Application of Wavelet Neural Network in Adaptive Coordination of Power System Damping Controllers and Stability Improvement

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Abstract: The application of wavelet neural network in adaptive coordination of power system damping controllers, i.e. power system stabilizers (PSSs) and flexible alternating current transmission system (FACTS) controllers is investigated and presented in this paper. In the present work, the wavelet neural network is utilized to represent the relationship between the power system states (operating conditions and configurations) and the controller parameters (gains and time constants) which is generally nonlinear. The proposed adaptive power system damping controller is intended to enhance and maintain power system stability even if the system operating conditions and/or configurations change. The developed wavelet neural network-based stabilizer has been tested with a representative multi-machine power system to verify its dynamic performance.

Key-Words: power system damping, wavelet neural network, adaptive controller, PSS, TCSC

1 Introduction

It is widely known that PSS and FACTS controllers or devices can be utilized to improve damping and enhance the stability of a power system. However, in using the devices for damping improvement and stability enhancement, the coordination amongst the controllers needs to be considered for achieving the best result.

Investigation in the above context of control coordination has been carried out by many researchers, and the results have been reported in many journal papers (for example in [1-9]). In the papers [1-9], the design procedures or coordination methods amongst different controllers have been proposed. However, the developed techniques were non-adaptive, and therefore, its performance might deteriorate with the changes of system operating conditions and/or configurations.

To overcome the above disadvantage, adaptive control coordination techniques have been proposed by some researches [10-13]. In the investigation, the proposed adaptive damping controllers have been successfully applied to improve and maintain the stability of small power systems. However, adaptive control coordination among different controllers in larger multi-machine power system environment was not considered in the papers.

Recently, the adaptive coordination amongst various damping controllers in larger multi-machine environment has been proposed and developed [14, 15]. In the proposed design, artificial neural network (ANN) has been utilized to produce different sets of stabilizer parameter values for different system conditions/configurations. This property makes the stabilizer adaptive, i.e. it can maintain system stability even if the system operating conditions/configurations change.

More recently, the use of wavelet neural network (WNN) as an alternative to neural network in designing adaptive controller has been proposed [16, 17]. The WNN has been utilized to represent the relationship between the power system states and the controller parameters which is generally nonlinear. The developed wavelet neural network-based adaptive damping controller has been tested with a representative three-machine power system. Although, it has been successfully applied to enhance the stability of a small power system, its performance, however, on larger interconnected multi-machine power systems environment is still unknown and needs to be investigated further.

Therefore, against the above background, the objective of the present work is to extend and apply the wavelet neural network-based power system damping controller proposed in [16, 17] to larger interconnected multi-machine power system containing PSSs and FACTS devices, i.e. thyristor-controlled series capacitor (TCSCs). Results of the investigation are also presented in the present paper, where eigenvalue calculations are used in the testing and verification of the proposed adaptive controller dynamic performance on larger multi-machine power system.

2 WNN-Based Adaptive Controller

2.1 Power System Damping Controllers

PSS is probably the most widely used device for improving the power system damping and stability. PSS contribution to oscillation damping is obtained by introducing a signal to the generator excitation system. Block diagram of a PSS controller used in the present paper is shown in Figure 1 and is adopted from [18, 19]. The PSS output signal is input to the excitation system and contributes to the system damping. Also, in the present work, the generator speed is taken as an input signal to the PSS.

TCSC, on the other hand, has the primary function of regulating a transmission line power. This function is generally carried out by changing the line impedance. This capability in controlling the power flow can be exploited to support the system damping and stability. Block diagram of a TCSC controller used in the present work is shown in Figure 2 [1, 2]. To make the oscillation damping more effective, a supplementary damping controller (SDC) with line power input as shown in Figure 3 is usually employed.

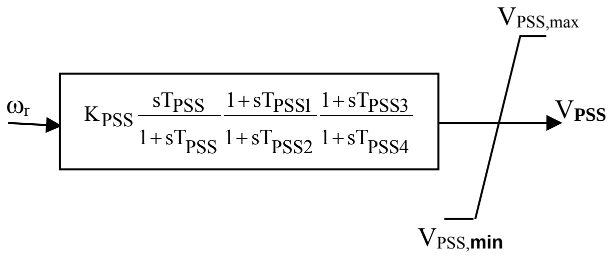

Figure 1 PSS control block diagram

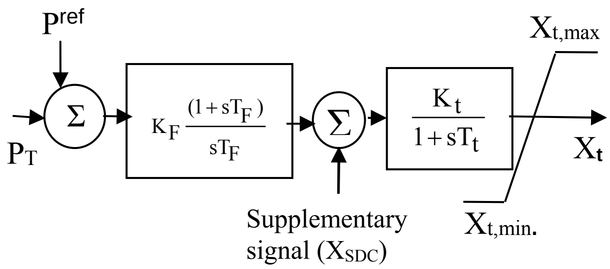

Figure 2 TCSC control block diagram

2.2 WNN-Based Adaptive Controller

Similar to ANN, WNN is also a universal approximator. Therefore, it can be used as an alternative to ANN [20, 21]. In the present work, the WNN is utilized to describe the relationship between the power system states and the controller parameters which is generally nonlinear.

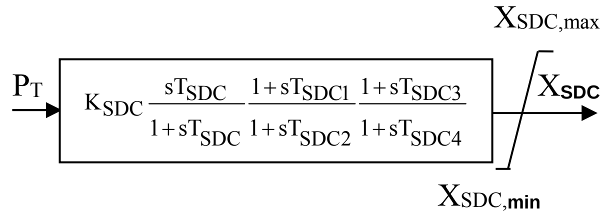

Figure 3 SDC control block diagram

The structure of the WNN is shown in Figure 4. It can be seen that there are two sets of inputs in the structure of Figure 4. The first set of inputs, which represents the power system configuration, is obtained from the real and imaginary parts of the reduced nodal impedance matrix. The second set of inputs, which represents power system operating condition, is obtained from generator active- and reactive-power. If there are Ng generator nodes, then the total number of inputs of the WNN in Figure 4 will be Ng^2+3Ng.

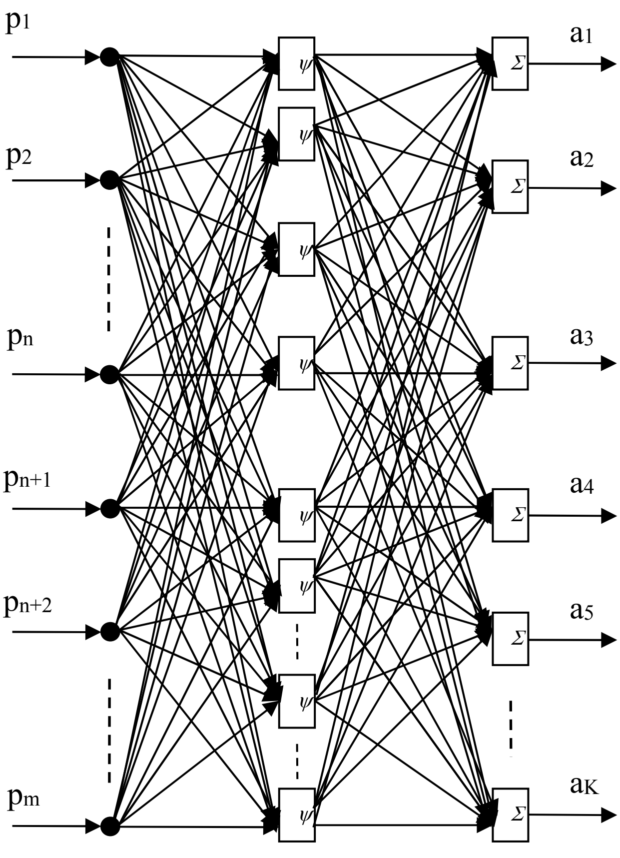

Figure 4 Structure of WNN

Also, it can be observed that the set of outputs in Figure 4 gives the optimal values of the controller parameters. For individual power system controller types, Tables 1 and 2 give the description of the wavelet neural network output parameters of Figure 4. The number of outputs is 6(Nc+Np), where Nc and Np are the number of PSSs and SDCs respectively.

Table 1 Stabilizer output for PSS

Controller Type	Parameters	Description
PSS	K_{PSS}	PSS gain
	T_{PSS}	Time constant of PSS washout block
	T_{PSS1}, T_{PSS2}, T_{PSS3}, T_{PSS4}	Time constants of PSS lead-lag blocks

Table 2 Stabilizer output for SDC

Controller Type	Parameters	Description
SDC	K_{SDC}	SDC gain
	T_{SDC}	Time constant of SDC washout block
	T_{SDC1}, T_{SDC2}, T_{SDC3}, T_{SDC4}	Time constants of SDC lead-lag blocks

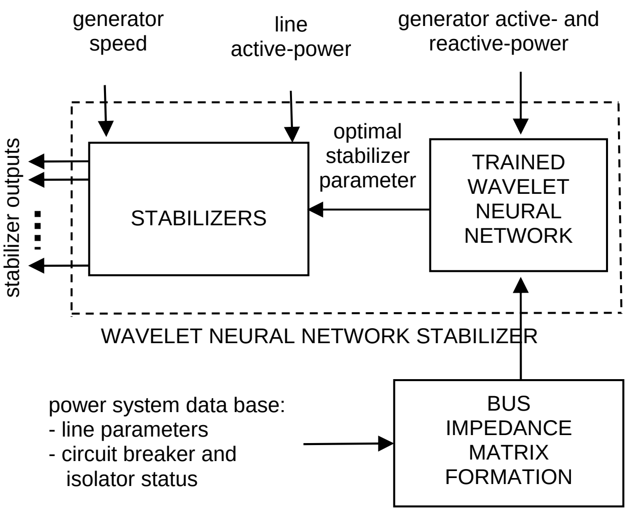

Figure 5 WNN-based stabilizer

The overall structure of the proposed WNN-based stabilizer is shown in Figure 5. It can be seen that the WNN (described previously) is the most important part of the structure. Therefore, it can be said that WNN is the brain of the proposed adaptive stabilizer. The WNN is trained so that it can always produce the optimal parameter values of the PSSs and SDCs, and thus, can improve and maintain the power system damping and stability.

3 Results and Analysis

3.1 Test System

The power system used to verify the proposed WNN-based adaptive controllers described in Section 2 is shown in Figure 6 [22]. Data for the test system, including its initial states, are presented in Appendix. Table 3 shows the dynamic performance of the system of Figure 6. Results in Table 3 indicate that the power system has poor damping and stability as there are modes with unacceptable damping ratios or lower than 0.1.

Therefore, to improve the stability, it is proposed to install PSSs in the system (each generator is equipped with PSS). It is also proposed to install supplementary controls for TCSCs in lines L1 and L22 for the purpose of further improvement of stability. The TCSCs has been installed in the system for the primary purpose of voltage support and power flow control. An opportunity is then taken to equip the TCSCs installed with supplementary controls to provide a secondary function for damping improvement of the electromechanical modes.

Table 3 Electromechanical modes for system of Figure 6

Mode	Eigenvalues	Freq. (Hz)	Damping Ratio
1	-0.3095±j4.6164	0.73	**0.07***
2	-0.9460±j9.8279	1.56	0.10
3	-0.8489±j9.7800	1.56	**0.09***
4	-1.4983±j9.2320	1.47	0.16
5	-0.7082±j7.1152	1.13	0.10
6	-0.5103±j8.1909	1.30	**0.06***
7	-1.0511±j8.3870	1.33	0.12
8	-1.0236±j7.6053	1.21	0.13
9	-0.7462±j7.9753	1.27	**0.09***

*: poor damping modes

3.2 Performance of WNN-Based Controller

Tables 4 - 7 show the comparisons of modal response characteristics (electromechanical mode eigenvalues, frequencies and damping ratios) between non-adaptive (fixed-parameter) and adaptive (wavelet neural network-based) controllers of the system in Figure 6 for a range of contingencies and operating conditions. For non-adaptive controller, the controller parameters derived from the base case design are used for all of the contingency cases and load change. It is to be noted that, as the system in Figure 6 has 9 electromechanical modes, only three modes with the lowest damping ratios are taken and shown for the comparisons.

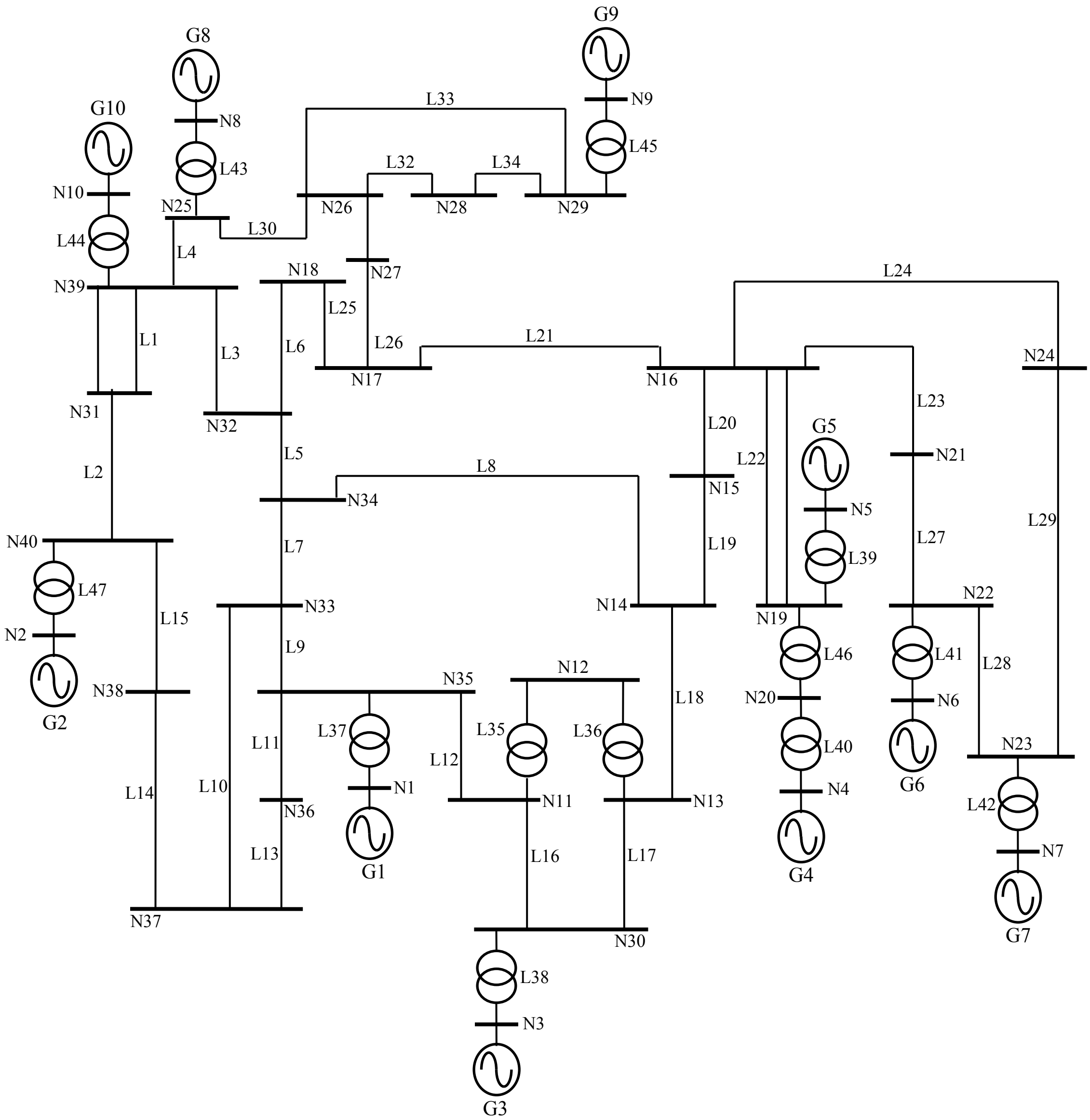

Figure 6. 10-machine 40-node power system

Table 4. Controller performances at load base case

Controller	Eigenvalues	Freq. (Hz)	Damping Ratio
Non-Adaptive	$-0.5045 \pm j4.5147$	0,72	0,11
	$-1.1271 \pm j10.1490$	1,62	0,11
	$-0.8230 \pm j8.0006$	1,27	0,10
Adaptive	$-0.5043 \pm j4.5123$	0,72	0,11
	$-1.1147 \pm j10.1736$	1,62	0,11
	$-0.8152 \pm j7.9964$	1,27	0,10

Table 4 shows the controller dynamic performances at the base case. The base case is the case with the full system (no line outages) in Figure 6, and load demands at all nodes are at their base load values. The comparison in Table 4 confirms that the damping ratios for the electromechanical modes achieved by the adaptive controller are closely similar to those obtained from the fixed-parameter controllers (i.e. non-adaptive) designed with the system configuration and operating condition specified in the base case.

Table 5 shows the controller dynamic performances at the load change case. In this case, the load demands at all nodes are increased to 150% of base load while the system configuration remains as that of the base case. With non-adaptive controllers, the damping ratios of the electromechanical modes decrease noticeably in comparison with those in the base case (there are modes with unacceptable damping ratios or lower than 0.1). However, with the adaptive controller, the damping ratios are maintained at the levels similar to those of the base case.

Table 5. Controller performances at load change case

Controller	Eigenvalues	Freq. (Hz)	Damping Ratio
Non-Adaptive	-0.8643 ± j10.4711	1,67	**0,08**
	-0.9314 ± j10.5194	1,67	**0,09**
	-0.7106 ± j8.0625	1,28	**0,09**
Adaptive	-1.0397 ± j10.2261	1,63	0,10
	-0.8736 ± j7.9257	1,26	0,11
	-0.4748 ± j4.2394	0,67	0,11

Table 6. Controller performances at line outage case

Controller	Eigenvalues	Freq. (Hz)	Damping Ratio
Non-Adaptive	-1.1450 ± j10.1453	1,61	0,11
	-1.1220 ± j10.1548	1,62	0,11
	-0.6515 ± j7.8715	1,25	**0,08**
Adaptive	-1.0511 ± j9.9964	1,59	0,11
	-1.0260 ± j10.0656	1,60	0,10
	-0.8291 ± j7.9021	1,26	0,10

Table 7. Controller performances at line outage and load change case

Controller	Eigenvalues	Freq. (Hz)	Damping Ratio
Non-Adaptive	-0.8653 ± j10.4805	1,67	**0,08**
	-0.9315 ± j10.5249	1,68	**0,09**
	-0.5451 ± j7.9697	1,27	**0,07**
Adaptive	-1.2345 ± j11.0760	1,75	0,11
	-1.0459 ± j10.2910	1,64	0,10
	-0.4383 ± j3.8909	0,62	0,11

Further comparison of Table 6 focuses on contingency where one transmission circuit (L4) is disconnected. The load demands are those in the base case. It can be seen that from Table 6 there is a substantial reduction in the mode damping in comparison with the base case. The damping ratio of this mode is reduced to 0.08, compared to 0.11 in the base case. With the adaptive controller, the damping ratios of all of the electromechanical modes are almost not affected by the outage, in comparison with those in the base case, as indicated in Table 6.

Table 7 focuses on contingency where transmission circuit (L4) is disconnected during higher system load (load demands at all nodes are increased to 150% of base load). This contingency affects the damping of the electromechanical modes significantly when the non-adaptive controllers are used. The damping ratio of 0.10 in the base case is now reduced to 0.07. The robustness of the adaptive controller in this outage case is confirmed by the results of Table 7. The controller parameters determined by the trained wavelet neural network are able to adapt to the new system condition for maintaining the modal damping ratios at the levels similar to those in the base case.

4 Conclusions

In the present paper, WNN-based adaptive power system damping controller has been developed to maintain and enhance the stability of a multi-machine power system. The WNN has been used as an alternative to ANN as it is also a universal approximator. The WNN is employed to represent the nonlinear relationship between the power system conditions and the parameters of damping controllers. The trained WNN-based adaptive controller is then used to produce optimal system damping and stability. The developed wavelet neural network-based controller has been tested with a representative multi-machine power system containing multiple damping controllers. The test results demonstrate that the proposed adaptive controller improves the system damping and dynamic performance even if the system operating conditions and/or configurations change.

Appendix

Table A1. Line data

Line	Series Impedance (pu)	Shunt Admittance (pu)
1	0.0035 + j0.0411	j0.6987
2	0.0010 + j0.0250	j0.7500
3	0.0013 + j0.0151	j0.2572
4	0.0070 + j0.0086	j0.1460
5	0.0013 + j0.0213	j0.2214
6	0.0011 + j0.0133	j0.2138
7	0.0008 + j0.0128	j0.1342
8	0.0008 + j0.0129	j0.1382
9	0.0002 + j0.0026	j0.0434
10	0.0008 + j0.0112	j0.1476
11	0.0006 + j0.0092	j0.1130
12	0.0007 + j0.0082	j0.1389
13	0.0004 + j0.0046	j0.0780
14	0.0023 + j0.0363	j0.3804
15	0.0010 + j0.0250	j1.2000

16	0.0004 + j0.0043	j0.0729
17	0.0004 + j0.0043	j0.0729
18	0.0009 + j0.0101	j0.1723
19	0.0018 + j0.0217	j0.3660
20	0.0009 + j0.0094	j0.1710
21	0.0007 + j0.0089	j0.1342
22	0.0016 + j0.0195	j0.3040
23	0.0008 + j0.0135	j0.2548
24	0.0003 + j0.0059	j0.0680
25	0.0007 + j0.0082	j0.1319
26	0.0013 + j0.0173	j0.3216
27	0.0008 + j0.0140	j0.2565
28	0.0006 + j0.0096	j0.1846
29	0.0022 + j0.0350	j0.3610
30	0.0032 + j0.0323	j0.5130
31	0.0014 + j0.0147	j0.2396
32	0.0043 + j0.0474	j0.7802
33	0.0057 + j0.0625	j1.0290
34	0.0014 + j0.0151	j0.2490
35	0.0016 + j0.0435	0
36	0.0016 + j0.0435	0
37	0.0000 + j0.0250	0
38	0.0000 + j0.0200	0
39	0.0007 + j0.0142	0
40	0.0009 + j0.0180	0
41	0.0000 + j0.0143	0
42	0.0005 + j0.0272	0
43	0.0006 + j0.0232	0
44	0.0000 + j0.0181	0
45	0.0008 + j0.0156	0
46	0.0007 + j0.0138	0
47	0.0007 + j0.0250	0

*pu on 100 MVA

Table A2. Bus data

Bus	Volt. Mag.	Volt. Angle	PGen (pu)	QGen (pu)	PLoad (pu)	QLoad (pu)
1	0.982	0	5.7324	2.0732	0.092	0.046
2	1.030	-11.12	10	0.8805	11.04	2.5
3	0.983	1.61	6.5	2.0591	0	0
4	1.012	0.61	5.08	1.6700	0	0
5	0.997	2.05	6.32	1.0897	0	0
6	1.049	4.02	6.5	2.1115	0	0
7	1.063	6.72	5.6	1.0046	0	0
8	1.028	1.13	5.4	0.0068	0	0
9	1.027	6.42	8.3	0.2268	0	0
10	1.048	-4.60	2.5	1.4496	0	0
11	1.012	-7.20	0	0	0	0
12	1.000	-7.22	0	0	0.085	0.880
13	1.014	-7.10	0	0	0	0
14	1.012	-8.77	0	0	0	0
15	1.016	-9.19	0	0	3.200	1.530
16	1.032	-7.79	0	0	3.294	0.323
17	1.034	-8.79	0	0	0	0
18	1.031	-9.63	0	0	1.580	0.300
19	1.050	-3.17	0	0	0	0
20	0.991	-4.58	0	0	6.800	1.030
21	1.032	-5.38	0	0	2.740	1.150
22	1.050	-0.94	0	0	0	0
23	1.045	-1.14	0	0	2.475	0.846
24	1.038	-7.67	0	0	3.086	0.922
25	1.058	-5.66	0	0	2.240	0.472
26	1.052	-6.92	0	0	1.390	0.170
27	1.038	-8.93	0	0	2.810	0.755
28	1.050	-3.41	0	0	2.060	0.276
29	1.050	-0.65	0	0	2.835	0.269
30	1.017	-6.39	0	0	0	0
31	1.048	-9.58	0	0	0	0
32	1.030	-9.87	0	0	3.220	0.024
33	1.005	-9.48	0	0	0	0
34	1.004	-10.66	0	0	5.000	1.840
35	1.007	-8.77	0	0	0	0
36	0.997	-10.98	0	0	2.338	0.840
37	0.996	-11.48	0	0	5.220	1.760
38	1.028	-11.31	0	0	0	0
39	1.049	-7.02	0	0	0	0
40	1.000	0	0	0	0	0

* pu on 100 MVA

Table A3. Machine resistance and reactance

Mach.	Ra (pu)	Xd (pu)	Xd' (pu)	Xq (pu)	Xq' (pu)
1	0	0.2950	0.0647	0.2820	0.0647
2	0	0.2000	0.0600	0.1900	0.0600
3	0	0.2495	0.0531	0.2370	0.0531
4	0	0.3300	0.0660	0.3100	0.0660
5	0	0.2620	0.0436	0.2580	0.0436
6	0	0.2540	0.0500	0.2410	0.0500
7	0	0.2950	0.0490	0.2920	0.0490
8	0	0.2900	0.0570	0.2800	0.0570
9	0	0.2106	0.0570	0.2050	0.0570
10	0	0.2000	0.0400	0.1960	0.0400

* pu on 100 MVA

Table A4. Machine inertia and time constant

Mach.	H (s)	Td0 (s)	Tq0 (s)
1	30.3	6.56	1.50
2	100.0	6.00	0.70
3	35.8	5.70	1.50
4	26.0	5.40	0.44
5	28.6	5.69	1.50
6	34.8	7.30	0.40
7	26.4	5.66	1.50
8	24.3	6.70	0.41
9	24.5	4.79	1.96
10	42.0	5.70	0.50

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