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# SECURITY-CONSTRAINED OPTIMAL RESCHEDULING OF REAL POWER USING HOPFIELD NEURAL NETWORK

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**Abstract**

A new method for security-constrained corrective rescheduling of real power using the Hopfield neural network is presented. The proposed method is based on solution of a set of differential equations obtained from transformation of an energy function. Results from this work are compared with the results from a method based on dual linear programming formulation of the optimal corrective rescheduling. The minimum deviations in real power generations and loads at buses are combined to form the objective function for optimization. Inclusion of inequality constraints on active line flow limits and equality constraint on real power generation load balance assures a solution representing a secure system. Transmission losses are also taken into account in the constraint function.

**Keywords:** *Feedback ANN, Real power optimal dispatch, corrective strategy, security enhancement.*

## 1.0 INTRODUCTION

A great deal of research has gone into finding fast and reliable solution techniques for security-constrained real power corrective rescheduling. Many solution techniques, each with its specific mathematical model and computational procedure, have been reported in the pertinent literature in the last twenty five years. All of these techniques can be broadly classified into two groups of mathematical models (i) Linear Programming (LP) based models [1-6] and (ii) Non Linear Programming (NLP) based models [7-9].

In this work, a method is proposed to solve Hopfield Network-based constrained linear programming problems. The real power security-constrained optimal dispatch (following P-Q decomposition philosophy) problem is based on the minimum deviations of the control variables approach. Our control variables are chosen as the real power generation and load at each bus. The real part of the transmission loss is considered as a function of the net real power injections.

Non-linear analog neurons connected in highly interconnected networks are proven to be very effective in computation [10]. These networks provide a collectively computed solution to a problem based on the analog input information. Tank and Hopfield have shown in their earlier work [10-13] that the interconnected networks of analog processors can be used for the solution of constrained optimization problem. The main idea behind solving the optimization problem is to formulate an appropriate computational energy function 'E(X)' so that the lowest energy state would correspond to the required solution of 'X'. Following this same philosophy, Hopfield Networks have been used to solve power system problems such as maintenance scheduling of thermal units [14], economic load dispatch [15], unit commitment [16] and reactive power optimal distribution [17,18]. The basic methodology followed in the optimization problems is to express a problem in the form of Hopfield network energy function and then solve for 'X' to seek the minimum of its energy function.

The proposed method is based on transformation of the energy function minimization problem into a set of ordinary differential equations [19]. In addition, a modified energy function has also been proposed to deal with the ill-conditioned problems. The method is used in active security-constrained dispatch problems with illustrations on two test systems. Since, our intent is to validate the results of the proposed method with those from a rigorous mathematical optimization procedure, we introduce a new LP-based security-constrained rescheduling algorithm first, and then discuss the customization of the Hopfield neural network for the constrained optimization. The following sections will describe the formulation. However, before expounding the details, it would be appropriate to explain the rationale for the work. The inspiration for developing an alternative for the optimization technique does not merely stem from a need for an alternate solution methodology. LP, as we know, is a mature optimization strategy and has been applied in many areas of power system problems. In this work, it is not our intent to re-invent the LP technique, but rather to re-formulate the LP-based problem which will then lend itself to convenient hardware implementation on transputers. The result will be an extremely fast parallel processor for obtaining optimal solutions.

## 2.0 LIST OF SYMBOLS

$P_i = P_{G_i} - P_{L_i}$ : real power net injection at bus 'i'

$V_i = |V_i| \angle \delta_i$ : voltage at bus 'i'

$\delta_i$ : voltage angle at bus 'i'

$Y_{ij} = G_{ij} + j B_{ij}$ : branch admittance between buses 'i' and 'j'

$G_{ij}$ : branch conductance between buses 'i' and 'j'

$B_{ij}$ : branch susceptance between buses 'i' and 'j'

$S_{fij} = P_{fij} + jQ_{fij}$ : power flow in a line between buses 'i' and 'j'

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| | |
|---|---|
| $P_{fij}$ | : branch active flow between buses 'i' and 'j' |
| $Q_{fij}$ | : branch reactive flow between buses 'i' and 'j' |
| $C_{Gi}$ | :cost coefficient of generation at bus 'i' |
| $C_{Li}$ | :cost coefficient of load at bus 'i' |
| $P_{Gi}^{max}$ | :maximum MW generation limit at bus 'i' |
| $P_{Gi}^{min}$ | :minimum MW generation limit at bus 'i' |
| $P_{Li}^{max}$ | :maximum MW load limit at bus 'i' |
| $P_{Li}^{min}$ | :minimum MW load limit at bus 'i' |
| $P_{ij}^{max}$ | :max. branch MW flow between buses 'i' and 'j' |
| $P_{ij}^{min}$ | :min. branch MW flow between buses 'i' and 'j' |
| NB | :number of buses in the system |
| NL | :number of lines in the system |
| A | :constraints coefficient matrix ; (3NB + 1)x(2NB) |
| $A^{/}$ | :flow constraints coeff. matrix; NL x NB |
| $A^{//}$ | :line losses constraint coeff. matrix; NL x NB |
| $J_{P-\delta}$ | :submatrix of the full Jacobian relating $P-\delta$ |
| $P_{ij}^{loss}$ | :real branch loss between buses 'i' and 'j' |

## 3.0 LP PROBLEM FORMULATION

The linear programming method for security-constrained rescheduling uses the submatrix $J_{P-\delta}$ of the full Jacobian matrix to exploit the advantage of decoupling between bus power P and bus voltage. The state of the system with economic schedule of generation can be an initial condition for the proposed technique. The optimization problem is defined as:

$$\text{minimize} \quad f = \mathbf{C}^t_G\,\Delta\mathbf{P}_G + \mathbf{C}^t_L\,\Delta\mathbf{P}_L \tag{1}$$

Subject to the following constraints:

Inequality constraints:

$$\Delta P_f^{min} \le \Delta P_f = A^{/}(\Delta P_G - \Delta P_L) \le \Delta P_f^{max} \tag{2}$$

$$\Delta P_G^{min} \le \Delta P_G \le \Delta P_G^{max} \tag{3}$$

$$\Delta\mathbf{P}_L^{min} \le \Delta\mathbf{P}_L \le \Delta\mathbf{P}_L^{max} \tag{4}$$

Equality constraints :

$$\Delta\mathbf{P}_G - \Delta\mathbf{P}_L - \Delta\mathbf{P}^{loss} = 0 \tag{5}$$

For the optimization model in its present state, the bus voltage magnitude at each bus is assumed to remain constant at the starting values.

### 3.1 Formulation of the coefficient matrix $A^{/}$

We know from full P-Q decomposition,

$$[\,\Delta P\,] = [\,J_{P-\delta}\,]\bullet[\,\Delta\delta\,] \tag{6}$$

$$[\,\Delta\delta\,] = [\,J_{P-\delta}\,]^{-1}\bullet[\,\Delta P\,] \tag{7}$$

$$[\,\Delta\delta\,] = [\,Z\,]\bullet[\,\Delta P\,] \text{ where } [\,Z\,] = [\,J_{P-\delta}\,]^{-1} \tag{8}$$

$\Delta\delta$ is solved for by LU facorization without inverting the $J_{P-\delta}$ sub-matrix. The Jacobian submatrix can be stored in factored form and any required row of $[\mathbf{Z}]$ can be calculated from the factored matrices. The real power flow and incremental flow in a branch connected between bus 'i' and bus 'j' can be represented as:

$$P_{fij} = |V_i|^2 G_{ij} - |V_i||V_j|\,G_{ij}\cos(\delta_i-\delta_j) - |V_i||V_j|\,B_{ij}\sin(\delta_i-\delta_j) \tag{9}$$

$$\Delta P_{fij} = \frac{\partial P_{fij}}{\partial\delta_i}\Delta\delta_i + \frac{\partial P_{fij}}{\partial\delta_j}\Delta\delta_j \tag{10}$$

Equation (10) can be written as follows:

$$[\Delta P_f] = [D]\bullet[\Delta\delta] = [D]\bullet[Z]\bullet[\Delta P] = [A^{/}]\bullet[\Delta P] \tag{11}$$

where $D_{ij} = |V_i||V_j|(B_{ij}\cos(\delta_i-\delta_j) - G_{ij}\sin(\delta_i-\delta_j))$

where $[\mathbf{A}^{/}] = [\,\mathbf{D}\,]\bullet[\mathbf{Z}]$

Now $A^{/t}_{mn} = D_{mn}(Z^t_m - Z^t_n)$

where $\mathbf{Z}_m$ = the $m^{th}$ column of $[\mathbf{Z}]$

$\mathbf{A}^{/}_{mn}$ = the column of $\mathbf{A}^{/}$ corresponding to line between bus 'm' and bus 'n'

$D_{mn}$ = the element of $\mathbf{D}$ corresponding to line between bus 'm' and bus 'n'

$(\mathbf{Z}_m^t - \mathbf{Z}_n^t)$ can be found from (6) by making $m^{th}$ and $n^{th}$ elements of the incremental power vector as '1' and '-1' respectively and solving for the incremental bus angle.

### 3.2 Formulation of loss increment term for equality constraint

The real power loss at a branch between buses 'i' and 'j' can be represented as follows:

$$P_{ij}^{loss} = G_{ij}\left(|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos(\delta_i-\delta_i)\right) \tag{12}$$

Following a procedure similar to equations (9) and (10), we can write the incremental real power line loss as follows

$$[\Delta P^{loss}] = [F]\bullet[\Delta\delta] = [F]\bullet[Z]\bullet[\Delta P] = [A^{//}]\bullet[\Delta P] \tag{13}$$

$$\text{where} \quad F_{ij} = 2|V_i||V_j|G_{ij}\sin(\delta_i-\delta_j) \tag{14}$$

where, $[\mathbf{A}^{//}] = [\mathbf{F}][\mathbf{Z}]$

The total loss of the system can be represented as the summation of the left hand and right hand sides of equation (13) as follows:

$$\sum_{K=1}^{NL}\Delta P_K^{loss} = \sum_{i=1}^{NB}[A_i^{//}]^t\Delta P_i \tag{15}$$

where $[A_i^{//}]$ = column 'i' of the matrix $[A^{//}]$

### 3.3 Formation of full constraint coeff. matrix

In the formation of the $\mathbf{A}$ matrix, we need to consider all the inequality and equality constraints as shown in equation (2) thru (5). Let us define the following matrices and vectors which would be required to form the complete $\mathbf{A}$ matrix.

| | | |
|---|---|---|
| [ I ] | : an identity matrix; | size (NB x NB ) |
| [O ] | : a null matrix ; | size (NB x NB ) |
| [U ] | : a matrix of all elements with value of (1-H); | size ( 1 x NB ) |

$$\text{where} \quad H = \sum_{i=1}^{NB} A_i^{//} \tag{16}$$

The final form of the $\mathbf{A}$ matrix can be written as follows

$$[A] = \begin{bmatrix} A^{t} & -A^{t} \\ U & -U \\ I & O \\ O & I \end{bmatrix} \quad (17)$$

### 3.4 Calculation of limits of the constraints

If the maximum flow limits are stored in the vector $P_f^{max}$ then limits for the incremental power flow can be represented as

$$P_f^{min} - P_f \le \Delta P_f \le P_f^{max} - P_f \quad (18)$$

The limits on the control variables can be represented as

$$P_G^{min} - P_G \le \Delta P_G \le P_G^{max} - P_G \quad (19)$$

$$P_L^{min} - P_L \le \Delta P_L \le P_L^{max} - P_L \quad (20)$$

## 4.0 METHODOLOGY

The linear programming problem can be defined as that of finding a vector of unknown variables $\mathbf{X} = [X_1, X_2, \ldots\ldots, X_n]$ so as to minimize an objective function of the form shown in (1) represented in vector form as:

$$F_c = \mathbf{C}^T \mathbf{X} \quad (21)$$

The constraint equations of the form shown in eqns.(2-5) can be represented in vector form as:

$$a_j^T \mathbf{X} \ge b_j \quad (22)$$

where, $a_{ji}$ s are the coefficients of the constraints,

$b_j$ s are the bounds, and

$C_i$ s are the cost coefficients.

In general, the optimization problem associated with (21) and (22) can be formulated so as to find a vector $\mathbf{X} \in \mathbb{R}^n$ that minimizes the energy function,

$$E(X) = \sum_{i=1}^{m} f(r_i) \quad (23)$$

where,

$$r_i(X) = \sum_{j=1}^{n} a_{ij} X_j - b_i \quad (24)$$

Following a general gradient to seek for the solution, the problem defined in (23) can be mapped to a set of differential equations [19] as follows:

$$\frac{d\mathbf{X}}{dt} = -\alpha(t)\, \nabla \mathbf{E}(\mathbf{X}) \quad (25)$$

where, $\alpha(t)$ is an n x n positive definite matrix and

$$\nabla \mathbf{E}(\mathbf{X}) = \left[\frac{\partial E(\mathbf{X})}{\partial X_1}, \frac{\partial E(\mathbf{X})}{\partial X_2}, \ldots\ldots, \frac{\partial E(\mathbf{X})}{\partial X_n}\right] \quad (26)$$

The above scheme works fine for well-conditioned problems, but for ill-conditioned problems, such schemes may have very slow convergence or may converge to a solution with large error. This can be explained by the fact that the ill-conditioned problems give rise to stiff differential equations. The stiff differential equations will have a slow varying solution and small perturbation to the solution can be very rapidly damped. This is the case when time constants of the system i.e., the inverse of the eigen values of the constraint coefficient matrix (**A**) are very different. To alleviate the stiffness of the differential equations, the following energy functions can be defined,

$$E(X) = \sum_{j=1}^{n} C_j X_j + \sum_{i=1}^{m} Y_i\left(\sum_{j=1}^{n} a_{ij} X_j - b_i\right) \quad (27)$$

This problem of energy minimization can be transformed into a set of differential equations as follows:

$$\frac{dX_j}{dt} = -\alpha_j\left(C_j + \sum_{i=1}^{m} a_{ij} Y_i\right) \quad (28)$$

$$\frac{dY_i}{dt} = \beta_i\left(\sum_{j=1}^{n} a_{ij} X_j - b_i\right) \quad (29)$$

The specific choices of $\alpha$ and $\beta$ ensure stability and fast convergence of the system.

The architecture of the two-layer (constraints and neurons) Hopfield network for solving the above system defined in (28) and (29) is shown in Fig. 1.

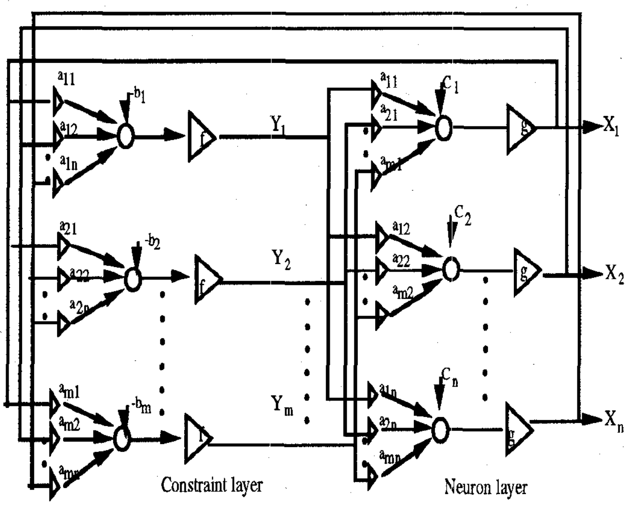


Fig.1. **Architecture of the Hopfield network**

The set of differential equations (28) and (29) can be written in the form of difference equations as follows:

$$\mathbf{X}^{(p+1)} = g\left[\mathbf{X}^{(p)} - \alpha^{(p)}(\mathbf{C} + \mathbf{a}^T \mathbf{Y}^{(p)})\right] \quad (30)$$

$$\mathbf{Y}^{(p+1)} = \mathbf{Y}^{(p)} + f\left[\beta^{(p)}(\mathbf{a}^T \mathbf{X}^{(p)} - \mathbf{b})\right] \quad (31)$$

The input and output relationships of the constraint and neuron layers are given in Fig. 2.

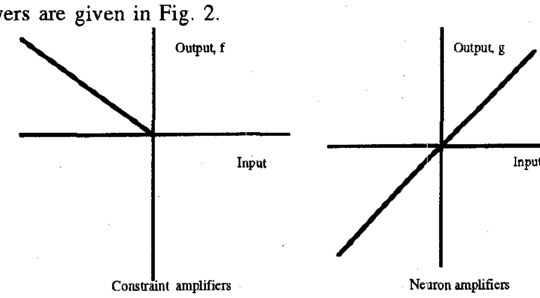


Fig. 2. **Input output relationships of the two layers**

The non-linear function 'f' is chosen for output of the

The non-linear function 'f' is chosen for output of the constraint amplifiers to provide a large positive output value when the corresponding inequality constraints are not satisfied. Each of the constraint amplifiers is provided with input values which are proportional to respective bound values ($b_j$) and a value expressed as the linear combination of the neurons' collective output. The outputs of the constraint amplifiers serve as inputs to all neuron amplifiers which are linear in nature (g). The inputs to the neurons are collective values of '$a_{ji}Y_j$' and the cost coefficients '$C_i$'. The solution is based on iteration with equations (30) and (31) until the energy function reaches its minimum value. During computation, once the energy exhibits a reducing trend, then convergence can be determined when the change in energy in two successive iterations is less than some small 'epsilon' value. The iterative procedure is shown in the flow diagram in Fig 3. If the trend of the energy at the beginning of the iteration is increasing, then appropriate adjustments need to be done in the values of $\alpha$ and $\beta$.

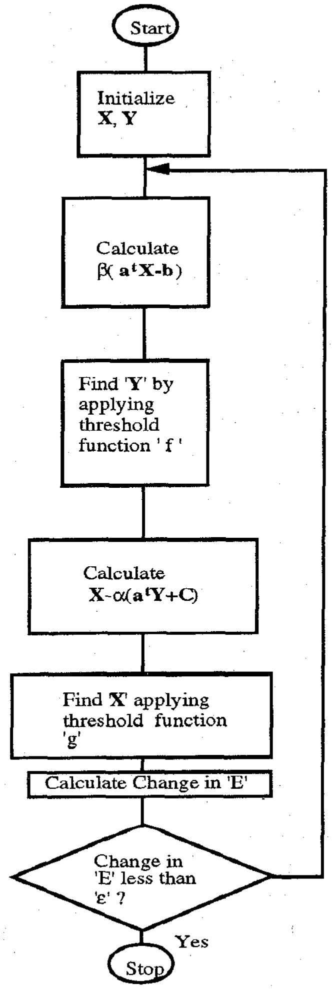


Fig. 3 **Iterative algorithm flow chart**

### 4.1 AC loadflow iterations for optimality of solution

Since we have considered complete P-Q decomposition in our modeling, the values of the control variables obtained from the optimization procedure(suggested values) need to be verified with a full fledged AC load flow for their viability. Our experience has shown that these values are conservative and that the required optimal changes can be somewhat less than the suggested values in order to maintain security of the system. The reasons for the conservative estimates include (i) MVA lineflow limit fixed were assumed to be the same as the MW lineflow limit (ii) the active dispatch is decoupled from the reactive dispatch. We therefore propose that, once the suggested values of the control variables are obtained either by Hopfield based LP or Dual simplex-based LP, the control variables should be changed in the suggested directions in small step sizes approaching the final optimal values iteratively. The results are checked with an AC power flow until all the overloads are released in the overloaded lines. On the average, it should take about 2 to 3 iterations to reach the final optimal values. The iterative algorithm is shown in Fig 4.

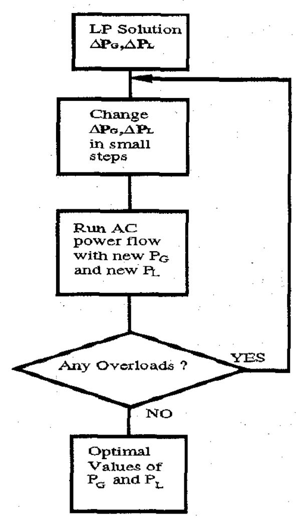


Fig. 4 **Iterative algorithm for optimal solution**

## 5.0 ILLUSTRATIONS

To illustrate the procedure, the proposed method is tested on a 6-bus system [20], the IEEE 14-bus system and the IEEE 118-bus system. The cost coefficients of the generators are selected as 0.5 and those for the loads are selected as 2.0. The coefficients $C_L$'s are chosen to be greater than $C_G$'s because variations in loads are not desired as long as the objective is fulfilled with only reallocation of generations. Fig 5. shows the 6-bus system with base case conditions.

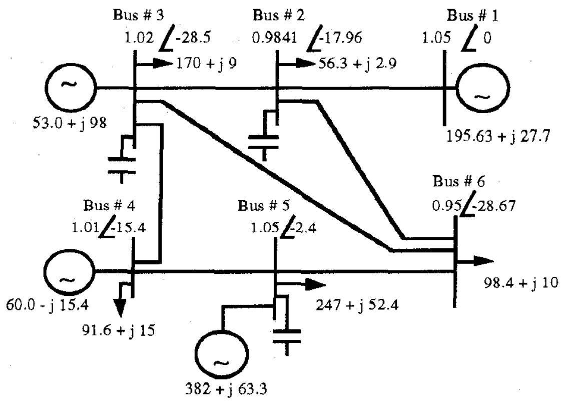


Fig. 5.. **6-bus system with base case load flow values.**

Table 1 shows the line parameters and information about real and reactive generation limits. Table 2 provides recommended values (defined later)- the changes in active generation schedules obtained by Linear Programming (LP- based method) and the proposed ANN-based method for the 6-bus test system

Table 1: **Line parameters and generator data for the 6-bus test system.**

| LINE PARAMETERS | | | | |
|---|---|---|---|---|
| Line between | R, pu | X, pu | B, pu | Flow limit (MVA) |
| Bus #1 - Bus #2 | 0.025 | 0.1682 | 0.259 | 175 |
| Bus #2 - Bus #3 | 0.0238 | 0.2108 | 0.3017 | 75 |
| Bus #3 - Bus #4 | 0.0328 | 0.1325 | 0.0325 | 75 |
| Bus #4 - Bus #5 | 0.1021 | 0.498 | 0.4984 | 100 |
| Bus #5 - Bus #6 | 0.213 | 0.8957 | 0.2406 | 75 |
| Bus #6 - Bus #2 | 0.1494 | 0.3692 | 0.0412 | 75 |
| Bus #6 - Bus #3 | 0.1191 | 0.2704 | 0.0328 | 75 |
| GENERATOR DATA | | | | |
| Bus Number | PGmin (MW) | PGmax (MW) | QGmin (MVAR) | Qgmax (MVAR) |
| Bus #1 | 150 | 200 | -138 | 138 |
| Bus #3 | 30 | 63 | 0 | 98 |
| Bus #4 | 50 | 70 | -81 | 81 |
| Bus #5 | 380 | 400 | -110 | 226 |

Table 2. **LP versus ANN results for the 6-bus system**

| Bus # | Change in Active Gen. (LP Values) | Change in Active Gen. (ANN Values) | % \| Error \| |
|---|---|---|---|
| 1 | -0.4 | -0.3965 | 0.8758 |
| 3 | 0.1 | 0.10567 | 5.67 |
| 4 | 0.1 | 0.10562 | 5.62 |
| 5 | 0.18 | 0.18524 | 2.91 |

Table 3 shows the line flows in the overloaded lines in the base case condition and also after the optimal reallocation.

Table 3. **Post-optimization line flows for the 6-Bus system.**

| Line Between | Flow Limit (MVA) | Base Case flow (MVA) | Optimal Solution (MVA) |
|---|---|---|---|
| Bus #1 - Bus #2 | 175 | 191.38 | 167.3 |
| Bus #2 - Bus #3 | 75 | 88.15 | 70.99 |

In the IEEE 14-bus example, there are only two generators in the system. One is at bus #1 and other is at bus #11.

Table 4 provides comparisons of suggested values of the changes in active generation schedules obtained by the LP-based method and the proposed ANN-based method for the 14-bus system. The iterated values for the same generators are -0.38 and 0.225 respectively. Table 5 shows the line flows in the overloaded lines in the base case and with optimal security-constrained reallocation.

Table 4. **LP versus ANN results for the IEEE 14-bus test system.**

| Bus # | Change in Active Gen. (LP Values) | Change in Active Gen. (ANN Values) | % \| Error \| |
|---|---|---|---|
| 1 | -0.42 | -0.4067 | 3.16 |
| 11 | 0.369 | 0.328 | 11.11 |

Table 5. **Post-optimization line flows for the 14-Bus system.**

| Line Between | Flow Limit (MVA) | Base Case flow (MVA) | Optimal Solution (MVA) |
|---|---|---|---|
| Bus #12 - Bus #3 | 22 | 25.36 | 21.97 |
| Bus #2 - Bus #3 | 60 | 65.5 | 55.07 |

Table 6 shows comparisons of the two methods for the IEEE 118-bus system. This test system has 20 generators. Two lines were found to be overloaded in the base case operating condition. These were the lines between bus#65-bus#68, and bus#68-bus#81. All generators were allowed to participate in the optimization. Some of the errors were somewhat larger for this system than for the other two systems. For larger systems, it might be necessary to select only a few of the generators or loads to participate in the process of security-constrained rescheduling. This can be done on the basis of their electrical proximity or sensitivities to the overloaded lines. In these situations, the maximum and minimum limits of the control variables of the designated non-participating units can be forced to remain at the pre-set values.

Table 6. **LP versus ANN results for the IEEE 118-bus test system**

| Bus # | Change in Active Gen. (LP Values) | Change in Active Gen. (ANN Values) | % \| Error \| |
|---|---|---|---|
| 1 | -0.17 | -0.1569 | 07.70 |
| 10 | 0.49 | 0.4385 | 10.50 |
| 12 | -0.56 | -0.4978 | 11.10 |
| 25 | -0.29 | -0.2669 | 07.90 |
| 26 | 0.75 | 0.7509 | 00.12 |
| 27 | -0.59 | -0.4976 | 15.67 |
| 31 | -0.14 | -0.1306 | 06.71 |
| 40 | -0.58 | -0.5479 | 05.53 |
| 42 | -0.81 | -0.8204 | 01.28 |
| 54 | 0.73 | 0.7521 | 03.02 |
| 59 | -0.46 | -0.4554 | 01.00 |
| 61 | 0.31 | 0.2313 | 25.40 |
| 65 | 0.81 | 0.7975 | 01.54 |
| 66 | -0.85 | -0.8452 | 00.56 |
| 69 | 0.93 | 0.8984 | 03.39 |
| 80 | 0.74 | 0.7623 | 03.01 |
| 89 | 0.49 | 0.3865 | 21.12 |
| 90 | -1.37 | -1.2696 | 07.32 |
| 100 | 0.88 | 0.824 | 06.36 |
| 112 | -0.48 | -0.3705 | 22.80 |

It can be seen from Tables 2, 4 and 6 that the results obtained from the LP-based method and the proposed ANN-based method are generally comparable. The real advantage of the proposed method is, of course, the possibility of implementation of the optimization procedure on transputeres for very fast results.

Selection of $\alpha$ and $\beta$ is very critical for convergence of the problems. We have found that for fast convergence, the values of $\beta$ should be in the range of 8,000-10,000 and the values of $\alpha$ should be in the range of $2.0*10^{-4}$ -$5.0*10^{-2}$ for the two test cases.

## 6.0 CONCLUSIONS

The procedure explained earlier is applied in the steady state condition of the power system and not in any transient condition. The algorithm can be easily expanded under the conditions of generator outage or line outage by suitably changing the incremental bus power vector and $A^{/}$ matrix respectively .

Although the LP block with conventional dual simplex-based method cannot yet be replaced by the proposed Hopfield network-based LP model, mainly because of longer times required by the latter to reach acceptable solutions, yet this paper introduces a unique method which presents good potential for the future. Since the behavior of the Hopfield neural network is essentially similar to parallel processing, its operation can be realized by the use of fast transputers. Such a hardware implementation on high-performance multi-processors promises fast computation of the optimal solutions.

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