A Novel Intelligent Approach for State Estimation of Power System Using Hopfield Neural Network

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Abstract
State estimation is an important element of the on-line security analysis function in power system control centers. A state estimator (SE) determines the state of the system given by the voltage magnitudes and phase angles at all buses, based on a redundant set of measurements. In power systems state estimation computation takes an important role in security controls, and the weighted least squares method and the fast decoupled method are widely-used at present. In order to solve the problem, the authors employ a neural network theory, the Hopfield network theory, which has an ultra-parallel algorithm and is different from the existing calculating algorithms, for state estimation computation. State estimation (SE) is an important element of power network analysis applications implemented at control centres, being instrumental in providing reliable data on the system operating conditions. Hopfield neural network (HNN) is employed to solve static sate estimation on 6 and 14 bus systems.

Keywords - Power electronics; smart grids; 1-φ full bridge inverter; State Space Averaging Technique; LCL filter; PR controller

1. Introduction

In State estimation power system, state variables are the voltage magnitudes and relative phase angles at the system buses. Measurements are required in order to estimate the system performance in real time for both system security control and constraints on economic dispatch. The inputs to an estimator are imperfect (noisy) power system measurements of voltage magnitudes, power, VAR, or ampere flow quantities. The estimator is designed to estimate the "best estimate" of the system voltage and phase angles recognizing that there are errors in the measured quantities and there may be redundant measurements [1]. The output data is then used in system control centers in the implementation of the security constrained dispatch and control of the system.

Load dispatcher in power system control centre is required to know at all times the value of voltages, currents and power throughout the network. Some of the values such as bus voltage magnitude and power line flows can be measured within a certain degree of variance. Difficulties are further encountered when some of the data is missing either due to meter being out of order or missing transmission loss [2].

State Estimation (SE) utilizes the available redundancy, for systematic cross checking of the measurements, to approximate the states as well as generate information in respect of missing observations or gross measurement errors called bad data. The prerequisite for state estimation is that the system must be observable with the available measurements [3].

States of a power system can also be computed with the load flow calculations, based on equal number of measurements, assuming them to be accurate. However, the implicit error will lead to imperfect data base and prejudice the security monitoring, whereas ,the state estimator is a data processing algorithm for use on a digital computer to transform meter readings (measurement vector) into an estimate of the system's states(state vector), which is not only accurate but best reliable also. A comparison between Load Flow Calculation and State Estimation has been shown in Figure1

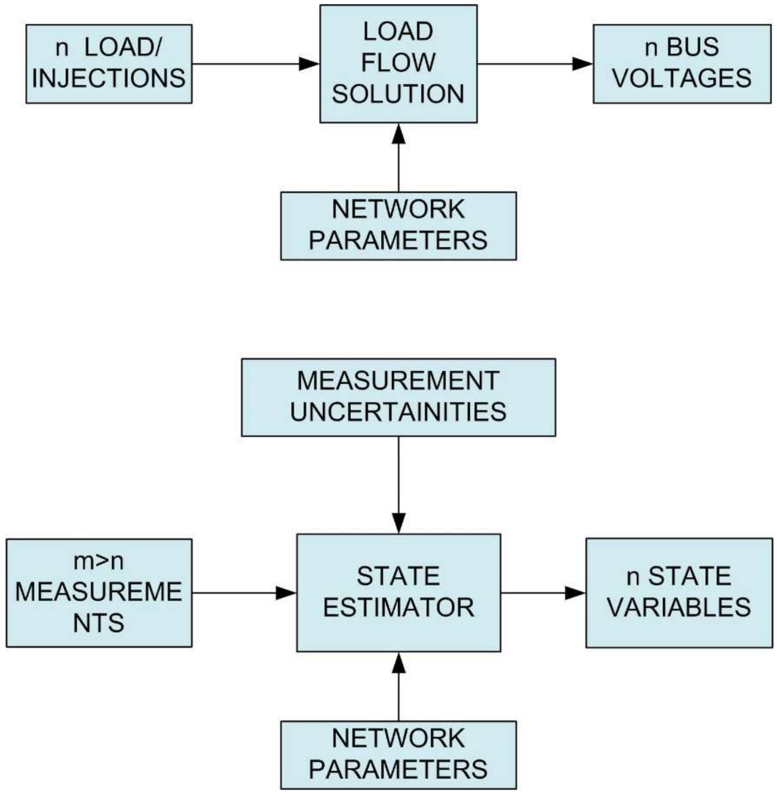

Fig1. Comparison between load flow calculations and state estimation

As the state estimator, is required to cater for the needs of online application, computation speed plays a vital role especially when systems are large. Alternate methods of state estimation are being reported to optimize on (i) numerical stability, (ii) computation efficiency, and (iii) implementation complexity. The following are the paper's primary contributions:

1. State estimation is an important element of the on-line security analysis function in power system control centers.
2. State estimation determines the state of the system given by the voltage magnitudes and phase angles at all buses, based on a redundant set of measurements
3. Digital processing technique called state estimation gives many of the central control and dispatch operations in a power system access to real-time data.
4. Hopfield neural network method has been tested with standard IEEE power system such as 6 and 14-bus, system.
5. The PF problem has been proposed to be solved by the Hopfield Neural Network.

It is found that state estimation computations are reaching a limit as far as conventional computer based algorithms are concerned. It is therefore required to find out newer methods for state estimation, which can be implemented on hardware to outperform their software counterpart. The algorithms based on neural networks can easily be implemented on dedicated hardware.

- To formulate the power system topological observability problem as an integer programming problem and to develop a new methodology based on Hopfield neural network for determination of topological observability in power system networks.

- To formulate power system state estimation problem as a constrained nonlinear programming problem.
- To apply a method based on modified Hopfield network, where the objective function and constraints are handled in two stages to solve constrained state estimation problem.
- To select a suitable mathematical model of a UPFC for studying the static performance of power systems, and to modify the N-R load flow method to incorporate UPFCs.
- To carry out state estimation of power system embedded with FACTs devices, with modified Hopfield neural network.
- To implement modified Hopfield neural network methodology on neural network processor (NNP) to solve nonlinear programming problems.

2. Power System State Estimation application

In real time environment the state estimator consists of different modules such as network topology processing, observe ability analysis, state estimation and bad data processing.

There is a schematic diagram showing the information flow between the various functions to be performed in an operation control centre computer system. The system gets its information about the power system from remote terminal units that encode measurement transducer output and opened/closed status information into digital signals that are transmitted to the operations centre over communication circuits. In addition, the control centre can transmit control information such as raise/lower commands to generators and open/close commands to circuit breakers and switches. The analog measurements of generator output must be used directly by the AGC program whereas all the other data will be processed by the state estimator before being used by other programs [4-5].

In order to run the state estimator, we must know how the transmission lines are connected to the load and generator buses, this information is called network topology. Since the breakers and switches in any substation can cause the network topology to change, a program must be provided that reads the telemeter breaker/switch status indications and restructures the electrical model of the system [6-7].

As seen in the Figure2. The electric model of the power system’s transmission system is sent to the state estimator program together with the analog measurements. The output of the state estimator consists of all bus voltage magnitudes and phase angles, transmission line MW and MVAR flows calculated from the bus voltage magnitude and phase angles, and bus loads and generations calculated from the line flows. These quantities, together with the electric load model developed by the network topology program provide the basis for the economic dispatch program [8].

The output of the state estimator i.e. $|V|$, δ, P_{ij}, Q_{ij} together with latest model form the basis for the economic load dispatch or minimum emission dispatch, contingency analysis program etc.

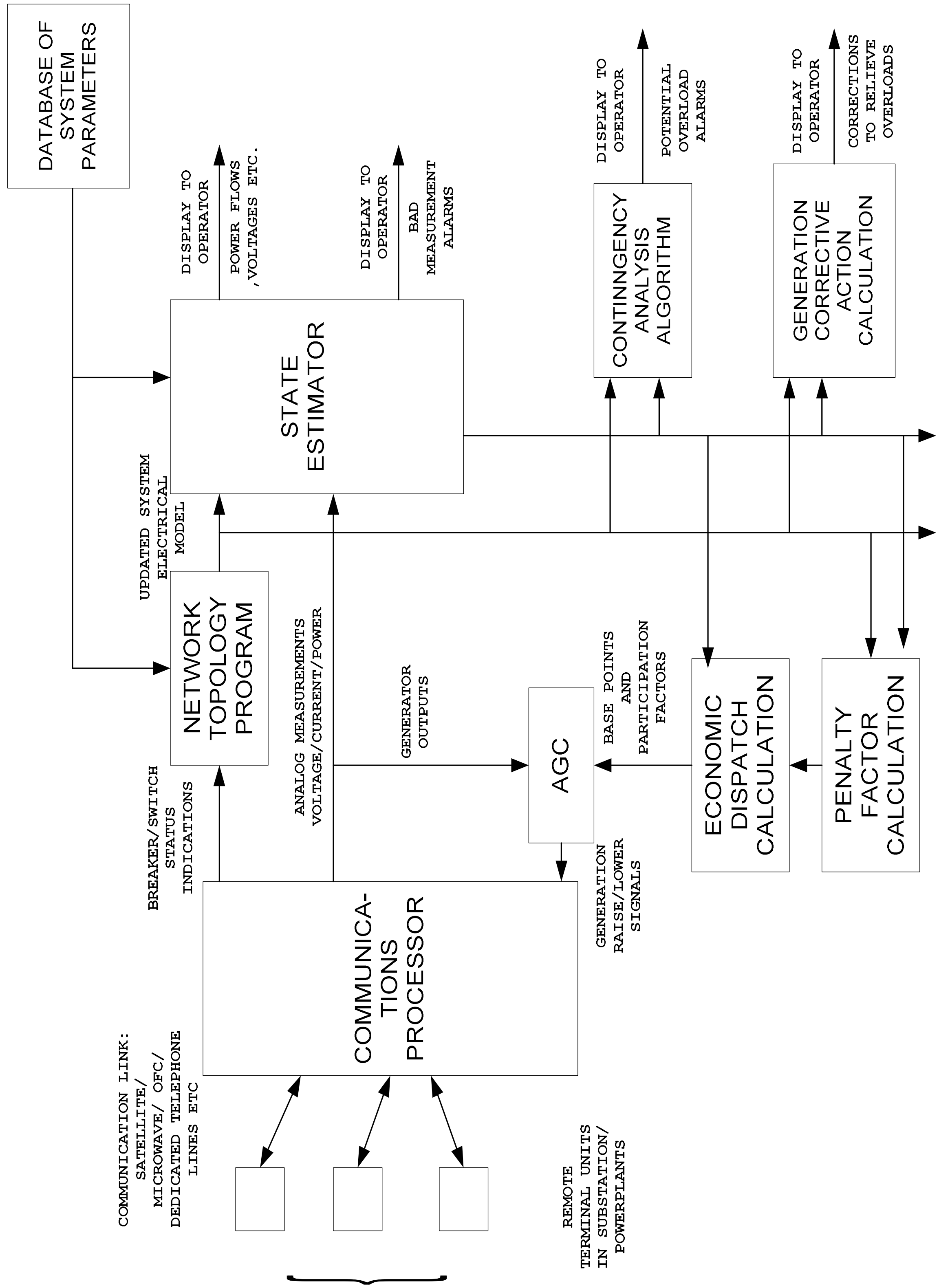

Fig. 2 Energy control centre system security schematic

3 Static State Estimation of Power System

Power systems are enormous in scale, typically spanning continents, and provide services for hundreds of millions of customers. These systems consist of numerous interconnected networks that contain various types of generators and consumers of electrical energy, which are also interconnected by high voltage equipment such as transmission lines and transformers. Each of these networks is operated and maintained by companies who are responsible for the consistently secure and economic operation of their network, as well as for the reliability of the larger power system. The famous 1965 blackout in the Northeastern United States awakened the power community to the fact that their means of providing this service would require the implementation of more thorough and advanced techniques [9-14].

The idea of using the redundant number of measurements, made available by the supervisory control and data acquisition (SCADA) system to statistically determine the state of the network. His proposition, the state estimator [2], was eventually accepted and serves as a basis for static state estimation [15-17].

The goal of control center design is security control under the three states of power system operation: the normal, emergency, and restorative states. There are several functions performed by a control center in the classical energy management system (EMS) environment, and the most difficult of these to implement are those that run in a real-time environment. The key functions include state estimation, security monitoring, on-line load flow, security analysis, supervisory control, automatic generation control, automatic voltage/VAR control, and economic dispatch control These functions often interact in a complex manner, but all are aimed at providing the system operator with a coherent view of the system and/or carrying out the operator's decisions. Since all of these functions are directly dependent on state estimation, it is essential that the system operator trust the result. The classical model as discussed above assumes steady-state functions; an introductory overview of dynamic-state functions is provided in though power systems are dynamic, real-time systems, dynamic state estimation is generally not employed, reasons being: static state estimation presently fills the control center needs; there are many difficulties in determining the dynamic system model; and dynamic state estimation is computationally intensive. Of these, the difficulty of defining a tractable, reliable model of the dynamic power system is the biggest inhibitor, due to the highly unpredictable and nonlinear nature of power systems [18-20].

The state estimator plays the essential role of a purifier, creating a complete and reliable database for security monitoring, security analysis and the various controls of a power system. The state estimator thus employs statistical methods to act as a tunable filter between the field data measurements and security and control functions.

The fundamental equation for the problem of power system state estimation can be formulated as

$$z = h(x) + e \tag{1}$$

Where $\boldsymbol{z}$ represents all measurements, including power injection, power flow and bus voltage magnitude measurements, $\mathbf{e}$ is the measurement noise vector, $\boldsymbol{x}$ is the state vector composed of the phase angles and magnitudes of the voltages at network buses, and $h(.)$ stands for the nonlinear measurement functions in terms of state variables. It is always assumed that the parameters and observability of the systems are already determined in advance.

3.1 Weighted Least Square Estimation (WLSE) Theory:

It is often desirable to put different weightings on the different components of measurements since some of the measurements may be more reliable and accurate than the others and should be given more importance. If a single parameter x, is estimated using Nm measurements, the WLSE problem can be described as [21-25]:

$$\min J(x) = \sum_{i=1}^{Nm} \frac{\left[z_i^{meas} - h_i(x)\right]^2}{\sigma_i^2} \tag{2}$$

where

σ_i =variance for the ith measurement

J(x) =measurement residual

Nm=number of independent measurements

z_i^{meas} = ith measured quantity

If Ns unknown parameters are to be estimated using Nm measurements, the estimation problem can be described as:

$$\min \; J(x_1, x_2, \ldots, x_{Ns}) = \sum_{i=1}^{Nm} \frac{\left[z_i^{meas} - h_i(x_1, x_2, \ldots x_{Ns})\right]^2}{\sigma_i^2} \tag{3}$$

Matrix Formulation

If functions $h_i(x_1, x_2, \ldots x_{Ns})$ are *linear functions* then

$$h_i(x_1, x_2, \ldots x_{Ns}) = h_i(x) = h_{i1}x_1 + h_{i2}x_2 + \ldots\ldots + h_{iNs}x_{Ns} \tag{4}$$

$$h(x) = \begin{bmatrix} h_1(x) \\ h_2(x) \\ \\ h_{Ns}(x) \end{bmatrix} = [H]x \tag{5}$$

Where, [H] is an (Nm x Ns) matrix containing the coefficient of the linear functions $h_i(x)$.

Placing the measurements in a vector form:

$$z^{meas} = \begin{bmatrix} z_1^{meas} \\ z_2^{meas} \\ \vdots \\ z_{Nm}^{meas} \end{bmatrix} \tag{6}$$

Eqn. (2.3) may be written in a very compact form as:

$$\min J(x) = \left[z^{meas} - f(x)\right]^T \left[R^{-1}\right]\left[z^{meas} - f(x)\right] \tag{7}$$

Where $[R] = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_{Ns}^2 \end{bmatrix}$

[R] is called covariance matrix of measurement errors.

To obtain the general expression for the minimum in Eqn. (.7), expand the expression and substitute [H]x for f(x) from Eqn. (5):

$$\min J(x) = \left\{ z^{meas^T}[R^{-1}]z^{meas} - x^T[H]^T[R^{-1}]z^{meas} - z^{meas}[R^{-1}][H]x + x^T[H]^T[R^{-1}][H]x \right\}$$

The minimum of J(x) is found when $\frac{\partial J(x)}{\partial x_i} = 0$, for i=1… Ns; this is identical to the stating that the gradient of J(x), $\nabla J(x)$ is exactly zero.

The gradient of J(x) is

$$\nabla J(x) = -2[H]^T [R^{-1}] z^{meas} + 2[H]^T [R^{-1}][H]x$$

Then, $\nabla J(x) = 0$ gives.\

$$x^{est} = \left[[H]^T [R^{-1}][H]\right]^{-1} [H]^T [R^{-1}] z^{meas} \quad (8)$$

It is to be noted here that Eqn. (8) holds when Ns<Nm, that is, when the number of parameters being estimated is less than the number of measurements being made.

When Ns=Nm, the estimation problem reduces to

$$x^{est} = [H]^{-1} z^{meas} \quad (9)$$

In power system state estimation, underdetermined problems (i.e., where Ns>Nm) are solved by adding pseudo measurements to the measurement set to give a completely determined (Ns=Nm) or over determined (Ns<Nm) problem,

3.2 State Estimation of an AC Network

In the Ac network, the measured quantities are MW, MVAR, MVA, amperes, transformer tap position, and voltage magnitudes. The state variables are the voltage magnitude at each bus and the phase angles at all but the reference bus. The equation for power flowing over a transmission line is clearly not a linear function of the voltage magnitude and phase angle at each end of line. Therefore, the h(x) functions will be nonlinear functions; except for a voltage magnitude measurement where h(x) is simply unity times the particular x_i that corresponds to the voltage magnitude being measured. For MW and MVAR measurements on a transmission line from bus i to bus j, J(x) will contain the following terms:

$$\frac{[MW_{ij}^{meas} - (|E_i|^2 (G_{ij}) - |E_i||E_j|(\cos(\theta_i - \theta_j)G_{ij} + \sin(\theta_i - \theta_j)B_{ij}))]^2}{\sigma_{MWij}^2} \quad (9a)$$

$$\frac{[MVAR_{ij}^{meas} - (-|E_i|^2 (B_{ij}) - |E_i||E_j|(\sin(\theta_i - \theta_j)G_{ij} - \cos(\theta_i - \theta_j)B_{ij}))]^2}{\sigma_{MVARij}^2} \quad (9b)$$

A voltage magnitude measurement would result in the following term in J(x).

$$\frac{(|E_i|^{meas} - |E_i|)^2}{\sigma_{|E_i|}^2} \quad (9c)$$

Similar functions can be derived for MVA or ampere measurements.

Since the relationship between the states (|E|'s and θ's) and the power flow in a network is nonlinear, some iterative technique is required to minimize J(x). A commonly used technique for power system state estimation is to calculate the gradient of J(x) and then force it to zero using Newton's method (briefly reviewed below)

Given the functions $g_i(x)$, i=1,….n, It is desired to find out x^{ans} that gives $g_i(x^{ans}) = g_i^{des}$, for i=1,….,n. .

Arranging the g_i functions in a vector form,

$$g^{des} - g(x) = 0 \text{ for } x = x^{ans} \quad (10)$$

By perturbing x, Eqn. (10) can be written as

$$g^{des} - g(x + \Delta x) = g^{des} - g(x) - [g^{'}(x)]\Delta x = 0 \quad (11)$$

Where g(x+ Δx) have been expanded in a Taylor's series about x, and all higher order terms are ignored. The $[g^{'}(x)]$ term is the Jacobian matrix of first derivatives of g(x). Then from Eqn. (11)

$$\Delta x = [g^{'}(x)]^{-1}(g^{des} - g(x)) \quad (12)$$

To solve for g^{des}, the value of Δx is obtained using Eqn. (12) and then $x^{new} = x + \Delta x$ is calculated. Eqn. (12) is reapplied until either Δx becomes very small or g(x) comes close to g^{des}.

Now returning to the state estimation problem as given in Eq. (2)

$\min J(x) = \sum_{i=1}^{Nm} \frac{\left[z_i^{meas} - h_i(x)\right]^2}{\sigma_i^2}$; The gradient of J(x) is formulated as follows:

$$\nabla_x J(x) = \begin{bmatrix} \frac{\partial J(x)}{\partial x_1} \\ \frac{\partial J(x)}{\partial x_2} \\ \vdots \\ \vdots \end{bmatrix} \quad (12a)$$

$$= -2 \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_2}{\partial x_1} & \frac{\partial h_3}{\partial x_1} & \cdots \\ \frac{\partial h_1}{\partial x_2} & \frac{\partial h_2}{\partial x_2} & \frac{\partial h_3}{\partial x_2} & \cdots \\ \vdots & \vdots & \vdots & \\ & & & \end{bmatrix} \begin{bmatrix} \frac{1}{\sigma_1^2} & & \\ & \frac{1}{\sigma_2^2} & \\ & & \ddots \end{bmatrix} \begin{bmatrix} z_1 - h_1(x) \\ z_2 - h_2(x) \\ \vdots \\ \vdots \end{bmatrix} \quad (13)$$

The Jacobian of h(x), is given by

$$[H] = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_2}{\partial x_1} & \frac{\partial h_3}{\partial x_1} & \cdots \\ \frac{\partial h_1}{\partial x_2} & \frac{\partial h_2}{\partial x_2} & \frac{\partial h_3}{\partial x_2} & \cdots \\ \vdots & \vdots & \vdots & \\ & & & \end{bmatrix} \quad (14)$$

Eqn. (13) can be written as

$$\nabla_x J(x) = \left\{ -2[H]^T[R]^{-1} \begin{bmatrix} z_1 - h_1(x) \\ z_2 - h_2(x) \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} \right\} \quad (15)$$

To make $\nabla_x J(x)$ equal zero, applying Newton's method as in Eqn. (12),

$$\Delta x = \left[\frac{\partial \nabla_x J(x)}{\partial x}\right]^{-1} \left[-\nabla_x J(x)\right] \quad (16)$$

The Jacobian of $\nabla_x J(x)$ is calculated as follows:

$$\frac{\partial \nabla_x J(x)}{\partial x} = \frac{\partial}{\partial x}\left\{-2[H]^T[R]^{-1}\begin{bmatrix} z_1 - f_1(x) \\ z_2 - f_2(x) \\ \vdots \\ \vdots \end{bmatrix}\right\} \tag{16a}$$

$$= -2[H]^T[R]^{-1}[-H]$$
$$= 2[H]^T[R]^{-1}[H] \tag{17}$$

then

$$\Delta x = \frac{1}{2}\left[[H]^{-1}[R]^{-1}[H]\right]^{-1}\left[2[H]^T[R]^{-1}\begin{bmatrix} z_1 - f_1(x) \\ z_2 - f_2(x) \\ \vdots \\ \vdots \end{bmatrix}\right] \tag{18}$$

$$= \left[[H]^{-1}[R]^{-1}[H]\right]^{-1}[H]^T[R]^{-1}\begin{bmatrix} z_1 - f_1(x) \\ z_2 - f_2(x) \\ \vdots \\ \vdots \end{bmatrix} \tag{19}$$

Eqn. (19) is applied iteratively to solve the AC state estimation problem.

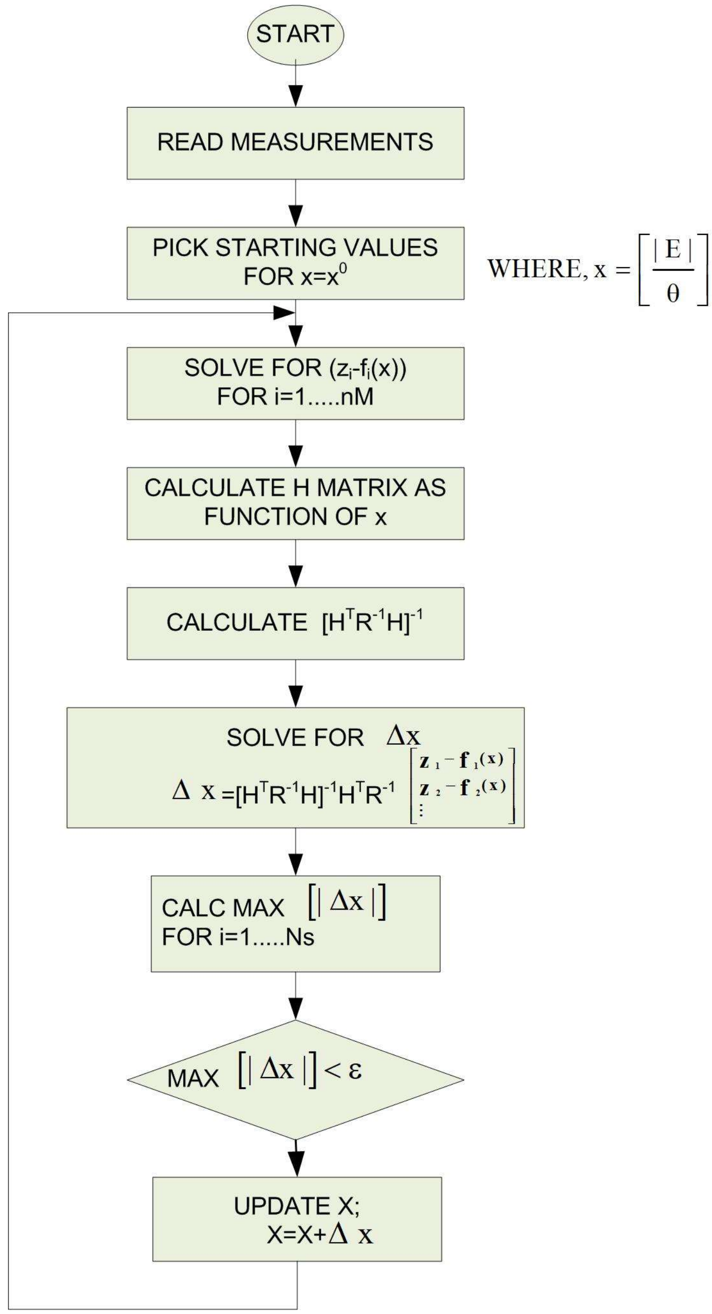

Fig.3 : State - Estimation solution algorithm

4. Hopfield Neural Network Approach for Solving Optimization Problems

It is realized that networks of neurons with this basic organization could be used to compute solutions to specific optimization problems by selecting weights and external inputs that properly represent the function to be minimized and the desired states of the problem. The analog nature of the neurons and the parallel processing of the updating procedure could be combined to create a rapid and powerful solution technique. Using the method proposed by Hopfield and Tank, the network energy function is made equivalent to the objective function of the optimization problem that needs to be minimized, while the constraints of the problem are included in the energy function as penalty terms. Consider the optimization problem:

(P1) minimize $f(V)$

$$\text{Subject to} \quad \begin{bmatrix} [A]_1 V = b_1 \\ [A]_2 V = b_2 \\ \ldots\ldots \\ [A]_r V = b_r \end{bmatrix} \tag{20}$$

where $[\mathbf{A}]_i$ (the i[th] row of the constraint matrix **A**) and **V** are *n*-dimensional vectors, and *r* is the number of constraints. Then the H-T energy function is

$$E(V) = \alpha f(V) + \beta_1 \left([A]_1 V - b_1\right)^2 + \beta_2 \left([A]_2 V - b_2\right)^2 + \ldots\ldots\ldots\ldots + \beta_m \left([A]_m V - b_m\right)^2 \tag{21}$$

$\alpha, \beta_1, \beta_2, \beta_3$ are penalty parameters that are chosen to reflect the relative importance of each term in the energy function. The non-linearity of the terms makes determination of the optimal penalty parameters unlikely. Clearly, a constrained minimum of P1 will also optimize the energy function, because the objective function, f (V), will be minimized, and constraint satisfaction implies that the penalty terms will be zero. Once a suitable energy function has been chosen, the network parameters (weights and inputs) can be inferred by comparison with the standard energy function The weights of the continuous Hopfield network, W_{ij}, are the coefficients of the quadratic terms V_iV_j, and the external inputs, i_i, are the coefficients of the linear terms V_i in the chosen energy function. The network can then be initialized by setting the activity level V_i of each neuron to a small random perturbation around 0.5. This places the initial state of the system at approximately the center of the n-dimensional hypercube, and ensures that the initial state is unbiased. From its initialized state, asynchronous updating of the network will then allow a minimum energy state to be attained, because the energy level never increases during state transitions. 0–1 solutions of combinatorial problems can be encouraged if desired by setting the parameter T of the activation function to a small enough value that the function approximates the discrete threshold (step) function

Although Hopfield networks do provide a useful tool in solving optimization problems, they are prone to get stuck in local minima as they basically employ a gradient descent process, this problem can be overcome by using the concept of simulated annealing in the network.

Hardware implementation of a neural network is ideal for industrial applications, where the same problem will need to be solved many times as the environment changes, Fortunately, recent work in the area of Field Programmable Gate Arrays (FPGA's) has enabled the speed advantages of hardware implementation to be simulated on a digital computer using reconfigurable hardware with desktop programmability. Such a simulation can easily achieve speeds of several million interconnections per second, making the advantages associated with hardware implementation of neural networks more readily attainable. Certainly, satisfactory hardware implementation is still the topic of much research and many design challenges lie ahead in this field. The Hopfield neural network techniques, for optimization problems, can effectively compete with traditional heuristic and exact approaches when simulated on a digital computer for solution quality. Flow chart for Hopfield Network shown in Figure 4

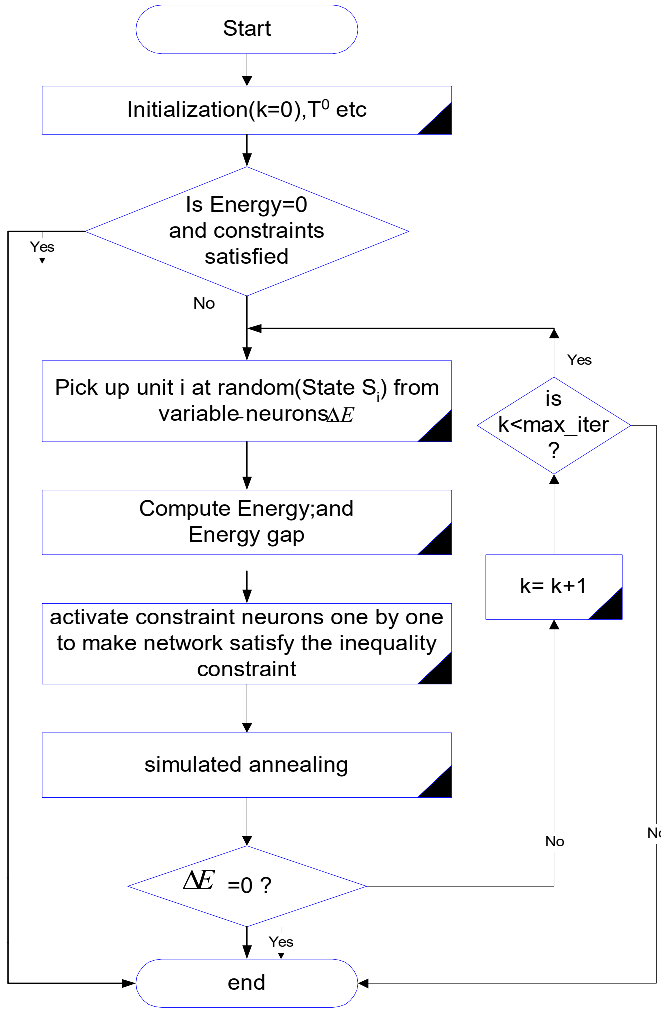

Fig. 4 Flow chart for Hopfield Network

4.1. State Estimation Problem by Modified 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(v)old.
Step 4: Calculate P_i and Q_i corresponding to equality constrained buses.

Step 5: Find $\nabla(h(v))$ by differentiating zero injection equations w.r.t. state variables using load flow equations..
Step 6: Calculate updated state variables by Eqn. (5.28).
Step7: Enforce the boundary limits by passing the state variables through a symmetrical ramp activation function defined by limits [V_{max}, V_{min}] and [δ_{max}, δ_{min}] corresponding to each state variable.
Step 8: Find i^{op} by differentiating the objective function w.r.t. state variables.
Step 9: Find Δv by Eqn. (5.19) and update v.
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(v)new and f(v)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.

5. Results and Discussion

Hopfield networks do provide a useful tool in solving optimization problems, they are prone to get stuck in local minima as they basically employ a gradient descent process, this problem can be overcome by using the concept of simulated annealing in the network.Hardware implementation of a neural network is ideal for industrial applications, where the same problem will need to be solved many times as the environment changes, Fortunately, recent work in the area of Field Programmable Gate Arrays (FPGA's) has enabled the speed advantages of hardware implementation to be simulated on a digital computer using reconfigurable hardware with desktop programmability. Such a simulation can easily achieve speeds of several million interconnections per second, making the advantages associated with hardware implementation of neural networks more readily attainable. Certainly, satisfactory hardware implementation is still the topic of much research and many design challenges lie ahead in this field. The Hopfield neural network techniques, for optimization problems, can effectively compete with traditional heuristic and exact approaches when simulated on a digital computer for solution quality. The load flow calculation has been carried out on the 6 and 14 IEEE bus test data, by modifying an existing N-R load flow program to allow UPFC model. In the modified load flow computation an accuracy tolerance of less than 10^{-4} pu in respect of the maximum absolute mismatch of nodal power injections are adapted, Load flow with and without UPFC has been carried out. For IEEE 14-bus system, solution converged in 5 iterations with tolerance of 0.0001 without UPFC while with UPFC it takes 6 iterations with tolerance of 0.00003. The results have been displayed with and without UPFC. The parameters of UPFC were set as (V_{s1}, φ_{s1} I_q) = (.1, .5, .1) respectively

5.1 IEEE 6 bus system [55]

The measurement set base value for the IEEE 6 bus system is shown in Figure 5, and table 5. Zero injection buses are those identified as 3 and 4.

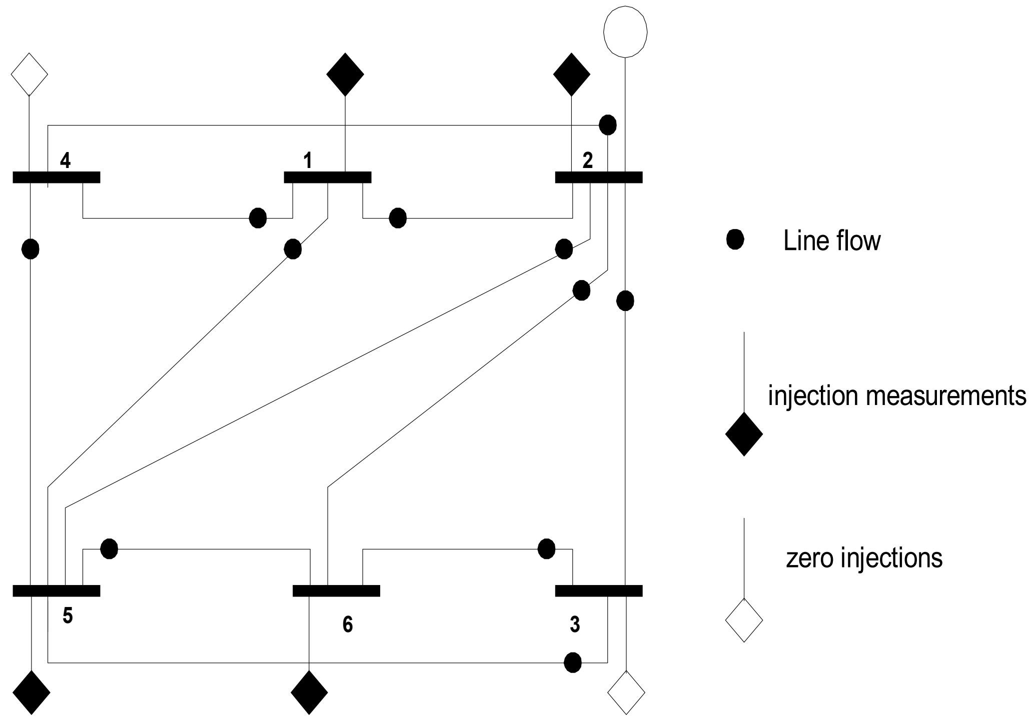

Figure 5 Measurement set for IEEE 6 bus systems

Table 5a

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

The estimated state using the method with equality constraints are as shown in table 5b

Table 5b

Bus	1	2	3	4	5	6
V	1.0503	1.0494	0.9892	1.0503	0.9656	0.9683
Δ	0	-4.7065	-7.6059	-3.8441	-6.9388	-8.8593

The errors of the estimate values are as shown in table 5c

Table 5c

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 Equation

5.2 IEEE 14 bus system [13]

The measurement set base value for the IEEE 14 bus system is shown in figure 6 and table 6. Zero injection buses are those identified as 5 and 7. 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} in Equation

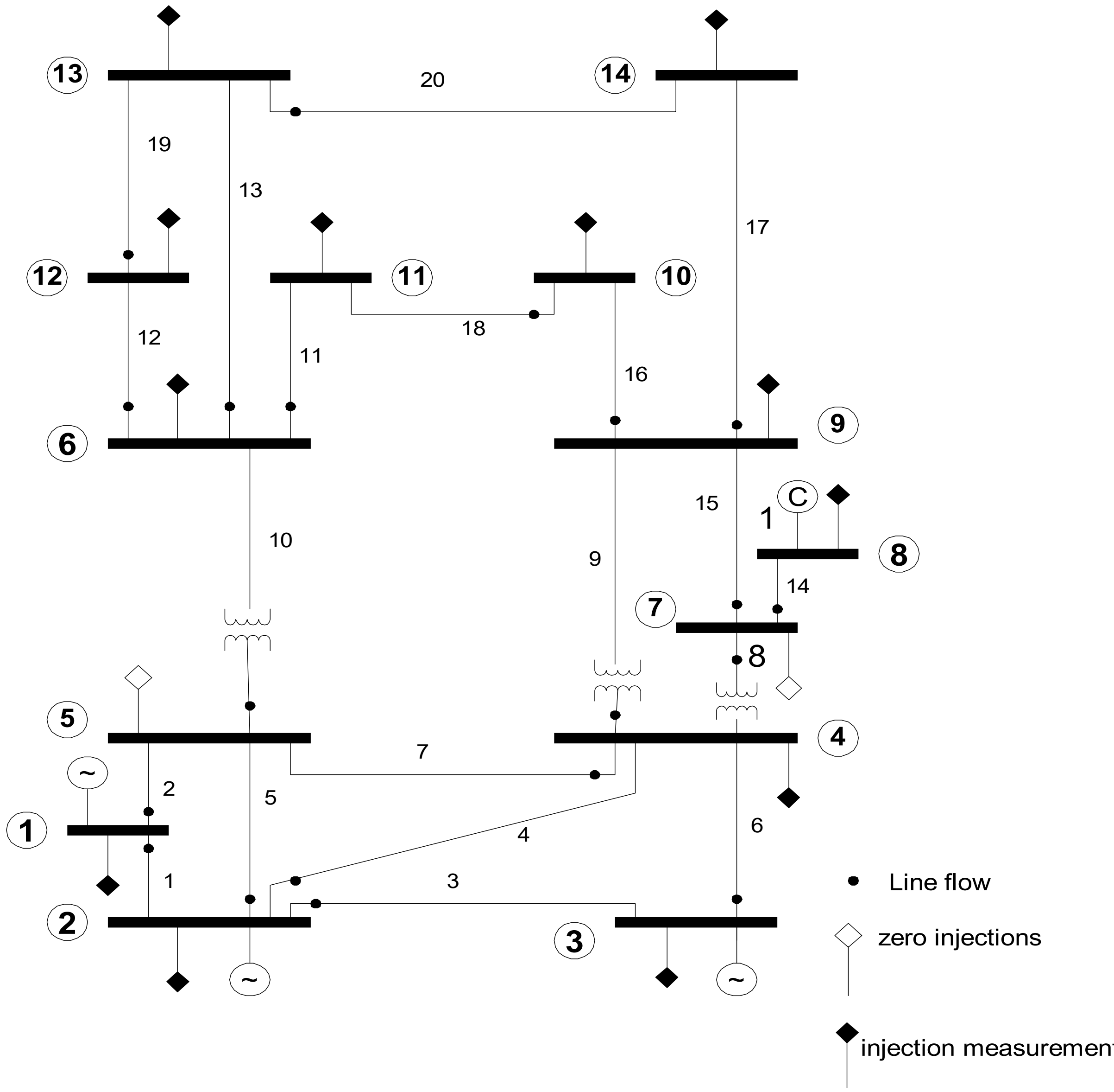

Fig 6 Measurement set for IEEE 14 bus systems

Table 6a

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

The state estimation results are shown below: Table 6b

Table 6b

Bus No.	V	δ	Bus No.	V	δ
1	1.060	0	2	1.045	-4.731
3	1.010	-12.309	4	1.022	-9.615
5	1.024	-8.046	6	1.071	-12.68
7	1.062	-12.080	8	1.090	-11.922
9	1.055	-13.481	10	1.051	-13.553
11	1.058	-13.167	12	1.057	-13.296
13	1.051	-13.443	14	1.037	-14.258

6. Conclusion

The state estimator plays the essential role of a purifier, creating a complete and reliable database for security monitoring, security analysis and the various controls of a power system. The state estimator thus employs statistical methods to act as a tunable filter between the field data measurements and security and control functions. State estimator should estimate the system states as quickly as possible, but conventional computer based methods are almost reaching a limit in terms of speed. On the other hand neural networks, having much potential for hardware implementation along with their inherent parallel architecture are being used in various areas of science and engineering. This work proposes a neural network method for solving state estimation problem which can be implemented on hardware. The common 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. Further an increasing concern about environmental aspect and optimal use of transmission capacities emphasize the use of FACTS devices, which offer several advantages, in the system, so there is requirement of such estimators which not only estimate the voltage magnitude and phase angle but also FACTS device control parameters. This work also proposes inclusion of FACTS device in state estimation algorithm. However, the work has been carried out only for the static system conditions it can be extended to dynamic system also.

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