APPLICATION OF ARTIFICIAL NEURAL NETWORK (ANN) FOR FREQUENCY RESPONSE IN POWER SYSTEM DYNAMICS

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ABSTRACT- This paper presents a new application of Artificial Neural Network (ANN) for frequency response in system dynamics. In order to perform the ANN, the power flow solution is obtained first for the system to be studied. The purpose of load flow simulation is to get some operating parameters which influence the system frequency behavior. The transient simulation of a power system is then simulated by DigSilent Simulator to analyze the frequency response of the system when it subjected to a disturbance. Simulations were carried out on the IEEE 9-Bus Test System considering load injection on the system. The data collected from transient simulation are then used as inputs to the ANN while the frequency response of the systems as the ANN output. The Lavernberg–Marquardt optimization utilizing very fast propagation algorithm has been adopted for training feed–forward Neural–Network. To verify the effectiveness of the proposed application of ANN method, its performance is compared with the actual value obtained from transient simulation. The ANN provides promising results in terms of error estimation, accuracy and computation time.

1. INTRODUCTION

Frequency is regarded as a paramount index of the operation of power systems because it can reflect the dynamic energy balance situation between generating power and load. Under steady state conditions the total power generated by power stations is equal to the system load and losses while frequency normally operated at a nominal value. Typically, the nominal frequency is assumed to be 50 Hz as in the ENTSO-E Continental Europe system (former UCTE) [1]. However, the deviations from this desired value arise due to imbalances between the instantaneous generation and consumption of electric power, which has an accelerating or decelerating effect on the synchronous machines.

The frequency of power system is dependent on real power balance. A change in real power demand at one point of a network is reflected throughout the system by a change in frequency. This behavior of a power system is shown in [2]. In most cases, the frequency can deviate from its nominal value due to the transient events occurred in the power system dynamics. A dynamic phenomenon in a power system is initiated by a disturbance. Therefore, the response of the system after disturbance occurred is depends on a how large the disturbance [3].

Practically, frequency variation range for the system operation is established as 50±0.5 Hz [4]. Beyond these limits may result abnormal conditions of electrical power system. A non-nominal frequency causes a lower quality of the delivered electrical energy. A large frequency deviation would damage equipment, degrade load performance, cause the transmission lines to be overloaded, also can interfere with system protection schemes and ultimately leading to a complete power system collapse [1, 3]. In comparison with the thermal units, hydro power plants are more robust and can normally cope with frequency down to 45 Hz [1]. From reference [5] shows an example of a defence plan against frequency instability. In short, off-nominal frequency can directly impact on power system operation and system reliability [3].

In the past several decades, a variety of algorithms for frequency estimation have been reported as elaborated in paper [6]. Approached methods for instance are Discrete Fourier Transform (DFT) [7-12], Prony's method [13], Orthogonal FIR digital filter [14], zero-crossing method [15], Least Error Squares (LES) [16], Kalman Filter [17-20], Least Mean Square (LMS) [21], Phase Lock Loop (PLL) [22], Adaptive Notch Filter (ANF) [23], and etc. Reference [24] presents review several methods, outlining strengths and weaknesses of each one.

An effective method for frequency estimation is an important task in the power system operation, monitoring, control and protection. Thus, this paper presents the new approach of ANN's application to determine minimum frequency response during dynamic phenomena. The performance of ANN in terms of error estimation is then compared with transient simulator.

To prepare the training database for an ANN, the power flow (steady state) and the transient simulations have been determined first through DigSilent Power Factory Simulator in Section 2. Next step in Section 3, deals with ANN implementation to determine minimum frequency using MATLAB Neural Network Toolbox. Results will be presented in Section 4 and conclusion in Section 5.

2. TRANSIENT SIMULATION ON THE TEST SYSTEM

The work procedure is summarized in Figure 1.

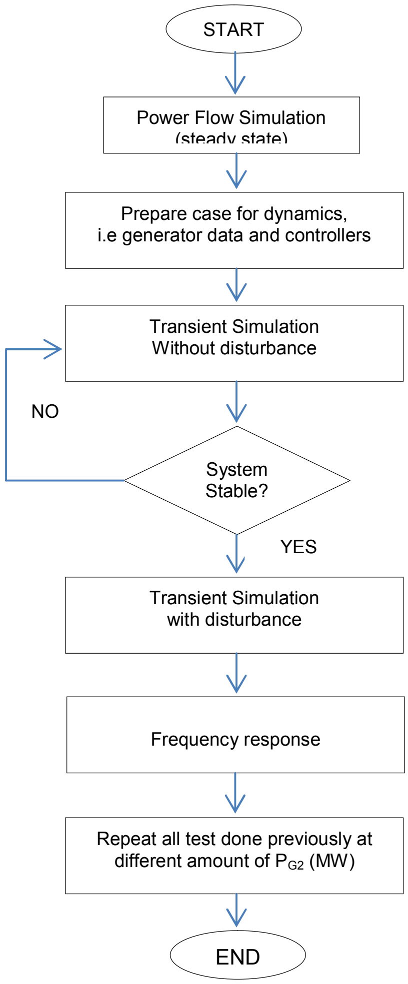

Fig. 1 Flow chart

2.1 Test System

Fig. 2 shows the IEEE 9-bus system in which the data used for this work is obtained from reference [25]. The system consists of three generators with AVR Type-1, three transformers, three transmission lines and three loads. Consider into account a realistic transient analysis and simulation; all generators are modeled by controller's parameters such as prime mover (turbine), governors and voltage controller parameters.

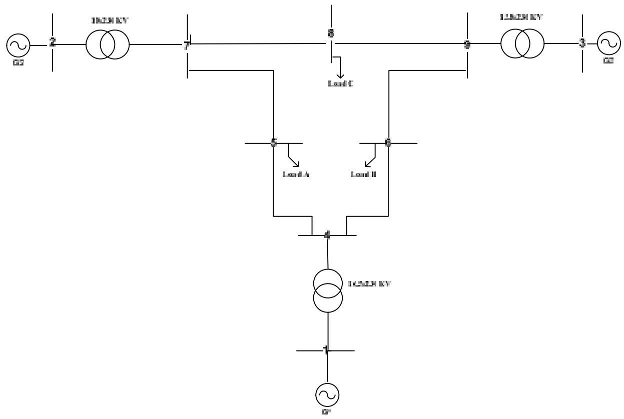

Fig. 2 IEEE 9-bus Test System

3. ARTIFICIAL NEURAL NETWORK (ANN)

3.1 Input Features Selection

The selection of input features is an important factor to be consideration in the ANN implementation. The input features selected for this work are generated real power (P_{gen}) and reactive powers (Q_{gen}), their change of generated real power (ΔP_{gen}) and reactive power (ΔQ_{gen}), real power (P_{load}) and reactive power (Q_{load}) of all loads respectively, their change of real power (ΔP_{load}) and reactive power (ΔQ_{load}) and also spinning reserved (SR). Overall there are 25 input features selected for the neural network. Table 1 shows the breakdown of the input features selected for the Neural Network.

Table 1 Input features selection

Name of input features	No. of features
P_{gen} & Q_{gen}	6
ΔP_{gen} & ΔQ_{gen}	6
P_{load} & Q_{load}	6
ΔP_{load} & ΔQ_{load}	6
SR	1
Total	25

Based on [26], one hidden layer is suitable enough to represent all nonlinear performances. The number of neurons in hidden layer however would vary for different applications and could usually depend on the size of the training set and number of input variables. Thus, a few heuristic rules are given on how to select the appropriate number of hidden neurons by refer to the [26].

Aforementioned the main objective of this work is to determine frequency response of the power system dynamics that is minimum frequency. Therefore, only one neuron is sufficient for the output of Neural Network, i.e.: target output. The Lavenberg-Marquardt back propagation algorithm has been trained for feed-forward Neural Network.

The next step is to divide the inputs and target output up into training, validation and test. About 70% of data are used for training and the rest of 15% of data are used for validation and testing.

4. RESULTS

The results obtained from the transient simulator and ANN tool are presented. The frequency response for transient simulation with 10% load injections to the network system is illustrated in Fig. 3. Different operation conditions may contribute to the change of frequency response. The value of frequency response from transient simulation is referred as actual value for comparison purpose. The ANN results of 35 test data with 51 neurons layer, 26 neuron layers and 13 neuron layers in the hidden layer are also presented. For the purpose of evaluating the effectiveness of the ANN's application, finally a comparison is made between transient simulation and ANN in terms of error estimation as shown as in Table 2. The total percentage error estimation between transient simulation and ANN with 51 neurons layer, 26 neurons layer and 13 neurons layer are 6.9% (8 cases), 5% (9 cases) and 0.8% (7 cases) respectively. It can be observed that the error is reduced as the number of neurons in hidden layer is also reduced. In Fig. 5, the Mean Square Error (MSE) is used as a goal for training the Neural Network with the best validation performance is 0.0044963 at epoch 3.

5. CONCLUSION

An application the ANN into power system dynamics to estimate minimum frequency is proposed in this paper. Time domain simulations were first carried out to generate training data for the ANN input layer and target output. By considering loads event in the network, the 10% load injection occur at 10 s, consequently gives the some variations of frequency response when generated real power (P_{G2}) was adjusted from 50% to 100% in steady state condition. The results from ANN are then compared with the transient simulations in terms of error estimation. It can be concluded that the ANN with 13 neurons in hidden layer gives better performance in terms of error estimation, small MSE and fast computational time compared with other neurons number in hidden layer. Thus, the ANN provides promising result for the frequency response in power system dynamics.

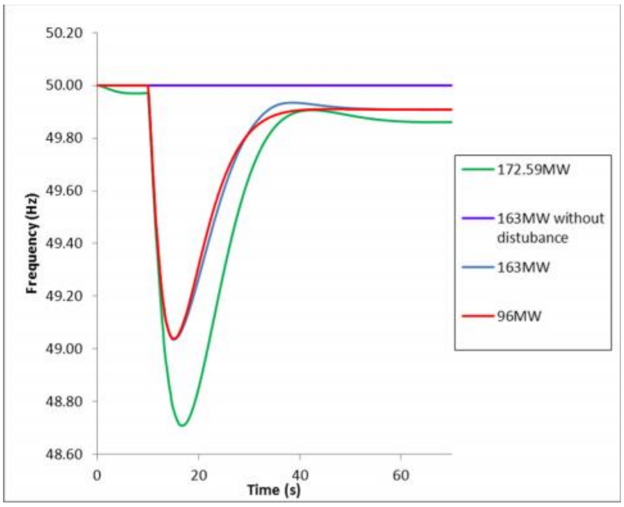

Fig. 3 Frequency response after 10% of load injection

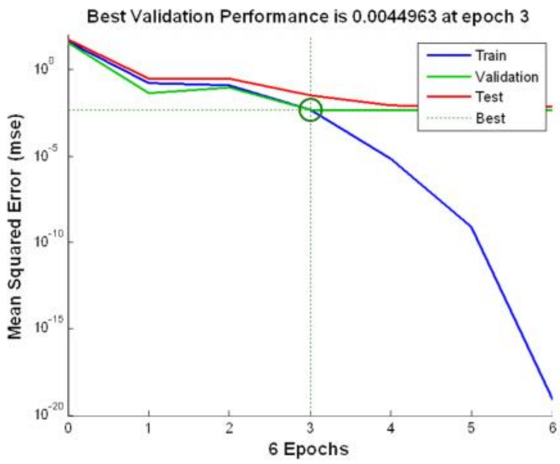

Fig. 4 Mean Square Error (MSE)

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Table 2 Estimation error for the frequency response both transient simulation and ANN

Test set	Transient Simulation	ANN (51 Neurons)			ANN (26 Neurons)			ANN (13 Neurons)		
	(Hz)	(Hz)	Error	I% errorI	(Hz)	Error	I% errorI	(Hz)	Error	I% errorI
1	48.24	48.24	0.00	0.00	48.24	0.00	0.00	48.24	0.00	0.00
2	48.71	48.71	0.00	0.00	48.71	0.00	0.00	48.72	-0.01	0.02
3	49.04	49.04	0.00	0.00	49.04	0.00	0.00	49.04	0.00	0.00
4	49.04	49.04	0.00	0.00	49.04	0.00	0.00	48.96	0.07	0.15
5	49.04	49.01	0.02	0.05	49.04	0.00	0.00	48.99	0.05	0.10
6	49.04	49.04	0.00	0.00	49.04	0.00	0.00	49.04	0.00	0.00
7	49.04	49.04	0.00	0.00	49.04	0.00	0.00	49.04	0.00	0.00
8	47.03	47.03	0.00	0.00	47.03	0.00	0.00	47.03	0.00	0.00
9	47.46	47.46	0.00	0.00	47.62	-0.16	0.34	47.46	0.00	0.00
10	47.88	47.88	0.00	0.00	47.88	0.00	0.00	47.85	0.03	0.06
11	48.09	48.09	0.00	0.00	48.09	0.00	0.00	48.09	0.00	0.00
12	48.10	48.10	0.00	0.00	48.10	0.00	0.00	48.10	0.00	0.00
13	48.10	48.08	0.02	0.03	48.10	0.00	0.00	48.12	-0.02	0.05
14	48.10	48.10	0.00	0.00	48.10	0.00	0.00	48.10	0.00	0.00
15	45.95	46.32	-0.37	0.81	45.95	0.00	0.00	45.95	0.00	0.00
16	46.35	46.89	-0.54	1.16	46.35	0.00	0.00	46.35	0.00	0.00
17	46.76	47.08	-0.32	0.69	46.76	0.00	0.00	46.76	0.00	0.00
18	47.12	47.12	0.00	0.00	47.12	0.00	0.00	47.12	0.00	0.00
19	47.24	47.24	0.00	0.00	47.28	-0.04	0.08	47.24	0.00	0.00
20	47.24	47.39	-0.15	0.32	47.24	0.00	0.00	47.24	0.00	0.00
21	47.25	47.24	0.00	0.00	47.14	0.11	0.23	47.25	0.00	0.00
22	44.80	45.34	-0.54	1.21	44.80	0.00	0.00	44.86	-0.06	0.13
23	45.32	45.75	-0.43	0.95	45.32	0.00	0.00	45.32	0.00	0.00
24	45.73	45.73	0.00	0.00	45.73	0.00	0.00	45.73	0.00	0.00
25	46.11	46.11	0.00	0.00	45.87	0.25	0.54	46.11	0.00	0.00
26	46.45	46.11	0.34	0.73	46.45	0.00	0.00	46.45	0.00	0.00
27	46.45	46.45	0.00	0.00	46.33	0.12	0.25	46.45	0.00	0.00
28	46.45	46.45	0.00	0.00	46.02	0.43	0.93	46.46	0.00	0.01
29	43.57	43.57	0.00	0.00	43.57	0.00	0.00	43.66	-0.09	0.22
30	44.21	44.21	0.00	0.00	44.21	0.00	0.00	44.21	0.00	0.00
31	44.69	44.69	0.00	0.00	45.01	-0.32	0.71	44.69	0.00	0.00
32	45.11	45.11	0.00	0.00	45.11	0.00	0.00	45.15	-0.04	0.08
33	45.68	45.19	0.50	1.09	45.13	0.55	1.20	45.69	-0.01	0.02
34	45.69	45.69	0.00	0.00	45.33	0.36	0.78	45.69	0.00	0.00
35	45.69	45.69	0.00	0.00	45.69	0.00	0.00	45.69	0.00	0.00

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