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A Neuro-Fuzzy Application to Power System

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Abstract. Vulnerability control is a problematic task for system operator who under economic pressure may be reluctant to take preventive action against very harmful contingencies in order to guarantee providing continued service. This paper presents fast and accurate load shedding technique based on neuro-fuzzy controller for determining the amount of load shed to avoid a cascading outage. A case study is performed on the IEEE 300-bus test system so as to validate the performance of neuro-fuzzy controller in determining the amount of load shed. The development of new and accurate techniques for vulnerability control of power systems can provide tools for improving the reliability and continuity of power supply. This was confirmed by the results obtained in this research of which sample results are given in this paper.

Keywords: Neuro-Fuzzy, Controller, Load shedding, Power system, Vulnerability control

1. Introduction

Nowadays, power systems have evolved through continuing growth in interconnection, use of new technologies and controls. Due to the increased operations which may cause power system to be in highly stressed conditions, the need for vulnerability control of power systems is arising [1]. However, due to emotional and psychological stress, an operator may not be able to adequately respond to critical conditions and make correct decisions. Mistakes can damage very expensive power equipment or worse still lead to the major emergencies and catastrophic situations. Clearly, there is a strong need for automated corrective procedures that can assist operators in vulnerability control. For power systems which are operated closer to their stability limits, it is desirable to use load shedding when there is a lack of adequate spinning reserve margin and a shortage of tie line capacity [2]. In the case of power deficit in a power system, load shedding schemes using relays are used to disconnect appropriate amount of load and maintain system stability.

The conventional load shedding techniques may not work as desired in emergency conditions due to the complexity and size of modern power systems. Therefore, alternative methods are required for solving certain difficult power problems where the conventional techniques have not achieved the desired speed and accuracy. Such techniques are referred to as computational intelligent techniques using fuzzy logic, neural network or expert systems. Fuzzy logic has been applied for safety analysis of power protection and automation system action [3]. The fuzzy expert system was proposed for voltage instability control to calculate the optimum and minimum ratio of load shedding [4]. In addition, a fuzzy logic stabilizer has been developed for stability control of a 1 KVA laboratory scale model of power system [5].

In this research work, an intelligent load shedding scheme is proposed using neuro-fuzzy controller as a means for vulnerability control of large scaled interconnected power systems. The neuro-fuzzy controller considers two inputs and one output in which the inputs are the calculated vulnerability index using power system loss (PSL) and the bus voltage magnitudes whereas the output is the amount of load shed for each contingency case [6]. The paper is organized as such that in section 2, background theory of neuro-fuzzy

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architectures is described. The approach for load shedding using neuro-fuzzy controller outlined in section 3. Finally, the test results and conclusions are presented in section 4 and 5.

2. Neuro-Fuzzy

Neuro-fuzzy system is a combination of neural network and fuzzy logic in which it combines the learning and adapting abilities of neural networks with the fuzzy interpretation of fuzzy logic system. An example of a neuro-fuzzy system is the adaptive neural network based fuzzy inference system (ANFIS) which combines the Takagi–Sugeno fuzzy inference system (FIS) with neural network. The ANFIS defines five layers which perform the function of fuzzification of the input values, aggregation of membership degree, evaluation of the bases, normalization of the aggregated membership degree and evaluation of function output values.

A typical ANFIS structure with five layers and two inputs, each with two membership functions is shown in Figure1. The five layers of the ANFIS are connected by weights. The first layer is the input layer which receives input data that are mapped into membership functions so as to determine the membership of a given input. The second layer of neurons represents association between input and output, by means of fuzzy rules. In the third layer, the output are normalized and then passed to the fourth layer. The output data are mapped in the fourth layer to give output membership function based on the pre-determined fuzzy rules. The outputs are summed in the fifth layer to give a single valued output. The ANFIS has the constraint that it only supports the Sugeno-type systems of first or 0^{th} order [7]. The system can only be designed as a single output system and the system must be of unity weights for each rule.

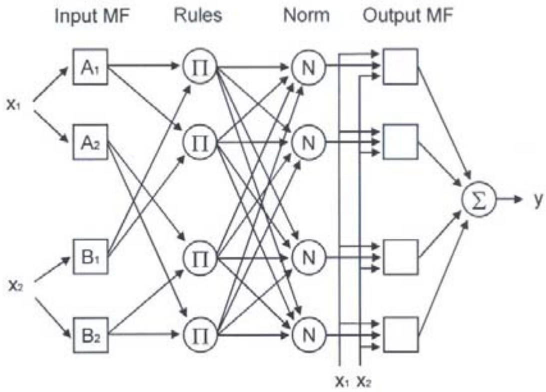

Fig.1: ANFIS Structure with 2 inputs, 1 Output, and 2 Membership Function for each input

3. Load Shedding Using Neuro-Fuzzy Controller

Fuzzy logic system needs rules to be defined first, but one may have no knowledge about a power system for the formation of rules. Therefore, automated parameters tuned by a neural network embedded inside a fuzzy system can replace the need for prior knowledge about a power system. To implement the proposed load shedding scheme for vulnerability control of power systems, firstly, base case simulation is carried out on a power system so as to analyze the system behavior at the base case condition. The next step is to analyze the system behavior when subjected to credible system contingencies such as line outage (LO), generator outage (GO), load increase (LI) and disconnection of loads (DL). The power flow simulation outputs for the contingency cases are used to check the voltage limits and the transmission line thermal limits. For each contingency, the vulnerability index based on PSL [6] is then calculated in which PSL considers total system loss, generation loss due to generation outage, power line loss due to line outage, increase in total load and amount of load disconnected. The selection of inputs to the controller is an important design consideration and therefore for power system vulnerability control, the PSL and voltage magnitudes are selected as input variables for the load shedding controllers. The overall output of the ANFIS is the estimated amount of load shed by NFC which calculates the sum of outputs of all defuzzification neurons and is given by [7],

$$S_{NFC} = \sum_{i=1}^{n} \bar{\mu}_i (k_{i0} + k_{i1}x_1 + k_{i2}x_2) \tag{1}$$

where;

k_{i0}, k_{i1} & k_{i2} : sets of consequent parameters of rule i

$\bar{\mu}_i$: normalized firing strength

4. Simulation Results and Discussion

In this study, a Takagi–Sugeno FIS is adapted to the ANFIS as it is more effective for system identification. For load shedding estimation using NFC, the ANFIS output is associated with the amount of load shed in MVA p.u., the inputs to the NFC are the PSL and lowest voltage magnitude. Figure 2 shows the initial membership functions of the input variables in which the membership function parameters are selected to satisfy the desired output.

A multilayer feed forward neural network trained by using the back propagation algorithm is used to adjust the membership function parameters according to the input-output characteristic of the training patterns. The neural network computation time depends on the number of rules, which on the other hand depend euphonically on the number of the membership function and inputs. The parameters associated with the membership function can change through the training process. The adjustment of these parameters is facilitated by a gradient vector, which provides a measure of how fuzzy inference system models the input/output relations. Once the gradient vector is obtained, any of the optimization routines can be applied to adjust the parameters so as to reduce an error usually defined by the sum of the squared difference between actual and desired outputs.

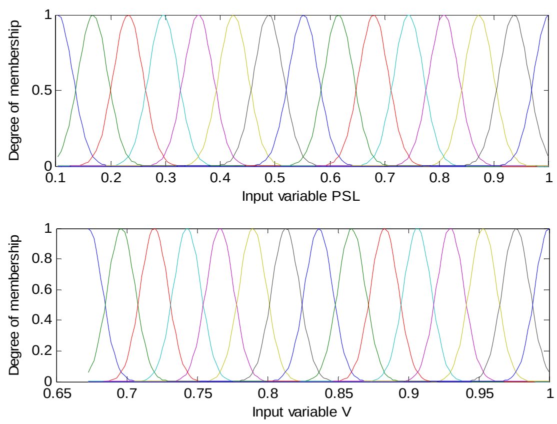

Fig.2: Initial membership functions of the input variables

In the ANFIS implementation, 70% of the data set is used for training, 20% for checking and 10% for testing. Each ANFIS is trained for 150 iterations. The ANFIS is generated using 15 Gaussian membership functions for each input. The number of inputs and the number of membership functions determine the number of fuzzy rules and therefore the training time. After training the ANFIS, the final membership functions of the input variables and the output variable which is the amount of load shed are obtained.

The results of load shedding using the NFC for various contingency cases are summarized as shown in Table 1. From the table, it is shown that for each contingency case, the amount of load to be shed is determined by NFC in terms of per unit MVA. An important factor to consider in load shedding is to determine the location where load is to be shed. Therefore, in determining the load shedding location, the weak buses are identified by considering buses with low voltage magnitudes in the range of (0.91-0.68) per unit. At these weak buses, it is noted that the voltage magnitudes are violated. After determining the weak buses, it is considered that load shedding is to be applied only at these buses. The determination of the weak buses can assist system operators in determining the appropriate load shedding location. Referring to Table 1, the critical contingency that causes greater amount of load shed is due to multiple outages of transformer 400 (TO-400) and line 219 (LO-219) and disconnection of load at bus 167 (DL-167), where the amount of load shed is 25.28 MVA p.u which is equal to 10% of the total generation.

Table 1: Results of Load Shedding Using NFC

Contingency Cases	Amount of Load Shed Estimated by NFLC (MVA p.u)	The number of weak buses
LO-93	7.65	47,43,44,113
LO-177	14.14	159,157,122,121,120,118,117,115
LO-182	9.40	159,157,122,121,118,117,115
LO-242	1.79	9038,9033,9032,9031
LO-305	1.63	225,224,223,192
TO-393	3.46	9042,9038,9037,9036,9035,9033, 9032,9031
TO-397	2.69	9042,9038,9035,9033,9031
TO-406	12.30	9042,9038,9035,9033,9032,9031,15
GO-84	2.49	9042,9038,9035,9033,9032,9031
GO-213	1.33	9038,9033,9031
GO-233	0.66	9038,9033,9031
GO-236	16.85	9072,9071,9052,9044,9043,9041,9038,9037,9036,903,9034,9033, 9032,9031,9004,9003,562,53,5,47
GO-7001	1.79	9038,9033,9032,9031
GO-7002	3.46	9042,9038,9037,9036,9035,9033,9032, 9031
GO-7061	4.56	9038,9033,9031,7061,61,59,58
GO-7017	19.35	9042,9038,9035,9033,9032,9031,9017,17,15
GO-7024	1.48	9038,9033,9031
GO-7166	5.57	9035,9033,9032,9031
LI-2.6%	8.99	9071,9052,9043,9042,9041,9038,9037,9036,903,9033,9032,9031, 9004
LI-3.1%	15.04	9072,9071,9052,9044,9043,9042,9041,9038,903,903,9035,9034, 9033,903,9031,9007,9004,900,52
LI-3.8%	23.67	9072,9071,9052,9044,9043,9042,9041,9038,903,9036,9035,9034, 9033,9032,9031,9007,9006,900,9004,9003,900,55,54,53,52,51,43 ,41,40,38,37,33
GO-(143 &185)	22.91	9072,9071,9052,9044,9043,9042,9041,9038,903,9036,9035,9034, 9033,9032,9031,9007,9006,900,9004,9003,9001,53,52,51,40,38, 37,33, 178
TO-400 &LO-219 & DL-167	25.28	9071,9052,9044,9043,9042,9041,9038,9037,903,9035,9034,9033, 9032,9031,9007,9006,9005,900,9003,9001,55,3,52,51,48,43,41, 40,38,37,33
LO-(101&305)	5.33	225,224,223,162
LO-(182&L272)	7.35	157,122,121,118,117,115

5. Conclusion

The problem of operating and managing large scale interconnected power systems in vulnerable condition is addressed in this paper. To counteract this problem, a new load shedding scheme is developed by means of using neuro-fuzzy controller to determine the optimal amount of load to be shed so that a power system can remain in a secure condition. The neuro-fuzzy load shedding technique combines the use of fuzzy logic and neural network techniques. The performance of the proposed neuro-fuzzy load shedding is validated using the IEEE 300 bus test system. The proposed neuro-fuzzy technique has proven to be a more effective method in determining the optimal value of load shed in which the average absolute error for the neuro fuzzy technique within tolerable limits. It is also demonstrated to be a useful load shedding tool for providing fast vulnerability control.

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