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SOLVING AN ECONOMIC DISPATCH PROBLEM WITH TRANSMISSION SYSTEM REPRESENTATION BY A MODIFIED HOPFIELD NETWORK

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Abstract: Economic Dispatch (ED) problems have recently been solved by artificial neural network approaches. In most of these dispatch models the transmission system representation is totally neglected. Therefore, such procedures may calculate dispatch policies that do not take into account important active power constraints. Another drawback pointed out in the literature is that some of these neural approaches fail to converge efficiently toward feasible equilibrium points. This paper discusses the application of a modified Hopfield architecture for solving an ED problem with transmission system representation. The transmission system is represented through linear load flow equations and constraints on active power flows. Simulation results and a sensitivity analysis involving IEEE 14-bus test system are presented to illustrate efficiency of the proposed approach. *Copyright © 2002 IFAC.*

Keywords: power systems, optimization problems, neural networks, power flow, parameter optimization.

1. INTRODUCTION

Economic Dispatch (ED) is the process of allocating generation levels to the generating units so that the system load is supplied entirely and most economically. Many ED approaches have been proposed in the literature to formulate and solve this problem. In Chowdhury and Rahman (1990) it is provided a review of the advances in such field. The economic dispatch definition above is quite large so that many specific optimization models applied to power system, such as optimal power flow, unit commitment, generation scheduling, etc., may be faced as economic dispatch models. It must be clear however that these models vary in complexity and have different scope of application.

The Classic Economic Dispatch (CED) discussed in Chowdhury and Rahman (1990) and Happ (1977) is the starting point of the ED problem. CED is concerned with minimization of total operating costs while supplying entirely the system demand and enforcing the limits on generation levels. In CED procedures, the transmission network representation is totally neglected. Therefore, CED procedures may calculate dispatch policies that do not take into account important active power constraints such as active power flows in transmission lines and transformers; and also load flow equations in the transmission system. In the economic dispatch formulation studied in this paper a detailed representation of the transmission system is adopted. The transmission system representation is incorporated through linear load flow equations and limits on active power flows. The dispatch model resulting from the formulation here adopted may also be faced as a model for one time interval (snapshot) of the short-term generation scheduling problem (Wong and Doan, 1992). The dispatch formulation here adopted is solved in this work by a neural network approach.

Some effective applications of artificial neural networks to the ED problem have recently been presented in the literature. In Walsh and O'Malley (1997) an approach trying to unify unit commitment and generation dispatch functions is described. A hybrid Hopfield network is adopted such that the energy function of the Hopfield network is able to deal with discrete and continuous terms. In Park *et al.* (1993) a Hopfield neural network is proposed to solve CED problem with general non-convex cost functions. The computation effort for solving the problem is high due to large number of iterations to obtain the optimality. In Su and Chiou (1997a) an analytic Hopfield method reducing considerably this computation effort is proposed. However the method is not applied to non-convex cost functions. In Su and Chiou (1997b) a Hopfield model for ED problem considering prohibited zones was developed. In a neural network approach for solving CED with transmission capacity constraints was proposed. In Yalcinoz *et al.* (2001) a restructuring of the approach described in Yalcinoz and Short (1998) was proposed for solving the unconstrained ED, i.e., the ED with transmission capacity constraints and also the multi-area ED problems.

Most of the neural network applications described above fail to converge efficiently to equilibrium points representing the dispatch problem solutions. A careful analysis of the results presented in some of these papers reveals that infeasible solutions are sometimes obtained. In the modified Hopfield approach proposed in Silva and Nepomuceno (2001) to solve CED problem, the optimization and constraint terms involved with problem mapping (Section 3) are treated in different stages. The modified Hopfield approach guarantees the network convergence to a feasible optimal solution (Silva *et al.*, 2000). The problems associated with speed of convergence, depicted in Walsh and O'Malley (1997) and Park et al. (1993), were also satisfactory handled in Silva and Nepomuceno (2001). As demonstrated in Silva *et al.* (2001) the modified Hopfield approach is also applicable to general non-convex cost functions (this includes CED problems with non-monotonically increasing incremental cost units, as that studied in Jiang and Ertem (1995).

This paper applies the modified Hopfield approach described in Silva and Nepomuceno (2001) to solve a more representative dispatch problem. In the problem being dealt with in this work, the transmission network is represented in detail, through linear load flow equations and active power flow constraints in the transmission system. The IEEE 14-bus test system is used in the case studies discussed in the paper. The results point out that the modified Hopfield approach is robust enough to represent the transmission system in dispatch problems.

The paper is organized as follows. In Section 2, the formulation of the dispatch problem is introduced. In Section 3, the modified Hopfield network is presented, and valid-subspace technique, used to design the network parameters, is described. A mapping of the economic dispatch problem using the modified Hopfield network is presented in Section 4. In Section 5, simulation results are presented to validate the developed approach. In Section 6, the main conclusions about the paper are presented.

2. DESCRIPTION OF THE ECONOMIC DISPATCH MODEL ADOPTED

The Economic Dispatch formulation adopted here is mathematically described by the following equations:

$$
\text{ED}\begin{cases}
\text{Minimize: } C_T = \sum_{i=1}^{NG} C_i(P_i) & (1)\\
\text{subjetct to:} & \\
\boldsymbol{P} = \boldsymbol{B}.\theta & (2)\\
P_i^{\min} \le P_i \le P_i^{\max} & (3)\\
F_i^{\min} \le F_i(\theta) \le F_i^{\max} & (4)
\end{cases}
$$

where:
C_T is the total fuel cost.
NG is the set of dispatchable generating units.
$C_i(P_i) = a_i + b_i.P_i + c_i.P_i^2$ is the fuel cost of the generating unit i.
P_i is the real power output of generating unit i.
a_i, b_i and c_i are cost coefficients for unit i.
$\boldsymbol{P}$ is the vector of active power injections.
$\boldsymbol{B}$ is the network susceptance matrix.
θ is the vector of voltage angles.
$P_i^{\min}$ is the minimum generation output of unit i.
$P_i^{\max}$ is the maximum generation output of unit i.
$F_i(\theta)=(\theta_k - \theta_l) / x_{kl}$ is the active power flow in branch (line or transformer) i connecting buses k and l.
θ_k is the voltage angle at bus k.
x_{kl} is the reactance of branch i connecting buses k and l.

The ED model described in (2) represents linear load flow equations. Equation (3) and (4) represent the limits on active power generation and on active power flows in transmission system. The active power flows in the system are represented by linear equations. The cost function (1) is sometimes expressed as a cubic polynomial (Jiang and Ertem, 1995). For fossil fired plants it is also sometimes represented as segmented piecewise quadratic function (Park et al., 1993). This is not a problem for the approach proposed here once it may cope with general non-convex cost functions.

3. THE MODIFIED HOPFIELD NETWORK

Artificial Neural Networks attempt to achieve good performance via dense interconnection of simple computational elements. Hopfield's networks have been applied to several classes of optimization problems and have shown promise for solving such problems efficiently. The node equation for the continuous-time network is given by:

$$\dot{u}_i(t) = -\eta.u_i(t) + \sum_{j=1}^{n} T_{ij}.v_j(t) + i_b^i \quad (5)$$

$$v_i(t) = g_i(u_i(t)) \quad (6)$$

where:
$u_i(t)$ is the current state of the i-th neuron.
T_{ij} is the weight connecting the j-th to i-th neuron.
$v_j(t)$ is the output of the j-th neuron.
i_i^b is the offset bias of the i-th neuron.
$\eta.u_i(t)$ is a passive decay term.
$g_i(u_i(t))$ is an activation function each neuron.

It can be verified in Hopfield (1984) that the equilibrium points of the network correspond to values $\boldsymbol{v}(t)$ for which the energy function (7) associated with the network is minimized:

$$E(t) = -\frac{1}{2}\boldsymbol{v}^T(t).\boldsymbol{T}.\boldsymbol{v}(t) - \boldsymbol{v}^T(t).\boldsymbol{i}^b \quad (7)$$

A mapping of the economic dispatch problem using a Hopfield network consists of determining the weight matrix $\boldsymbol{T}$ and the bias vector $\boldsymbol{i}^b$ to obtain equilibrium points, which are the problem solutions. A modified energy function $E^m(t)$ is used here. This function is defined as follows:

$$E^m(t) = E^{conf}(t) + E^{op}(t) \quad (8)$$

where $E^{conf}(t)$ is a confinement term that groups the constraints given by (2), (3) and (4); and $E^{op}(t)$ is an optimization term that conducts the network output to the equilibrium points. This method is in contrast to most neural approaches used in economic load dispatch problems, which become inefficient because they treat these terms as a single function of energy.

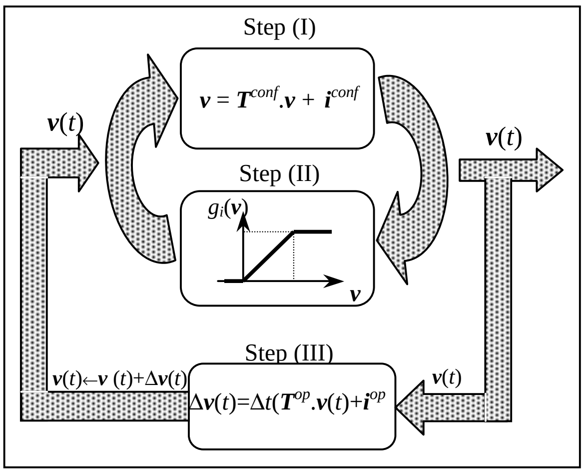

Fig. 1. Modified Hopfield network.

The operation of the modified Hopfield network consists of three main steps, which are shown in Fig. 2. These steps can be explained as follows:
Step (I): Minimization of E^{conf}, corresponding to the projection of $\boldsymbol{v}(t)$ in the valid subspace defined by:

$$\boldsymbol{v}(t+1) = \boldsymbol{T}^{conf}.\boldsymbol{v}(t) + \boldsymbol{i}^{conf} \quad (9)$$

where: $\boldsymbol{T}^{conf}$ is a projection matrix ($\boldsymbol{T}^{conf}.\boldsymbol{T}^{conf} = \boldsymbol{T}^{conf}$) and the vector $\boldsymbol{i}^{conf}$ is orthogonal to the subspace ($\boldsymbol{T}^{conf}.\boldsymbol{i}^{conf} = \boldsymbol{0}$). An analysis of the valid-subspace technique is presented in Aiyer *et al*. (1990).

Step (II): Application of a nonlinear "symmetric ramp" activation function constraining $\boldsymbol{v}(t)$ in a hypercube:

$$g_i(v_i) = \begin{cases} \lim_i^{\inf}, & \text{if} \quad \lim_i^{\inf} > v_i \\ v_i, & \text{if} \quad \lim_i^{\inf} \le v_i \le \lim_i^{\sup} \\ \lim_i^{\sup}, & \text{if} \quad v_i > \lim_i^{\sup} \end{cases} \quad (10)$$

where $v_i(t) \in [\lim_i^{\inf}, \lim_i^{\sup}]$.

Step (III): Minimization of E^{op}, which involves updating of $\boldsymbol{v}(t)$ in direction of an optimal solution (defined by $\boldsymbol{T}^{op}$ and $\boldsymbol{i}^{op}$) corresponding to network equilibrium points, which are the solutions for the economic load dispatch problem, by applying the gradient in relation to the energy term E^{op}:

$$\frac{d\boldsymbol{v}(t)}{dt} = \dot{\boldsymbol{v}} = -\frac{\partial E^{op}(t)}{\partial \boldsymbol{v}}$$

$$\Delta\boldsymbol{v} = -\Delta t.\nabla E^{op}(\boldsymbol{v}) = \Delta t.(\boldsymbol{T}^{op}.\boldsymbol{v} + \boldsymbol{i}^{op}) \quad (11)$$

Therefore, minimization of E^{op} consists of updating $\boldsymbol{v}(t)$ in the opposite direction of the gradient of E^{op}.

As seen in Fig. 2, each iteration has two distinct stages. First, as described in Step (III), $\boldsymbol{v}$ is updated using the gradient of the term E^{op} alone. Second, after each updating, $\boldsymbol{v}$ is directly projected in the valid subspace. This is an iterative process, in which $\boldsymbol{v}$ is first orthogonally projected in the valid subspace defined in (9), and then thresholded so that its elements lie in the range $[\lim_i^{\inf}, \lim_i^{\sup}]$.

4. FORMULATION OF ECONOMIC DISPATCH PROBLEM BY MODIFIED HOPFIELD NETWORK

As observed in Section 2, an economic dispatch problem is a problem of minimizing a cost function in presence of linear constraints of the inequality and/or equality type. Since equality constraints can be easily converted to inequality constraints (Bazaraa and Shetty, 1979), it is used (by simplicity) only inequality constraints. Consider the following constrained optimization problem, with m-constraints and n-variables, given by the following equations:

$$\text{Minimize } E^{op}(\boldsymbol{v}) = C_T \quad (12)$$

$$\text{Subject to: } E^{conf}(\boldsymbol{v}): \boldsymbol{A}^T.\boldsymbol{v} \le \boldsymbol{b} \quad (13)$$

$$\boldsymbol{z}^{min} \le \boldsymbol{v} \le \boldsymbol{z}^{max} \quad (14)$$

where $\boldsymbol{A} \in \Re^{nxm}$, $\boldsymbol{b} \in \Re^m$, and $\boldsymbol{c}$, $\boldsymbol{v}$, $\boldsymbol{z}^{min}$, $\boldsymbol{z}^{max} \in \Re^n$. The conditions in (13) and (14) define a bounded convex polyhedron. In this case, the vector $\boldsymbol{v}$, which corresponds to the variables in (1) {i.e. $\boldsymbol{v}^T = [\boldsymbol{P}^T \ \boldsymbol{F}^T]$}, must remain within this polyhedron if it is to represent a valid solution for the optimization problem (12). A solution can be obtained by a modified Hopfield network, whose valid subspace guarantees the satisfaction of the condition (13). Moreover, the initial hypercube represented by the constraints in (14) is mapped by the ‘symmetric ramp’ function (10) used as network activation function .

The terms $\boldsymbol{T}^{conf}$ and $\boldsymbol{i}^{conf}$ are calculated by transforming the inequalities in (13) into equalities by introducing a slack variable $\boldsymbol{w} \in \Re^n$ for each inequality constraint:

$$g_i(\boldsymbol{v}) + \sum_{j=1}^{q} \delta_{ij}.w_j = 0 \qquad (15)$$

where w_j are slack variables, treated as the variables v_i and δ_{ij} is defined by the Kronecker impulse function:

$$\delta_{ij} = \begin{cases} 1 \text{ , if } i = j \\ 0 \text{ , if } i \neq j \end{cases} \qquad (16)$$

After this transformation, the problem defined by (12), (13) and (14) can be rewritten as:

$$\text{Minimize } E^{op}(\boldsymbol{v}) = C_T \qquad (17)$$

$$\text{subject to } E^{conf}(\boldsymbol{v}): (\boldsymbol{A}^+)^T.\ \boldsymbol{v}^+ = \boldsymbol{b}^+ \qquad (18)$$

$$\boldsymbol{z}^{min} \leq \boldsymbol{v}_i^+ \leq \boldsymbol{z}^{max} \text{ , } i \in \{1..n\} \qquad (19)$$

$$0 \leq \boldsymbol{v}_i^+ \leq \boldsymbol{z}^{max} \text{ , } i \in \{n+1..N^+\} \qquad (20)$$

where $N^+ = n + m$, and $\boldsymbol{v}^{+T} = [\boldsymbol{v}^T \ \ \boldsymbol{w}^T] \in \Re^{N^+}$ is a vector of extended variables. Note that E^{op} does not depend on the slack variable $\boldsymbol{w}$. If the rows of $\boldsymbol{A}^+$ are linearly independent, a solution for (18) is given by:

$$\boldsymbol{v}^+ = \boldsymbol{A}^+.(\boldsymbol{A}^{+T}.\boldsymbol{A}^+)^{-1}.\boldsymbol{b}^+ \qquad (21)$$

and the expression of the valid subspace in (9) must take into account this solution, i.e.,

$$\boldsymbol{i}^{conf} = \boldsymbol{A}^+.(\boldsymbol{A}^{+T}.\boldsymbol{A}^+)^{-1}.\boldsymbol{b}^+ \qquad (22)$$

From (22), the parameter $\boldsymbol{T}^{conf}$ is derived as follows:

$$\boldsymbol{v}^+ = \boldsymbol{T}^{conf}.\boldsymbol{v}^+ + \boldsymbol{i}^{conf} \qquad (23)$$

$$\boldsymbol{v}^+ = \boldsymbol{T}^{conf}.\boldsymbol{v}^+ + \boldsymbol{A}^+.(\boldsymbol{A}^{+T}.\boldsymbol{A}^+)^{-1}.\boldsymbol{b}^+ \qquad (24)$$

Inserting the value of (18) in (24), the expression for $\boldsymbol{T}^{conf}$ is given by:

$$\boldsymbol{T}^{conf} = \boldsymbol{I} - \boldsymbol{A}^+.(\boldsymbol{A}^{+T}.\boldsymbol{A}^+)^{-1}.\ \boldsymbol{A}^{+T} \qquad (25)$$

where $\boldsymbol{I}$ is identity matrix.

The parameters $\boldsymbol{T}^{op}$ and $\boldsymbol{i}^{op}$ in this case are such that the vector $\boldsymbol{v}^+$ is updated in the opposite gradient direction that of the energy function E^{op}. Since conditions given by (18), (19) and (20) define a bounded convex polyhedron, the objective function (17) has a unique global minimum ($|\boldsymbol{T}^{op}=\boldsymbol{0}|$). Thus, using (7) and (11), the equilibrium points of the network can be calculated by assuming the following values to $\boldsymbol{T}^{op}$ and $\boldsymbol{i}^{op}$:

$$\boldsymbol{i}^{op} = -\left[\frac{\partial f(\boldsymbol{v})}{\partial v_1} \ \frac{\partial f(\boldsymbol{v})}{\partial v_2} \cdots \frac{\partial f(\boldsymbol{v})}{\partial v_N}\right] \qquad (26)$$

$$\boldsymbol{T}^{op} = \boldsymbol{0} \qquad (27)$$

The simulation results describing performance of the proposed approach are presented in the next section.

5. SIMULATION RESULTS

This section shows some simulation results involving IEEE 14-bus system in which 5 generating units supply the total demand (259 MW). Table 1 provides the parameters associated with the generating units. Some case studies are proposed as follows to analyze the sensitivity of the proposed Hopfield approach with respect to some specific modeling characteristics (constraints, objective function, etc.).

Table 1 Input Parameters

Unit	a_i	b_i	c_i	$P_i^{\min}$ (MW)	$P_i^{\max}$ (MW)
1	550	8.10	0.00028	0	680
2	126	8.60	0.00284	0	120
3	240	7.74	0.00324	0	180
6	309	8.10	0.00056	0	360
8	240	7.74	0.00324	0	180

The dispatch computed by the modified Hopfield network proposed in this paper is shown in Table 2.

Table 2 Simulation Results

Unit	P_i (MW)
1	30.004
2	34.276
3	75.043
6	53.839
8	65.782

Figure 2 shows the cost evolution during the convergence of the modified Hopfield network. The network reached the lowest cost solution after around thirty iterations. Thus, problems related to the convergence speed of are effectively handled by the proposed approach.

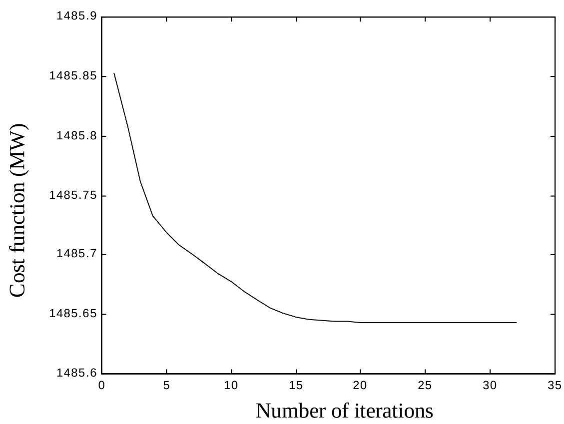

Fig. 2. Evolution of the cost function – Case I.

In case study II, the maximum generation limit for unit 8 was changed to 20 MW in order to evaluate the network behavior when generation limits should be enforced. The dispatch calculated by the proposed model is depicted in table 3. As seen in the table the generation output for unit 8 was conveniently set to its maximum value.

Table 3 Enforcing Generation Constraints – Case II

Unit	P_i (MW)
1	30.033
2	34.305
3	120.716
6	53.870
8	20.000

The evolution of the cost function for this case study is presented in Fig. 3. The neural network reached the solution in approximately forty iterations.

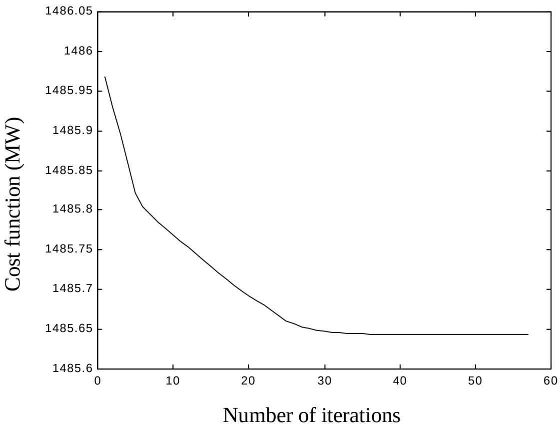

Fig. 3. Evolution of the cost function – Case II.

In case study III, the Hopfield network behavior when active power flow limits are to be enforced, is analyzed. In this case the limits in two system lines (connecting buses 1-5 and 7-9) were set to zero, simulating a line contingency. The new dispatch calculated by the proposed approach is depicted in Table 4. The dispatch is completely rearranged so as to supply the system demand. Fig. 4 shows the evolution for cost function in this case. From this figure it can be noted that the number of iterations was really few (the method took only 8 iterations) due to the enforcement of active power flow constraints. In this case, the number of iterations is extremely small if compared with other neural approaches (Walsh and O'Malley, 1997; Park *et al.*, 1993), which present thousands of iterations to reach equilibrium points.

Table 4 Line Contingency – Case III

Unit	P_i (MW)
1	23.363
2	27.199
3	29.153
6	156.840
8	22.362

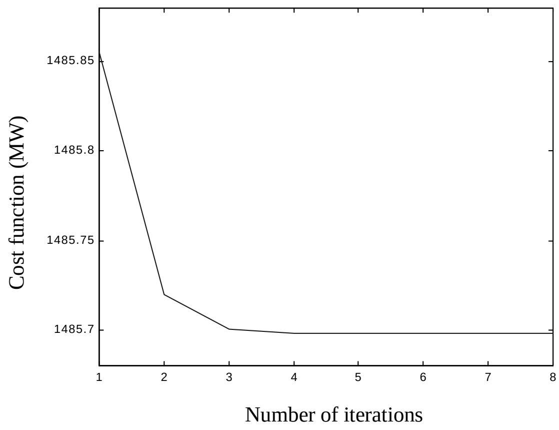

Fig. 4. Evolution of the cost function – Case III.

In case study IV, the parameter *b* of the cost function of unit 8 was multiplied by 3, in order to make this generator more expensive. The aim of such study is to evaluate how the generation cost structure affects the dispatch calculated by the modified Hopfield approach. Since the network calculates the lowest cost generation and since the generation cost was increased for unit 8, the generation level of such unit must be reduced when compared to case study I. This result is confirmed by inspecting Tables 5 and 2.

Table 5. Changing the Cost Structure of Generator 8 – Case IV

Unit	P_i (MW)
1	25.175
2	27.939
3	135.203
6	46.115
8	24.507

Figure 4 shows the evolution of the cost function for case study IV. The method took approximately sixty iterations to reach the equilibrium point.

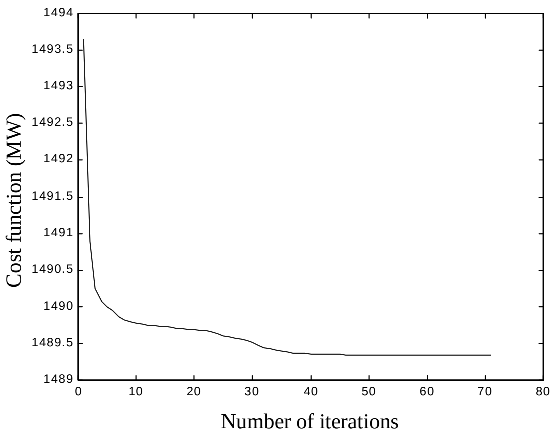

Fig. 4. Cost function for a constraint of cost parameter.

The modified Hopfield network presented here treats optimal and constraint terms in different stages. The terms $\boldsymbol{T}^{conf}$ and $\boldsymbol{i}^{conf}$ (belonging to E^{conf}) of the modified Hopfield network were developed to force the validity of the structural constraints associated with the economic load dispatch problem, and the terms $\boldsymbol{T}^{op}$ and $\boldsymbol{i}^{op}$ (belonging to E^{op}) were projected to find the optimal solution associated with the cost function.

Thus, the main advantages of using a modified Hopfield network to solve economic load dispatch problems are i) consideration of optimization and constraint terms in distinct stages with no interference with each other, ii) use of the unique energy term (E^{conf}) to group all constraints imposed on the problem, and iii) lack of need for adjustment of weighting constants for initialization.

No alteration in the parameter initialization structure was necessary during the simulations performed in the case studies. The network output vector $\boldsymbol{v}$ was initialized with zeros. It should be noted that the increase in the number of constraints (generating units) does not degrade the performance of the network, but rather shows its efficiency. This consideration only emphasizes the robustness of the proposed approach.

6. CONCLUSIONS

The proposed neural method can solve efficiently economic dispatch problems involving the transmission system representation. As shown in the sensitivity analysis made throughout the studies presented in this paper, the modified Hopfield network has been globally stable and it has not required any special treatment for initialization. Simulated Results have confirmed the validity and robustness of the proposed approach.

In addition to providing a new approach for economic dispatch problems, the proposed algorithm presents the following advantages: i) improved accuracy of equilibrium points representing the solutions of ED problems; ii) inclusion of constraint terms in single energy term, represented by $E^{conf}(t)$; iii) simplicity of implementation of economic load dispatch problem in digital computers; and iv) lack of need for adjustment of weighting constants for initialization.

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