SELF-HEALING SMART GRID SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK
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ABSTRACT
In this paper, a novel logic decomposing method in self-healing smart grid system based on neural networks is presented and the theoretical fundamentals of the design are expounded. The proposed automatic smart grid topology search algorithm, which is based on artificial neural network (ANN), realizes the adaptive function of analyzing and updating the self-healing system logic in the grid automatically. Furthermore, the configuration design in a neural network mode makes the system have the parallel processing mechanism and the ability of learning and fault decision-making. The outlet of protection is transferred from the neural networks by adjusting the connecting weights. Therefore, the system can classify and recognize arbitrarily complex connecting mode and acting logic.

KEY WORDS
self-healing, artificial neural network , parallel processing mechanism, fault decision

1. Introduction

With the rising of voltage level, the Smart Grid has evolved into a high-order nonlinear and highly complex topological network. The stability of each device in the network mainly concerns recent users [1-2]. Whether we can locate the fault point immediately, and troubleshooting of it in minimal impact way at the time of failure, has been the subject of study in State Grid corporation for long time [3-6]. Measuring and protection device, as the most important part of smart grid self-healing properties, is widely used in the power grid. We have to consider its effects during the EMS system in the master station, DTS simulation, steady-state analysis, network fault analysis etc. Due to consideration of the changes in the structure and operation of special grid, the traditional code-based development of device is becoming more and more complex and difficult to maintenance.

Taking advantage of artificial neural network (ANN) theory[7], those issues within the design of device upon, can be solved effectively. The difficulty of model design will reduce by decomposing a complex protection logic into several basic units, with the help of model decomposition approach. A novel algorithm of network topology discovery is proposed. The device can have the ability to run the way of learning the grid changes, analyzing automatically and update the model itself by this algorithm. Benefit from the theory of ANN, device has a parallel processing system, learning adaptively and fault policy-making functions. Whole status will be given by the appropriate information from adjusting the connection weights. After study from input sample, the device will have the ability to classify and recognize for any complex connection mode and action logic.

2. Theory of Self-healing Smart Grid System

The smart grid self-healing system can be considered to be composed of three major components: neuron management, network building and neural network training.

Functional equivalence between a radial basis function neural networks and a companion fuzzy system (CFS) is built up throughout the neural network training process, therefore the black-box-like knowledge in a neural network will be rule-based and transparent in its CFS. Through useful knowledge extraction from the old CFS and insertion back to the new CFS piece by piece, the neural networks retraining issue under network expansion and topology change can be solved effectively and efficiently.

The process of imitating neuron network is to mimic the structure and function of brain cells, and to use basic components as neurons, so that self-healing network can “learn” the operation mode of power grid. That is, when the operating mode changes, the self-healing system logic does not require manual intervention to complete the automatic update, the formation of a new mode of operation under the self-healing logic. In this paper, a real-time topology information is proposed to automatically stimulate the neural network self-learning algorithm. The algorithm identifies the current topology of the power grid and the connected switches by retrieving the grid supply mode and busbar units. The
self-healing scheme of the fault is automatically determined by the neural network.

2.1 Proposed methodology

As for each neuron in artificial neural network system, it can accept a set of input signals from other neurons in the system. Each input corresponding to a weight, the weighted sum of all inputs decides the activation state of the neuron. In this paper, each weight is similar to synapse "connection strength"[8-13].

For neurons such as trip, assuming information from other neurons is $X_i$, these neurons may be over-flow, loss of pressure, etc. the weights between each is $W_i$, $i = 0,1,..., n-1$, the internal threshold neurons is $\theta$.

Sum of the weights :

$$\sigma = \sum_{i=1}^{n} x_i w_i + s \cdot \theta \quad (1)$$

Export function:

$$y = f(\sum_{i=1}^{n} W_i X_i - \theta) \quad (2)$$

Eq.(1). $X_i$ represents the input of the i-th element, $W_i$ represents the Internet weight from i-th element. Eq.(2). $f(\sigma)$ is called the excitation function or action function, which determines the output of neurons. For example, trip neurons to be exported must receive signal from overcurrent neurons or Overvoltage neurons.

2.2 Neurons definition

Function module such as charging conditions, tripping conditions, failure alarm, action sequences, etc., can be designed as multi-input, single-output nonlinear neuron model shown in Fig.1.

![Artificial neural network](image)

This process deserves a few explanations. Device input signal can be Boolean calculated in advance. It will address the protection of a switching position information, voltage and current exchange amount of information into a Boolean. That switch’s closed bit is 1, and sub bit is 0. If alternating signals are greater than the set, then the value is 1 or 0 on the counter. Threshold type activation function is also known as a step function. It represents the activation value of the relationship between $\sigma$ and its output $f(\sigma)$ between. This binary type neurons, the output value of 1 or 0 state, represents the excited neurons and suppressed state. At some point, the state of neuronal excitation function by (2) is decided.

2.3 Neurons work process

The premise is dividing information of protection into neurons and diagnostic burden on each one is basically the same. Assuming that a given fault has been divided into N neurons, distributed fault management system based on neural network is shown in Fig.1. Entering the system is grid protection and breaker status (-1 or 1), the output of the system components (such as line, bus or transformer, etc.) (failed or intact). Entering the system is grid protection measurements and breaker status (-1 or 1), the output of the system components status (such as line, bus or transformer) and operation instructions.

3. Neural network design

3.1 Hopfield neural networks

The hopfield neural networks(HNN) is valuable for associative memory and optimization in a balanced assembly [14-16]. The general assembly of the Hopfield NN diagram is illustrated in Fig. 2. In the figure, the Hopfield NN consists of a two-state neuron threshold and a stochastic algorithm, where each neuron $y_i$ has dual positions of either 1 or -1.Every input neuron comes from dual sources, one being the external input ($X_i$), and the second input is from another neuron.

![Neural network mode of Hopfield](image)

The sum of two input neurons ($Y_1$) is as Eq.(3).

$$f(\sigma) = \begin{cases} +1, & \sum_{j} x_j w_j > 0 \\ -1, & \sum_{j} x_j w_j < 0 \end{cases} \quad (3)$$

Fig. 3 shows the conceptual process of getting from an initial vector x (with all components known or guessed) to a Logic bowl. With this bowl, HNN will know what to do, and we can train HNN by it also.
3.2 AMNN Learning algorithm

An effective training method is necessary to keep the neural network learning both quickly and effectively in the presence of the variety of Network Fault forms. HNN generally uses more HEBB rules. It has to learn information storage fast and easy, but it requires training weights for associative memory mode in a set of orthogonal vector set. For practical engineering problems, the training sample structure is difficult to meet the harsh conditions, resulting in the limited ability to build a network of memory. In the paper, we find an algorithm to solve issues for trouble shooting power system protection based on the principle of projection matrix theory.

Different with traditional energy matrix methods, this algorithm uses a different set of constraints between alternating projection to complete the study. [14-17].

Assume there are N samples in Hopfield Logic bowl like Fig. 3.

\[ S^n = [x^n, w^n] = [x^n_1, x^n_2, x^n_3, ..., x^n_N, w^n_1, w^n_2, w^n_3, ..., w^n_J] \]

where \( x^n_i, w^n_j \in \{1, -1\}, n = 1, 2, 3...N. \)

For any \( i, j (1 \leq i \leq N, 1 \leq j \leq N) \), has the rule below:

\[ \sigma_{sij} = \sum_{n=1}^{N} w^n_i v^n_j \]  

(4)

\[ \sigma_{sij} = \sum_{n=1}^{N} x^n_i v^n_j \]  

(5)

For any \( v^n_i, v^n_j \), \( i, j (1 \leq i \leq N, 1 \leq j \leq N) \), has the rule below:

\[ \sum_{j=1}^{N} v^n_j = \begin{cases} 1, & m = k \\ 0, & m \neq k \end{cases} \]  

(6)

\[ \sum_{j=1}^{N} x^n_j = \begin{cases} 1, & m = k \\ 0, & m \neq k \end{cases} \]  

(7)

Such a sample of any of the above is all NN steady state mode.

Let \( Z^n = [v^n_1, v^n_2, v^n_3, ..., v^n_J] \), \( U^n = \frac{Z^n}{|Z^n|} \),

\[ U^n = \begin{bmatrix} (x^1, x^1) & (x^1, x^2) & ... & (x^1, x^n) \\ (x^2, x^1) & (x^2, x^2) & ... & (x^2, x^n) \\ ... & ... & ... & ... \\ (x^n, x^1) & (x^n, x^2) & ... & (x^n, x^n) \end{bmatrix} \]

\[ K = \begin{bmatrix} (x^1, x^1) & (x^1, x^2) & ... & (x^1, x^n) \\ (x^2, x^1) & (x^2, x^2) & ... & (x^2, x^n) \\ ... & ... & ... & ... \\ (x^n, x^1) & (x^n, x^2) & ... & (x^n, x^n) \end{bmatrix} \]

If \( K_y \) is cofactor of \( (x^1, x^1) \) in \( K \), then

\[ [v^1, v^2, ..., v^n] = \frac{1}{K} \begin{bmatrix} k_{11} & ... & k_{1N} \\ k_{21} & ... & k_{2N} \\ ... & ... & ... \\ k_{N1} & ... & k_{NN} \end{bmatrix} \]

where Eq.4 will turn into:

\[ \sigma_y = \frac{1}{K} \begin{bmatrix} k_{11} & ... & k_{1N} \\ k_{21} & ... & k_{2N} \\ ... & ... & ... \\ k_{N1} & ... & k_{NN} \end{bmatrix} \]

\[ (X^T X)^{-1} = \frac{1}{K} \begin{bmatrix} k_{11} & ... & k_{1N} \\ k_{21} & ... & k_{2N} \\ ... & ... & ... \\ k_{N1} & ... & k_{NN} \end{bmatrix} \]

Thus we can obtain the following equations:

\[ \sigma_y = W (X^T X)^{-1} X^T \]  

(8)

\[ \sigma_y = X (W^T W)^{-1} W^T \]  

(9)

Typically, when using the NN to solve practical problems with the power system, the number of required samples prototype is established and the number is greater than the input network output neuron. So \( X^T X \) and \( W^T W \) by the prototype sample consisting of input and output are not guaranteed to be full rank. Therefore, this paper introduces the regression estimator \( \beta \). Then (8) and (9) will change into:

\[ \sigma_y = W (X^T X - \beta I)^{-1} X^T \]  

(10)

\[ \sigma_y = X (W^T W - \beta I)^{-1} W^T \]  

(11)

where \( \beta \in (0, 1) \).

4. Engineering modeling

Self-healing system for fault identification is based on the formation of the form grid, power distribution, the
current set of dry-voltage network, as well as the position of the switch. First of all, with the corresponding fault current value and the corresponding non-fault current training neural network, the use of neural network memory function is to remember the size of the corresponding fault current range, and then determine the fault according to the input current size. For the frequency of power grid vibration, the power grid partial solves problem. Self-healing system can make cash withdrawal forecast. And the discrimination is performed using the synchronizing vector measuring apparatus data. In the frequency oscillation, the initial phase of the abnormal load, the voltage and current will appear marked changes in phase angle. With this trained neural network, the self-healing system can have a good risk prediction function. The structure of the neural network is shown in Fig.4:

![Neural Network Structure](image)

**Fig. 4 Neural Network Structure**

Self-healing system training process is shown in Fig.5

![Training Process](image)

**Fig. 5 Training Process**

If the network structure and various parameters can not meet the requirements in the network training process, then the structure and parameters of the network need to be changed, and then the network will be re-trained as Fig.5 shown. In order to make the neural network model to achieve the required functions, it must be stored in the relevant information, which must be on the neural network training. In the training of neural networks, as much as possible for the sample to be enough for their training.

### 4.1 Simulation examples

For a number of 110kV substations in the chained power supply mode, the self-healing system automatically recognizes the operating mode according to the position of the open-loop point, and determines the self-healing system action logic corresponding to the different faults in that mode. When the power failure occurs in the substation, the self-healing system firstly identifies the fault location, and then jumps off the original main power switch of the power station immediately adjacent to the fault point (at the same time, the fault point and the open-loop point are cut off between the small power supply for the string).

![Typical Chained System Power Mode](image)

**Fig. 6 Typical Chained System Power Mode**

Training algorithm uses a hopfield algorithm with additional items, and weights are modified as follows:

\[ \Delta W_{ij}^k (t + 1) = \eta \delta_j^k (t) + \alpha \Delta W_{ij}^k (t) \]  \hspace{1cm} (12)

\[ W_{ij}^k (t + 1) = W_{ij}^k (t) + \Delta W_{ij}^k (t + 1) \]  \hspace{1cm} (13)

Where \( \alpha \) is the inertia factor, \( \eta \) is the learning efficiency coefficient, \( k \) is the sample number, \( t \) is the learning number, \( w \) is the weight vector, and \( j \) is the output error value of node \( j \). The parameters are set to \( \alpha = 0.2 \), \( \eta = 0.2 \), \( W_{max} = 1.0 \), and the number of samples was 10.

The trained neural networks with hidden layers of 12, 14, 16, and 18 are trained with the maximum error of 0.05. The training condition is shown in Table 1. After training, the number of hidden nodes is 16, And the number of nodes in the hidden layer of fault diagnosis sub-network is 16. Then train the network of 16 hidden layer nodes. The training error curve is shown in Fig.7.

<table>
<thead>
<tr>
<th>Number of hidden layer nodes</th>
<th>Number of training sessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>14685</td>
</tr>
<tr>
<td>14</td>
<td>13892</td>
</tr>
<tr>
<td>16</td>
<td>9632</td>
</tr>
<tr>
<td>18</td>
<td>11963</td>
</tr>
</tbody>
</table>

**Table 1 Situation of Training**
4.2 Simulation samples and results

In order to test the training results, choose different faults to test. The results are shown in Table 2:

<table>
<thead>
<tr>
<th>Line fault</th>
<th>Transformer fault</th>
<th>Frequency failure</th>
<th>Phase failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>Relay</td>
<td>Ideal</td>
<td>Relay</td>
</tr>
<tr>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0.0015</td>
</tr>
<tr>
<td>1</td>
<td>0.999</td>
<td>1</td>
<td>0.9996</td>
</tr>
<tr>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0.0013</td>
</tr>
<tr>
<td>1</td>
<td>0.999</td>
<td>1</td>
<td>0.9993</td>
</tr>
<tr>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0.0016</td>
</tr>
<tr>
<td>1</td>
<td>0.999</td>
<td>1</td>
<td>0.9995</td>
</tr>
<tr>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0.0014</td>
</tr>
<tr>
<td>1</td>
<td>0.999</td>
<td>1</td>
<td>0.9995</td>
</tr>
<tr>
<td>0</td>
<td>0.001</td>
<td>0</td>
<td>0.0018</td>
</tr>
<tr>
<td>1</td>
<td>0.999</td>
<td>1</td>
<td>0.9996</td>
</tr>
</tbody>
</table>

Results in Table 2 shows the actual output of the neural network is very close to the ideal output, the network can correctly identify all kinds of faults, and can give the trip signal instantly irrespective of the fault type. It has a good selectivity and sensitivity; System for all test samples can be correctly identified, there is no malfunction.

5. conclusion

It is significant to introduce the concept of neural network into the smart grid. In this paper, we start with a single neuron and finally constructs a neural network suitable for self-healing system. Finally, it has good practical effect in simulation, which has high practical value.

Acknowledgements

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References


[2]. Sun Jing,Qin Shi Yin,Song Yong Hua,"Fuzzy petri neta and ITS application in the fault diagnosis of electric power systems", Proceedings of the CSEE, Vol.24 No.9 Jul. 2004


[6]. Chia-Hung Lin, Cong-Hui Huang, Yi-Chun Du, Jian-Liung Chen, Maximum photo-voltaic power tracking for the PV array using the fractional-order incremental conductance method, Appl. Energy 88 (2011) 4840–4847
