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Real Power Contingency Ranking Using Wavelet Transform Based Artificial Neural Network (WNN)

[1]S. Sutha and [2]N. Kamaraj
[1]Department of Electrical and Electronics Enggineering,
PSNA College of Engineering and Technology, Dindigul-624622, Tamil Nadu, India
[2]Department of Electrical and Electronics Engineering,
Thiagarajar College of Engineering, Madurai 625 015, Tamil Nadu, India

Abstract: In deregulated operating regime power system security is an issue that needs due thoughtfulness from researchers in the horizon of unbundling of generation and transmission. Real power contingency ranking is an inherent part of security assessment. The target of contingency ranking and screening is to rapidly and precisely grade the decisive contingencies from a large list of plausible contingencies and rank them according to their severity for further rigorous analysis. In the proposed work, Wavelet Transform Based Artificial Neural Networks (WNN) is used for real power contingency ranking of the system. The results from offline AC load flow calculation are used to train the WNN for estimating the performance index. The effectiveness of the purported method is exhibited by contingency ranking on IEEE 14 bus, IEEE 5 bus systems and comparisons are made with conventional method. Good calculation accuracy, faster analysis times are obtained by using WNN.

Key words: Contingency ranking, wavelet transform, neural network, performance index, static security assessment

INTRODUCTION

Power system security, congestion management, power quality and power regulations are major concepts that draw the attention of power researchers in deregulated surroundings. Security assessment is an issue of at most grandness under 'open market access system' to render authentic and procure electricity to its customers. The goal of security assessment is to provide selective information to the system operator about the secure or insecure nature of the functioning state in the consequence of an unanticipated contingency, so that pertinent control measurements can be taken on to make the system secure.

Static security assessment of a power system copes with analyzing the system steady state operation after disturbances. The function of security assessment is contingency analysis which is performed in three stages; contingency definition, selection and evaluation. The ordering of insecure contingencies in terms of their severity is known as contingency ranking. The severity of contingencies is assessed based on a Performance Index (PI). A mere and straight approach to this problem would involve performing full AC load flow for each contingency event followed by operating limit violations has been reported in Scott and Alsac (1974). Various PI-based methods for contingency screening and ranking have been reported in literature (Ejebe and Wollenberg, 1979; Mikoliniias and Wollenberg, 1981; Lauby *et al*., 1983; Chen and Bose, 1989). These traditional approaches are hard to put through online due to high computational requirements.

With the advent of artificial intelligence in modern era, expert system techniques (Sobajic and Pao, 1994) are keyed out for contingency screening and ranking. Fuzzy set method (Hus and Kuo, 1992) has been proposed for contingency ranking, which deals with the human linguistic variables to describe the degree of severity. The pattern recognition technique has been reported in (Lo *et al*., 1998) to estimate the severity of contingencies.

Recently Artificial Neural Networks (ANN) have found wide applications in the area of power system engineering due to their ability to synthesize complex mappings accurately and quickly. Research work related to fault protection (Sidhu, 1997), loss calculation (Sidhu and Ao, 1995), Dynamic security analysis (Sobajic and Pao, 1989) and load forecasting (Lee *et al*., 1992) have been reported in literature. Fourier transform based ANN has been used in Sidhu and Cui (2000) for contingency

Corresponding Author: S. Sutha, Department of Electrical and Electronics Enggineering, PSNA College of Engineering and Technology, Dindigul – 624 622, Tamilnadu, India

screening and ranking. In this research, FFT is forecasted to pick the most characteristic harmonic components as the input to ANN. This method does not furnish information about other harmonic components. Also with Fourier Transform, both time and space domain analysis is not possible. These comes the chance of missing the spatial domain information. To incorporate all the information associated with time and frequency domain the above said reference (Sidhu and Cui, 2000) can be implemented with Wavelets Transform. Theoretically, it can be stated that Wavelets Transform provide the resolution in different level, the proposed work will improve the accuracy and efficiency of the system.

This study depicts the use of Wavelet Transform Based Neural Networks (WNN) for executing single contingency screening. The results obtained from AC load flow calculations, done in an offline mode are used to construct performance index and these data are used as input data. The wavelet transform decomposed the input data into several wavelet coefficients at different levels, which in turn are fed to various training pattern for the neural network architecture. The performance of the Wavelet Neural Network (WNN) has been demonstrated for IEEE 14 bus, IEEE 5 bus systems and found to be suitable for on-line screening and ranking of contingencies.

PROPOSED WAVELETS NEURAL NETWORKS

Wavelet Transform (WT) is a scalable windowing technique. The adjustable window size allows the use of long time intervals when more precise low-frequency information is desired and short time intervals when desiring high-frequency information. The Discrete Wavelet Transform (DWT) can be used to analyze or decompose the signals and images. DWT algorithm is capable of producing coefficients of fine scales for capturing high frequency information and coefficients of coarse scales for capturing low frequency information. Figure 1 shows single stage wavelet decomposition process.

In wavelet decomposition, original Signal (S) is passed through two complementary filters (LPF and HPF) to obtain Detailed (D) and Approximation coefficients (A). This decomposition process can be iterated with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This process is called multiple levels of decomposition, which is shown in Fig.2.

ANN model: An artificial neural network is modeled as a massively parallel-interconnected network of elementary

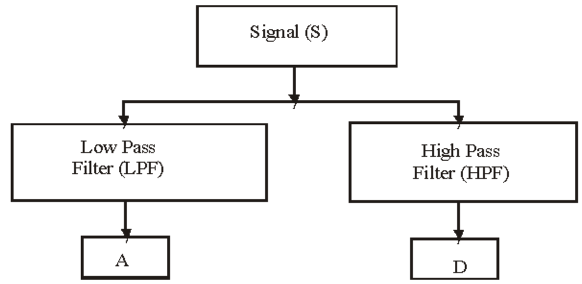

Fig. 1: Single stage wavelet decomposition

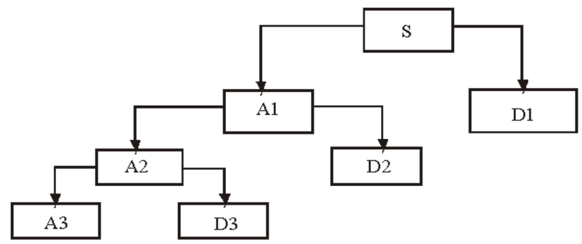

Fig. 2: Multiple level decomposition

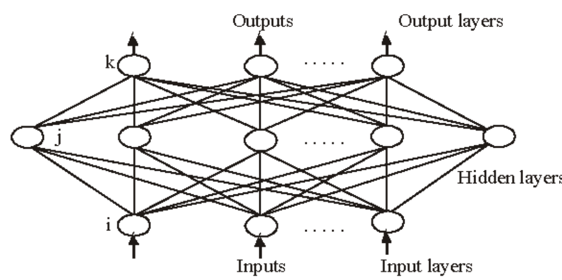

Fig. 3: Schematic diagram of multi layer neural network

neurons. Figure 3 illustrates a three layer neural network consisting of input, hidden and output layers. The neurons within each layer of neuron are being fully connected to proceeding layer and next layer by inter connection weights The input variables are assigned to each neuron in the input layer and are connected to the hidden layer with synaptic weights. Supervised training algorithm is used in back propagation. During training the network weights are modified by minimizing the error between the target and computed outputs. The least mean square error method along with a generalized delta rule is used to optimize the network weights in back propagation networks. The gradient descent method and the chain rule of derivative are employed to modify the network weights.

Training is composed of two major phases, forward pass and reverse pass. In the forward pass first the input data are multiplied by the initial weights and then the weighted inputs are added by simple summation to yield the net to each neuron. The net of the neuron is passed through an activation or transfer function to produce the output of a neuron. In the BPN the modification of the network weights are accomplished by the derivative activation function. Therefore, continuous transfer function such as sigmoid is used in this study. After that the output of the neuron is transmitted to the next layer as input. This procedure is repeated with each pattern pair assigned for training the network. The error between the output of the network and the target outputs are computed at the end of each forward pass. If the error is higher than the selected value the procedure continues with a reverse pass, otherwise training is stopped. In the reverse pass the network weights are modified by using error value. The number of neurons in the input layer and the output layer is determined from wavelet coefficients which are obtained by wavelet decomposition process. The number of hidden neurons and hidden layers are determined by experimentation.

Real Power Index (RPI): The operating state of the power system is a function of time. It keeps on changing due to variation of loads at different buses. To keep the system secure, it is important to know the impact of unexpected outages well in advance, so that appropriate control measures can be taken to make the system secure. For on-line security assessment, only critical contingencies are picked up for further rigorous assessment from the large list of credible contingencies and are ranked according to their severity. The real power index (Dimitrios and Nikolaos, 2000) has been taken in this study.

$$RPI = \sum_{\alpha} W_{PL} \left(\frac{P_L}{P_{Llim}} \right)^2 \qquad (1)$$

Where,

P_L = Active power flow on line L.
P_{Llim} = Active power flow on limit L.
W_{PL} = Weight of active power flow on line L.
α = Line set only including the line whose act power flow are beyond their limit.

Functional diagram: The functional diagram is of the proposed method is presented in Fig. 4. Here the wavelet technique is implemented for the analysis to extract the input for ANN and then the synthesis to get back the original target. In first stage, a large number of input patterns were generated with wide variation of load at each bus and for different contingency cases. The I/P's and the target are decomposed by wavelet transform in order to get several detailed and approximation co-efficient. In second stage, these coefficients are used as input to three different ANN architecture modules (ANN1, ANN2and ANN3) to get the predicted outputs. In third stage, the predicted outputs are recombined by wavelet reconstruction technique to get the final predicted output.

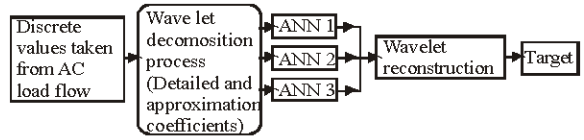

Fig. 4: Functional diagram of the proposed WNN

RESULTS AND DISCUSSION

The effectiveness of the proposed WNN has been demonstrated for IEEE 14 bus system (Pai, 1979) and IEEE 5 bus system (Stagg and El-Abiad, 1968).

IEEE 14-bus system, Twenty branch system: The data set for input feature were generated randomly by changing the real loads at all the PV and PQ buses and reactive loads at PQ buses from 50 to 150% of their base case values. Hence out of 28 variables only nonzero values were considered. In this study, 115 load scenarios were generated and for each condition, the real power index was computed using (1) in an off-line mode by using full AC load flow calculations. Each input pattern for the proposed work is of the following form:

$$[X] = [P_2, P_3, P_4, P_5, P_6, P_9, P_{10}, P_{11}, P_{12}, P_{13}, P_{14}, Q_4, Q_5, Q_9, Q_{10}, Q_{11}, Q_{12}, Q_{13}, Q_{14}]$$

Where,

X = Input Vector consists of P and Q, at generator and load buses.
P = Real Loads for generator and load buses
Q = Reactive Loads at load buses.

With line no.1 outage for the base case, the input vector is:

$$[X] = [21.7, 94.2, 47.8, 3.9, 7.6, 1.6, 11.2, 29.5, 16.6, 9.0, 5.8, 3.5, 1.8, 6.1, 1.6, 13.5, 5.8, 14.9, 5.0]$$

Because of its discrete characteristic, [X] can be regarded as a periodic digital sequence. These discrete values are processed by wavelet transform into series of

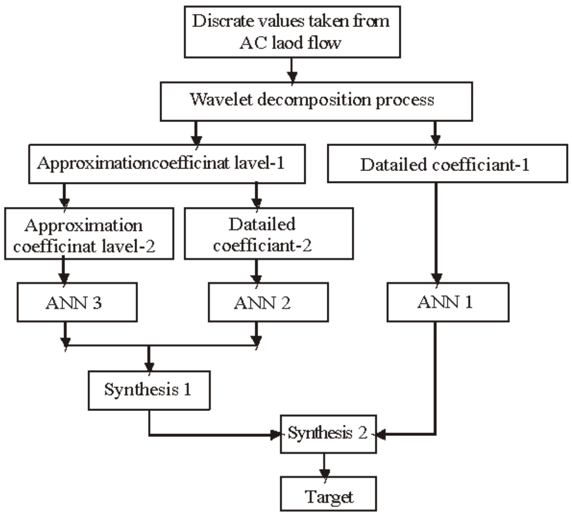

Fig. 5: The proposed WNN

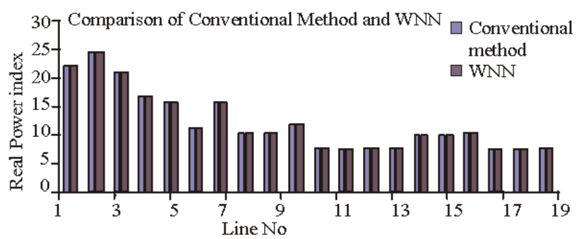

Fig. 6: Real power index estimated using conventional method and WNN

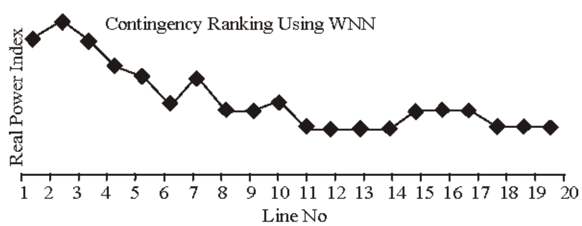

Fig. 7: Contingency ranking and real power index using WNN

wavelets coefficients. In this work Dbauhichies mother wavelet and DB_2 type filter is chosen for two stage decomposition, the following detailed and approximation coefficients were obtained:

D1 = [-44.3970, 14.1794, -1.4752, -6.2206, 1.4779, -1.0041, -2.9754, -6.7818, -5.5774,- 2.3226, 7.89510]

D2 = [-26.4352, -8.0839, 14.9557, -5.6428, 0.2475, -1.760, 4.3940]

A2 = [94.9124, 116.1877, 21.7397, 30.0825, 6.9417, 19.5601, 14.1691]

Table 1: Comparison of result obtained using conventional method (Method-1) and proposed WNN (Method-2)

Line Number	RPI method-1	RPI method-2	Ranking I	Ranking II	Errors
1	22.0183	22.0096	2	2	0.0087
2	24.7403	24.7501	1	1	0.0098
3	21.3150	21.3151	3	3	0.0001
4	17.1852	17.1846	4	4	0.0006
5	15.8605	15.8603	6	6	0.0002
6	11.2505	11.2508	8	8	0.0003
7	15.9021	15.9130	5	5	0.0109
8	10.2505	10.2471	10	10	0.0031
9	10.2416	10.2420	11	11	0.0004
10	11.9309	11.9310	7	7	0.0001
11	7.4851	7.4698	17	17	0.0153
12	7.4662	7.4655	19	19	0.0007
13	7.5133	7.5121	16	16	0.0012
14	7.5162	7.5158	15	15	0.0004
15	10.2315	10.2362	12	12	0.0047
16	10.2332	10.2312	12	13	0.0020
17	10.2704	10.2715	9	9	0.0011
18	7.5516	7.5603	14	14	0.0087
19	7.4526	7.4519	20	20	0.0007
20	7.4830	7.4534	18	19	0.0296

Table 2: Combarison of result obtaind using conventional method (Method-1) and proposed WNN (Method-2)

Line number	RPI method-1	RPI method-2	Ranking I	Ranking II	Errors
1	0.4184	0.4186	2	2	0.0002
2	0.3986	0.3947	3	3	0.0039
3	0.3835	0.3837	4	4	0.0002
4	0.3002	0.2964	7	4	0.0038
5	0.6127	0.6126	1	1	0.0001
6	0.3168	0.3159	5	5	0.0009
7	0.3057	0.3051	6	6	0.006

These wavelet coefficients are used as an input to three ANN architecture modules which is shown in Fig. 5. The network is trained with error back propagation algorithm. In this work, the WNN has been trained for 115 patterns with (11+7+7) input neurons, 32 hidden neurons and 2 output neurons to get the desired RPI. The WNN network took 88.4850 Sec for 5000 iteration when trained with-HP computer with 1.99GHZ, 512 MB RAM, 80GB Hard drive. The training error for this research was 4.1389e-006 and the maximum testing time was 0.0780 Sec and average testing error was 0.0024.The learning rate and momentum factor taken for this work is 0.12 and 0.83 the results obtained by this method has been compared with conventional method (AC load flow method) which is given in Table 1.

Table 1 shows the value of Real Power Index (RPI) estimated for an operating condition when one line at a time in the IEEE 14 bus test system is outaged for different contingency cases. RPI is estimated using proposed WNN and conventional AC load flow method. The contingencies are ranked according to their highest performance index value. From the comparison, it was

Table 3: Training and testing details for the two IEEE. Test systems

Test	No. of training patten	No. of testing patten	No. of hidden patten	Training errors	Testing errors	Training time (sec.)
IEEE 5-Bus	80	30	19	3.2081e-^{006}	0.0017	61.25
IEEE 14-Bus	115	46	32	4.1389e-^{006}	0.0024	88.49

found that both methods provide very closer results and the maximum % error was 0.0296 which indicate that the proposed trained WNN capable to handle new topologies and operating conditions effectively. Figure 6 shows the exact matching of RPI for the Conventional method and the proposed WNN. Figure 7 shows the RPI variation for each line outage.

IEEE. 5-bus seven branch system: The proposed WNN was further demonstrated to IEEE 5 bus 7 branch system for single line contingency screening and ranking. For this test system 80 load scenarios were generated for training and 30 load scenarios for testing. These patterns were processed by Wavelet Transform in the same manner as explained in the study three layer feed forward WNN with 13 input neurons, 19 hidden neurons and 2 output neurons was trained to estimate the RPI and perform the contingency screening and ranking. The test result for this test system is given in Table 2. The number of training epochs, hidden neurons and training times for WNN depends on the size of the test system. The training patterns, test patterns, hidden neurons and error for the two test system are given in Table 3.

CONCLUSION

Wavelet transform based Artificial Neural Network (WNN) has been modelled to estimate and rank the severity of critical contingencies accurately and rapidly. The training of the WNN requires less computation time as compared to traditional AC load flow method.

The well trained WNN are able to estimate the RPI of all the critical contingencies under any loading conditions accurately whereas the computation of RPI by traditional method requires large computation time because the load flow requires system remodeling every time in the event of an outage of line, transformer, change in load or generation. The effectiveness of the proposed method has been demonstrated by applying it to the two IEEE. test systems and of other systems also reveals that the trained WNN is capable of on-line real power contingency ranking under uncertain loading conditions and handle greater number of contingencies for larger systems. The FFT based ANN (Sidhu and Cui, 2000) has been provide harmonic components in time domain only. It is unable to handle space or frequency domain analysis. This drawback is overcome by using the proposed method in which the Wavelet Transform split the signal into many lower resolution components in both time and frequency domain analysis which will improve the accuracy and efficiency of the system. The training of WNN has been made still faster by using adaptive momentum factor and learning rate. The WNN method can be extended for multiple contingency cases also.

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