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Graph Partitioning applied to Fault Location in power transmission Lines

Salif B. Sissoko, Ahmed N. Abdalla, Jing Zhang and S.J. Cheng
College of Electrical and Electronic Engneering, Huazhong University of Sciences and Technology,
Wuhan 430074, Peoples Republic of China

Abstract: The application of Radial Basis Function (RBF) neural networks for Fault Section Estimation (FSE) and fault classification and fault location within faulty section in transmission lines is presented. At the first step, a multi-way graph partitioning method based on weighted minimum degree reordering is proposed for effectively partitioning the original large-scale power system into desired number of connected sub-networks. After partitioning, the proposed scheme for each part of system consists of six RBFNNs, one networks for FSE, one for fault classification and four networks for fault location one for each fault type within the faulty section. For FSE, the relay and circuit breaker states are taken as the input to the distributed FSE system, while the states (faulted or normal) of transmission lines as the outputs. For fault classification, pre-fault and post-fault samples of the three-phase currents and another input from FSE are taken as the input, while faulty phase(s) as the output. For fault location, post-fault samples of both currents and voltages of the three phases and another input from both FSE and fault classification are taken as the input, while the fault locator as the output. To validate the proposed approach simulation studies have been carried out on IEEE 11-bus system in normal and faulty conditions to train and test the RBFNN. Testing results proved that the proposed RBF networks could provide great performance for high speed relaying. It is accurate, fast and reliable.

Key words: Fault section estimation, fault classification, fault location, radial basis function

INTRODUCTION

Power system protection is a vital prerequisite for the efficient operation and continuing development of power systems (Horowitz and Phadke, 1995). Transmission lines are the connecting links between the generation stations and the distribution systems and lead to other power system networks over interconnections. Fast and accurate location of the faults in an electrical power transmission line is vital for the secure and economic operation of power systems. This is more so in view of the fact that as a result of an increase in transmission requirements and environmental pressures, utilities are being forced to maximize the transmission line capabilities of the existing transmission lines. This effectively means that in order to maintain system security and stability, there is a demand for minimizing damage by restoring the faulty line as quickly as possible. Thus, the protective system shall be reliable, selective and very sensitive to all types of faults.

Over the past decade, many artificial intelligence techniques have found their use in solving the problems such as expert-system-based (Horowitz and Phadke, 1995; Coury and Jorge, 1998), fuzzy-set-based (Wang and Keerthipala, 1998), artificial-neural-network-based (Sidhu *et al.*, 1995; Dalstein and Kulicke, 1995), stochastically optimization-based (Dalstein *et al.*, 1995) and logic-based (Sultan *et al.*, 1992) approaches. However, Fault Section Estimation (FSE) and faulty phase(s) identification and fault location within faulty section of large-scale power networks still remains unsolved, because of the large amount of information to be dealt with and the estimation speed and accuracy required.

Since fault and the operation of relevant relays and circuit breakers in power networks are local phenomena, based on the idea of divide and conquer, distributed intelligent systems for FSE of large-scale power networks are suggested, which will be more efficient than centralized FSE systems. The distributed structure can handle the fault classification and location fault information more effectively and the FSE task can be implemented in a multiprocessor system without difficulty.

This study presents fault section estimation and the fault classification and location algorithm within faulty section using RBFNN for the protection of multi terminal transmission line. An intelligent learning procedure is used. It constructs a compact RBF networks in a rational way, preserving the advantages of linear learning. In this strategy the network starts with no hidden unit and hidden units are added based on the novelty of the data

Corresponding Author: Salif B. Sissoko, College of Electric and Electronics Engineering,
Huazhong University of Science and Technology, Wuhan, 430074, Hubei Province, China

(Yingwei *et al*., 1998; Tageldin *et al*., 2003). The main objectives of this paper are: Firstly, After system partitioning, the distributed FSE system based on hybrid Radial Basis Function Neural Network (RBF NN) and companion fuzzy system, secondly realizing the powerful and robustness of RBFNN for classifying different states of operation for transmission system within the faulty section including normal operation, single line to ground fault, double line fault, double line to ground fault and three lines to ground fault, thirdly, accurately allocating the fault within the faulty section. In this study two neural network for fault section estimation, one neural network is capable to achieve both, fault classification and faulty phase identification and four networks are used for accurate fault location within the faulty section one for each type. Existing IEEE 11-bus system is used as a real application to show the validity of the proposed algorithm. The system is simulated using Power System Stability (PSS/E) and Matlab. A large number of fault data have been generated using PSS/E considering wide variations in fault inception angle, fault location, fault resistance and pre-fault load. Using these data, fault section estimation, fault classification and location are carried out by means of MATLAB programs that make use of the neural network toolbox.

PROPOSED MULTI-WAY GRAPH PARTITIONING ALGORITHM

The multi-way graph partitioning method consists of two basic steps: realizing an initial partition by the proposed multi-way graph partitioning algorithm based on weighted minimum degree reordering and further minimizing the number of the frontier nodes of the sub-networks through iterations so as to reduce the interaction of FSE in adjacent sub-networks.

Proposed graph partitioning algorithm: Suppose G is a labeled undirected graph with n vertices. Minimum Degree (MD) reordering (Rose, 1972) can be best described by elimination graphs. The number of edges incident on the node x is called degree of node x. After eliminating the node x from the graph G, the corresponding elimination graph can be obtained by deleting the node x and its incident edges and then adding edges between any pair of nodes j and k for which (x, j) and (x, k) belong to the graph G but (j, k) does not. The elimination process can thus be modeled by a sequence of graphs, each having one node less than the previous graph, until only one node remains. At each step of the elimination process, MD algorithm selects, as the next node to be eliminated, a node of minimum degree in the current elimination graph. If more than one node meets this criterion, the node with smallest node number is chosen.

A 14-bus power network (Fig. 1a) is used as an illustrative example. Each node is denoted by its I (k), where I is the node number and k is the assigned reordering label through MD algorithm. The dotted lines represent the added edges in the elimination process. It can be seen that the MD reordering is 1 6 9 11 10 8 7 2 3 4 5.

In order to balance the calculation burdens of sub-networks, we assign each node a weight, which is an integer and used to represent the calculation burden of the corresponding node. Investigation shows that the calculation burden of a sub-network is mainly determined by the total number of possible fault elements in the network and hence the weight of a node is defined as the number of its incident possible fault elements (bus and lines).

Suppose Yn is the bus admittance matrix of the given power network in ascent order of MD reordering k. For node I, we use the number of the nonzero elements in row I of the upper triangular matrix (including the diagonal element) of Yn as its node weight (Fig. 1b) and denote it as node wt(I) = wi. With the weights, the previously formed MD reordering becomes a weighted MD reordering.

For graph G with n nodes, let 1, 2,..., n be the obtained weighted MD reordering, weights denote the total weight of n nodes and ng the desired number of sub-graphs.

Frontier node reduction algorithm: After performing the graph partitioning algorithm, the frontier node sets crossing different sub-graphs are determined, which should be further minimized to reduce the interaction of the FSE in adjacent sub-graphs. The node separator improving method suggested in (Joseph, 1991) is extended here for the purpose. The original method is applied to minimize the number of the node separators in two-way rather than multi-way graph partitioning.

Let AdjG(x, U) or Adj(x, U) denote the adjacent nodes of x in U, that is, Adj(x, U) = /Adj(x)$\cap$/U. The same way, for a subset W, Adj(W, U) = /Adj(W)$\cap$/U.

For any obtained sub-graph Cl (l = /1, 2,..., ng), the initial value of its corresponding frontier node set is represented by Fl (l = /1, 2,..., ng) and defined as:

$$F_l = \{u | u \quad Adj(C_l , U); U = \bigcup_{j>1} C_j, \quad j = 1,.......n_g\}, l=1,.....ng \tag{1}$$

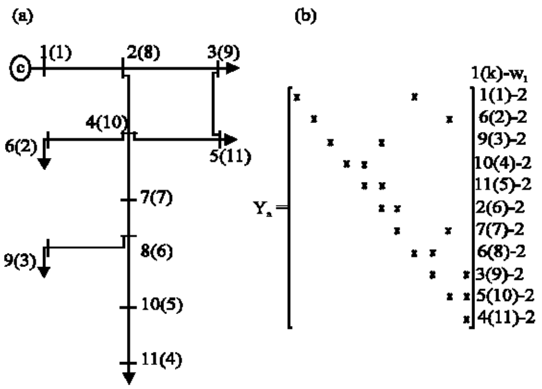

Fig. 1: The reordering weighted MD of 11 bus power network. a): The 11 bus power network and b) Upper tri angular matrix of Yn

Consider a subset Y of any given frontier node set Fi, where Adj(Y, Cl) =/Cl. The following important propositions are valid.

Proposition 1: Suppose Fl is the frontier node set crossing Cl and U, then the set $F_i = (F_1 - Y) \cup Adj(Y, C_1)$ is the frontier node set of the two sets $\bar{C}_1 = C1 - Adj(Y, C_1)$ and $\bar{U} = U \cup Y$.

Proposition 2: If $|Adj(Y, C_1)| < |Y|, \text{then} |\bar{F}_i| < |F_1|$.

It can be observed that the core issue of the frontier node reduction algorithm is how to determine a subset Y of any frontier node set Fl so that the size of Adj(Y, Cl) is less than that of Y. This problem is associated with a well-known combinatorial problem called bipartite graph matching (Joseph, 1989; Clark and Holton, 1991).

It should be pointed out that the node-transfer in the frontier node reduction algorithm might aggravate the unbalance degree of the obtained sub-networks. However, consider the weights of sub-networks are usually much larger than that of the transferred nodes, the additional unbalance degree caused by node-transfer is marginal. Since the frontier node reduction algorithm can reduce the frontier nodes effectively, this will reduce the interaction of the sub-networks apparently.

DESIGN OF RADIAL BASIS FUNCTION NEURAL NETWORK

The proposed scheme can achieve protective relaying tasks including fault section estimation and fault classification and fault location within faulty section.

Fault section estimation: Once the large-scale power network is divided into appropriate sub-networks, the overall FSE system structure with ng sub-networks can be worked out (Fig. 2). The relay and circuit breaker states (0 or 1) are taken as the inputs to the distributed FSE system, while the states (faulted or normal) of transmission lines as the outputs. Both preprocessing system and postprocessing system are simple expert systems. The preprocessing system collects the input signals and feeds them to the corresponding subsystems. The postprocessing system is responsible for acquiring the outputs of the subsystems and giving a complete diagnosis result (Bi *et al*., 2002).

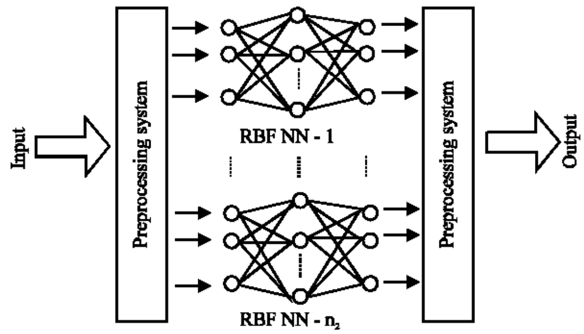

Fig. 2: The overall system structure of the distributed FSE system

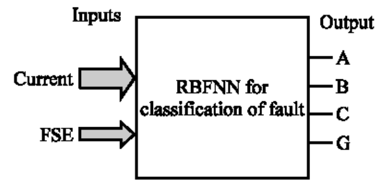

Fig. 3: RBFNN based fault classifier

For sub-network FSE, the RBF NN can be trained independently based on training samples and the elements at the frontier of various sub-networks will have impacts on adjacent sub-networks, which should be considered in RBF NN building and training.

Fault classifier: The RBFANN-based scheme for classification of transmission line faults (Fig. 3). The fault classifier consists of one NN, five pre-fault and five post-fault samples of the three-phase currents and another input FSE from fault section estimation, while faulty phase(s) as the output. A hidden layer of 50 neurons is selected. The NN outputs have been termed as A, B, C and G, which represent the three phases and ground. Any one of the outputs A, B, C approaching 1 indicates a fault in that phase. If G approaches 1, it indicates that the fault is connected to ground, e.g. output 1001 indicates A-G

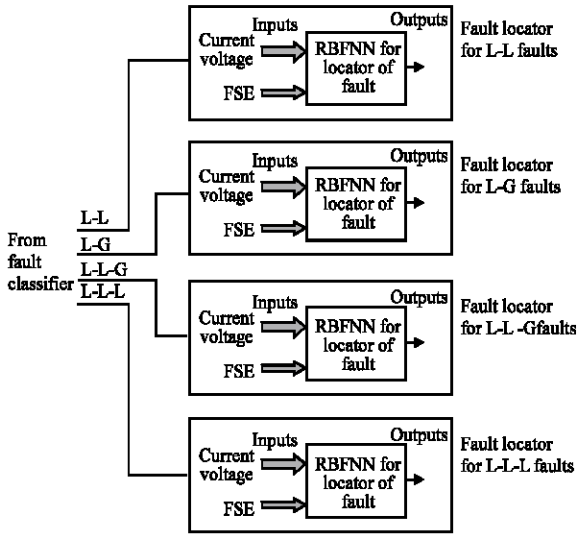

Fig. 4: RBFNN Fault locator

fault. Similarly, output 0110 indicates B-C fault and so on. Simulation studies have been carried out on the power system model in Fig. 1.

Fault locator: To estimate the exact fault locator within faulty section (Fig. 4) four RBFNN, one NN for each type of fault, i.e., one NN for L-G faults, one NN for L-L faults and so on, five per-fault and five post-fault samples of both currents and voltages of the three phases and another input from both Fault section estimation and fault classification are taken as the input, while the fault locator as the output. The hidden layer of 60 neuron selected.

COMPUTER SIMULATION RESULTS

Faulty Section Estimation RBFNNs

Performance of the proposed graph partitioning method: The proposed multi-way graph partitioning method has been implemented with sparse storage technique, which only stores and operates nonzero elements and improves the calculation efficiency significantly (Mahanty and Dutta Gupta, 2004).

The test results of IEEE 11-bus system (with ng = /2) are presented below to show the effectiveness of the proposed multi-way graph partitioning method systematically. The corresponding initial value of the sub-networks and frontier node sets are listed in Table 1. The initial frontiers and the reduction results of the Algorithm 2 are shown in Table 2. The fact that only one frontier node is reduced is mainly due to the simplicity and structure of the test system. It can be seen that the proposed multiple-way graph partitioning method works

Table 1: Obtained sub-networks of IEEE 11-bus system

	Obtained sub-networks	
l = [1, ng]	Cl = {x|x ∈ Cl}	Wt(Cl)
1	6,9,11,10,8,7	11
2	1,2,3,4,5	10

Table 2: The frontier node of IEEE 11-bus system

l = [1,ng-1]	Fl before reduction	Fl after reduction
1	4	No change

Table 3: Five test cases

Operated relays and tripped CBs	Fault section
MLP1 MLP2 CB1 CB2	L1
MLP3 MLP4 BLP6 CB3 CB4 CB6	L2
MLP5 MLP6 BLP9 CB5 CB6 CB9	L3
MLP7 MLP8 BLP9 CB9 CB7 CB8	L4
MLP9 MLP10 BLP5 CB9 CB10 CB5	L5

effectively and can satisfy all the requirements of FSE problem simultaneously.

The training and performance of distributed hybrid intelligent system: A sub-network from the IEEE 11-bus system (ng = 2) is used for the training and performance of RBF NNs for FSE and fault classification and location within faulty section. The final state of this power network is depicted in Fig. 5, in which part 1 (P1) has 5 transmission lines and 5 buses including one on the frontier. The protection relay system considered in the computer test is a simplified system, which includes main protection for transmission lines (MLP) and backup protection for transmission line (BLP).

In computer tests for P1, 28 typical fault scenarios (N = 28) are worked out to constitute the training sample set. For each fault scenario, the states of all relays and circuit breakers (0 or 1) are taken as the NN inputs (ni = 31). The states of the 10 system components (5 buses: B1/B5 and 5 lines: L1/L5) are the outputs. If a certain output approaches to 1, then the corresponding component is considered in fault.

Fault classification RBFNNs within faulty section: Different fault types (Table 3) at various locations of each section of the system under study with different inception angles and fault resistance were used to test the RBFNN. Table 4 shows some of the test results for different system conditions and not presented to the neural network during the training process. For each case it can be seen that the values of (A, B, C and G) converge to the required values and are either very close to zero or to one.

Accurate fault location RBFNNs: All types of faults with different inception angles and different locations at (0, 20, 40... 100%) of from the circuit under study were simulated to get the training and testing patterns for the RBFNNs.

Table 4: Testing results of the RBF NN for fault classification with in faulty section

Case	Fault inception	Fault resistance	Faulty section	Result output A	B	C	G
n	n	n	n	-0.0000	-0.0000	-0.0000	-0.0000
a-g	54	0	1	1.0207	0.0188	0.0270	1.0275
a-g	0	100	4	0.9646	-0.0026	0.0131	0.9957
b-g	90	100	3	-0.0103	1.0281	0.0318	0.9813
c-g	0	0	4	0.0825	-0.0202	0.9988	1.0572
a-b	0	0	2	0.9845	1.0141	0.0072	0.0032
b-c	54	0	5	-0.323	0.9793	1.0405	-0.0585
c-a	54	0	4	0.9986	0.0118	0.9974	-0.0154
ab-g	54	0	6	1.0554	0.8705	-0.0329	1.1097
bc-g	54	0	2	-0.0899	1.0508	0.9319	0.9192
ca-g	0	0	6	1.2345	-0.2098	0.9470	1.1821
abc-g	90	100	4	1.2484	0.8527	1.0343	1.1475

Table 5: Testing results of the minimal RBF network for single line to ground fault

Fault type	Fault inception angle (θo)	Actual fault location	Estimated fault location	Error (%)
a-g	0	0.30	0.3009	0.09
a-g	54	0.30	0.3065	0.65
a-g	0	0.50	0.4983	0.17
a-g	0	0.70	0.7017	0.17
b-g	54	0.30	0.2868	1.32
b-g	54	0.50	0.5103	1.03
b-g	90	0.90	0.8894	1.06
c-g	54	0.10	0.1004	0.04
c-g	54	0.30	0.2986	0.14
c-g	54	0.50	0.4967	0.33
c-g	90	0.50	0.5058	0.58

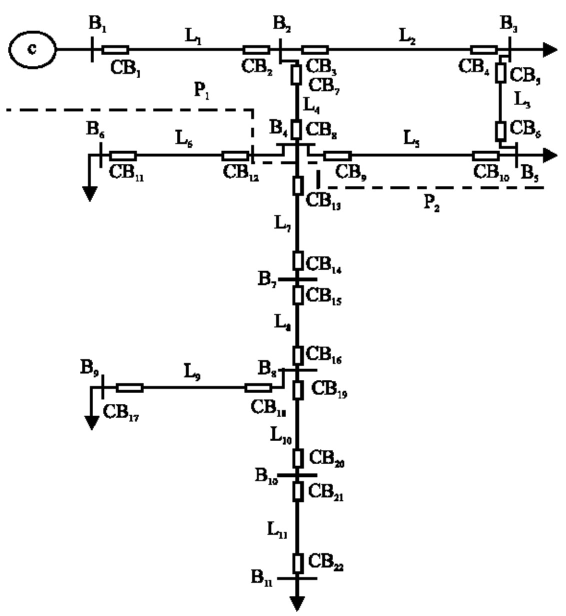

Fig. 5: Power network for FSE by Distributed RBFNNs

During the testing process, the output digit of the ANN is formed within a tolerance 0.003%.

Selective testing results for different fault types (which were not presented to the neural networks during the training process) are shown in Table 5-9.

Table 6: Testing results of the minimal RBF network for three line to ground fault

Fault type	Fault inception angle (θo)	Actual fault location	Estimated fault location	Error (%)
abc-g	54	0.30	0.3250	2.50
abc-g	90	0.90	0.9160	1.60
abc-g	0	0.50	0.5132	1.32
abc-g	90	0.70	0.6729	2.71

Table 7: Testing results of the minimal RBF network for double line to ground fault

Fault type	Fault inception angle (θo)	Actual fault location	Estimated fault location	Error (%)
ab-g	54	0.10	0.1176	1.76
ab-g	0	0.50	0.5153	1.53
ab-g	90	0.50	0.4952	0.48
ab-g	90	0.70	0.7094	0.94
bc-g	54	0.30	0.3025	0.25
bc-g	90	0.30	0.2994	0.06
bc-g	54	0.50	0.5013	0.13
bc-g	90	0.50	0.5081	0.81
bc-g	90	0.70	0.7078	0.78
ca-g	54	0.30	0.3212	2.12

Table 8: Testing results of the minimal RBF network for double line to ground fault (NN8)

Fault type	Fault inception angle (θo)	Actual fault location	Estimated fault location	Error (%)
ab-g	54	0.10	0.1176	1.76
ab-g	0	0.50	0.5153	1.53
ab-g	90	0.50	0.4952	0.48
ab-g	90	0.70	0.7094	0.94
bc-g	54	0.30	0.3025	0.25
bc-g	90	0.30	0.2994	0.06
bc-g	54	0.50	0.5013	0.13
bc-g	90	0.50	0.5081	0.81
bc-g	90	0.70	0.7078	0.78
ca-g	54	0.30	0.3212	2.12

Table 9: Testing results of the minimal RBF network for three lines to ground fault (NN9)

Fault type	Fault inception angle (θ)	Actual fault location	Estimated fault location	Error (%)
abc-g	54	0.30	0.3250	2.50
abc-g	90	0.90	0.9160	1.60
abc-g	0	0.50	0.5132	1.32
abc-g	90	0.70	0.6729	2.71

The error is calculated by:

$$\text{Error}\ (\%) = \frac{\begin{vmatrix}\text{Actual fault location} - \\ \text{Calculated fault location}\end{vmatrix}}{\text{Total faultry section leagh}} \quad 100 \qquad (3)$$

CONCLUSIONS

In this study, a novel integrated protective scheme for large scale power system is introduced. A new structure of neural network diagnostic system for fault classification, faulty phase identification, faulty section estimation and reasonably accurate fault location is proposed.

The technique is based on the use of the Radial Basis Function Artificial Neural Network. The proposed scheme deals with all types of faults and all fault conditions, including different fault types, fault inception angles, fault resistance and fault location. As a case study, the IEEE 11BUS transmission system was established by collecting elemental samples of voltage and current waveforms using PSS/E. The diagnosis system consists of two hierarchical levels. The first is for pre-processing and the second for neural networks. These networks are responsible for fault classification as well as faulty phase identification, faulty section estimation and fault location within the faulty section. The new structure of the RBFANN can be easily adapted to deal with the changes of relaying scheme through the user interface. Accuracy in testing results was reasonable, irrespective of different system conditions. Therefore, it validates the proposed Diagnosis system for cases contained in the training set as well as for new testing cases.

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