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ANN - Based Distribution System Reconfiguration

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Abstract

This paper describes an Artificial Neural Network (ANN) - based distribution system reconfiguration scheme to reduce system loss. The ANN is trained for different load levels and different network topologies. The proposed scheme has been tested using a 38 - bus distribution system. The results are very promising.

Keywords: Artificial Neural Network, Distribution System Reconfiguration, Loss Minimization, Load Balance.

Introduction

Reconfiguration is an important issue for distribution system automation. It is a process of altering the topology structures of distribution feeders by changing the open/closed status of the sectionalizing and tie switch. As operating conditions change, networks are reconfigured for the following purposes: (1) to reduce the network real power losses; (2) to relieve overloads in the network, or to balance network load; (3) to optimize voltage profile; and (4) to enhance system reliability. Since the distribution systems are configured radially, there may be a number of switches to be considered in the reconfiguration process. Heuristic approaches (based mostly on approximate power flow estimation methods) have been suggested to solve the reconfiguration problem.

The majority of studies in the field have concentrated on loss minimization [1-6]. Merlin and Back [1] utilized a branch and bound type optimization technique to determine the minimum loss configuration. The scheme starts with a meshed network by initially closing all network switches (Normally Open Switches). The switches are then opened successively to restore the radial configuration. Several implementation schemes are proposed in [2-6]. In order to deal with the multiple objective reconfiguration problem, a multiple objective optimization technique was proposed in [7, 8, 9, 10]. This approach can simultaneously handle loss minimization, load balancing, voltage deviation minimization, as well as reliability. Also, capability constraints must be taken into account. In order to get a globally optimum solution, a two-stage solution approach is introduced. The first stage is expected to yield a reasonably good solution for stage 2 using a power flow type solution approach. The branch exchange scheme is employed to find a better solution until the stopping criteria is met. The optimization procedure to solve these problems is complicated and requires exhaustive solution times. This makes the method unsuitable for on-line applications. On the other hand, since the optimization criteria for loss minimization, load balancing, and voltage profile are different, these problems are often studied separately.

Because of the various advantages ANNs offer over conventional tools, they have been successfully applied in many areas in power systems [11 - 14]. Most works focused on load forecasting, security assessment and fault diagnosis, while few work has been performed in reconfiguration.

This paper investigates an unique integrated scheme of distribution system reconfiguration using the ANN technique. System losses and load balancing indices under different configurations are determined by the proposed ANN-based reconfiguration scheme. Based on this information, the final configuration can be determined immediately.

The proposed scheme was tested on a 38-bus distribution system for the different initial network configurations. The test results show that the proposed ANN scheme can determine the final configuration quickly and accurately with consideration of loss minimization and load balancing.

Distribution System Models

Distribution system models include loss and load balancing models. A brief discussion is as follows:

Loss model

System loss can be expressed by:

$$P_{Loss} = \sum_{i=1}^{NB} r_i \bullet I_i^2 \qquad (1)$$

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where r_{bi}, I_{bi} are the resistance and current of line i, respectively. I_{bi} is a non-linear function of node voltages and line impedances, i.e.,

$$I_{bi} = \sqrt{\frac{[V_j \cos\theta_j - V_k \sin\theta_k]^2 + [V_j \sin\theta_j - V_k \sin\theta_k]^2}{r_{bi}^2 + x_{bi}^2}} \tag{2}$$

where V_j, V_k, θ_j, and θ_k are magnitudes and angles of node voltages (Figure 1). They can be expressed by node loads and line impedances, i.e. power flow equation. Therefore, the system loss (1) can be re-written as a non-linear function of node loads.

$$P_{Loss} = P_{Loss}[(P_1, Q_1, \ldots, P_{ND}, Q_{ND}), (r_{b1}, x_{b1}, \ldots, r_{bNB}, x_{bNB})] \tag{3}$$

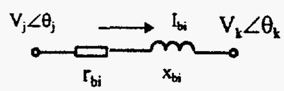


Figure 1

In order to avoid overloads in the distribution system after reconfiguration, line capability constraints are incorporated in the process, i.e.,

$$\frac{P_{bi}}{P_{bi}^{Max}} < L_{bi}^{Max} \tag{4}$$

where
P_{bi}^{Max} is the current capability of line i and
L_{bi}^{Max} is the maximum load index of line i.

Load Balancing Model
Load balancing index (LBI) is defined as:

$$LBI = \sum_{i=1}^{NB} w_i \left(\frac{P_{bi}}{P_{bi}^{Max}}\right)^2 \tag{5}$$

where w_i is the weighting factor for line i.

Since active line flows can be expressed as a non-linear function of node loads and line impedances, LBI is a nonlinear function of node loads and line impedances, i.e.,

$$LBI = LBI[(P_1, Q_1, \ldots, P_{ND}, Q_{ND}), (r_{b1}, x_{b1}, \ldots, r_{bNB}, x_{bNB})] \tag{6}$$

where LBI is the load balancing index.

ANN Model

Figure 2 shows the structure of the ANN-based reconfiguration scheme which consists of two parts. The first part evaluates system loss and load balancing index, and the second part determines the optimal configuration. The final configuration can be determined for either loss minimization or load balance or for both.

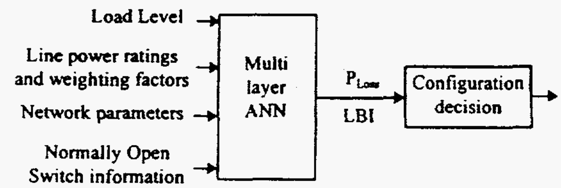


Figure 2. ANN-based distribution system reconfiguration scheme

A multiple layer ANN scheme is used for determinations of system loss and load balancing index. Figure 3 shows the architecture. The inputs are system load level, line power ratings and weighting factors, network parameters, and normally open switch information. The outputs are system loss and load balancing index.

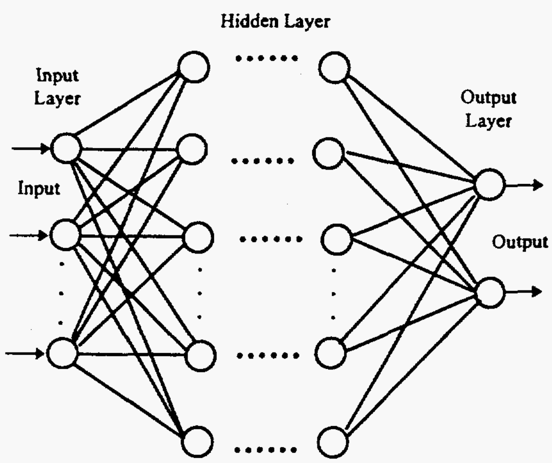


Figure 3. Multiple layer ANN

Back propagation is the most widely used algorithm for training ANN weights. The network layers are classified into three units: input, hidden, and output layer. The units are connected from input to output layers in a feed-forward way. In a fully-connected layered network, each neuron receives inputs from every output in the preceding layer. Defining the output of unit i of the previous layer as x_i, the input of unit j at the present layer can be written as:

$$net_j = \sum_i w_{ij} x_i \tag{7}$$

where w_{ij} is the weight between unit i and j.

Output o_j of unit j is expressed as a function of the unit input net_j as

$$o_j = f(net_j) \tag{8}$$

where $f(x) = \frac{1}{1+e^{-x}}$ is a sigmoid function.

Implementation Scheme

ANN-based distribution system reconfiguration is an integrated process. The integrated process includes following steps:

__Step 1:__ Prepare input information including system load level, line power ratings and line weighting factors, network parameters, and normally open switches.

__Step 2:__ Generate training data and test data which covers all possible load levels and network configurations.

__Step 3:__ Train ANN for determination of system losses and load balancing indices under different load levels and different initial configurations. The detailed of ANN training process can be found in [15].

__Step 4:__ Test ANN scheme.

__Step 5:__ Perform loss and load balance analysis to determine which objective, or both, should be optimized.

__Step 6:__ Determine final configuration based on the objective(s) selected.

__Step 7:__ Output the final configuration and the corresponding loss and load balancing index.

The first three steps are designed for ANN training, while the last four steps are used for testing the ANN-based distribution system reconfiguration scheme.

Validation Studies

The proposed scheme is tested on a 38-bus distribution system. Figure 4 shows the system diagram. The system has 32 lines and 5 normally open switches (7-33, 8-34, 11-35, 17-36, and 24-37). Node 0 is the only power source in the system. The system data can be found in [4].

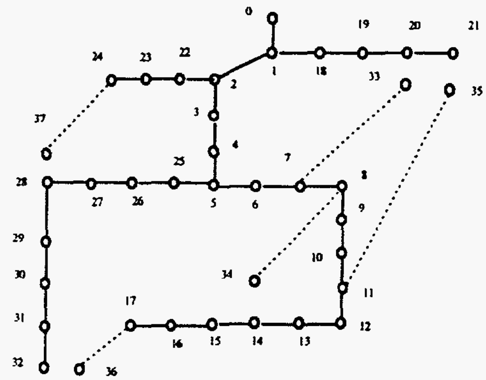


Figure 4. 38-bus test system

In this study, different system load levels are obtained by scaling node loads. The loads at buses were varied from 30% to 200% in 10% steps to generate training data. Six different initial configurations are considered in the generation of training data, resulting in 108 cases for ANN training. The test data is generated by scaling loads from 35% to 155% in 10% steps under three different initial configurations. Table 1 shows normally open switches for the six initial configurations.

Table 1. Three Cases for Program Test

Case	NOS 1	NOS 2	NOS 3	NOS 4	NOS 5
	from - to bus	from - to bus	from - to bus	from - to bus	from - to bus
1	7 - 33	8 - 34	11 - 35	17 - 36	24 - 37
2	3 - 4	11 - 12	11 - 35	17 - 36	24 - 37
3	2 - 3	9 - 10	20 - 21	29 - 30	22 - 23
4	4-5	12-13	20-21	30-31	2-22
5	1-18	9-10	20-21	17-36	24-37
6	18-19	12-13	11-35	30-31	2-22

ANN weights are trained by the training data. The training error is set to be 1.0E-05. The trained ANN is tested using the designed test data. System test errors are shown in Table 2. The error is defined as:

$$\varepsilon = \left| \frac{x_{calculated} - x_{desired}}{x_{Desired}} \right| \times 100\%$$

It can be seen from Table 2 that for the designed 57 test cases, only three cases' errors are larger than 5.0%. The maximum error is 12.231 in test case 42. Therefore, the proposed ANN can predict system loss accurately.

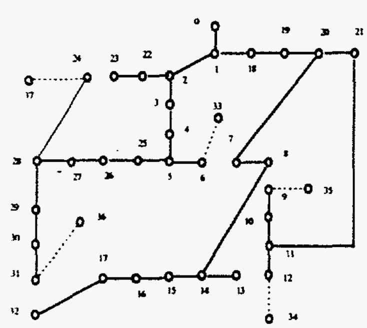
Using the proposed ANN-based distribution reconfiguration scheme, distribution system reconfiguration under different load conditions and initial configurations can be determined immediately. Figure 5 shows some reconfiguration results determined by the proposed scheme. Some lines can be opened for loss minimization without overloads in other lines, while in heavy load cases, some lines cannot be opened for loss minimization because of overloads in other lines.

We also tested the scheme with more cases. At the same load level, the final configuration is the same no matter how different the initial configuration is.

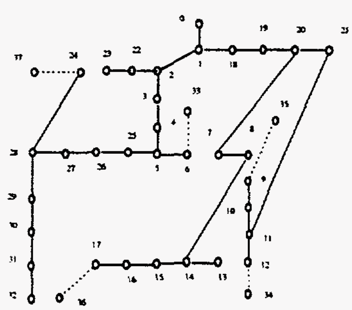
The loss reductions for the six cases in Figure 5 are shown in Figure 6. It can be seen that system losses are decreased significantly after reconfigurations. The system losses are reduced more than 30% as compared to their original losses. For each case, there is no overload in the system.

Table 2. Training Errors

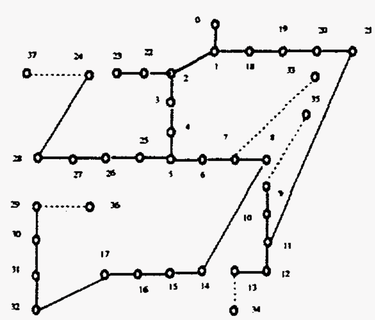
Case No.	Error	Case No.	Error	Case No.	Error	Case No.	Error	Case No.	Error	Case No.	Error
1	0.5186	11	0.4243	21	1.9122	31	1.5845	41	4.4662	51	0.0033
2	0.5158	12	2.3834	22	1.1974	32	1.4244	42	6.2401	52	3.1124
3	3.6312	13	0.9078	23	2.0634	33	2.1160	43	1.5618	53	3.5037
4	3.4910	14	0.9148	24	0.5845	34	4.4600	44	3.9479	54	2.2812
5	2.3365	15	1.5067	25	0.3142	35	3.4787	45	2.7638	55	0.3745
6	1.6918	16	0.6017	26	2.2812	36	11.607	46	2.1202	56	0.0212
7	4.2945	17	2.2308	27	0.3738	37	2.0485	47	1.5139	57	1.1974
8	1.6324	18	1.6112	28	0.0212	38	2.9258	48	0.4918	58	
9	1.7873	19	1.5713	29	4.8507	39	12.231	49	2.2719	59	
10	3.3376	20	3.4366	30	3.9348	40	4.9167	50	1.2029	60	



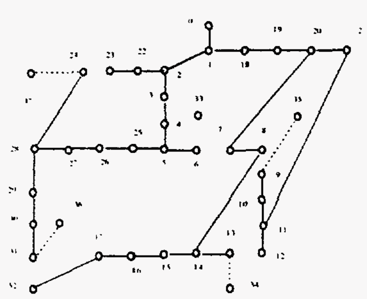
(a) 70% load level
(initial configuration 1)



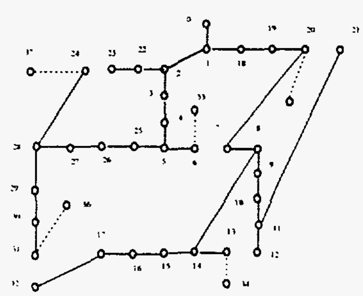
(b) 100% load level
(initial configuration 1)



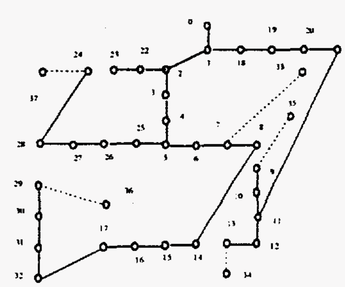
(c) 120% load level
(initial configuration 1)



(d) 94% load level
(initial configuration 2)



(e) 105% load level
(initial configuration 2)



(f) 113% load level
(initial configuration 2)

Figure 5. More reconfiguration results

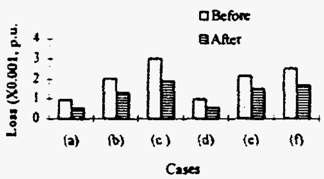


Figure 6. System losses before/after reconfiguration

Conclusion

The performance of the ANN based distribution system reconfiguration scheme for loss minimization and load balance with line capability limits yielded the following:

(1) ANN is an efficient tool to solve the distribution system reconfiguration problem. System losses and load balancing indices can be predicted quickly and accurately. This information can be used to determine the final configuration.

(2) Different initial configurations converge to the same optimum solution at the same load level regardless of how different their initial configurations are.

(3) Network losses are reduced significantly without overloads existing in system using the proposed ANN-based distribution system reconfiguration scheme.

(4) For the different load levels, the final configurations are different because of line capability limits.

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