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# Topology Observability for State Estimation using a Neural Network

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***ABSTRACT***.- In robust state estimation a space is necessary to provide a random set of measurements selected. This means to solve a set of equations which are often not observable, topological and numerically, this is a natural feature of the method. This paper proposed a neural network model for determining the topological observability of a set of measurements from electrical power system. Using a five and IEEE 14 nodes test systems, the results obtained by the neural network are compared with the method of graphs. It notes the difference in computation time in both methods. Also we obtain the advantage of training the neural network with the umbral system, which the numerical robustness of the system of equations to solve is more stable.

***KEYWORDS*: Robust State Estimation, Topology Observability, Neural Network.

## *I. INTRODUCTION*

Development of artificial neural networks has led to extend new technologies to solve nonlinear problems that require rapid solutions. This has enabled to solve a variety of real problems in different fields of engineering. For this reason, this paper intends to use artificial neural network for determining the topological observability of a set of measurements from electric power system, quickly and reliably. It is important to mention that there are several methods to solve this problem [1, 2]. The robust state estimation using least median square [7,8], it resolves a number of subsamples to obtain the estimated state vector of the electrical system. The number of subsamples to resolve depends of the grid's size, these are random selected of the total set of measurements. The first step is to determine if the sample selected is observable, before to solving the corresponding system of equations. This process is a natural feature of the robust estimate, therefore at this phase the computation time is great, that has a reason to solve this problem with a neural network. The results of the neural network are compared to the graph method to analyze the reliability and the advantages; the development of the above uses a grid of five and fourteen nodes.

## *II. REVIEW OF ARTIFICIAL NEURAL NETWORK (ANN)*

### *A. Artificial Neural Network Characteristics*

Some papers reported that the technologies and features of ANN, but [3,4] are widely developed. An important feature of artificial neural network is its ability to learn. Unlike traditional algorithmic methods which are known in equations or rules, however an ANN generated by its rules and equations to solve problems, learning from examples. This learning and training is similar to programming with traditional and computational methods are achieved through adaptive processes.

### *B. Neural Calculation Advantages*

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The advantages of calculation neuronal methodologies [3,4] :

*i.* Quick calculation: this is due to parallelism of the operation and topological structure.
*ii.* Ability learn: trained by simulation data and real-time system.
*iii.* Adaptive factors: weight of connection of an artificial neural network may change over time using actual results to improve their performance.
*iv.* Data Management: ANN can handle volumes of data cards or collectively.
*v.* Robustness: parallelism of ANN provides high fault tolerance due to the distributed representation and processing of information.

## *III. ARTIFICIAL NEURAL NETWORKS IN POWER SYSTEMS*

There are several works using ANN for power systems which are reported [5]. In this paper, we use the neural network for determining the topological observability of a power system from set measurements (measurements of active and reactive power flow, voltages and injections of active and reactive power). To solve this problem using the perceptron model which is described below.

### *A. Perceptron*

The perceptron model is a tool that has solved a variety of real problems in different areas, if problems can be represented by a perceptron. It is important to mention that in ANN to solve two problems, the first is to represent the model to simulate a specific function to determine the number of perceptron used and the number of hidden layers, and the second one is to train the network to generate outputs according to specific input vector.
In [3, 6] can be found the development of this model, in this paper we represent the outline of the method used to solve the problem. Figure 1 presents the perceptron ANN, which consists of an input layer, one hidden layer and output layer. The variable $w_{ji}$ represents the weights of the neural network. The perceptron ANN with unsupervised training, weights are adjusted according to the characteristics or patterns of input data. The training consists of an input class and there is a specific output vector.

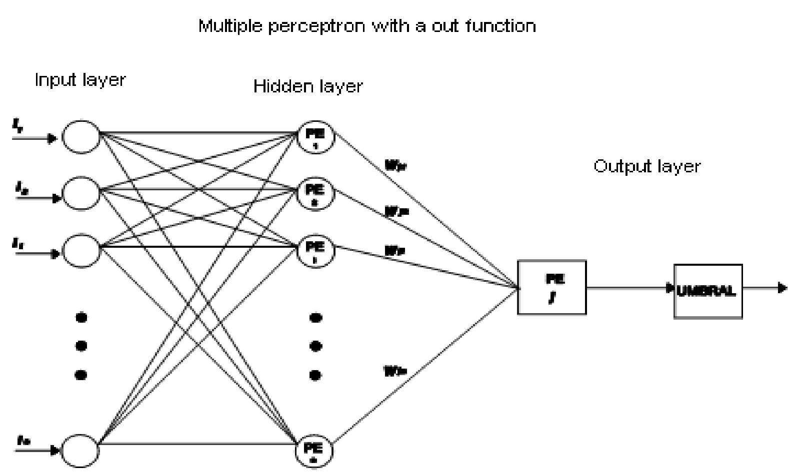


**Figure 1. Multiple perceptron with an output function.**

### *B. Patterns of entry*

The topological observability to be determined based on a selected random set of measurements in the power system, which consists of:

• Measurements of flow-active and reactive power in transmission lines.
• Measurements of injection-active and reactive power.
• Measurement of voltage.

The input patterns are determined by the type of measurement to be taken in the vector of measurements for a power system test, for the case under study are four kinds of patterns of entry:

i. - If you have a flow measurement of active and reactive power then the input model for the neurons activated perceptron according to measurement point. For example, if we have a measurement on the line between nodes 2 and 3 from grid in Figure 2, located at node 2 (2-3) the pattern of entry will be activated in the manner as shown in Figure 3, where an activation and a zero indicates the opposite.

ii .- When there is a voltage measurement is only activated perceptron as the measuring point, that is, if we have a measurement of voltage on node 1 (Figure 2) we obtain the model of entry which is shown in Figure 4.

iii .- The third pattern corresponds to that generated by injections of nodal active and reactive power, here perceptron neurons activated according to the node that is being measured, for example, if we have a shot at the nodal node 3 ( Figure 2 ), then the input pattern is as shown in Figure 5.

iv .- The fourth input pattern corresponds to the characteristics from set of measurements are taken and that is to activate the neuron for the perceptron. If the perceptron is two activated neurons that are adjacent to it then activates the neuron. This can be seen in Figure 6 which highlights the line that represents the neuron is active because there are two adjacent neurons activated in the perceptron.

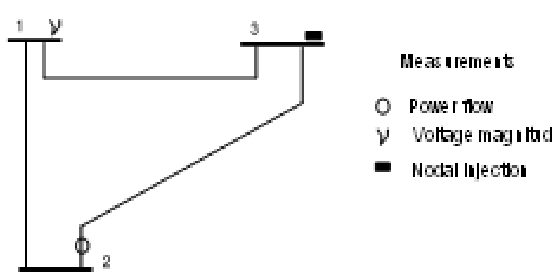


**Figure 2. Test system 3 nodes.**

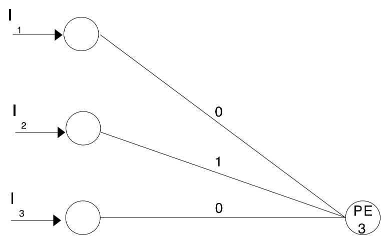


Figure 3. Model type 1 entry.

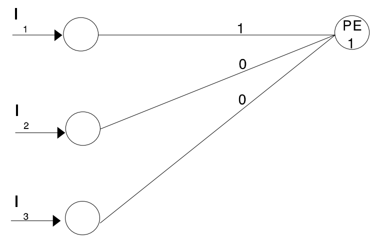


Figure 4. Model type 2 entry.

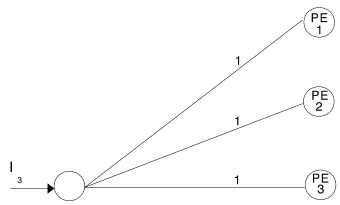


Figure 5. Model type 3 entry.

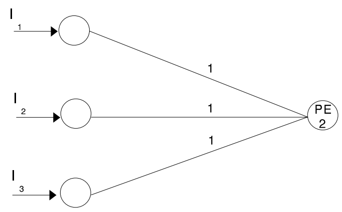


Figura 6. Model type 4 entry.

### *C. Hidden layer*

This layer exists between the input layer and output layer. This phase determines the weighting to continue training the network and simultaneously generates outputs according to the vector of training. When the weights can be determined appropriately, according to characteristics of the input data, is achieved to reduce the training time and therefore the processing time is also lower. The function that is proposed at this stage is:

$$f_i(x) = \begin{cases} 1 & \text{if} \quad a_i > 0 \\ 0 & \quad\quad ai \leq 0 \end{cases} \tag{1}$$

The following Section describes the criteria for weighting links of the perceptron.

### *D. Calculation of the weights*

1.- The perceptron hidden layer of a weight of 0.5 assigned to the output neuron is activated if an adjacent neuron in the input layer. This approach is supported by the notion that a flow measurement of active and reactive power only determines the observability of the measurement.

2 .- If the perceptron has activated two adjacent neurons then the weight of the output of this neuron is a perceptron, this criterion is a consequence of the concept, making the clarification that the maximum value of weight is one.

3 .- If the perceptron is a neuron activated for itself, the output neuron takes a weight of one, it is a voltage or nodal power injection measurements.

When the weight of the neuron is 0.5, it implies that a node that has minimum redundancy, while the weight of the neuron takes the maximum value indicates that it has a strength greater than the previous case. This feature allows to determine the umbral of the neural network.

### *E. Umbral*

It is the objective function of the neural network to determine the output vector for training. In the problem solving, the output is expected to indicate the neural network if the network is observable or not, given a training vector The training consists of a selected random set of measurements. The umbral to use for this case is that which is obtained from equation (2):

$$um = 1 + nb / 2 \tag{2}$$

where *nb* is the number of nodes. The umbral determines which training vectors, random selected, are topologically observable. These results can be compared with a conventional method to verify the results.The neural network is proposed in this paper and the training is conducted with the input vectors. Also to train the neural network with the umbral, this is to initially use the umbral that is obtained from equation (2) and subsequently modified to improve the numerical robustness from system of equations corresponding the grid that is observable. Achieving the above that ANN topology generated and numerically observable systems, thus improving the efficiency of the robust state estimation.

### *F. Output layer*

This phase determines if the training vector is topologically observable or not, the function proposed is:

$$S(x) = \begin{cases} 1 & if \quad b \geq um \\ 0 & if \quad b \leq um \end{cases} \tag{3}$$

where:

$$b = \sum_{i=1}^{n} (f_i(x))(ws_i) \tag{4}$$

In equation (3) can be seen that the output from neural network are one or zero, where one indicates that the input vector is topologically observable.

## *IV. APPROACH TO PROBLEM*

The model of ANN described is used to obtain a set of measurements that are topologically observable, which are employed in the robust estimation of state. Figure 7 presents a diagram of the robust estimate, where the application of ANN, consists of:

1.- The input vector is obtained by a random selected set of measurements.

2.- ANN determines whether this set of measurements is topologically observable.

3.- If the set is topologically observable, then numerically to solve the corresponding system of equations and the resulting solution is obtained.

4 .- Returned to point 1 and the process end when the condition number of subsamples to be resolved.

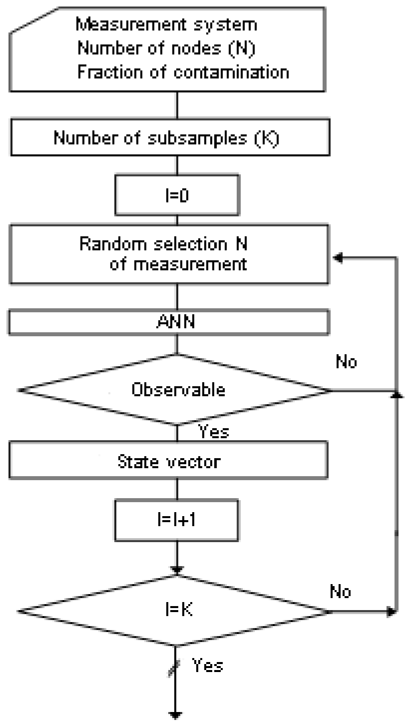


**Figure 7. Flowchart of least median square method.**

## *V. COMPUTATIONAL ASPECTS*

The size of each vector in the hidden layer is determined by the number of nodes in the electrical system and represented by the matrix *A*, where each row corresponds to input vector in the hidden layer. The matrix *A* has order nxn, where n represents the number of nodes; the weighting matrix *W* has the same structure and order of *A*. This may become a limiting when the size of the power system is large, when this problem occurs it is perform the operations in vector form, this process causing a longer time of computation, however, this problem is solved using a computer that is capable of conducting operations using vectors or processing parallel.

## *VI. CASES UNDER STUDY*

Here we studyt four cases to determine the power system topological observability using ANN, starting from a random selected set of measurements.

i. - The first study is an electrical system of five nodes and the unifilar diagram shown in Figure 8. In this case the output of the neural network is compared with the results obtained using the Echelon method. Table 1 provides a review of the results.

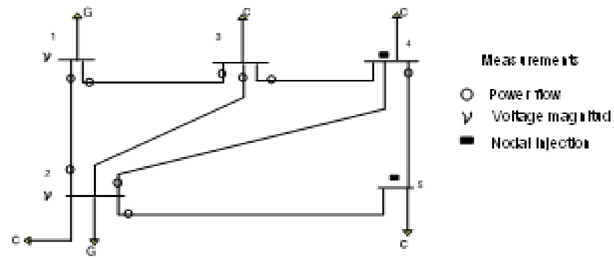


**Figure 8. Diagram of measuring system of 5 nodes.**

***Table 1. Results of ANN and Echelon method: umbral constant.***

| subs./umbral | Solution of ANN | Result of graph method | Result of numerical convergence | Random selected set of measurements |
|---|---|---|---|---|
| 1/3.0 | observable | Observable | Converges | {2-1;1-3;3-4}O;{2}ν |
| 2/3.0 | observable | Observable | Converges | {2-1;3-4}O;{2}ν;{4;5}■ |
| 3/3.0 | observable | Observable | not converges | {1-2;1-3;2-5;3-4}O;{2}ν |
| 4/3.0 | not observable | Observable | not converges | {1-2;3-1;2-4;4-5}O;{2}ν |
| 5/3.0 | observable | Observable | Converges | {2-1;2-5}O;{2}ν;{4;5}■ |
| 6/3.0 | observable | Observable | Converges | {2-1;2-4;3-4}O;{2}ν;{5}■ |
| 7/3.0 | not observable | Observable | not converges | {1-3;3-2;2-5;4-5}O;{2}ν |
| 8/3.0 | observable | Observable | not converges | {2-1;3-2;3-4}O;{2}ν;{4}■ |
| 9/3.0 | observable | Observable | Converges | {1-2;3-2;2-4}O;{2}ν;{5}■ |

O.**- Measurements of active and reactive power flow;** ν.**- Measurements of voltage;** ■.**- Measurements of nodal power.**

ii .- In second case we use the same grid. Umbral training is considered for the process to analyze the behavior of ANN and to compare with the results from graph method,Table 2 provides the results.

***Table 2. Results of ANN and Echelon method: umbral training.***

| subs./umbral | Solution of ANN | Result of graph method | Result of numerical convergence | Random selected set of measurements |
|---|---|---|---|---|
| 1/3.0 | observable | observable | Converges | {2-1;1-3;3-4}O;{2}ν |
| 2/4.0 | observable | observable | Converges | {2-1;3-4}O;{2}ν;{4;5}■ |
| 3/4.0 | not observable | observable | not converges | {1-2;1-3;2-5;3-4}O;{2}ν |
| 4/4.0 | not observable | observable | not converges | {1-2;3-1;2-4;4-5}O;{2}ν |
| 5/4.0 | observable | observable | Converges | {2-1;2-5}O;{2}ν;{4;5}■ |
| 6/4.0 | not observable | observable | not converges | {2-1;3-1;2-4;4-5}O;{2}ν |
| 7/4.0 | observable | observable | Converges | {2-1;2-4;3-4}O;{2}ν;{5}■ |
| 8/3.5 | not observable | observable | converges | {1-2;3-2;2-4}O;{2}ν;{5}■ |

iii .- This case is an electrical system of fourteen nodes and measurement scheme shown in Figure 9. The output from ANN is compared with the results obtained using the graph method. Table 3 presents a summary of the results obtained by both methods.

***Table 3. Results of ANN and Echelon method: umbral constant.***

| subs./umbral | Solution of ANN | Result of graph method | Result of numerical convergence | Random selected set of measurements |
|---|---|---|---|---|
| 1/7.5 | observable | observable | Converges | {1-2;4-3;5-2;5-4;10-11;13-12;14-9}O {6}ν;{4;6;10;14;7;11}■ |
| 2/7.5 | observable | observable | Converges | {1-2;2-4;5-1;6-11;7-8;9-7;13-12}O {6}ν;{4;10;12;13;7;11}■ |
| 3/7.5 | observable | observable | Converges | {1-2;2-4;3-4;5-6;7-8;10-11;13-12;14-9}O {3}ν;{4;10;12;7;11}■ |
| 4/7.5 | observable | observable | Converges | {1-2;4-3;5-1;5-10;10-9;13-6;14-9;}O {6}ν;{6;8;12;7;11}■ |
| 5/7.5 | observable | observable | Converges | {1-2;3-4;4-7;5-2;9-4;10-9;13-12}O {6}ν;{4;10;12;14;7;11}■ |
| 6/7.5 | observable | observable | Converges | {1-2;4-3;4-7;5-2;9-4;10-11;13-6;14-9}O {3}ν;{4;12;14;7;11}■ |
| 7/7.5 | observable | observable | Converges | {1-2;3-2;5-1;5-4;9-7;13-12;14-9}O {3}ν;{4;10;12;14;7;11}■ |
| 8/7.5 | observable | observable | Converges | {2-4;4-3;5-1;5-2;5-6;7-8;10-9;13-12;13-14}O {2}ν;{10;12;7;11}■ |
| 9/7.5 | observable | observable | Converges | {1-2;4-3;4-7;5-2;8-7;13-6}O {2}ν;{4;6;10;12;13;7;11}■ |
| 10/7.5 | observable | observable | Converges | {1-2;3-4;5-1;5-4;9-4;10-9;13-6;13-12}O {6}ν;{6;8;13;7;11}■ |
| 11/7.5 | observable | observable | Converges | {1-2;4-3;5-2;5-2;5-4;9-4;13-12}O {6}ν;{6;8;10;12;13;7;11}■ |

***Table 4. Results of ANN and Echelon method: umbral training.***

| subs./umbral | Solution of ANN | Result of graph method | Result of numerical convergence | Random selected set of measurements |
|---|---|---|---|---|
| 1/7.5 | observable | observable | Converges | {1-2;4-3;5-2;5-4;10-11;13-12;14-9}O {6}ν;{4;6;10;14;7;11}■ |
| 2/8.0 | observable | observable | Converges | {1-2;2-4;5-1;6-11;7-8;9-7;13-12}O {6}ν;{4;10;12;13;7;11}■ |
| 3/8.5 | observable | observable | Converges | {1-2;2-4;3-4;5-6;7-8;10-11;13-12;14-9}O {3}ν;{4;10;12;7;11}■ |
| 4/9.0 | Observable | observable | Converges | {1-2;4-3;5-1;5-10;10-9;13-6;14-9;}O {6}ν;{6;8;12;7;11}■ |
| 5/9.0 | Observable | observable | Converges | {1-2;3-4;4-7;5-2;9-4;10-9;13-12}O {6}ν;{4;10;12;14;7;11}■ |
| 6/9.5 | Observable | observable | Converges | {1-2;4-3;4-7;5-2;9-4;10-11;13-6;14-9}O {3}ν;{4;12;14;7;11}■ |
| 7/9.5 | Observable | observable | Converges | {1-2;3-2;5-1;5-4;9-7;13-12;14-9}O {3}ν;{4;10;12;14;7;11}■ |
| 8/10.0 | Observable | observable | Converges | {2-4;4-3;5-1;5-2;5-6;7-8;10-9;13-12;13-14}O {2}ν;{10;12;7;11}■ |
| 9/10.0 | Observable | observable | Converges | {1-2;4-3;4-7;5-2;8-7;13-6}O {2}ν;{4;6;10;12;13;7;11}■ |
| 10/10.5 | Observable | observable | Converges | {1-2;3-4;5-1;5-4;9-4;10-9;13-6;13-12}O {6}ν;{6;8;13;7;11}■ |
| 11/10.5 | Observable | observable | Converges | {1-2;4-3;5-2;5-2;5-4;9-4;13-12}O {6}ν;{6;8;10;12;13;7;11}■ |

**O.- Measurements of active and reactive power flow; ν.- Measurements of voltage; ■.- Measurements of nodal power.**

iv.- Here we use the same grid as previous point. Umbral training is considered for the process to analyze the behavior of ANN and to compare with the results obtained using the graph method, Table 4 provides the results.

### *A. Analysis of Results*

In the first case (Table 1) can be noted that in subsamples 1,2,5,6 and 9, the result of ANN is equal to the graph method, which are observed and the solution. However, in subsamples 3 and 8 the results of both methods is observable, but do not converge, this indicates that systems of equations are not numerically observable. The results of subsamples 4 and 7, in both cases, the ANN determines are not observable, while the graph method determines otherwise. In trying to solve systems of equations do not converge because they are not numerically observable. This shows that umbral given by equation (1) is appropriate. The results of the second case are obtained using the same seed for initialization as first case (Table 2), the two subsamples and the fifth result of both methods are equal, which are observable. The results in subsamples for 3, 4 and 6 shows that in these cases the ANN determines are not observable, however, the graph method determines otherwise, these results are similar the last point that was analyzed in the first case. Therefore the results of the subsamples 7 and 8, the result of the ANN is not observable, while the graph method determines otherwise. The phase of solution of these two subsamples converges, but their solutions differ compared with those obtained with another subsamples,Table 5 presents these results.

***Table 5. Results of voltages obtained in the subsamples of the measurements.***

**VOLTAGES ESTIMATED**

| subsample 1 polar form | | | subsample 2 polar form | | | subsample 5 polar form | | | subsample 7 polar form | | | subsample 8 polar form | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **node** | **voltage** | **angle** | **node** | **voltage** | **angle** | **node** | **voltage** | **angle** | **node** | **voltage** | **angle** | **node** | **voltage** | **angle** |
| 1 | 1.02988 | .00000 | 1 | 1.02988 | .00000 | 1 | 1.02988 | .00000 | 1 | 1.02988 | .00000 | 1 | 1.02988 | .00000 |
| 2 | 1.04250 | 2.88892 | 2 | 1.04250 | 2.88892 | 2 | 1.04250 | 2.88892 | 2 | 1.04250 | 2.88892 | 2 | 1.00654 | -3.00397 |
| 3 | 1.00664 | -2.25413 | 3 | 1.00523 | -2.41289 | 3 | 1.00664 | -2.19605 | 3 | 1.00679 | -2.86621 | 3 | 1.00647 | -2.29775 |
| 4 | 1.00599 | -2.58906 | 4 | 1.00458 | -2.74878 | 4 | 1.00600 | -2.53097 | 4 | 1.00580 | -3.10926 | 4 | 1.00600 | -2.53097 |
| 5 | .99983 | -3.43852 | 5 | .99932 | -3.49260 | 5 | .99985 | -3.41940 | 5 | .99966 | -3.60988 | 5 | .99985 | -3.41940 |

The third case (Table 3) can be noted that all subsamples are equal with the result of ANN and graph method, which are observed and solution. This shows that the umbral given by equation (1) is adequate, therefore the process of robust state estimation considered the result of ANN and the computation time decreases. This is because do not try to solve a set of equations that has not numerical robustness. In fourth case, which is obtained using the same seed for initialization as first case (Table 4), the results of both methods are equal in all subsamples, which are observable. However, in the process of determining the topological observability, many subsamples do not pass the phase of solution because they do not exceed the umbral set by the ANN. Therefore, when including the umbral training of ANN, the solutions obtained are those which have better numerical robustness. It is expected a shorter computing topology determination using ANN, that graph method, because they are used only vectors and operations. While in the case of graphs, for large systems it is necessary to use vectors and simulated operations.

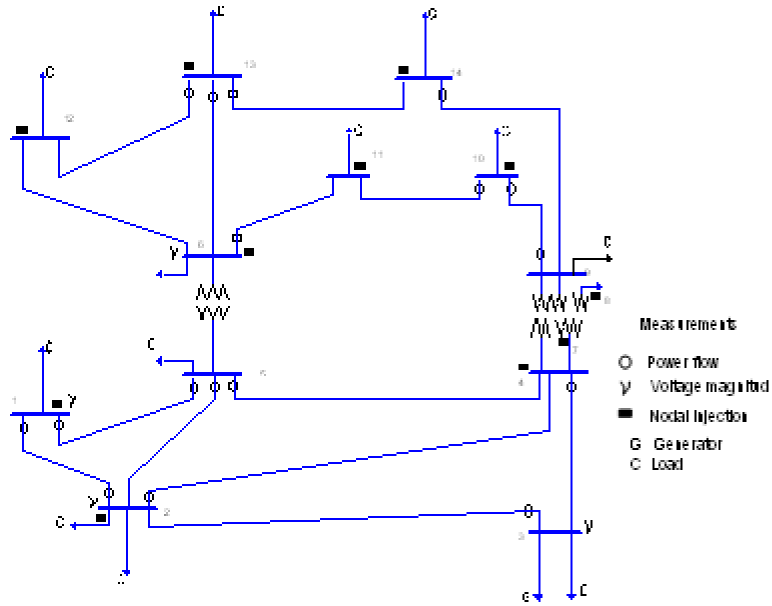


**Figure 9. Diagram of measuring system of 14 nodes.**

## *VII. CONCLUSIONS*

When the weights can be determined appropriately, according to the characteristics of the input data, it is possible to reduce the training time and the processing.

The results presented show that umbral determined by equation (1) is appropriate. It is important to mention that during the process of robust state estimation is considered the ANN, the process is more efficient. It is not convenient to solve a set of equations that has not numerical robustness.

From Tables 2 and 4 can be concluded that, when including the training of the ANN, the solutions obtained are those that possess better numerical robustness.

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