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FAST POWER FLOW WITH CAPABILITY OF CORRECTIVE CONTROL USING A NEURAL NETWORK

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ABSTRACT

It is common practice for the power system dispatcher before taking any action to precede it with power flow analysis so as to avoid costly experimentation with the real system. Hence speed of power flow solutions is an extremely important factor for real-time implementation of corrective actions. The advantage of fast computation of Artificial Neural Network (ANN) is used for obtaining power flow solutions in real time. The input to the ANN are the real and reactive power generations and demands in the system, and the output data are the complex bus voltages. A few configurations of the neural network are experimented with, and the best results are achieved with a single-layer feedforward neural network with nonlinear feedback. Using the trained neural network, an approximate solution of power flow can be obtained almost immediately. One particular configuration of the ANN can be used for determining corrective strategies during abnormal conditions of the power system.

INTRODUCTION

Undoubtedly, the importance of power flow analysis in modern-day power system operation and planning is one of monumental proportions. It provides snapshots in time of the system behavior under both normal and abnormal conditions. Operators depend on it i) for performing security assessment under normal system operation and ii) for applying appropriate corrective strategies under emergency conditions.

A typical power system is modeled by a large set of non-linear equations which are normally solved by using any of the widely acclaimed power flow solution techniques viz., the Gauss-Seidel method, the Newton-Raphson method or the fast-decoupled method. Of these three, the fast-decoupled method provides the fastest solutions. However, all of these methods require significant computational effort and are therefore difficult to use in real time applications. This paper presents arguments that the conventional tedious approach to obtaining solutions of power flow by using numerical methods can be avoided by using simulated neural computing.

In the recent past, several attempts have been made to investigate the suitability of artificial neural networks in power system applications [1-3]. All of the authors have reported relative success with their formulations. This paper presents a number of different configurations of the neural network and identifies a particular case which is most suitable for power flow analysis in real-time applications.

THE ONE LAYER NEURAL NETWORK

A one layer neural network is characterized by a layer of input neurons and a layer of output neurons interconnected to one another by weights to be determined by the training process. This process is illustrated in Fig. 1.

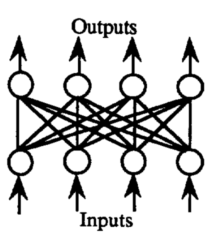

Fig. 1. One Layer Neural Network

For application to power flow, the power system is linearized and then modeled by one layer of the forward neural network, as shown in Fig. 2. The input data are the real and reactive power generations and demands in the system, and the output data are the complex bus voltages.

Single layer neural network represents a linear system and it is obvious that results obtained for a nonlinear system such as a power system can not be accurate. One possible solution is to introduce additional input layers to generate second and higher order nonlinear terms. This approach however, will result in significant increase of the size of a neural network and it will be impractical for large power systems to be analyzed.

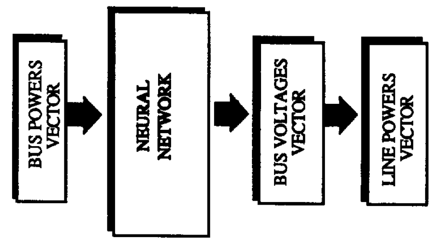

Fig. 2. Linear Neural Network for Power Flow

ONE LAYER NEURAL NETWORK WITH NON-LINEAR FEEDBACK

A possible approach to increase accuracy is to use a feedback loop, as shown in Fig. 3. Line power vector can be directly computed from bus voltages and line impedances. Using simple summation with complex arithmetic, the input vector IN_F (bus powers) can be obtained from line powers summation. At the initial state, the vector of line powers S_L is zero and there is no feedback - IN_F is zero. Therefore in the first step the input vector IN alone, is applied to the neural network and an approximate initial vector of bus voltages V_B is obtained. In the second step the difference between input vector IN and feedback vector IN_F is computed from line powers S_L and bus voltages V_B. Therefore the neural network operates on the difference (error) and the vector of line powers is corrected.

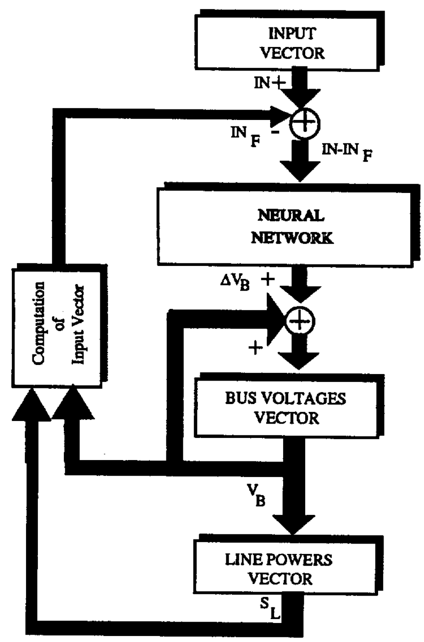

Fig. 3. Neural Network With Feedback for Power Flow Analysis

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By adding the non-linear feedback, we can obtain significant improvement over the case with no feedback. Usually a few iterations are enough to obtain convergence as shown in the results section. The results are very much comparable with those from a rigorous mathematical analysis, but the computational effort is negligibly smaller in comparison.

Training of the Neural Network

For a given power system such a network can be trained using, for example the back propagation algorithm, where the error between the actual and the desired outputs is fed back to the neuron to adjust its weights. The projection algorithm based on the least squares approximation technique can also be used for training and was also found to be efficient and reliable.

For supervised training the exact solutions obtained from a conventional power flow program was used. The training procedure was verified on the IEEE-24 bus test system [4]. The latter system was slightly modified for the purpose of demonstrating corrective control. Relevant data for the system pertinent to power flow are shown in Table A1 of the appendix. A training set consisting of 96 input and 96 output vectors was used to train the neural network for the test system. The input training data is comprised of:

(i) net real bus powers (real power generations minus the real power demands) at all buses except the slack bus,
(ii) net reactive bus powers (reactive power generations minus the reactive power demands) at load buses only,
(iii) the voltage magnitudes at voltage-controlled buses only.

The output vectors consisted of:

(i) bus voltage angles at all buses except the slack bus,
(ii) voltage magnitudes at load buses,
(iii) reactive power generations at voltage-controlled buses.

After training is completed, the ANN was tested for validation. Sets of new input test patterns were applied to the neural network. Comparisons of the performance of the ANN relative to a fast-decoupled solution showed an acceptable degree of accuracy. These comparisons are tabulated in the next section.

RESULTS

Figure 4 shows the IEEE 24-bus test system used in the analysis.

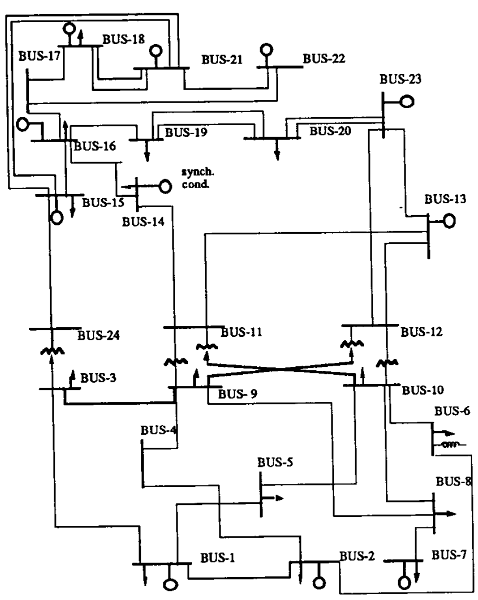

Fig. 5. The Modified IEEE 24-Bus Test System

Table 1 shows results of using the one-layer neural network without the feedback for predicting power flow results for the test system. The table shows bus voltage magnitudes and angles and real and reactive power generations after the first iteration. Before the next iteration, a non-linear feedback as mentioned in an earlier section, is employed, and results after the first iteration following the application of the feedback are shown in Table 2. The instant increase in accuracy due to the feedback is obvious from the data. Table 3 shows the same after the second iteration following feedback. This table should be compared with Table 4 which shows results of applying the fast-decoupled method on the test system. It can be observed from these tables that the ANN solution approaches the numerically found accurate values within only two iterations.

Table 1. Results From the ANN Without Feedback

	Type	Voltage		Power generated	
		[P.U.]	[deg]	[MW]	[MVAR]
BUS- 1	slack	1.00000	0.0000	52.22	70.67
BUS- 2	|V| - cont	1.00000	-0.0039	192.00	64.05
BUS- 3	load	0.93111	1.5279	0.00	6.54
BUS- 4	load	0.94321	-2.3291	0.00	5.01
BUS- 5	load	0.97315	-2.4885	0.00	20.60
BUS- 6	load	0.96663	-5.0386	0.00	3.16
BUS- 7	|V| - cont	0.96000	1.6768	300.00	53.07
BUS- 8	load	0.93704	-3.1830	0.00	44.14
BUS- 9	load	0.94240	1.2245	0.00	1.08
BUS- 10	load	0.96485	-1.0000	0.00	3.29
BUS- 11	load	0.97516	8.5366	0.00	36.58
BUS- 12	load	0.96463	9.9677	0.00	28.54
BUS- 13	|V| - cont	0.99000	14.8287	591.00	117.46
BUS- 14	|V| - cont	1.00000	10.7915	0.00	126.67
BUS- 15	|V| - cont	1.01000	18.2637	215.00	100.69
BUS- 16	|V| - cont	1.01000	17.7543	155.00	77.13
BUS- 17	load	1.01897	21.7430	0.00	55.20
BUS- 18	|V| - cont	1.01500	22.8606	387.89	-27.39
BUS- 19	load	1.00376	17.3551	0.00	28.40
BUS- 20	load	1.00825	19.3239	0.00	61.89
BUS- 21	|V| - cont	1.02500	23.8085	386.42	78.47
BUS- 22	|V| - cont	1.04500	29.6516	296.09	30.94
BUS- 23	|V| - cont	1.01000	21.2384	660.00	23.71
BUS- 24	load	0.98753	12.0867	0.00	20.79

Table 2. Results From the ANN With Non-Linear Feedback After One Iteration

	Type	Voltage		Power generated	
		[P.U.]	[deg]	[MW]	[MVAR]
BUS- 1	slack	1.00000	0.0000	254.14	40.72
BUS- 2	|V| - cont	1.00000	-0.1558	192.00	26.83
BUS- 3	load	0.95837	-0.2835	0.00	0.00
BUS- 4	load	0.96995	-1.8450	0.00	0.00
BUS- 5	load	0.98891	-1.8256	0.00	0.00
BUS- 6	load	1.00920	-3.5718	0.00	0.00
BUS- 7	|V| - cont	0.96000	0.4373	300.00	37.07
BUS- 8	load	0.95182	-2.3122	0.00	0.00
BUS- 9	load	0.96951	-0.5304	0.00	0.00
BUS- 10	load	0.99624	-1.5948	0.00	0.00
BUS- 11	load	0.98755	2.7948	0.00	0.00
BUS- 12	load	0.98508	3.6223	0.00	0.00
BUS- 13	|V| - cont	0.99000	6.1452	591.00	18.95
BUS- 14	|V| - cont	1.00000	3.7534	0.00	88.03
BUS- 15	|V| - cont	1.01000	7.3503	215.00	-2.25
BUS- 16	|V| - cont	1.01000	7.1286	155.00	104.51
BUS- 17	load	1.01559	9.0756	0.00	0.00
BUS- 18	|V| - cont	1.01500	9.6873	387.89	-84.52
BUS- 19	load	1.00413	7.0270	0.00	0.00
BUS- 20	load	1.00631	8.1231	0.00	0.00
BUS- 21	|V| - cont	1.02500	10.1649	386.42	170.04
BUS- 22	|V| - cont	1.04500	12.9786	296.09	81.94
BUS- 23	|V| - cont	1.01000	9.2032	660.00	78.28
BUS- 24	load	1.00422	4.5016	0.00	0.00

Table 3. Results From the ANN With Non-Linear Feedback After Two Iterations

	Type	Voltage [P.U.]	Voltage [deg]	Power generated [MW]	Power generated [MVAR]
BUS- 1	slack	1.00000	0.0000	194.31	51.59
BUS- 2	$\lvert v\rvert$ - cont	1.00000	-0.0627	192.00	25.88
BUS- 3	load	0.95868	0.5812	0.00	0.00
BUS- 4	load	0.97035	-1.2976	0.00	0.00
BUS- 5	load	0.98903	-1.4075	0.00	0.00
BUS- 6	load	1.00951	-2.9111	0.00	0.00
BUS- 7	$\lvert v\rvert$ - cont	0.96000	1.4201	300.00	35.76
BUS- 8	load	0.95199	-1.3848	0.00	0.00
BUS- 9	load	0.96985	0.3613	0.00	0.00
BUS- 10	load	0.99652	-0.8065	0.00	0.00
BUS- 11	load	0.98731	3.8174	0.00	0.00
BUS- 12	load	0.98486	4.5582	0.00	0.00
BUS- 13	$\lvert v\rvert$ - cont	0.99000	7.1105	591.00	20.08
BUS- 14	$\lvert v\rvert$ - cont	1.00000	4.9288	0.00	88.54
BUS- 15	$\lvert v\rvert$ - cont	1.01000	8.6599	215.00	-4.82
BUS- 16	$\lvert v\rvert$ - cont	1.01000	8.4001	155.00	100.26
BUS- 17	load	1.01562	10.3777	0.00	0.00
BUS- 18	$\lvert v\rvert$ - cont	1.01500	10.9673	387.89	-90.48
BUS- 19	load	1.00419	8.2201	0.00	0.00
BUS- 20	load	1.00635	9.2323	0.00	0.00
BUS- 21	$\lvert v\rvert$ - cont	1.02500	11.4018	386.42	165.48
BUS- 22	$\lvert v\rvert$ - cont	1.04500	14.1829	296.09	81.30
BUS- 23	$\lvert v\rvert$ - cont	1.01000	10.2304	660.00	75.71
BUS- 24	load	1.00386	5.5917	0.00	0.00

Table 4. Results From the Fast-Decoupled Power Flow

	Type	Voltage [P.U.]	Voltage [deg]	Power generated [MW]	Power generated [MVAR]
BUS- 1	slack	1.00000	0.0000	166.76	57.24
BUS- 2	$\lvert v\rvert$ - cont	1.00000	-0.0173	192.00	25.81
BUS- 3	load	0.95883	0.9976	0.00	0.00
BUS- 4	load	0.97041	-1.0363	0.00	0.00
BUS- 5	load	0.98914	-1.2155	0.00	0.00
BUS- 6	load	1.00972	-2.6025	0.00	0.00
BUS- 7	$\lvert v\rvert$ - cont	0.96000	1.8815	300.00	35.12
BUS- 8	load	0.95207	-0.9556	0.00	0.00
BUS- 9	load	0.96997	0.7806	0.00	0.00
BUS- 10	load	0.99671	-0.4394	0.00	0.00
BUS- 11	load	0.98721	4.3018	0.00	0.00
BUS- 12	load	0.98477	5.0025	0.00	0.00
BUS- 13	$\lvert v\rvert$ - cont	0.99000	7.5685	591.00	20.52
BUS- 14	$\lvert v\rvert$ - cont	1.00000	5.4819	0.00	88.65
BUS- 15	$\lvert v\rvert$ - cont	1.01000	9.2781	215.00	-6.27
BUS- 16	$\lvert v\rvert$ - cont	1.01000	8.9984	155.00	97.81
BUS- 17	load	1.01561	10.9951	0.00	0.00
BUS- 18	$\lvert v\rvert$ - cont	1.01500	11.5735	387.89	-93.03
BUS- 19	load	1.00420	8.7829	0.00	0.00
BUS- 20	load	1.00635	9.7558	0.00	0.00
BUS- 21	$\lvert v\rvert$ - cont	1.02500	11.9861	386.42	163.28
BUS- 22	$\lvert v\rvert$ - cont	1.04500	14.7520	296.09	81.04
BUS- 23	$\lvert v\rvert$ - cont	1.01000	10.7158	660.00	74.61
BUS- 24	load	1.00369	6.1056	0.00	0.00

It was felt that a good indicator of relative speeds of solution would be the time it took for solutions to converge for both the ANN and the conventional methods viz., the Gauss-seidel and the fast-decoupled methods. Fig. 6 shows a comparison of these factors. Two cases for the fast-decoupled method are shown in the figures. These are:

FD-I: Solution by the fast decoupled method with the Jacobian matrix already calculated and inverted.

FD-II: Solution by the fast decoupled method before the Jacobian matrix has been calculated and inverted.

The time shown is that on an "80286" IBM-compatible machine running at 12 MHz. From the figure, it is obvious that the Gauss-Seidel method is not appropriate for real-time applications. The ANN solutions compare very well with the fast-decoupled method. In fact, the ANN solution approaches the actual solution faster. However, no significant improvement in the iteration errors are observed in the ANN case after the initial iterations.

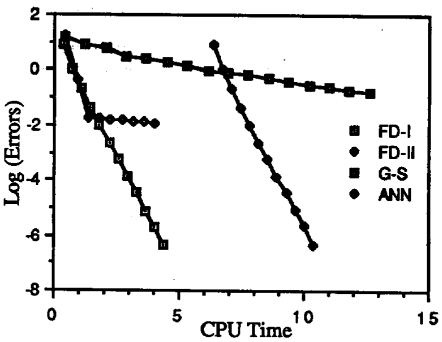

Fig. 6. Comparison of Errors vs. CPU Time on "80286" IBM Machine at 12 MHz.

CORRECTIVE CONTROL WITH THE TRAINED ANN

It is not unusual for a power system to reach an abnormal condition during daily operations. A situation where certain lines or transformers become overloaded or bus voltages tend to drift outside the set upper or lower limits, can be considered as abnormal operating conditions from system security point of view. Such situations can be brought about by unexpected variations in demands or the occurrences of disturbances, such as the opening of a line due to a fault. If the abnormality exists for only a brief period , the system operator may overlook the problem. However, if the condition persists for longer periods of time than allowed by equipment tolerances, the operator has to make decisions on remediating the problems. Fast control strategies have to be implemented to bring the system back to its normal operating regime. The operator has several options in making the corrective control. These options range from parametric changes to certain control elements such as, reactive compensators, generator real powers, etc. to more drastic measures such as, line switching and load shedding.

The neural network described in this paper can be trained to yield recommendations for corrective control under system emergencies. Of course, the ANN has to be trained with control elements as inputs and the controlled quantities as outputs. For instance, capacitor switching at certain buses can correct a low voltage problem at a bus which is sensitive to the var injections at those buses. Therefore, such information has to be fed to the neural network during training. However, before using the trained network for corrective control, the operator must have information on sensitivities of controlled quantities such as, voltages, to the corresponding controlling elements such as, capacitors or synchronous condenser outputs.

Table 5 shows results of using real power generation change at buses 15 and 2 in order to bring about a reduction in line flow in the branch between buses 14 and 16. The table shows a comparison of the neural network output with a fast decoupled load flow output. The bus loads and generations used for the results shown in the table are somewhat different from that shown in the appendix.

Table 6 shows the effect of capacitor switching at buses 4 and 8 separately, and also when they are switched on simultaneously. Voltages corrections are observed in buses 3, 4, 8 and 9. Once again, comparisons are shown with the output from a fast decoupled load flow.

Table 5. Branch Overload Relief by Generators

Load Scenario	Generation Change	Line	Avg. Line flow (Fast Decoupled)	Avg. Line flow (Neural Network)
I	None	14 - 16	(248.64, 0.8)	(248.15, 6.08)
I	Bus 15: -25MW Bus 2: +25MW	14 - 16	(239.52, 4.97)	(243.61, 5.50)

Table 6. Voltage Correction by Capacitor Switching

Load Scenario	Capacitor Switching	Bus Voltage (Fast Decoupled)	Bus Voltage (Neural Network)
II	None	Bus-3: 0.93036 Bus-4: 0.95037 Bus-8: 0.92653 Bus-9: 0.94716	Bus-3: 0.930213 Bus-4: 0.950412 Bus-8: 0.926623 Bus-9: 0.947233
II	Bus 4: 15 MVAR	Bus-3: 0.93132 Bus-4: 0.96013 Bus-8: 0.92719 Bus-9: 0.94972	Bus-3: 0.931031 Bus-4: 0.960276 Bus-8: 0.927071 Bus-9: 0.949570
II	Bus 8: 45 MVAR	Bus-3: 0.93172 Bus-4: 0.95237 Bus-8: 0.94342 Bus-9: 0.95072	Bus-3: 0.932086 Bus-4: 0.952415 Bus-8: 0.943528 Bus-9: 0.951071
II	Bus 4: 15 MVAR Bus 8: 45 MVAR	Bus-3: 0.93277 Bus-4: 0.96216 Bus-8: 0.94410 Bus-9: 0.95329	Bus-3: 0.933454 Bus-4: 0.962550 Bus-8: 0.944533 Bus-9: 0.953632

CONCLUSION

The advantage of fast analog computing is taken for power system analyses. Such analog neural network with single layer performs linear operation and therefore limited accuracy can be obtained for a nonlinear system such as a power system. To increase accuracy, the nonlinear feedback to evaluate an error can be applied. Although the method was applied to a power system only, it is obvious that the approach is quite general and can be used for fast analysis of any other nonlinear system.

The neural network can be trained using operating data such as bus powers, bus voltages, tap ratios, phase shifter angles and reactive compensations in order for it to be used for corrective control during system emergencies. This approximate solution should be adequate for taking fast control decisions.

Acknowledgement: The help of Mr Soumen Ghosh in running the neural net simulations and the ac power flows is greatly appreciated.

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APPENDIX

Table A1. Power flow data for the IEEE-24 bus test system

	Type	Voltage [P.U.]	[deg]	Power generated [MW]	[MVAR]	Power demand [MW]	[MVAR]
BUS- 1	slack	1.0	0.0	185.91	97.28	115.0	32.0
BUS- 2	|v| - cont	1.0	-	192.0	-14.91	117.0	35.0
BUS- 3	load	-	-	0.0	0.0	208.0	38.0
BUS- 4	load	-	-	0.0	0.0	90.0	23.0
BUS- 5	load	-	-	0.0	0.0	85.0	22.0
BUS- 6	load	-	-	0.0	0.0	151.0	35.0
BUS- 7	|v| - cont	0.96	-	300.0	0.0	155.0	45.0
BUS- 8	load	-	-	0.0	0.0	202.0	45.0
BUS- 9	load	-	-	0.0	0.0	218.0	52.0
BUS- 10	load	-	-	0.0	0.0	250.0	65.0
BUS- 11	load	-	-	0.0	0.0	0.0	0.0
BUS- 12	load	-	-	0.0	0.0	0.0	0.0
BUS- 13	|v| - cont	0.99	-	591.0	0.0	305.0	74.0
BUS- 14	|v| - cont	1.0	-	0.0	0.0	215.0	49.0
BUS- 15	|v| - cont	1.010	-	215.0	0.0	349.0	78.0
BUS- 16	|v| - cont	1.010	-	155.0	0.0	128.0	38.0
BUS- 17	load	-	-	0.0	0.0	0.0	0.0
BUS- 18	|v| - cont	1.015	-	387.89	0.0	380.0	79.0
BUS- 19	load	-	-	0.0	0.0	212.0	53.0
BUS- 20	load	-	-	0.0	0.0	145.0	36.0
BUS- 21	|v| - cont	1.025	-	386.42	0.0	0.0	0.0
BUS- 22	|v| - cont	1.045	-	296.09	0.0	0.0	0.0
BUS- 23	|v| - cont	1.01	-	660.0	0.0	0.0	0.0
BUS- 24	load	-	-	0.0	0.0	0.0	0.0

LINE DATA

	From	To	R	X	B	MVA Rat.
1	BUS-1	BUS-2	.0026	.0139	.23055	140.0
2	BUS-1	BUS-3	.0546	.2112	.02860	140.0
3	BUS-1	BUS-5	.0218	.0845	.01145	140.0
4	BUS-2	BUS-4	.0328	.1267	.01715	140.0
5	BUS-2	BUS-6	.0497	.1920	.02600	140.0
6	BUS-3	BUS-9	.0308	.1190	.01610	140.0
8	BUS-4	BUS-9	.0268	.1037	.01405	140.0
9	BUS-5	BUS-10	.0228	.0883	.01195	140.0
10	BUS-6	BUS-10	.0139	.0605	1.2295	140.0
11	BUS-7	BUS-8	.0159	.0614	.00830	140.0
12	BUS-8	BUS-9	.0427	.1651	.02235	140.0
13	BUS-8	BUS-10	.0427	.1651	.02235	140.0
18	BUS-11	BUS-13	.0061	.0476	.04995	240.0
19	BUS-11	BUS-14	.0054	.0418	.04395	240.0
20	BUS-12	BUS-13	.0061	.0476	.04995	240.0
21	BUS-12	BUS-23	.0124	.0966	.10150	240.0
22	BUS-13	BUS-23	.0111	.0865	.09090	240.0
23	BUS-14	BUS-16	.0050	.0389	.04090	240.0
24	BUS-15	BUS-16	.0022	.0173	.01820	240.0
25	BUS-15	BUS-21	.0063	.0490	.05150	240.0
26	BUS-15	BUS-21	.0063	.0490	.05150	240.0
27	BUS-15	BUS-24	.0067	.0519	.05455	240.0
28	BUS-16	BUS-17	.0033	.0259	.02725	240.0
29	BUS-16	BUS-19	.0030	.0231	.01155	240.0
30	BUS-17	BUS-18	.0018	.0144	.01515	240.0
31	BUS-17	BUS-22	.0135	.1053	.01106	240.0
32	BUS-18	BUS-21	.0033	.0259	.02725	240.0
33	BUS-18	BUS-21	.0033	.0259	.02725	240.0
34	BUS-19	BUS-20	.0051	.0396	.04165	240.0
35	BUS-19	BUS-20	.0051	.0396	.04165	240.0
36	BUS-20	BUS-23	.0028	.0216	.02275	240.0
37	BUS-20	BUS-23	.0028	.0216	.02275	240.0
38	BUS-21	BUS-22	.0087	.0678	.07120	240.0

TRANSFORMER DATA

	From	To	Tap	Phase	X	MVA Rat.
7	BUS-3	BUS-24	0.95	0.00000	.0839	400.0
14	BUS-9	BUS-11	1.00	0.00000	.0839	400.0
15	BUS-9	BUS-12	1.00	0.00000	.0839	400.0
16	BUS-10	BUS-11	1.00	0.00000	.0839	400.0
17	BUS-10	BUS-12	1.00	0.00000	.0839	400.0