A MODIFIED HOPFIELD NEURAL NETWORK METHOD FOR EQUALITY CONSTRAINED STATE ESTIMATION

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ABSTRACT

Electric power system is a highly complex and non linear system. Its analysis and control in real time environment requires highly sophisticated computational skills. Computations are reaching a limit as far as conventional computer based algorithms are concerned. It is therefore required to find out newer methods which can be easily implemented on dedicated hardware. It is a very difficult task due to complexity of the power system with all its interdependent variables, thus making the neural networks one of the better options for the solution of different issues in operation and control. In this project an attempt has been made to implement ANN's for State Estimation. A Hopfield neural network model has been developed to test Topological Observability of Power System and it is tested on two different test systems. The results so obtained, are comparable with those results of conventional root based observability determination technique. Further a Hopfield model has been developed to determine State Estimation of power system. State Estimation of 6 bus and IEEE 14 bus system is attempted using this Hopfield neural network.

KEYWORDS*: *State Estimation, Hopfield neural network, Observability, Electrical power systems, conventional algorithms.

I. INTRODUCTION

State Estimation processes a set of measurements to obtain the best estimate of the current state of the power system. The set of measurements includes telemetered measurements and pseudo-measurements. Telemetered measurements are the online telemetered data of bus voltages, line flows, injections, etc. Pseudo-measurements are manufactured data such as guessed MW generation or substation load demand based on historical data, in most cases. Telemetered measurements are subject to noise or error in metering, communication system, etc. The errors of some of the pseudo-measurements, especially the guessed ones, may be large. However, there is a special type of pseudo-measurements, known as the zero injections, for which the information contains no error. Zero injection occurs at a node, for example, representing a switching station where the power injection is equal to zero. Zero injection is an inherent property of such a node and no meter need to be installed but the information is always available. A state estimation algorithm must compute estimates, which satisfy exactly such constraints, independent of the quality of online measurements. The enforcing of constraints is in particular useful in networks, consisting of large unobservable parts of network or having very low measurement redundancy.
In its conventional form, the Weighted Least Square method does not enforce the equality and limit constraints explicitly. However, the constraints contain reliable information about physical restrictions and equipment limits and can be used to increase the quality of state estimation result. The zero

injections can be represented by a set of equalities. Various methods have been proposed to process constraints, literature review section lists some of the proposed methods for solving equality constrained State Estimation problem.

Various algorithms of State Estimation using the conventional computer are reaching a limit as far as the solution techniques are concerned, and as long as these computer based algorithms are used, faster methods cannot be expected. However for security monitoring and control in power system, improvement in calculation time is always desired in order to obtain necessary information more quickly and accurately.

In recent years, it has been found that Artificial Neural Networks (ANN's) are well suited as computational tools for solving certain classes of complex problems, although software implementations of the algorithm on general-purpose computers can be too slow for time-critical applications, but the small number of computational 'primitives', suggests advantages of hosting ANN's on dedicated Neural Network Hardware (NNH) to maximize performance at a given cost target. ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

In this chapter a new method for enforcing equality and limit constraints in State Estimation algorithm using a modified Hopfield neural network is presented. This method is tested for 6 bus system and IEEE 14 bus system. The main advantages of using the modified Hopfield neural network proposed in this work are

- The internal parameters of the network are explicitly obtained by the valid-subspace technique of solutions
- Lack of need for adjustment of penalty factors for initialization of constraints
- For real time application, the modified Hopfield network offers simplicity of implementation in analog hardware or a neural network processor
- Training and testing of the neural network under human supervision is not required.

II. STATE ESTIMATION WITH CONSTRAINTS

State vector of an electric network consists of the complex voltages at the buses. Unmeasured tap positions of transformers may also be included into the state vector. A measurement vector consists of power flows, power injections, voltage and current magnitudes and tap positions of transformers. For a N bus system, the state vector $X=[\delta,V]^T$, of dimension n=2N-1, consists of the N-1 bus voltage angles δ_i with respect to a reference bus and the N bus voltage magnitudes V_i for i=1,2,3,....N.

The static state estimator measurement model is given as:

$$z=h(X)+\epsilon \qquad \dots (1)$$

Where z is the measurement vector, h(.) is a vector of nonlinear functions, relating the measurement and state vectors, and ϵ is the vector of measurement errors.

The error-free data are modeled as equality constraints

$$g(X)=0 \qquad \dots (2)$$

Limits on some network variables are modeled as inequality constraints which can be expressed in a compact form by p-dimensional functional inequalities

$$f(x)\leq 0 \qquad \dots (3)$$

General nonlinear programming algorithms for the solution of a constrained minimization problem [2] are not efficient enough for the on-line application. Hence a neural network approach is used for solving this nonlinear programming problem.

2.1. Objective function

The objective is to minimize the weighted squared mismatch between measured and calculated quantities. Considering system to be observable and with m>n , where m is the total number of measurements and n is the number of state variables , the mathematical problem is given as follows:

$$\min \frac{1}{2}[Z-h(X)]^T R^{-1}[Z-h(X)] \qquad \dots (4)$$

Subject to the equality and inequality constraints as defined below. The diagonal matrix R^{-1}

represents the weights of the individual measurements in the objective function.

2.2. Equality constraints

Power flow equations, corresponding to both real and reactive power balance are the equality constraints for all the buses characterized as zero injections, which can be expressed as follows:.

$$P_i = \sum_{m=1}^{N_b} V_i V_m (g_{im}\cos\delta_{im} + b_{im}\sin\delta_{im}) = 0 \quad \ldots (5) \qquad Q_i = \sum_{m=1}^{N_b} V_i V_m (g_{im}\sin\delta_{im} - b_{im}\cos\delta_{im}) = 0 \quad \ldots (6)$$

For $i \in$ (set of zero injection buses)

Where

P_i = Real power injection at bus-i
Q_i = Reactive power injection at bus-i
V_i = Voltage magnitude at bus-i
δ_i = Load angle at bus-i
$Y_{ij} = g_{ij}+b_{ij}$=i-jth element of Y-bus Matrix.

N_b, N_l, N_g=number of total buses, load buses and generator buses in the system respectively.

2.3. Inequality Constraints:

(i) Voltage Limit: This includes upper (V_i^{max}) and lower (V_i^{min}) limits on the bus voltage magnitude.

$$V_i^{min} \le V_i \le V_i^{max} \qquad i=1,2,\ldots\ldots.N_b \qquad \ldots (7)$$

(ii) Phase Angle Limits: The phase angle at each bus should be between lower (δ_i^{min}) and upper (δ_i^{max}) limits.

$$\delta_i^{min} \le \delta_i \le \delta_i^{max} \qquad i=1,2,\ldots\ldots.N_b \qquad \ldots (8)$$

These limits may vary depending upon the problem under consideration. Imposing phase angle limits at load buses is another way of limiting the power flow in the transmission lines and for generator buses this limiting is done for stability reasons. Along with the above two constraints the following constraints can also be imposed.

(a) Line Flow Limit, representing the maximum power flow in a transmission line and is usually based on thermal and dynamic stability considerations. Let P_{Li}^{max} be the maximum active power flow in line-*i* respectively. The line flow limit can be written as

$$P_{Li}^{max} \ge P_{Li} \qquad i=1,2,\ldots\ldots\ldots\ldots.N_L \qquad \ldots (9)$$

(b) Reactive Power Generator Limit: Let Q_{gi}^{min} and Q_{gi}^{max} are the minimum and maximum reactive power generation limit of the reactive source generators (N_g) respectively.

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max} \qquad i=1,2,\ldots\ldots.N_g \qquad \ldots (10)$$

III. THE MODIFIED HOPFIELD NEURAL NETWORK

Artificial neural networks attempt to achieve good performance via dense interconnection of simple computational elements. Hopfield networks [1] are single-layer networks with feedback connections between nodes. In the standard case, the nodes are fully connected. The node equation for the continuous-time network with n-neurons is given by:

$$u_i(t) = -\eta . u_i(t) + \sum_{j=1}^{n} T_{ij} . v_j(t) + i_i^b \qquad \ldots (11)$$

$$v_i(t) = g(u_i(t)) \qquad \ldots (12)$$

Where $u_i(t)$ is the current state of the 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 the passive decay term, and T_{ij} is the weight connecting the j^{th} neuron to i^{th} neuron. In Eqn. (12), $g(u_i(t))$ is a monotonically increasing threshold function that limits the output of each neuron to ensure that network output always lies in or within a hypercube. It is shown in [3] that the equilibrium points of the network correspond to values of v(t) for which the energy function associated with the network is minimized:

$$E(t)=-\frac{1}{2}v(t)^T.T.v(t)-v(t)^T.i^b \qquad \ldots (13)$$

Mapping of constrained nonlinear optimization problems using a Hopfield network consists of determining the weight matrix T and the bias vector i^b to compute equilibrium points. Some mapping techniques codes the validity constraints as terms in the energy function which are minimized when the constraints ($E^{cons}{}_i = 0$) are satisfied :

$$E(t)=E^{op}(t)+b_1.E^{cons_1}(t)+b_2.E^{cons_2}(t)+.... \qquad \ldots (14)$$

Where $E^{op}(t)$ represents the objective function to be optimized and E^{cons} represents the constraints of the problem. The b_i parameters in Eqn. (14) are constant weightings given to various energy terms. The multiplicity of terms in the energy function tends to frustrate one another, and success of the network is highly sensitive to the relative values of b_i .It has been shown in [3] that the E^{op} and E^{cons} terms in Eqn. (14) can be separated into different subspaces so that they no longer frustrate one another. A modified energy function E'(t) can be defined as follows:

$$E'(t) = E^{conf}(t) + E^{op}(t) \qquad \ldots (15)$$

Where $E^{conf}(t)$ is a confinement term that groups all the constraints imposed by the problem, and $E^{op}(t)$ is an optimization term that conducts the network output to the equilibrium points. Thus, the minimization of E'(t) of the modified Hopfield network is conducted in two stages:

1): minimization of the term $E^{conf}(t)$:

$$E^{conf}(t)=-\frac{1}{2}v(t)^T.T^{conf}.v(t)-v(t)^T.i^{conf} \qquad \ldots (16)$$

Where: v(t) is the network output, T^{conf} is weight matrix and i^{conf} is bias vector belonging to $E^{conf}(t)$.

2): minimization of the term $E^{op}(t)$:

$$E^{op}(t)=-\frac{1}{2}v(t)^T.T^{op}.v(t)-v(t)^T.i^{op} \qquad \ldots (17)$$

Where: T^{op} is weight matrix and i^{op} is bias vector belonging to E^{op}. This minimization moves v(t) towards an optimal solution (the equilibrium points).

Thus, the operation of the modified Hopfield network can be summarized as combination of three main steps, as shown in Fig. 1:

Step (1): Minimization of E^{conf} Corresponding, to the projection of v(t) in the valid subspace defined by [4,5]:

$$v(t)=T^{conf}.v(t)+i^{conf} \qquad \ldots (18)$$

Where: T^{conf} is a projection matrix such that $T^{conf}.T^{conf}=T^{conf}$ and i^{conf} is defined such that $T^{conf}.i^{conf} = 0$. This operation corresponds to an indirect minimization of $E^{conf}(t)$.

Step (2): Application of a nonlinear 'symmetric ramp' activation function constraining v(t) in a hypercube

$$g_i(v_i) = v^{min} \quad \text{if} \quad v^{min} > v_i$$

$$= v_i \quad \text{if} \quad v^{min} \le v_i \le v^{max}$$

$$= v^{max} \quad \text{if} \quad v_i > v^{max}$$

Where $v_i \in [\ v^{min}, v^{max}\ ]$

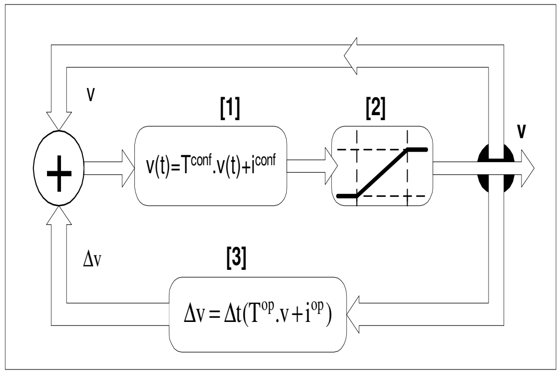

Figure-1: Modified Hopfield Neural Network

Step (3): Minimization of E^{op}, which involves updating of v(t) so as to direct it to an optimal solution (defined by T^{op} and i^{op}) corresponding to network equilibrium points, which are the solutions for the constrained optimization problems. Using the symmetric ramp activation function and $\eta = 0$, Eqn. (12) becomes.

$v(t)=g(u(t))=u(t)$

Comparing Eqn. (11) and Eqn. (16),

$$\frac{dv}{dt} = \dot{v} = -\Delta t.\tilde{N}E^{op}(v) = \Delta t(T^{op}.v+i^{op}) \quad \Delta v=\Delta t.\dot{v} \quad \ldots (19)$$

Therefore, minimization of E^{op} consists of updating v (t) in the opposite direction to the gradient of E^{op}. Each iteration has two distinct stages. First, as described in Step (iii) v is updated using the gradient of the term E^{op} alone. Second, after each updating, v is directly projected in the valid subspace. In the next section, the parameters T^{conf}, i^{conf}, T^{op} and i^{op} are defined.

IV. FORMULATION OF STATE ESTIMATION PROBLEM BY MODIFIED HOPFIELD NETWORK METHOD

Consider the following nonlinear optimization problem:

Minimize

$$E^{op}(X)=f(x)=\frac{1}{2}[Z-h(X)]^T R^{-1}[Z-h(X)] \quad \ldots (20)$$

Where X= [δ,V], z =measurement vector and h(X) represent nonlinear relationship between state vector x and z,

Subject to $E^{conf}(X)$: $h_i(X) = 0$,

i.e $P_i=0$ and $Q_i=0$ … (21)

For $i\in$ (buses identified as zero injections)

$V^{min} \le V \le V^{max}$

$\delta^{min} \le \delta \le \delta^{max}$ … (22)

Where V, V^{min}, V^{max}, δ, δ^{max}, δ^{min} $\in R^n$; and all first and second order partial derivatives of f(X) and $h_i(X)$ exist and are continuous. The conditions in Eqn.(21) and (22) define a bounded convex polyhedron. The vector x must remain within this polyhedron if it is to represent a valid solution for the optimization problem (Eqn.20). However if inequality constraints are also present, they must be transformed into equality constraints by introducing a slack variable s_w for each inequality constraints prior to calculating the parameters T^{conf} and i^{conf}. It is to be noted here that E^{op} does not depend on the slack variables s_w. A projection matrix to the system can be shown as [6].

$$T^{conf} = [I - \nabla h(X)^T.(\nabla h(X).\nabla h(X)^T)^{-1}.\nabla h(X)] \ \ldots (23)$$

where

$$\nabla h(X) = \begin{bmatrix} \frac{\partial h_1(X)}{\partial x_1} & \frac{\partial h_1(X)}{\partial x_2} & \cdots \frac{\partial h_1(X)}{\partial x_N} \\ \frac{\partial h_2(X)}{\partial x_1} & \frac{\partial h_2(X)}{\partial x_2} & \cdots \frac{\partial h_2(X)}{\partial x_N} \\ \vdots & \vdots & \cdots \vdots \\ \frac{\partial h_p(X)}{\partial x_1} & \frac{\partial h_p(X)}{\partial x_2} & \cdots \frac{\partial h_p(X)}{\partial x_N} \end{bmatrix} \quad \dots (24)$$

Inserting the value of T^{conf} from Eqn. (23) into Eqn. (18).

$$X = [I - \nabla h(X)^T.(\nabla h(X).\nabla h(X)^T)^{-1}.\nabla h(X)].X + i^{conf} \quad \dots (25)$$

By the definition of the Jacobian, when X leads to equilibrium point h(X) may be approximated as follows:

$$H(X) \approx h(Xc)+J.(X-Xc) \quad \dots (26)$$

where $J=\nabla h(X)$

In the proximity of the equilibrium point Xc=0,

$$\lim_{v \to vc} \frac{\|h(X)\|}{\|X\|} = 0 \quad \dots (27)$$

Finally from Eqns. (25-27), X can be written as

$$X=X - \nabla h(X)^T.((\nabla h(X).\nabla h(X)^T)^{-1}).h(X) \quad \dots (28)$$

Parameters T^{op} and i^{op} in this case are such that the vector X is updated in the opposite gradient direction of the energy function E^{op}. Since Eqns. (21) and (22) define a bounded convex polyhedron, the objective function (20) has a unique global minimum. Thus, the equilibrium points of the network can be calculated by assuming the following values of T^{op} and i^{op},

$$i^{op} = -\left[\frac{\partial f(X)}{\partial x1}, \frac{\partial f(X)}{\partial x2}, \dots\dots\dots\dots, \frac{\partial f(X)}{\partial xN}\right] \quad \dots (29)$$

$$T^{op} = 0$$

4.1 Estimation Algorithm

The steps followed have been given as under:

Step 1: Get the system data, measurements and define the zero injection buses together with boundary limits on the state variables.

Step 2: Select an initial erroneous state vector, tolerance limit and set the iteration count.

Step 3: Calculate the objective function and say it $f(X)_{old}$.

Step 4: Calculate P_i and Q_i corresponding to equality constrained buses.

Step 5: Find $\nabla(h(X)$ by differentiating zero injection equations w.r.t. State variables using load flow equations.

Step 6: Calculate updated state variables by Eqn. (28).

Step7: Enforce the boundary limits by passing the state variables through a symmetrical ramp activation function defined by limits $[V_{max}, V_{min}]$ and $[\delta_{max}, \delta_{min}]$ corresponding to each state variable.

Step 8: Find i^{op} by differentiating the objective function w.r.t. state variables.

Step 9: Find ΔX by Eqn. (19) and update X computed in step 7.

Step 10: Find the mismatch vector between measurements and calculated values and get its weighted squared sum to find out the new objective function value and find the difference between $f(X)_{new}$ and $f(X)_{old}$. If this difference is less than tolerance go next step, else go to step 3 after increasing the iteration count.

Step11: Display the results and Stop.

V. RESULTS

In this chapter 6 bus system and IEEE 14 bus system are used for simulation. The true values were obtained by the result of load flow calculation, and the measurement values were obtained by adding (sigma=0.01) errors to those values. As equality constraints, nodes with zero power injections (nodes with no load and no generators) are taken.

5.1 Six bus system

The measurement set base value for the 6 bus system is shown in Fig. 2 and table (1). Bus no 3 and 4 are characterized as zero injection buses.

	Hopfield method		Non linear SE	
Bus No.	V	δ	V	δ
1	1.0503	0	1.0482	0
2	1.0494	-4.7065	1.0469	-4.7832
3	0.9892	-7.6059	0.9854	-7.2324
4	1.0503	-3.8441	1.0513	-3.7833
5	0.9656	-6.9388	0.9729	-6.0465
6	0.9683	-8.8593	0.9691	-8.4704

Table 1

Measurements	Type	Buses	P	Q
z_1	Injection	1	0.9740	-0.0661
z_2	Injection	2	0.5005	0.5075
z_3	Injection	5	-.7007	-0.7007
z_4	Injection	6	-.7007	-0.7007
z_5	Line flow	1-2	0.2880	-0.1550
z_6	Line flow	1-4	0.2830	-0.0880
z_7	Line flow	1-5	0.4010	0.1760
z_8	Line flow	2-3	0.2310	0.1940
z_9	Line flow	2-4	-0.090	-0.0700
z_{10}	Line flow	2-5	0.2060	0.2110
z_{11}	Line flow	2-6	0.4320	0.0440
z_{12}	Line flow	3-5	0.0110	0.0520
z_{13}	Line flow	3-6	0.2150	0.1810
z_{14}	Line flow	4-5	0.1890	0.0900
z_{15}	Line flow	5-6	0.073	-0.044

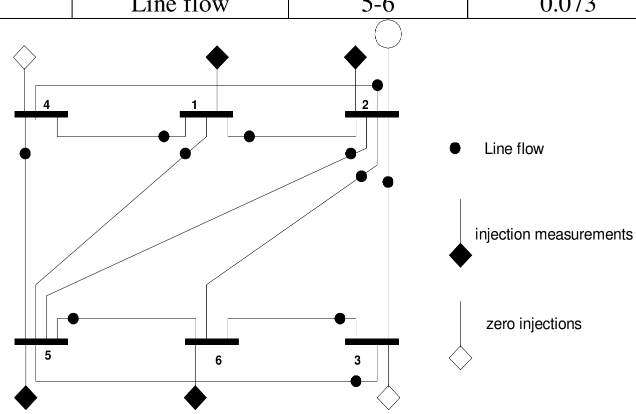

Figure 2: Measurement set for 6 bus system

The estimated state using the method with equality constraints are as shown in table 2

Table 2

	Hopfield method		Non linear SE	
Bus No.	V	δ	V	δ
1	1.0503	0	1.0482	0
2	1.0494	-4.7065	1.0469	-4.7832
3	0.9892	-7.6059	0.9854	-7.2324
4	1.0503	-3.8441	1.0513	-3.7833
5	0.9656	-6.9388	0.9729	-6.0465
6	0.9683	-8.8593	0.9691	-8.4704

Table 3 shows the errors of the estimate values.

Table 3

Measurements	ΔP	ΔQ
z_1	-0.021	0.0051
z_2	0.0068	0.0005
z_3	0.0037	-0.0003
z_4	0.0077	-0.0093
z_5	-0.0083	0.0008
z_6	-0.0068	-0.0013
z_7	-0.006	-0.0022
z_8	-0.0021	-0.0014
z_9	0.0046	-0.0131
z_{10}	-0.0001	-0.0016
z_{11}	-0.0033	-0.0233
z_{12}	0.0012	-0.0038
z_{13}	-0.0027	0.002
z_{14}	-0.0011	-0.0036
z_{15}	-0.0019	-0.0007

The energy mismatch delta E was used for the convergence criteria with the tolerance 10^{-02}. The time step used was $\Delta t=10^{-04}$ in Eq. (19). The convergence characteristics of the energy function with respect to number of iterations is shown in Fig. 3.

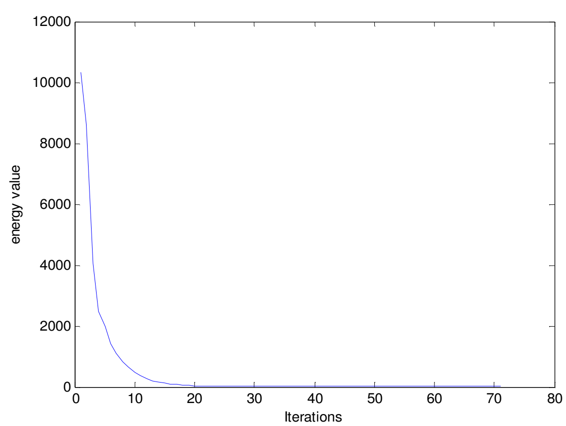

Figure 3: Convergence of energy function

5.2 IEEE 14 bus system

The measurement set base value for the IEEE 14 bus system is shown in Fig. 4 and table (4). Bus no 5 and 7 are characterized as zero injection buses. The energy mismatch delta E was

used for the convergence criteria with the tolerance 10^{-05}.
The time step used was delta $t=10^{-04}$.

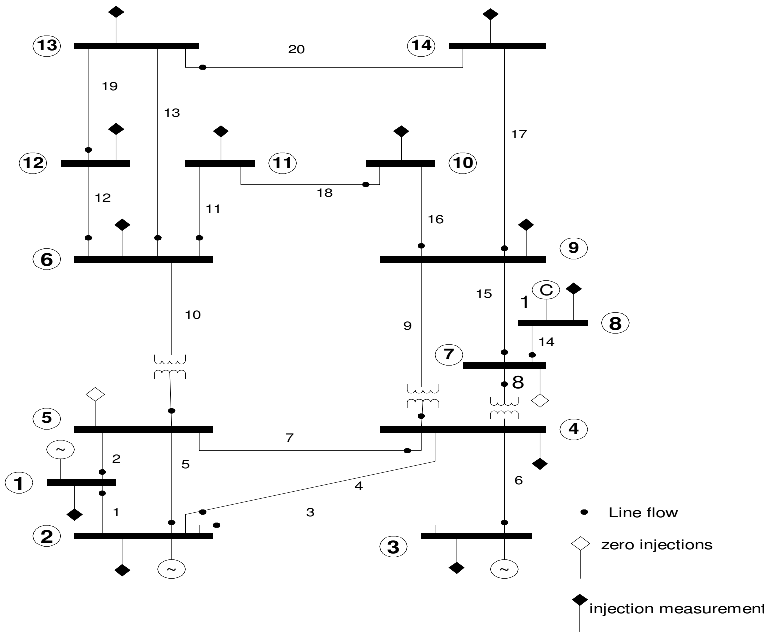

Figure 4: Measurement set for IEEE 14 bus system

Table: 4

Measurements	Type	Buses	P	Q
z_1	Injection	1	2.2462	-0.1722
z_2	Injection	2	0.1823	0.2535
z_3	Injection	3	-0.9453	0.0426
z_4	Injection	4	-0.4783	0.0704
z_5	Injection	6	-0.1129	0.0344
z_6	Injection	8	0.000	0.1733
z_7	Injection	9	-0.2955	0.0234
z_8	Injection	10	-0.0922	-0.0635
z_9	Injection	11	-0.0327	-0.0125
z_{10}	Injection	12	-0.061	-0.016
z_{11}	Injection	13	-0.1366	-0.0605
z_{12}	Injection	14	-0.1487	-0.0489
z_{13}	Line flow	1-2	1.5196	-0.1628
z_{14}	Line flow	1-5	0.7265	0.0479
z_{15}	Line flow	2-3	0.7243	0.0603
z_{16}	Line flow	2-4	0.5447	-0.0123
z_{17}	Line flow	2-5	0.3926	0.0099
z_{18}	Line flow	3-4	-0.2437	0.036
z_{19}	Line flow	4-5	-0.6384	0.139
z_{20}	Line flow	4-7	0.2806	-0.1972
z_{21}	Line flow	4-9	0.1607	-0.0579
z_{22}	Line flow	5-6	0.444	-0.1794
z_{23}	Line flow	6-11	0.0737	0.035
z_{24}	Line flow	6-12	0.0784	0.0256

z_{25}	Line flow	6-13	0.1791	0.0745
z_{26}	Line flow	7-8	0.000	-0.1688
z_{27}	Line flow	7-9	0.2805	0.0714
z_{28}	Line flow	9-10	0.0521	0.0428
z_{29}	Line flow	9-14	0.0936	0.0348
z_{30}	Line flow	10-11	-0.0402	-0.021
z_{31}	Line flow	12-13	0.0166	0.008
z_{32}	Line flow	13-14	0.0568	0.0177

Table 5: The state estimation results

	Hopfield method		**Non linear SE**	
Bus No.	V	δ	V	δ
1	1.060	0	1.060	0
2	1.045	-4.731	1.045	-4.98
3	1.010	-12.309	1.010	-12.74
4	1.022	-9.615	1.019	-10.28
5	1.024	-8.046	1.020	-8.76
6	1.071	-12.68	1.070	-12.52
7	1.062	-12.080	1.062	-12.15
8	1.090	-11.922	1.090	-12.08
9	1.055	-13.481	1.056	-13.48
10	1.051	-13.553	1.051	-13.55
11	1.058	-13.167	1.057	-13.15
12	1.057	-13.296	1.055	-13.07
13	1.051	-13.443	1.050	-14.44
14	1.037	-14.258	1.036	-15.12

Table 6 shows the errors of the estimate values for proposed method and Non Linear WLS method.

Table: 6

	HOPFIELD METHOD		NR WLS METHOD	
Measurements	ΔP	ΔQ	ΔP	ΔQ
z_1	0.0061	-0.0046	0.0037	-0.0019
z_2	0.0042	-0.0066	-0.0018	-0.0061
z_3	0.0018	-0.0025	-0.0028	0.0028
z_4	0.0017	0.0023	-0.0014	0.0024
z_5	-0.0017	-0.0051	-0.0016	-0.0022
z_6	-0.0018	0.0021	-0.0012	-0.0081
z_7	-0.0017	-0.0014	-0.0082	0.0126
z_8	-0.0011	0.0012	-0.0028	-0.0155
z_9	-0.0016	0.0022	0.0019	0.0657
z_{10}	-0.0021	0.0055	0.0001	0.0509
z_{11}	-0.0017	0.0016	0.0083	0.0852
z_{12}	-0.0023	0.0066	-0.0405	-0.0067
z_{13}	0.0275	-0.0025	0.0329	-0.0087
z_{14}	0.0329	-0.0021	0.0161	-0.0433
z_{15}	0.0063	-0.0016	0.0173	-0.0147
z_{16}	0.0316	-0.0037	0.0128	-0.0046
z_{17}	0.0305	-0.0082	0.0085	-0.0054
z_{18}	0.0237	-0.0057	-0.0058	0.0013
z_{19}	-0.0063	-0.0138	-0.0018	0.0129

z_{20}	0.0522	0.0021	0.0096	-0.0276
z_{21}	0.0256	0.0015	0.0525	-0.0058
z_{22}	0.0666	0.0095	0.0148	0.0499
z_{23}	0.0086	-0.0012	-0.0012	-0.0057
z_{24}	0.0173	-0.0027	0.0003	-0.0046
z_{25}	0.0239	-0.0045	-0.0001	-0.0086
z_{26}	0.0181	-0.0061	0.0126	0.0074
z_{27}	0.0308	-0.0008	0.0083	0.0016
z_{28}	0.0194	-0.0019	0.0243	0.0081
z_{29}	0.0204	-0.0043	0.0298	0.0043
z_{30}	0.0079	-0.0011	0.0047	-0.0075
z_{31}	-0.0034	0.0023	0.0022	0.0032
z_{32}	0.0029	-0.0014	0.0011	0.0041

The convergence characteristics of the energy function with respect to number of iterations is shown in Fig.5

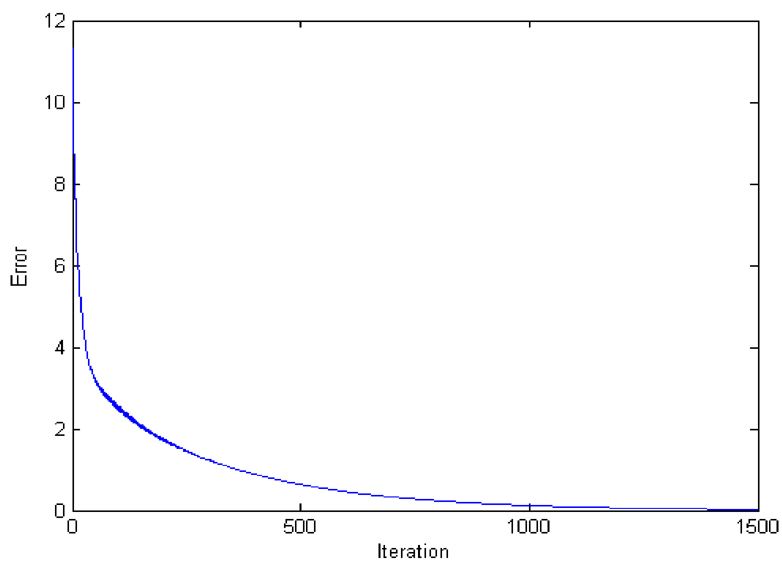

Figure 5: Convergence of energy function

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