Topology Error Identification for the NEPTUNE Power System using an Artificial Neural Network

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***Abstract* – The goal of the North Eastern Pacific Time-Series Undersea Networked Experiment (NEPTUNE) is to construct a cabled observatory on the floor of the Pacific Ocean, encompassing the Juan de Fuca Tectonic Plate. The power system associated with the proposed observatory is unlike conventional terrestrial power systems in many ways due to the unique operating conditions of cabled observatories. The unique operating conditions of the system require hardware and software applications that are not found in terrestrial power systems. This paper builds upon earlier work and describes a method for topology error identification in the NEPTUNE system that utilizes an Artificial Neural Network (ANN) to determine single contingency topology errors.**

***Index Terms*–DC power systems, Neural networks, State Estimation, Topology, Underwater equipment, Underwater technology**

I. Introduction

The topology of a power system is determined by the positions of the breakers and switches as well as the cables that interconnect them. In a conventional terrestrial power system the position of breakers and switches are generally indicated either remotely or by a manual method. Under ocean power system are severely limited in their ability to determine the position of breakers and switches due to space limitations imposed by hardware in addition to the extreme remote locations of the hardware. The uncertainty in the present topology of a power system can severely limit the ability of the energy management system to function properly.

In the past fifteen years artificial neural networks (ANNs) have begun to be utilized through out the power industry. ANNs have found applications in areas such as load forecasting, power system stabilization, and hardware modeling [1-3]. One of the great advantages of an ANN is that when it is properly trained it can quickly generate data, using simple algebraic manipulation, which would normally require the computation of complicated non-linear equation. This drastic reduction in required computation lends ANNs to applications requiring real-time functionality.

The main contribution of this paper is the derivation and implementation of an Artificial Neural Network for single contingency topology identification in a highly interconnected under ocean DC system with a high degree of unobservability.

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II. Background

In a conventional terrestrial power system there are redundant sources of information to determine the position of breakers; breaker auxiliary contacts, measurements of current through the breaker, measurements of voltage across a breaker, power flow along a line, visual inspection, etc. In the absence of direct indications such as auxiliary contacts conventional topology identification methods make use of indirect measurements, such as voltage differences and line flows, to perform the combined function of state estimation and topology identification [4-7]. The lack of comparable indications, direct or indirect, in the NEPTUNE systems requires new methods of topology identification to deal with the high degree of unobservability of the system.

In addition to a high degree of unobservability, the NEPTUNE system also contains non-linear elements, zener diodes, in series with the lines that transmit the power, as well as constant power loads at the science nodes. A method of topology identification has been developed that will account for the non-linearities in the system as well as the unobservability, but it has the undesirable characteristic of needing to vary the systems source voltages [8]. The problem with the developed method is that operational constraints may prohibit the varying of the systems source voltages at certain times.

In the absence of an effective topology identification technique that does not require the varying of the systems source voltage, it is proposed to attempt to use an ANN to determine the topology of the system assuming that there is no more than a single contingency. In this situation a topology contingency refers to a single line being out of service. A single line out of serve indicates that two breakers are out of position, one at either end of the line.

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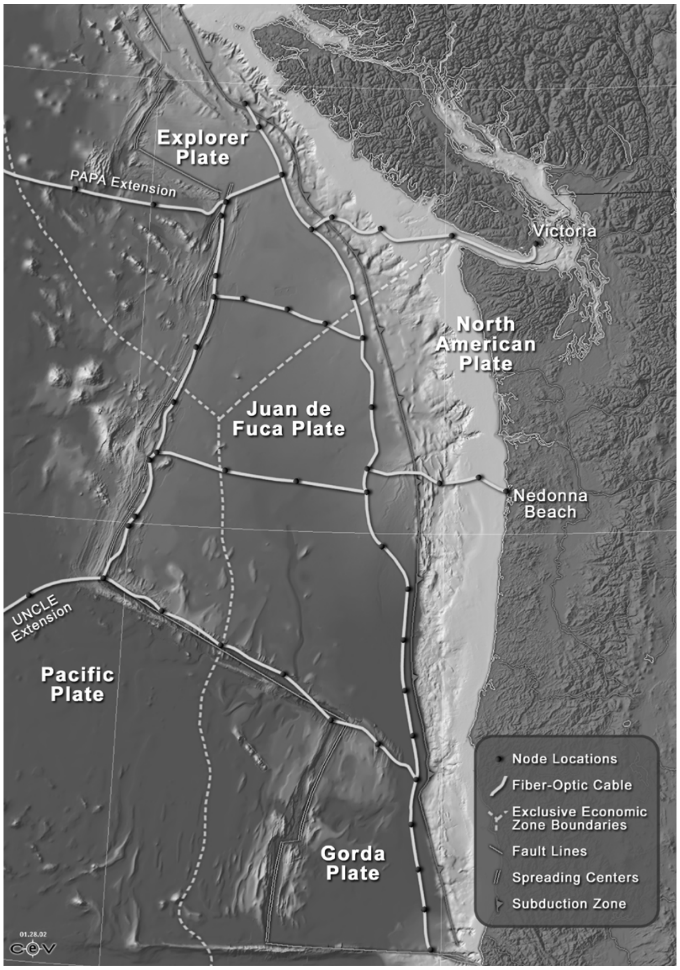

Fig. 1. NEPTUNE system

III. System Description

The proposed system is a highly interconnected DC system with a combination of series and parallel loads connected by a 3000 km cabled sub-sea network with two shore landings, intended to supply power at specified locations, nodes, Fig. 1.

Each of the forty-six node locations, a tentative number of points, shown in Fig. 1 will contain a node branching unit, BU, which will branch the main cable, Fig. 2. The cable coming off of the BU may be several km long and will supply power and communications to the science nodes.

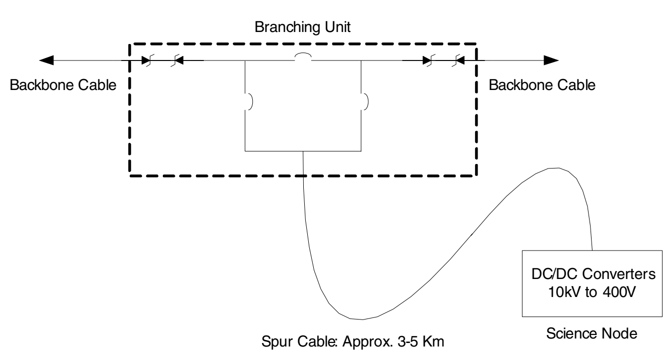

Fig. 2. Branching Unit (BU) to science node connection

At the science nodes voltage and currents, as well as load information, are available to the system operator. While the communications path for this data passes through the BUs, the communications system does not interface with this component of the system. For this reason there are no indications, direct or indirect, of the status of the power system breakers in the BUs.

IV. Basis for use of a Neural Network

In order to properly train a neural network there must be a correlation between the input values and the output values. For the system of Fig. 1 the inputs will be voltage, current, and load at each of the science nodes and the outputs will be the binary position of 64 system breakers.

The correlation between the inputs and the status of the breakers can be found in the sensitivities of the residuals calculated by a weighted least squares state estimation algorithm [8].

Using the voltage and current measurements made at the science nodes, in conjunction with the assumed topology of the system, the voltages at the BU's can be calculated using a weighted least squares estimation:

$$x^{est} = H^T R^{-1} Z^{meas} \left(H^T R^{-1} H\right)^{-1} \tag{1}$$

Where:

x^{est} : column vector of BU voltages

H : matrix of assumed topology

R^{-1} : diagonal matrix of measurement variances

Z^{meas} : column vector of measured values

In order to determine the level of measurement error present in the system, a comparison is made between the measured values and the measured values as calculated from the estimated BU voltages; the difference is indicated by the calculated residual.

$$R_{calc} = \frac{\sum \left|Z^m - x^{est}\right|}{n} = \frac{\sum \left|T * Z^m\right|}{n} \tag{2}$$

Where:

$T : H^T \left(H^T R^{-1} H\right)^{-1}$

n : number of measured quantities

Due to the multiple source of error in the system, the residual alone is not a valid indication of the accuracy of the assumed system topology. For this reason the sensitivity of the calculated residual with respect to the system source voltage, V_{SS}, is examined.

When the assumed topology is the correct topology, the residual will vary in a roughly linear manner that can be calculated. If the assumed topology is incorrect then the residual will vary in a strongly non-linear manner [8].

$$\frac{\partial R}{\partial V_{SS}} = \frac{\partial}{\partial V_{SS}}\left(\sum_{k=1}^{n+2}\left|T * Z^m\right|\right) \tag{3}$$
$$= \sum_{k=1}^{n+2}\left(sign\left(T_k * Z^m\right) * T_k * \frac{\partial Z^m}{\partial V_{SS}}\right)$$

Where:

$\frac{\partial R}{\partial V_{SS}}$: sensitivity of the residual

T_k : k^{th} row of the assumed topology matrix, T , from (2)

n : number of science nodes in the system

In order to calculate (3) it is necessary to vary the system source voltages, an action that is not desirable and potentially impossible due to system constraints. In an attempt to determine the topology of the system without varying the source voltage, an ANN will be used to detect the nearly linear, or highly non-linear, relationship between the residual and the source voltage without direct calculation of (3).

V. Neural Network Structure and Training

Artificial neural networks are structured, in a fashion, after elements of the human nervous system [9]. The advantage to this structure is that it allows for the calculation of large non-linear problems with relatively simple computations, once the network has been trained.

The major structural elements of an artificial neural network are the neurons and their interconnecting weights, Fig. 3.

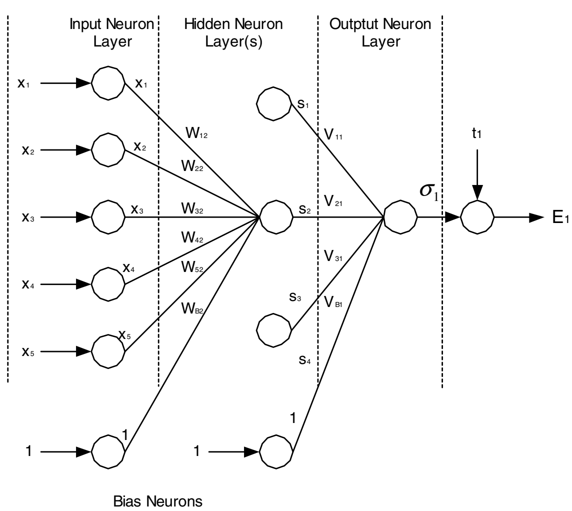

Fig. 3. Three Layer Neural Network Structure

The ANN of Fig. 3 is governed by (4-7):

$$S_i = \frac{1}{1+e^{-\lambda(net_i)}} \tag{4}$$

$$net_i = \sum_{j=1}^{5}\left(W_{ij}X_j\right) + W_{i6} \tag{5}$$

$$\sigma_1 = \sum_{j=1}^{3}\left(V_{ij}S_j\right) + S_4 \tag{6}$$

$$E = \frac{1}{2}\left(t_1 - \sigma_1\right)^2 \tag{7}$$

Where:

λ : Gain that determines non-linearity of the sigmoid

t : The output associated with the inputs from the training data

The method used to train the ANN for this work is the well established method of back error propagation, where the weights of the k+1 iteration are calculated based on the value of the k^{th} iteration (8) and (9).

$$V_{ij}^{(k+1)} = V_{ij}^{(k)} - \eta\frac{\partial E^K}{\partial V_{ij}^{(k)}} \tag{8}$$

$$W_{ij}^{(k+1)} = W_{ij}^{(k)} - \eta\frac{\partial E^K}{\partial W_{ij}^{(k)}} \tag{9}$$

Where:

$V_{ij}^{(k)}$: Weight between hidden neuron i and output neuron j

$W_{ij}^{(k)}$: Weight between input neuron i and hidden neuron j

$\eta^{(k)}$: Step size of the iteration

$E^{(k)}$: Difference between the output neuron value and the output value of the training data

The sensitivity of the error $E^{(k)}$ with respect to the weights, $V_{ij}^{(k)}$ and $W_{ij}^{(k)}$, is calculated at each iteration of the training processes. The general forms are found through the use of the chain rule:

$$V_{ij}^{(k+1)} = V_{ij}^{(k)} - \eta\left(-\left(t_1 - \sigma_1\right)S_j\right) \tag{10}$$

$$W_{ij}^{(k+1)} = W_{ij}^{(k)} - \eta\left(\left(\sum_{k=1}^{p}\left(t_1-\sigma_1\right)V_{ki}\right)\left(S_i\lambda\left(1-S_i\right)\right)\left(X_j\right)\right) \tag{11}$$

As the number of iterations, epochs, increases, the RMS error, $E^{(k)}$, should converge. Once the error has converged to a satisfactory value, as determined by the desired level of accuracy, the system can then be considered trained.

V. Training Data

For topology identification of the system shown in Fig. 1, training data will be generated using a Newton-Raphson power flow scheme. A power flow algorithm has been designed that will allow for the non-linear zener diodes that are in the lines of the system to be taken into account. In addition, a Gaussian error of .1% will be introduced into the voltage and currents calculated by the power flow in order to simulated measurements error. A Gaussian error of .1% will also be introduced into the load values to reflect unknown/unexpected system loads.

The inputs of the ANN will be the 46 voltages and 46 currents measured at the science nodes in addition to the loads at the 46 nodes. The output will be the position of 64 breakers, which will determine the topology of the system. The outputs will be binary with 1 indicating a closed breaker and 0 indicating an open breaker.

From Fig.1 there are three classifications that each of the cable sections fall under:

1) Radial, connected to shore
2) Radial, not connected to shore
3) Networked

A topology error can easily be identified if it is in a cable section that falls within the first 2 classifications. In the first case a simple adjustment of the shore station voltage will only affect the science nodes between the topology error and the shore station. In the second case all of the science nodes down stream of the topology error will be disconnected from the system. It is only topology errors within the networked portion of the system that will be identified using the ANN.

Within the networked potion of the system there are 37 cable sections that could potentially become disconnected. Including the case where all of the breakers are closed, there are 38 potential topologies that must be examined for a complete *single contingency* analysis. For each of the 38 potential topologies 200 power flow calculations are performed with varying system loads and random measurements errors in order to create the training data. The order in which the training data is presented to the ANN was randomized in order to prevent the possibility of the ANN memorizing the data instead of training properly.

VI. Results

The ANN that was used to obtain the results of Table 1 consisted of 138 input neurons, 20 hidden neurons in a single layer, and 64 output neurons. Initially the network was trained with the previously mentioned 7600 test patterns for 1000 epochs with a single line out of service. The out of service line is represented by the open state of breakers 44 and 45, while all other breakers are in the closed state. The raw results of the ANN are shown in Table 1.

Table 1: Typical ANN outputs (1-64), for 1000 epochs

1	1.00000	23	1.00000	45	0.000435
2	1.00000	24	1.00000	46	0.996269
3	1.00000	25	0.999999	47	0.999738
4	1.00000	26	1.00000	48	0.999996
5	1.00000	27	1.00000	49	1.00000
6	1.00000	28	1.00000	50	1.00000
7	0.999986	29	1.00000	51	0.999966
8	1.00000	30	1.00000	52	1.00000
9	1.00000	31	1.00000	53	1.00000
10	1.00000	32	1.00000	54	1.00000
11	1.00000	33	0.999974	55	1.00000
12	1.00000	34	1.00000	56	0.999473
13	1.00000	35	1.00000	57	1.00000
14	1.00000	36	1.00000	58	1.00000
15	1.00000	37	1.00000	59	1.00000
16	1.00000	38	1.00000	60	1.00000
17	1.00000	39	1.00000	61	1.00000
18	0.994556	40	0.999257	62	1.00000
19	0.999561	41	0.997703	63	1.00000
20	0.999976	42	1.00000	64	1.00000
21	1.00000	43	0.999964		
22	0.999998	44	0.008322		

From Table 1 it is clear that the output values are not the ideal binary values, 0 and 1, but instead vary by some small amount. Fortunately the variation from the ideal values is small enough that the breaker positions can be determined by using threshold values:

$$\begin{aligned} &value > .99 \Rightarrow \text{ Breaker is closed} \\ &value < .01 \Rightarrow \text{ Breaker is open} \end{aligned} \tag{12}$$

Using the threshold values of (12) allows for clear discrimination between the two possible breaker positions, open or closed. Table 2 shows the data from Table 1 after the threshold values have been applied in post processing. The open state of breaker 44 and 45, output 44 and 45 of the ANN, are clearly distinguished from the closed state of the rest of the system breakers. The identification of the improper position of the two breakers gives the operation a clear indication of the topology error

The values in Table 1 and 2 are typical of the values that the ANN gives for a number of different load and topology configurations, as such the threshold values of (12) as valid for all possible single contingency topology errors for the system of Fig. 1.

Table 2: ANN outputs after threshold values

1	closed	23	closed	45	open
2	closed	24	closed	46	closed
3	closed	25	closed	47	closed
4	closed	26	closed	48	closed
5	closed	27	closed	49	closed
6	closed	28	closed	50	closed
7	closed	29	closed	51	closed
8	closed	30	closed	52	closed
9	closed	31	closed	53	closed
10	closed	32	closed	54	closed
11	closed	33	closed	55	closed
12	closed	34	closed	56	closed
13	closed	35	closed	57	closed
14	closed	36	closed	58	closed
15	closed	37	closed	59	closed
16	closed	38	closed	60	closed
17	closed	39	closed	61	closed
18	closed	40	closed	62	closed
19	closed	41	closed	63	closed
20	closed	42	closed	64	closed
21	closed	43	closed		
22	closed	44	open		

It is also possible to train the system for more than 1000 epochs in order to gain greater discrimination between the two possible breaker states. The need for further discrimination is not necessary for the system in Fig. 1 but may be necessary for other systems. For this reason the training results beyond 1000 epochs will be examined.

As can be seen from Fig. 4 the ANN output value for breaker 44, an open breaker, continues to asymptotically approach 0 as the ANN is trained for a greater number of epochs. Conversely, Fig. 5 shows that the ANN output value for breaker 41, a closed breaker, continues to asymptotically approach 1 as the ANN is trained for a greater number of epochs. Some ANN outputs such as 42, from Table 1, converge to their correct value, 1 in the case of output 42, after only a few hundred epochs.

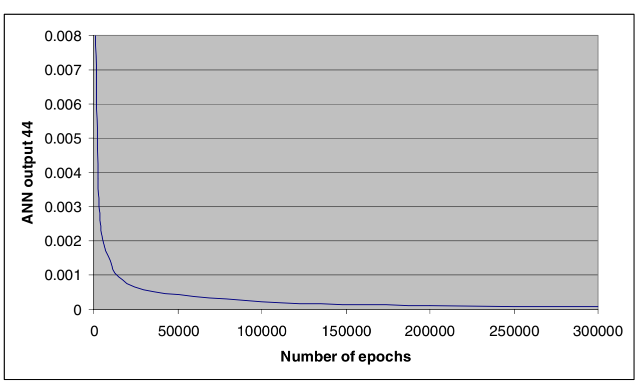

Fig. 4. Training results up to 300000 epochs, open status

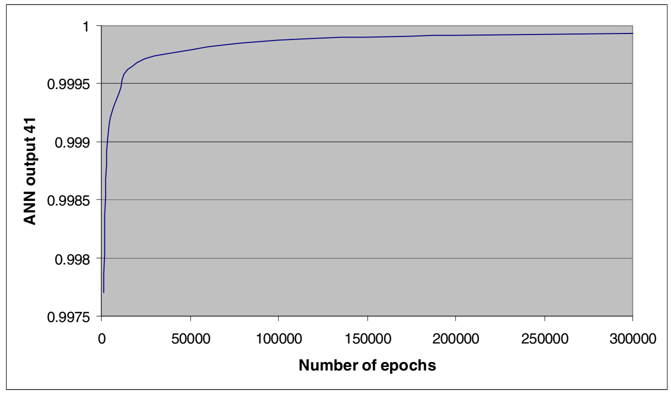

Fig. 5. Training results up to 300000 epochs, closed status

The level of training required is dependent on the desired level of discrimination between the two breaker states. If the training is allowed to continue for too long there is the possibility of the ANN memorizing the data instead of training. This was prevented from occurring in the data presented in Fig. 4 and Fig. 5 by randomly varying the order of the test patterns in the training process as well as verifying the results against patterns not included in the 7600 training patterns.

VII. Conclusions

This paper represents the continuation of work that has been in progress for over two years. The major contribution of this paper is that it outlines a method of topology identification utilizing an artificial neural network that is capable of identifying single contingency topology errors in a highly interconnected direct current system. The results show that for the system of Fig. 1, an ANN is able to determine single contingency topology errors with a high degree of accuracy. This is accomplished in the absence of any direct indication of the breaker position or any indirect indications such as current through the breaker, one of which is required for any of the conventional topology identification methods.

The primary advantage of the ANN method is that it allows for the voltage residual relationship of (3) to be exploited without having to directly calculate (3). After the time required to perform the initial training of the network, the actual calculations time required to determine the topology of the system is much lower than if (3) had been directly calculated for each potential topology.

The results have been confirmed for single line outages that represent the single contingency cases. Multiple contingency cases, more than one line out of service, have not yet been investigated but work in this area is planned.

While the use of an ANN has only been tested on the proposed NEPTUNE system of Fig. 1 the methodology used is equally valid for terrestrial power systems. Expansion of this method to alternating current terrestrial power system will be the next stage of this work.

VIII. References

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IX. Biographies

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