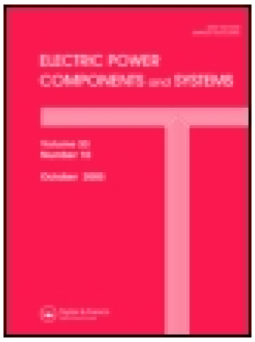

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POWER SYSTEM NETWORK TOPOLOGY PROCESSING BASED ON ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this paper, a new approach for the determination of power system network topology based on Artificial Neural Networks (ANN) has been suggested. For the determination of power system network topology, three models of ANN based on Multilayer perceptron using Backpropagation Algorithm (BPA), Functional Link Network (FLN) and Counterpropagation Network (CPN) have been utilized and tested for both noisy as well as noise free data sets. ANN models based on BPA, FLN and CPN have been tested on IEEE 14-bus, IEEE 57-bus and a 75-bus practical Indian system. It has been established that the CPN based model predicts network topology more accurately as compared to the FLN and BPA based models in all test cases. Further, the CPN model is able to determine the network topology even if the network is unobservable for which the conventional network topology algorithm [8] fail to determine the topology.

1. INTRODUCTION

A modern Energy Management System (EMS) is a sophisticated information and control system which uses advanced software and hardware techniques to perform its functions. The problem of automatic connectivity determination for a power network is a necessary and important step in EMS. In real-time environment, system configuration changes dynamically. Real-time power system modeling rely on the correctness of the topology, previously determined from telemetered data by the system network topology processor. Two types of measurements are collected by the supervisory control and data acquisition (SCADA) system, namely the logic measurements, which consists of status of breakers and switches and analog measurements consisting of real and reactive power line flows, bus voltage magnitudes etc. A set of these measurements can be used by a topology processor to determine the real-time topology of the power system network. The updated topology information is utilized by various EMS functions such as, state estimation, power flow etc.

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Two types of conventional topology processing methods have been used namely the direct and indirect methods [1]. Topology of the network can be determined directly by using the circuit breaker and switch status measurements. This information has to be updated in real-time whenever there is a connectivity change in the network. Sasson et al [2] updated network configuration in real-time using tree search algorithm. Singh and Alvarado [3] formulated the topology processing similar to state estimator algorithm and solved it by using Least Absolute Value (LAV) method. Singh and Glavitch [4] used a rule based approach. Yehsakul and Dabbaghchi [5] used the algorithm for tracking network connectivity of islands for the determination of the network topology. Prais and Bose [6] introduced tree search algorithm to avoid reordering and/or refactorizing the whole state estimation matrix from the previous solution. However, any error in breaker status measurements resulted into misconfiguration of the system, significantly affecting the state estimation results. Simoes-Costa and Leao [7] determined topology errors by utilizing the state estimator recursively.

Alves da Silva et al [9] used pattern analysis approach based on artificial neural network using multilayer perceptron model and optimal estimate training to determine network topology. In [10] Alves da Silva et al used modified Optimal Estimate Training (OET2) for the topology determination. However, in the presence of noisy breaker status information their method could not determine accurate topology in many cases.

In general the network topology processor based on algorithmic methods utilizes computation intensive search algorithms. Further it has been found [8] that the algorithmic models fail to predict the topology, when the system becomes unobservable such as in case of removal of some of the branches from the original network.

Hence, in this paper, Artificial Neural Network (ANN) models have been tried out for the network topology processing. Multilayer perceptron based on Backpropagation Algorithm (BPA), Counterpropagation Network (CPN) and Functional Link Network (FLN) models of ANN have been used. The effectiveness of the proposed ANN models have also been tested for unobservable cases. The studies have been conducted on IEEE 14-bus, IEEE 57-bus and 75-bus practical Indian system to establish the accuracy and effectiveness of the proposed artificial neural network based models for the network topology prediction.

2. CONVENTIONAL NETWORK TOPOLOGY PROCESSOR

A conventional topology processor program uses circuit breaker status information and network connectivity data to determine the topology of the network. The data base describes the network connectivity in terms of bus-section and the circuit breakers. All equipment, such as generators, load feeders, shunt reactors, transformers, transmission lines etc., are connected to bus-sections. Bus sections within one voltage level at a substation may be connected together by circuit breakers.

As the status of circuit breakers changes in real-time, the bus-branch topology is expected to change. The network topology processor must determine the new topology whenever there is a change. Thus this program is required to be re-run only if there is a status change.

The output of the network topology processor is the traditional data that describe a bus-ranch oriented network. Thus each of the buses must be identified together with the generation, loads and shunts connected at these buses. Also the connectivity between the buses through the transmission lines and transformers has to be described.

Topological errors arise from the misconfiguration of one or more network elements, as a consequence of erroneous input data to the network configurator connecting the status of circuit breakers and switches. The system topology provided by the configurator thus becomes inconsistent with the actual network topology. State estimator based models have been used [8] to detect and identify the topology errors.

A topological error may be single, if the misconfiguration involves only one network element, or multiple , if more than one element is involved. Single topological errors may occur two forms: exclusion error, when a network element is in operation but does not appear in the topology provided by the configurator and inclusion error, when the opposite situation occurs.

The effect of topology error is reflected in the Jacobian matrix. Let the H_t be the true measurement Jacobian matrix, H be the one from the topology processor with errors and B be the resulting error in the measurements Jacobian matrix, i.e.,

$$H_t = H + B$$

The true linearized equation for the state estimation should be

$$z = H_t x + v$$

where v is the measurement error vector.

However, due to topology error, the equation becomes,

$$z = H x + v$$

The estimated state $\hat{x}$ is given by following WLS equation

$$\hat{x} = (H^t W H)^{-1} H^t Wz$$

The residual vector can be defined as [8]

$$r = (I - M) \ (B x + v)$$

where

$$M = H (H^t R^{-1} H)^{-1} \ H^t W$$

The expected value and covariance of the residual vector will be

$$E(r) = (I - M)\ Bx$$

where

$$\mathrm{Cov}\ (r) = (I - M)\ W^{-1}$$

With topology error, the residual will be nonzero and equal to (I - M) Bx.

Let ϵ = Bx be the basis vector. We can analyze the structure of the error matrix B for branch outages. The branch outage includes transmission line or transformer outage. In most practical cases, errors in recognizing line or transformer outages may involve a single outage.

For the outage p ($p \geq 1$) branches $l_1, l_2, \ldots, l_p$ that is not recognized by the topology processor, the real power state estimation should be used. Let us call any line flow measurement of $l_1, l_2, \ldots, l_p$ or any injection measurement on a bus with connection to $l_1, l_2, \ldots, l_p$ a measurement related to $l_1, l_2, \ldots, l_p$.

One can notice that, only rows corresponding to the related measurements are non-zero in B. Furthermore, these rows have the following structures.

(i) Flow Measurement: For a flow measurement that is related to an outage branch with susceptance b connecting buses h and k, the corresponding row of B looks like:

h	k
-b	b

(ii) Injection Measurement: For an injection measurement on bus h that is related to an outage branch with susceptance b_l, the corresponding row of B looks like

h	k
$-b_l$	b_l

The bias vector ϵ = Bx, can be expressed in terms of the state variables. Since the non-zero rows of B are the related measurements and each corresponding row of ϵ is actually either a branch flow, say

$$f_j = -b_j\,[x(h) - x(k)]$$

or a combination of several branch flows (if an injection measurement is related to several branches of $l_1, l_2, \ldots, l_p$). We may also express the bias vector in terms of branch flows f_j, $j = l_1, l_2, \ldots, l_p$. Let us define the vector f and the matrix L as follows:

$$f = (f_{l1}, f_{l2}, \ldots, f_{lp})^T$$

$$Bx = Lf$$

Suppose the branch -j connects buses h and k if the i-th measurement includes the flow from h to k, then the (i,j) th element of L is +1, if it includes the flow from k to h, then the (i,j) th element is -1, otherwise it is zero.

Detection and identification of the topology error can be carried out based on (normalized residue) hypothesis testing [8].

From the above description of the conventional topology processor and the literature survey, it is found that,

(i) The state estimation is a part of the determination of network topology.

(ii) The process for detection and identification of topology error is recursive in nature. Hence, these methods are tedious and time consuming.

(iii) Non-detectability of branch outages may occur due to,

 (a) The outage of irrelevant branch (i.e., outage of a branch that has neither a flow measurement nor an injection measurement at the nodes it is connected).
 (b) The removal of branch from the original network that makes the rest of the network unobservable.

3. ARTIFICIAL NEURAL NETWORK MODELS

ANNs are adaptable learning systems [12,13,14,15] based on the methods of information processing. They consist of a large number of massively interconnected simple processing units. Such processing architectures have capability to create its own subsymbolic representation to learn and recall associatively.

Following ANN models have been used to predict the topology of the network.

(i) Multilayer perceptron using Backpropagation Algorithm (BPA)
(ii) Functional Link Network (FLN)
(iii) Counterpropagation Network (CPN)

3.1 Multilayer Perceptron Using Backpropagation Algorithm

A Multilayer perceptron is a feed forward neural network architecture in which a number of perceptrons are arranged in layers with weighted interconnections as shown in Figure-1. The multilayer perceptron employs a learning rule as Backpropagation Algorithm (BPA). The BPA uses a gradient descent technique and backward error propagation. The training set for the network must be presented many times in order for the interconnection weight between the neurons to settle to a stable value. In essence it learns a mapping from a set of input patterns (e.g., extracted features) to a set of output patterns (e.g., class information). The BPA has been popularly utilized for several applications and covered in the text books [12,13,14,15].

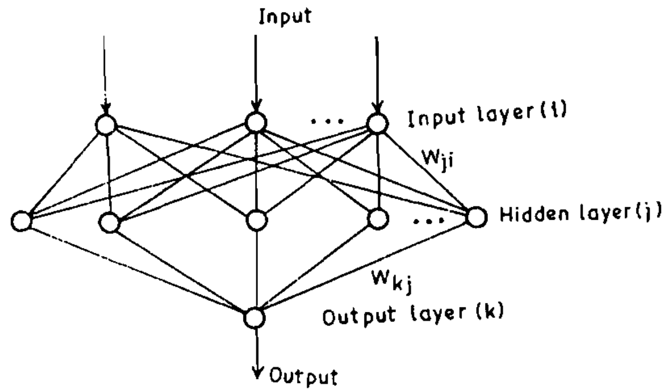

Figure 1: Multilayer Perceptron Feedforward Network

3.2 Functional Link Network

In Functional link network [12] the input patterns are enhanced by means of functional transformations, before feeding to the input layer of the actual network. That is an enhanced input pattern is used in addition to the actual pattern. The enhanced input/output pair is learnt with a flat net, that is a net with no hidden layer. Problems which might be difficult in the original pattern space generally become quite straight forward, in the enhanced representation space. The functional link net is illustrated schematically in Figure-2.

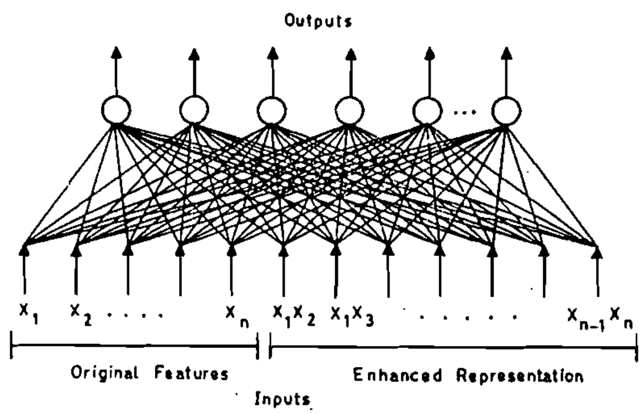

Figure 2: Functional Link Newtork

There are two models for the FLN [12], the tensor (or outer product) model and the functional expansion model. In this paper supervised tensor model of FLN has been used. In the tensor model, each component of the input pattern multiplies the entire input pattern vector. The functional link in this case generates an entire vector from each of the individual components. If $\{x_i, i = 1,\ldots,n\}$ represents set of original inputs or features, FLN model utilizes enhanced inputs along with these original inputs obtained through a sequence of transformation such as,

$$\{x_i\} \Rightarrow \{x_i, x_ix_j\} \Rightarrow \{x_i, x_ix_j, x_ix_jx_k\} \Rightarrow \ldots.$$

In the present work only up to second order products of inputs (x_1x_2, x_2x_3, ..., $x_{n-1}x_n$) have been considered as enhanced inputs (as shown in Figure-2). The original inputs to the ANN and the outputs for topology processing is shown in Figure-3. Since functional link network does not have hidden layer, simple delta rule [13] can be used for training.

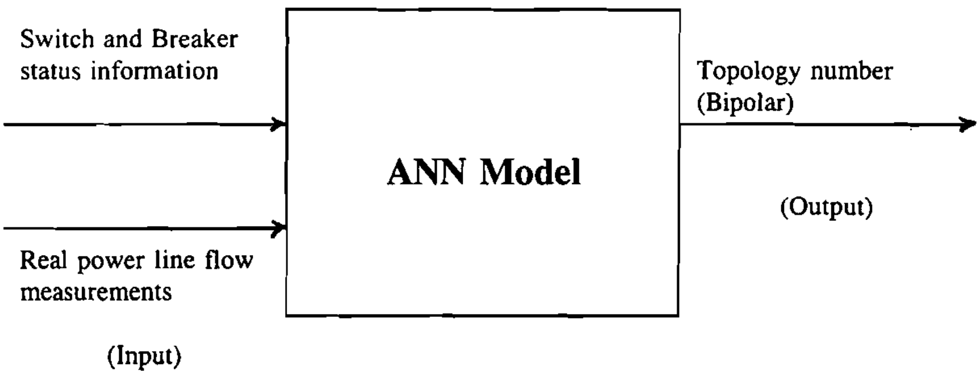

Figure 3: ANN Based Topology Processor

3.3 Counterpropagation Network

The Counterpropagation network architecture [11,14,15] as shown in Figure-4, is a combination of self organizing map of Kohonen and out star structure of Grossberg. The advantages of the CPN are that it forms a good statistical model of its input vector environment. It functions as a look up table capable of generalization. It functions as a look up table capable of generalization. CPN requires a number of Kohonen units (hidden units) to achieve high mapping approximation accuracy.

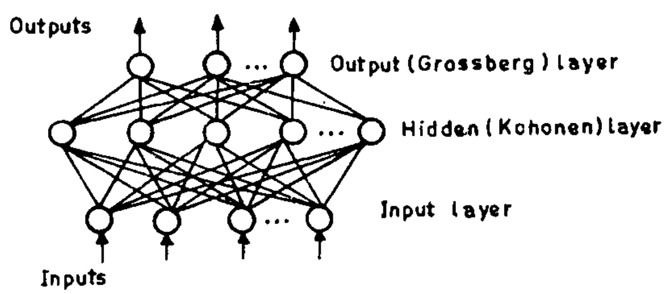

Figure 4: Counterpropagation Network

The Kohonen layer classifies the input vectors into groups that are similar. The Kohonen layer functions in a *winner take-all-fashion,* that is for a given vector, one or more than one neuron outputs a logical one and all others output a zero. The learning rule to update the weight (W) of the winner is,

$$W_{new} = W_{old} + \lambda \ (x - W_{old})$$

Where

W_{new}	=	the new value of a weight connecting an input component x to the winning neuron
W_{old}	=	the previous value of the weight
λ	=	a training rate co-efficient that may vary during the training process

The training rate co-efficient (λ) is usually [14] taken as 0.7 in the beginning and may be gradually reduced during training.

Each weight in the Grossberg layer is adjusted only if it connected to Kohonen neuron having a non-zero output. In the present work, only one neuron (say neuron q) in the Kohonen layer has been considered as winner having output as unity. The amount of the weight adjustment is proportional to the difference between the weight and desired output of the neuron to which it connects. The training rule to update weight V is,

$$V_{new} = V_{old} + \beta \ (Y_r - V_{old}) \ k_q$$

Where
k_q = the output of Kohonen neuron q
Y_r = component *r* of the vector of desired outputs

Initially β can be set [14] to 0.1 and is gradually reduced as training progresses.

4. DEVELOPMENT OF ANN BASED TOPOLOGY PROCESSOR

The ANN based topology processor is shown in Figure-3. In the present application of the ANN models to topology processing the inputs considered to the neural networks were telemetered status data of circuit breakers, switches and also the real power line flow measurements. The real power line flow measurements have been considered to generate redundant set of data because when any change in network topology occurs, sudden variations in flow measurements appear in the branch. The output of the ANN models were a string of bipolar numbers (+1 and -1) representing the topology number corresponding to the base case and network outages. The length of output string depends on the topology cases simulated in a system. For example, in IEEE 14-bus system total 16 topologies were considered which can be represented by a bipolar string of four numbers as given in Table-1. Input information of the breaker status has been represented in bipolar form, that is, when a breaker is closed, its value was taken a +1 and when opened, its value was -1. Though lines may consist of two breakers one at each end, only one breaker status has been used as input to the ANN models to determine the topology of the network.

TABLE 1. IEEE 14 - Bus Network Topology and Respective Topology Number

S.No.	Network Topology	Topology Number
1.	Base Case	-1 -1 -1 -1
2.	Outage of Line 1	-1 -1 -1 1
3.	Outage of Line 2	-1 -1 1 -1
4.	Outage of Line 3	-1 -1 1 1
5.	Outage of Line 4	-1 1 -1 -1
6.	Outage of Line 5	-1 1 -1 1
7.	Outage of Line 6	-1 1 1 -1
8.	Outage of Line 7	-1 1 1 1
9.	Outage of Line 13	1 -1 -1 -1
10.	Outage of Line 14	1 -1 -1 1
11.	Outage of Line 15	1 -1 1 -1
12.	Outage of Line 16	1 -1 1 1
13.	Outage of Line 17	1 1 -1 -1
14.	Outage of Line 18	1 1 -1 1
15.	Outage of Line 19	1 1 1 -1
16.	Outage of Line 20	1 1 1 1

The number of nodes in hidden layer of BPA and CPN were obtained by hit and trial. A general rule to select the hidden nodes in the CPN is that it should not be greater than the number of input training pattern-s. The output of CPN remains a string of bipolar numbers (+1 and -1) even for the unknown test patterns, as it provides a kind of look-up table, whereas the outputs of BPA and FLN can assume string of any positive or negative values. For the purpose of topology determination, the BPA and FLN outputs were approximated to +1 if they were positive and -1 if they were negative.

All the three ANNs have been trained using the training patterns generated corresponding to different topologies and loading conditions of the system. After training, the accuracy of the models have been tested for the set of patterns not utilized during the training. These sets were generated for different network loading conditions (not included in the training set).

The topology of the network has also been determined by using Counterpropagation network for network unobservable cases, specially when a node becomes unobservable due to lack of measurements during outage of a branch.

5. SIMULATION RESULTS

The proposed ANN based models viz. BPA, CPN and FLN were trained and tested for IEEE 14-bus, IEEE 57-bus and practical 75-bus Indian systems. The 75-bus Indian system represents 400-kV and 220-kV network of Uttar Pradesh State Electricity Board (UPSEB).

5.1 Training of the ANN Based Topology Processor

For the determination of ANN based network topology, training patterns were generated for base case and different network outages using a load flow program by varying the loads at each bus randomly covering the whole range of operating conditions upto 120% of the base case loading value. For each of the power systems, total 1000 patterns were generated. Out of these 800 patterns were used to train the BPA, CPN and FLN and remaining 200 patterns were used to test the accuracy and robustness of the trained ANN models.

The total inputs to each of the ANNs were equal to twice the number of lines in the system (20 lines in case of IEEE 14-bus system, 80 lines in case of IEEE 57-bus system and 95 lines in case of 75-bus practical Indian system) which consists of switch and breaker status information and real power line flow measurements. In IEEE 14-bus system, total 16 topologies and in IEEE 57-bus as well as 75-bus practical Indian system, total 10 topologies were considered. Hence four bipolar outputs were selected for all the three systems. An error criterion on outputs used for training the CPN and FLN based topology processor was 0.001 p.u. at a base power of 100 MVA.

The number of hidden nodes in BPA model for 14-bus, 57-bus and 75-bus systems were 70, 275 and 350 respectively. In all the three cases, Backpropagation algorithm did not converge to prespecified tolerance even after 45,000 iterations. The sum of square errors at the end of 45,000 iterations were 27.70%, 30.37% and 31.43% for the 14-bus, 57-bus and 75-bus systems respectively.

The number of hidden nodes in CPN model for the IEEE 14-bus, 57-bus and 75-bus practical Indian systems were 475, 350 and 325 respectively. For FLN the learning rate (η) and momentum (α) for the three systems were taken as 0.8 and 0.3 for the first 100 iterations and 0.65 and 0.35 in subsequent iterations. It was experimentally found that the change in η and α values after 100 iterations helped accelerating the convergence.

5.2 Testing of the ANN based Topology Processor

After training BPA, CPN and FLN models for the topology processing, these were tested for the unknown loading patterns corresponding to different topologies. The test results were obtained for the cases assuming no bad data in the breaker status information and also with the presence of bad data. The bad data in breaker status was introduced by assuming a closed breaker as open and vice versa. Bad data in upto four breakers' status were considered to test the robustness of the ANN models.

Some of the results for the three systems without bad data in the breaker status information are presented in Table-2 to 4 and with bad data in the breaker status information are presented in Tables-5 to 7. In all the test systems the topology number predicted by the CPN based model was found to be the same as the actual number (true number). From the results shown in Tables-5 to 7, it is observed that the CPN based topology processor predicts accurate topology number in each of the three systems even with considering the noise in the breaker status information. BPA and FLN models, on contrary, has provided wrong topology information in almost all the cases. In the present work only single line outage cases have been considered to illustrate the approach of the suggested ANN models. However, it can be extended to the multiple branch outages of the power system elements, on similar lines, to determine the network topology.

TABLE 2. Results of Topology Processor for IEEE 14-Bus System Without Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Base Case	-1-1-1-1	-1-1-1-1	1-1-1 1	1 1 1 1
Outage of Line # 1	-1-1-1 1	-1-1-1 1	-1 1-1 1	1-1 1-1
Outage of Line # 2	-1-1 1-1	-1-1 1-1	-1 1 1 1	-1 1 1-1
Outage of Line # 5	-1 1-1 1	-1 1-1 1	1 1-1 1	1-1 1-1
Outage of Line # 6	-1 1 1-1	-1 1 1-1	1 1-1-1	1-1 1 1

TABLE 3. Results of Topology Processor for IEEE 57-Bus System Without Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Outage of Line # 10	-1-1-1-1	-1-1-1-1	-1 1-1 1	1-1 1-1
Outage of Line # 25	-1-1 1-1	-1-1 1-1	-1-1-1 1	-1 1-1 1
Outage of Line # 40	-1 1-1-1	-1 1-1-1	-1 1-1 1	1 1-1 1
Outage of Line # 60	-1 1 1-1	-1 1 1-1	-1-1 1 1	-1-1 1 1
Outage of Line # 70	-1 1 1 1	-1 1 1 1	-1-1 1-1	1 1-1 1

TABLE 4. Results of Topology Processor for Practical 75-Bus Indian System Without Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Outage of Line # 35	-1-1-1 1	-1-1-1 1	-1 1-1 1	1-1 1-1
Outage of Line # 60	-1 1-1 1	-1 1-1 1	1-1-1 1	1 1-1 1
Outage of Line # 75	-1 1 1 1	-1 1 1 1	-1 1 1-1	-1 1-1 1
Outage of Line # 85	1-1-1-1	1-1-1-1	-1-1 1-1	1 1-1 1
Outage of Line # 90	1-1-1 1	1-1-1 1	-1-1-1 1	1 1 1 1

TABLE 5. Results of Topology Processor for IEEE 14-Bus System With Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Base Case	-1-1-1-1	-1-1-1-1	1-1-1 1	-1 1-1 1
Outage of Line # 1	-1-1-1 1	-1-1-1 1	-1-1 1 1	1-1 1-1
Outage of Line # 2	-1-1 1-1	-1-1 1-1	1-1 1 1	1-1-1 1
Outage of Line # 5	-1 1-1 1	-1 1-1 1	1-1-1 1	1-1-1 1
Outage of Line # 6	-1 1 1-1	-1 1 1-1	1 1-1-1	-1-1 1-1

TABLE 6. Results of Topology Processor for IEEE 57 - Bus System With Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Outage of Line # 10	-1-1-1-1	-1-1-1-1	-1 1 1-1	-1 1-1 1
Outage of Line # 25	-1-1 1-1	-1-1 1-1	-1-1-1 1	1-1-1-1
Outage of Line # 40	-1 1-1-1	-1 1-1-1	-1 1-1 1	1-1-1-1
Outage of Line # 60	-1 1 1-1	-1 1 1-1	-1-1 1 1	-1-1-1-1
Outage of Line # 70	-1 1 1 1	-1 1 1 1	-1 1-1-1	1 1 1 1

TABLE 7. Results of Topology Processor for Practical 75-Bus Indian System With Bad Data

Test Case	Topology Number (True)	Topology Number with		
		CPN	FLN	BPA
Outage of Line # 35	-1-1-1 1	-1-1-1 1	-1 1 1 1	-1 1-1-1
Outage of Line # 60	-1 1-1 1	-1 1-1 1	1-1-1 1	1-1 1 1
Outage of Line # 75	-1 1 1 1	-1 1 1 1	-1-1 1 1	-1-1-1-1
Outage of Line # 85	1-1-1-1	1-1-1-1	-1 1-1-1	1-1 1 1
Outage of Line # 90	1-1-1 1	1-1-1 1	-1-1-1-1	-1 1-1-1

6. NETWORK TOPOLOGY DETERMINATION FOR UNOBSERVABLE CASES

Wu and Liu [8] showed that the algorithmic method (normalized residual method) may not detect branch outages, if the removal of the branch from the original network, makes the rest of the network unobservable. To establish the potential of the proposed ANN model to overcome this limitation, the Counterpropagation network based model was utilized, to determine the network topology in such cases. Only CPN based model was tested since it provided more accurate results for the network topology determination as established in section 5.2 in comparison with BPA and FLN based models. Different unobservable cases in two of the sample systems (14-bus and 57-bus) were simulated as following.

Suppose at a bus-i, two lines-j and k are incident. If the outage of line-j is considered and at the same time if line flow measurement of line-k is assumed to be missing, the node-i and hence the system becomes unobservable.

Three different unobservable cases were simulated for each of the IEEE 14-bus and IEEE 57-bus systems, shown in Table-8 and Table-9 respectively. For each of the cases the results were obtained for various system loading patterns to determine the network topology using the CPN model already trained (as described in section 5.1). The results for the two systems are given in Table-10 and Table-11. From these tables, it can be observed that the proposed ANN based topology processor using CPN model has provided almost accurate (more than 90%) results for different unobservable cases of the network.

TABLE 8. IEEE 14-Bus System: Examples of Unobservable Cases

Case Studies	Line Outage Between Buses	Measurement (s) Not Available (Line Flow / Bus Injection)	Unobservable Bus
Case - I	13 - 14	14 - 9	14
Case - II	2 - 3	3 - 4	3
Case - III	13 - 12	12 - 6	12

TABLE 9. IEEE 57-Bus System: Examples of Unobservable Cases

Case Studies	Line Outage Between Buses	Measurement (s) Not Available (Line Flow / Bus Injection)	Unobservable Bus
Case - I	30 - 31	31 - 32	31
Case - II	22 - 23	23 - 24	23
Case - III	45 - 44	44 - 38	44

TABLE 10. IEEE 14-Bus System: Results for Unobservable Cases

Case Studies	Number of Patterns Tested	Number of Patterns Correctly Identified	Accuracy (in %)
Case - I	100	95	95
Case - II	100	94	94
Case - III	100	90	90

TABLE 11. IEEE 57-Bus System: Results for Unobservable Cases

Case Studies	Number of Patterns Tested	Number of Patterns Correctly Identified	Accuracy (in %)
Case - I	100	93	93
Case - II	100	90	90
Case - III	100	91	91

7. CONCLUSIONS

In this paper, three different ANN models for network topology processing based on the Backpropagation algorithm, Counterpropagation network and Functional Link Network have been developed and tested for the IEEE 14-bus system, IEEE 57-bus system and a 75-bus practical Indian system. The test results of the three systems provide the following observations.

(i) The Counterpropagation network model process the network topology without any error even in the presence of noisy breaker status information.

(ii) The Backpropagation algorithm and Functional link network models, however were unable to determine accurate topology of the network in almost all the cases.

(iii) The CPU time required to test the ANN models is less than 0.1 seconds in all the cases. Hence, the proposed CPN model can be used for real-time applications to the topology processing.

(iv) The CPN based model also provided almost accurate results for the network topology determination even when the network was made unobservable in different cases of branch outages. Thus it offers a distinct superior feature over the conventional methods.

In view of the above, the CPN based model can be used for real-time determination of the network topology as it is extremely fast and accurate.

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