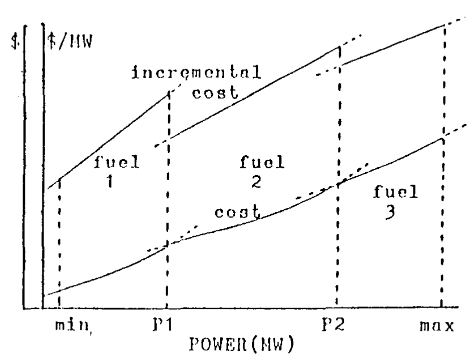

Fig. 3 Hybrid cost and incremental cost function.

$$L(f,p,\lambda) = F(f,p) + \lambda^T G(p) \tag{18}$$

where

f : discrete index for fuel type,
λ : Lagrangian multiplier or incremental cost,
p : vector of power generations,
F(f,p) : total cost,
G(p) : power balance constraint(demand-generation).

The hierarchical structure of a power system is composed of several subsystems. Each subsystem includes several generation units as shown in Fig. 4. The power outflow from each subsystem is referred to as the subsystem demand. The details of this approach are shown in reference[19].

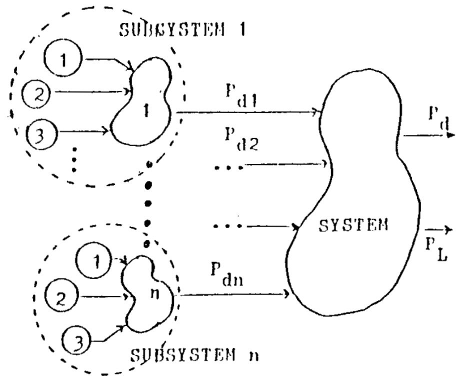

Fig.4 Hierarchical structure of a power system.

5. SIMULATION RESULTS AND DISCUSSIONS

Prior to applying the Hopfield model to the ELD problem with piecewise quadratic cost functions, it has been applied to simple ELD problem to prove its usefulness. The chosen ELD problem is in reference[20] which has 3 cases. Simulation results by the Hopfield neural network are compared with the results by numerical method in reference[20]. Total load in each case is 850[MW]. This system has three generator units. Transmission losses are neglected in case 1 and case 2.

a) Case 1

Table 1 Cost coefficients for case 1.

Unit	a	b	c	$\underline{P}$	$\overline{P}$
1	561.0	7.92	0.001562	150.0	600.0
2	310.0	7.85	0.00194	100.0	400.0
3	78.0	7.97	0.00482	50.0	200.0

b) Case 2

All the conditions are the same as case 1, but the cost function for unit 1 becomes

$$C_1 = 0.00128P_1^2 + 6.48P_1 + 459[\$/h].$$

c) Case 3

All the conditions are the same as case 1 except that the constraint equation includes the network losses. Simplified loss formula is give by

$$P_L = 0.00003P_1^2 + 0.00009P_2^2 + 0.00012P_3^2[MW].$$

During simulation, it was found that the assumed initial solutions did not affect the results for all cases since they are convex problems. Determination of weighting factors in optimization problems is generally not easy.

In eq.(12), A is the penalty factor to the constraint of total load demand and B is the penalty factor to the constraint of the objective function. It was found that when A was bigger than 0.4 regardless of B values, the network oscillated. Usually when there is self-feedback($T_{ii} \neq 0$), the solutions can be in oscillation[9]. Through simple trial and error method, it was found that A=0.4 and B= 0.05 were appropriate values. The inequality constraints of maximum-minimum limits are dealt by the sigmoidal function variation, eq.(16).

The results of case studies are shown in Table 2 and compared with those of conventional methods[20]. The results of the Hopfield network method shows small error in power balance(the mismatch power is 0.8[MW] in case 1 and 0.5[MW] in case 2.). When we convert this error into the fuel cost of a power plant with the highest cost function, the total cost increase is extremely small compared with the total cost of conventional method.

Table 2 The simulation results for case studies.

Case \ Results / Method		P_1[MW]	P_2[MW]	P_3[MW]	Total Power [MW] (P_1+P_2+P_3)	Total Cost [$/h]
Case 1	Numerical method	393.2	334.6	122.2	850.0	8194.3
	Neural network	393.8	333.1	122.3	849.2	8187.0
Case 2	Numerical method	600.0	187.1	62.9	850.0	7252.1
	Neural network	600.0	186.6	62.9	849.5	7247.9
Case 3	Numerical method	435.1	300.0	130.7	865.8 (loss=15.8)	8344.3
	Neural network	432.4	288.5	144.1	865.0 (loss=15.6)	8340.5

The energy change for case 1 during iterations is shown in Fig. 5. The aspects of convergence for each case are shown in Figs. 6, 7, and 8. In case 3, where the transmission loss is considered, the neural network method also shows good results. This neural network method has the special advantage of solving the ELD problem by a simple neural network without calculating incremental fuel costs and incremental losses required by conventional numerical methods.

The Hopfield neural network is applied to the ELD problem with nonconvex cost functions which is in reference[19]. In reference[19] this problem was solved by a hierarchical structure method, which is a numerical method. In order to prove the usefulness of the proposed neural network method, the same data used in the numerical method[19] have been used for computer

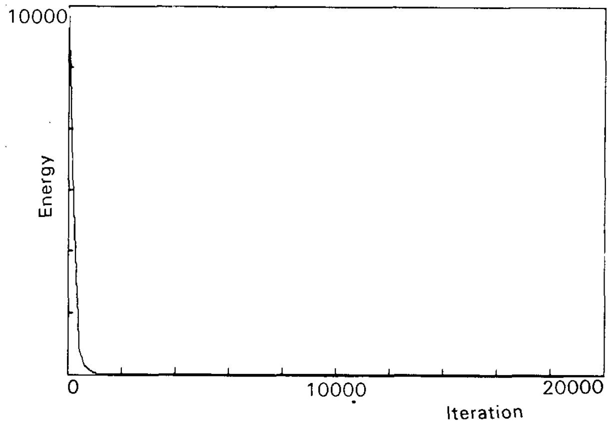

Fig. 5 Energy vs. iteration(case 1)

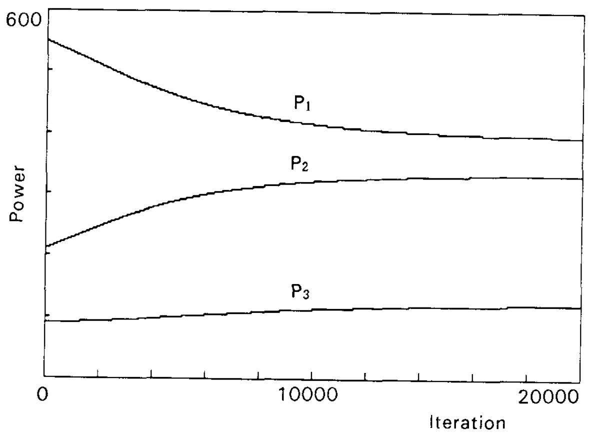

Fig. 6 Each power vs. iteration(case 1)

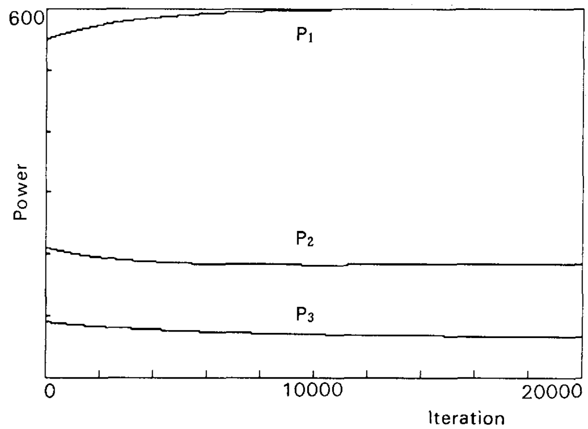

Fig. 7 Each power vs. iteration(case 2)

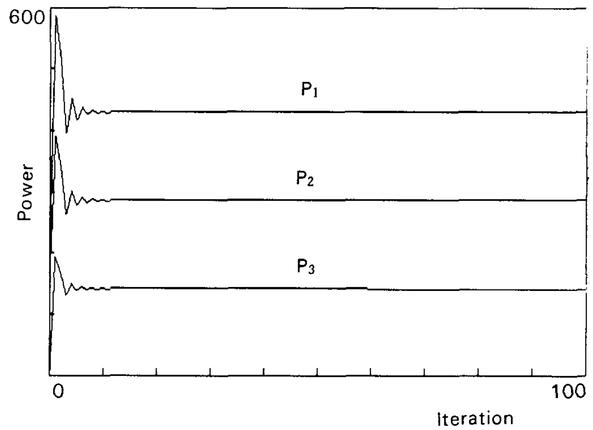

Fig. 8 Each power vs. iteration(case 3)

simulation. The hierarchical system characteristics are shown in Table 3. Generation (MIN) and (MAX) are the lower and upper limits of each generation unit. There are three different types of fuels: type 1, 2, and 3.

The optimal power dispatch with system demands rising from 2400[MW] to 2700[MW] is shown in Table 4 and Table 5. In Table 4 the results of the hierarchical structure method are shown. In Table 5 the results of the proposed neural network method are shown. The total costs of two methods are shown in Table 6. Comparing Table 4 with Table 5, the following results are observed. First it is observed that in Table 4, obtained by numerical methods proposed in reference[19], the power outputs of unit 4 are exchanged with those of unit 6. Second, the neural network method satisfies total load better than the hierarchical structure method. In the results of the neural network method the mismatched powers are -0.2 to 0.3[MW], while in the results of numerical method the mismatched powers are +1.2[MW] at a system demand of 2400[MW], +1.1[MW] at a system demand of 2500[MW], -0.7[MW] at a system demand of 2600[MW], and +2.2[MW] at a system demand of 2700[MW]. Third, when the total loads are 2400[MW], 2500[MW] and 2600[MW], the power outputs for two methods do not show large differences. When the total load is 2700[MW], the power outputs of the two methods are much different from each other. But total cost obtained by the neural network method is nearly the same as the hierarchical structure method as shown in Table 6. Therefore the solutions by the neural network method are very close to those of the numerical method.

The algorithm of the proposed neural method is simple as shown in this paper; in contrast to the proposed method, the algorithm of the hierarchical method is much more complicated.

The simulation time of the hierarchical structure method with VAX 11/780 is a little bit more than 1 sec., while the simulation time of the proposed neural network method with IBM PC-386 is about 1 min.. Considering the use of a personal computer rather than a main frame, there is practically no difference in calculation time. When implemented in hardware, the proposed neural network method can achieve much faster real time response than the hierarchical structure method. Therefore the proposed method promises to have a good merit in its applications.

6. CONCLUSIONS

It is more accurate to represent the generation cost function for a fossil fired plant as a segmented piecewise quadratic function. However, it requires a much complicated algorithm to solve the ELD problem through

Table 3. The data of cost coefficients for piecewise quadratic cost function.

S	U	GENERATION MIN	P1	P2	MAX	F1	F2	F3	F	COST COEFFICIENTS a	b	c
1	1	100	196	250		1	2		1	.2697E2	-.3975E0	.2176E-2
									2	.2113E2	-.3059E0	.1861E-2
	2	50	114	157	230	2	3	1	1	.1184E3	-.1269E1	.4194E-2
									2	.1865E1	-.3988E-1	.1138E-2
									3	.1365E2	-.1980E0	.1620E-2
	3	200	332	388	500	1	3	2	1	.3979E2	-.3116E0	.1457E-2
									2	-.5914E2	.4864E0	.1176E-4
									3	-.2876E1	.3389E-1	.8035E-3
	4	99	138	200	265	1	2	3	1	.1983E1	-.3114E-1	.1049E-2
									2	.5285E2	-.6348E0	.2758E-2
									3	.2668E3	-.2338E1	.5935E-2
2	5	190	338	407	490	1	2	3	1	.1392E2	-.8733E-1	.1066E-2
									2	.9976E2	-.5206E0	.1597E-2
									3	-.5399E2	.4462E0	.1498E-3
	6	85	138	200	265	2	1	3	1	.5285E2	-.6348E0	.2758E-2
									2	.1983E1	-.3114E-1	.1049E-2
									3	.2668E3	-.2338E1	.5935E-2
	7	200	331	391	500	1	2	3	1	.1893E2	-.1325E0	.1107E-2
									2	.4377E2	-.2267E0	.1165E-2
									3	-.4335E2	.3559E0	.2454E-3
3	8	99	138	200	265	1	2	3	1	.1983E1	-.3114E-1	.1049E-2
									2	.5285E2	-.6348E0	.2758E-2
									3	.2668E3	-.2338E1	.5935E-2
	9	130	213	370	440	3	1	3	1	.8853E2	-.5675E0	.1554E-2
									2	.1530E2	-.4514E-1	.7033E-2
									3	.1423E2	-.1817E-1	.6121E-3
	10	200	362	407	490	1	3	2	1	.1397E2	-.9938E-1	.1102E-2
									2	-.6113E2	.5084E0	.4164E-4
									3	.4671E2	-.2024E0	.1137E-2

S : subsystem, U : unit, F : fuel,
a,b,c : cost coefficients in eq.(16)
MIN,P1,P2,MAX : breakpoints in Fig. 3
F1,F2,F3 : operating fuel between breakpoints

Table 4. Results using hierarchical structure method.

S	U	2400 MW F	GEN.	2500 MW F	GEN.	2600 MW F	GEN.	2700 MW F	GEN.
1	1	1	193.2	2	206.6	2	216.4	2	218.4
	2	1	204.1	1	206.5	1	210.9	1	211.8
	3	1	259.1	1	265.9	1	278.5	1	281.0
	4	3	234.3	3	236.0	3	239.1	3	239.7
2	5	1	249.0	1	258.2	1	275.4	1	279.0
	6	1	195.5	3	236.0	3	239.1	3	239.7
	7	1	260.1	1	269.0	1	285.6	1	289.0
3	8	3	234.3	3	236.0	3	239.1	3	239.7
	9	1	325.3	1	331.6	1	343.3	3	429.2
	10	1	246.3	1	255.2	1	271.9	1	275.2
GT		2401.2		2501.1		2599.3		2702.2	

S : subsystem
F : fuel
U : unit
GEN. : Unit Generation(MW)
GT : Total Generation(MW)

Table 5. Results using neural network.

S	U	2400 MW F	GEN.	2500 MW F	GEN.	2600 MW F	GEN.	2700 MW F	GEN.
1	1	1	192.7	2	206.1	2	215.3	2	224.5
	2	1	203.8	1	206.3	1	210.6	1	215.0
	3	1	259.1	1	265.7	1	278.9	3	291.8
	4	2	195.1	3	235.7	3	238.9	3	242.2
2	5	1	248.7	1	258.2	1	275.7	1	293.3
	6	3	234.2	3	235.9	3	239.1	3	242.2
	7	1	260.3	1	269.1	1	286.2	1	303.1
3	8	3	234.2	3	235.9	3	239.1	3	242.2
	9	1	324.7	1	331.2	1	343.5	1	355.7
	10	1	246.8	1	255.7	1	272.6	1	289.5
GT		2399.8		2499.8		2599.8		2699.7	

Table 6. The comparison of total costs.

Total Load	numerical method	neural method
2400.0	488.50	487.87
2500.0	526.70	526.13
2600.0	574.03	574.26
2700.0	625.18	626.12

general numerical methods such as the hierarchical structure approach[19].

In comparison with the hierarchical structure method the proposed Hopfield neural network method demonstrates a much simpler algorithm with nearly the same results. The Hopfield neural network method can be easily applied to situations involving a large number of generators. Through case studies, we have shown the possibility of the application of the Hopfield neural network to the ELD problem with general nonconvex cost functions. Specifically, the neural network method does not require the calculation of incremental fuel costs and incremental losses needed in conventional numerical methods. The hardware implementation is also promising because of the advantage of the real time response.

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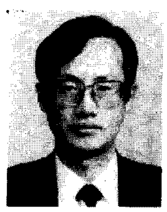
Biographies



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Discussion

M. E. El-Hawary (Technical University of Nova Scotia, Halifax, N.S., Canada): The authors are to be commended for an interesting paper, highlighting experience with using the Hopfield network model as a tool to solve a simple economic dispatch problem. The main contribution of the paper is to point out the feasibility of using the Hopfield model for this class of problems. The authors' response to the following points would be appreciated:

— The optimal power flow (OPF) problem is a more complex problem than that treated by the authors of the papers. The authors contention in the introduction that OPF problems were treated using Hopfield model, is strictly speaking inaccurate. References [13–15] did not address the OPF problem but rather dealt with simple economic dispatch and unit commitment problems.

— The use of a penalty factor A to account for the power balance constraint is one way of dealing with this issue. Note that the minimum of E takes place at the same solution point as that for E/B, assuming that B is positive. As a result, the introduction of the factor B unnecessarily complicates the procedure, since it can be set to one without loss of generality. This in turn will affect the values of T_{ii}.

— The role of the transformation (16) in treating the simple inequality constraints of the form (11), needs more elaboration. How would the authors proceed in the case of functional inequality constraints?

— It is obvious that the present formulation cannot directly handle the quadratic loss formula (10), since the penalty factor approach adopted by the authors leads to fourth order form. Two points must be pondered. It appears that a linear loss formula can be easily treated using the authors formulation. The second is that if we used the Lagrangian approach, with a value of system lambda determined beforehand, then quadratic loss formula can be easily dealt with. Did the authors consider these options, and if so, what were their conclusions?

— The paper's title mentions the piece-wise quadratic cost curves, but the paper's text does not cover this aspect adequately. It would be interesting, and would enhance the utility of the paper if the authors would expand on this issue.

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D.P. Kothari, P.R. Bijwe (Indian Institute of Technology, Delhi, India) and L.D. Arya, R.S. Tare (Sh. Govindram Seksaria Institute of Technology and Science, Indore, India): We wish to commend the authors for their valuable contribution in providing a new method to solve the problem of economic power dispatch with piecewise quadratic cost function using the Hopfield neural network. However, we would like to seek the authors' clarification on the following points.

1. Would the authors throw some light on the method of selection of weighting factors A and B ? Are they dependent on the system and the initial solution ?

2. How does the performance and accuracy of the method get affected if the complete cost curve is approximated by a single quadratic function as is normally done ?

3. In the simulation method why have the mutual loss coefficients terms not been considered ?

4. One of the main advantages of the proposed method is the absence of the need of the calculation of incremental fuel cost and incremental transmission losses. But this does not seem to be a major problem in ED solution with quadratic cost function and usual loss coefficients.

Once again we congratulate the authors for their very useful and interesting paper.

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J. H. Park, Y. S. Kim, I. K. Eom, and K. Y. Lee : The authors are appreciative of the interest in the paper and thank the discussers for their comments.

References[13-15] only addressed the economic load dispatch and unit commitment problems as professor El-Hawary pointed out. The paper dealing with the OPF problem using the Hopfield neural network was presented by professor Mori in Meiji University, Japan. I have a copy of professor Mori's paper, which is written in Japanese, therefore I have not referred to it in this paper.

The discusser pointed out that the factor B is unnecessary. However, If the discusser observes the parameters of the network proposed by Hopfield and Tank to solve the Traveling Salesman Problem (see ref. [17] in this paper), the discusser will find that the characteristics of optimization technique using the Hopfield network are different from those of conventional optimization techniques. Two parameters have to be properly chosen in these problems and carefully tuned for the network to operate satisfactorily. If the parameter settings are not correct, the network may not even converge to a feasible solution, let alone an optimal one. The problem of selecting the parameters for a Hopfield and Tank network implemented to solve TSP for moderately large problem sizes has been studied by Wilson and Pawley[1].

Modified sigmoidal function of the equation(16) was defined such that the maximum and minimum value of the neuron output V_i are $\overline{P}_i$ and $\underline{P}_i$, respectively. Thus, the solutions of Hopfield network always satisfy inequality constraints of the form(11). Other methods must be suggested in the case of functional inequality constraints.

For the asymptotical stability in the Hopfield network, an energy function must be positive definite. Since an equality constraint may have a positive or negative value, the Lagrangian approach does not satisfy the positive definite condition.

I agree with the discusser's comment on the paper's title in some respects. However, the algorithm was expressed as a general formulation to cover the ELD problems with both a quadratic cost function and piecewise quadratic cost functions, since the simulations were performed for both cases. In the case of ELD problems with piecewise quadratic cost functions, equation(17) is substituted for equation(8) and cost coefficients in equation(14) are replaced by cost coefficients of relevant fuel type. The paper's title mentioned the piecewise quadratic cost function because authors would like to stress the merit of neural network in ELD problems with piecewise quadratic cost functions particularly.

The authors did not find a systematic rule for selecting the weighting factors. However, two parameters were easily found in our simulations. They are dependent on the system, but we have not done a number of simulations to study the interrelation between initial solution and weighting factors.

The authors don't understand exactly the key point of professor Kothari's the second question. The performance and accuracy of the neural network method have been shown in the first simulations, which refer to the same cases as the complete cost curve is approximated by a single quadratic function.

The ELD problems chosen to compare with numerical methods are in reference[20], in which mutual loss coefficient terms have not been given. It is also expected that there are no problems in such cases.

The authors don't insist that the absence of the need of the incremental fuel cost calculation is the advantage of the proposed method. It is only one of the characteristics of the neural network method.

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