B. H. Choudhury, B. M. Wilamowski, S. Ghosh, R. Khare "Use of Expert Systems and Artificial Neural Networks for Security Control in Power Systems", to be presented at the 7-th National Power System Conference Calcutta, India, December 19-22, 1992

USE OF EXPERT SYSTEMS AND ARTIFICIAL NEURAL NETWORKS FOR SECURITY CONTROL IN POWER SYSTEMS

Badrul H. Chowdhury   Bogdan M. Wilamowski   Soumen Ghosh   Rahul Khare
Department of Electrical Engineering
University of Wyoming
Laramie, WY 82071, USA

ABSTRACT

Security control is complex task that is becoming an integral part of emergy management systems. Its inherent complexity is derived from the requirements of its on-line structure as well as the maintenance of general availability of controls under all network conditions. The type, amount and the periods of most control actions have to be determined prior to the inception of a disturbance. Artificial neural networks can be trained to recognize the inter-relationships of security control and network abnormalities. At the same time, expert systems can be used to take advantage of the heuristics that are involved in the process of determining the controls and ensuring their adequacy. Both techniques are described in some detail, including the development of working computer models for each. These are tested on a small power system network and results are shown.

1. INTRODUCTION

Modern power systems are arguably more vulnerable to frequent abnormality in operation than the systems of the past. Present-day transmission lines are being stressed more heavily than ever before. Delays in new construction of generating and transmission equipment have led to loading of lines at close to their thermal limits, thereby leaving inadequate security margins. Certain lines have relatively heavier loadings than others because they serve as the major arteries for shipping power from large, remote generating stations to urban load centers. Therefore, loss of these or neighboring lines can cause line overloads, voltage instability, and power imbalance on the system. Since occurrences of contingencies cannot be ruled out, control centers have to be prepared with corrective measures to counter voltage drifts and line overloads. A number of major blackouts in recent history, which have caused extensive harm, have contributed toward the placing of a high emphasis on fast and efficient security control. When carried out properly, such actions can correct potentially hazardous situations, which otherwise can lead to system islanding.

Pertinent technical literature on the subject of corrective control shows a mix of linear and non-linear methods for optimizing the use of control sources. The linear programming technique has been extensively used for voltage control and/or for real power flow shifts in lines [1-6]. First order sensitivities between the dependent quantities and the controlling quantities have been also been used for revealing appropriate control sources for corrective strategies [11-13]. Others have used non-linear optimization approaches, such as the full optimal power flow solutions [7-10]. The expert system approach has also been experimented with, in conjunction with linear sensitivities, to provide fast control measures [14-18]. The bus-impedance method was used in [19] to select lines for switching actions to relieve overloads.

Typical security control actions entail dispatching of var sources for voltage control and redistribution of branch flows through active power rescheduling. A complete list of controls may include:

- Generator real power shifts.
- Voltage schedules at voltage-controlled buses.
- Synchronous condensers.
- Phase shifters.
- Load tap changing transformers.
- Switchable capacitors/reactors.
- Static var compensators.
- Interruptible load curtailment.
- Network topology change by line switching.
- Interchange schedules.

This paper categorizes corrective control actions under two scenarios: (i) emergency control and (ii) preventive control. The former actions conceivably go into effect when abnormal conditions occur in the present state of the system and the latter control actions are targeted toward the vulnerable or "alert" state wherein credible contingencies can potentially create abnormal operating states. This classification is illustrated in Fig. 1. As seen in the figure, emergency controls can lead the system from the "emergency" state to either an "alert" state or the "normal" state.

Preventive control strategy is meant to encounter security deviations under known contingencies. It can be a very complex task because, the operator has to ensure the most reliable and economic solutions while maintaining system security. The task is complicated by the availability of several control measures out of which, only a few may be <u>optimally</u> applied toward preventive control. Optimality is the key word in these control measures.

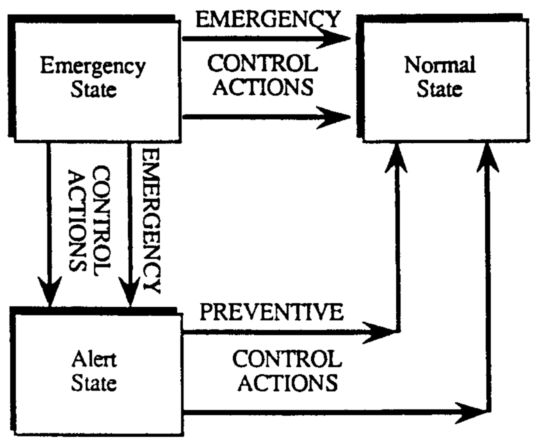

Fig. 1. Relationship between emergency and preventive Control.

Use of an expert system and a number of artificial neural network (ANN) configurations are shown separately in this paper for recommending emergency and preventive control actions. Artificial intelligence (AI) techniques have made on-line implementation of corrective strategies more convenient. At the same time, these techniques capture both the experience and the intelligence of the operator and therefore AI-based methods, when implemented, are suitable for use by inexperienced operators.

A cursory survey of recent technical literature reveals the increased attention being paid to both expert systems [20-25] and artificial neural networks [26-34] for application in power system operation studies. The timeliness of these techniques is also evident from the well attended international conferences on expert systems application in power systems (initiated in 1988), a recently concluded NSF-sponsored workshop on neural networks and the annual international forum on neural networks applications in power systems (initiated in 1990). Judging from the existing state of the literature, there is little doubt in one's mind that artificial intelligence (AI) techniques and neural nets have great potentials in solving complex power system problems with the likelihood of improvement in performance.

Before proceeding any further, brief descriptions of both paradigms are given in the following sections.

2. THE EXPERT SYSTEM

An expert system is a computer program which is capable of mimicking the problem solving behavior of a human expert from both an internal and an external point of view. The program should be capable of explaining its natural reasoning and should be able to add new information to its collection of knowledge, called the knowledge base. In narrow problem domains, expert systems can provide higher performance, equalling or even exceeding that of human experts.

An expert system acts as a repository for the knowledge and skill of an expert within a particular field of expertise called the "domain". Fig. 2 is a block representation of the parts of an expert system. The collection of rules and facts form the knowledge base. The inference engine uses the knowledge base and data for a particular case to infer a conclusion, in the form of a diagnosis of a fault. The program requests case data which the user can provide, and uses this with the rules, to produce a conclusion. Knowledge elicitation is the process of obtaining an expert's knowledge and presenting it in the form of facts and rules.

Symbolic representation of knowledge is a unique feature of expert systems. Natural languages, symbolic logic, production rules, semantic nets, frames, conceptual graphs and objects can be used for representing knowledge. The most commonly used representation scheme is of course, production rules. These are rules like:

IF A THEN B.

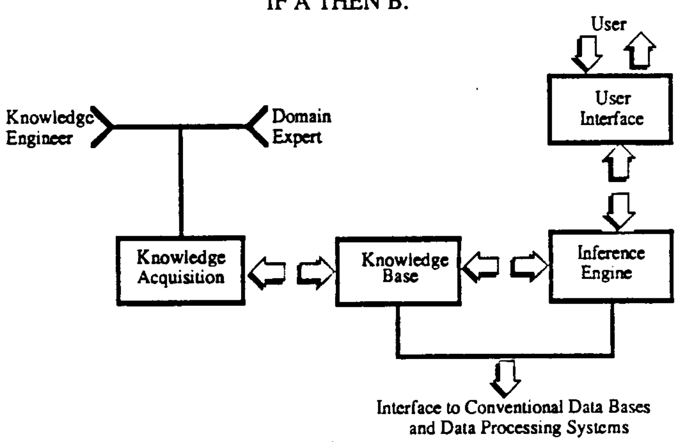

Fig. 2. Parts of an expert system.

3. THE ARTIFICIAL NEURAL NETWORK

The suitability of ANNs to solve pattern classification problems that require massively parallel computation is now being widely researched by the scientific community. An artificial neuron as shown in Fig. 3, is designed to mimic the first order characteristic of a biological neuron [35]. A number of inputs which could simply be from external stimuli or represent the outputs of other neurons are all multiplied by corresponding weights and these weighted inputs are then summed to determine the activation level of the neuron shown as the immediate output of the neuron. This output signal is usually further processed by an activation function f, to produce the neuron's final output. The neuron's output could be input to itself as a feedback, in which case it would be part of a recurrent neural network. Otherwise, it would be a feedforward neural network. The function f in Fig. 3 usually represents a hard limiter, a sigmoid function or a radial basis function.

The simplest ANNs are constructed with just two layers of neurons called the input and the output layers. Other networks may include a number of intermediate levels called the hidden layers as shown in Fig. 4. Reference [36] describes different networks that can be used for classification of static patterns. Of these, the perceptron, the Hopfield net and the Kohonen net have been applied in power system security classifications.

ANNs learn by changing their input and output behavior according to changes in the environment. The basic learning strategies fall under the categories of supervised and unsupervised learning schemes. In supervised learning, the actual output is compared with the desired output; the difference is used to adjust the weights for the next cycle. Simulated annealing and backpropagation methods are the most widely used techniques in supervised training. In the former method, random changes are made to the weights to determine those changes that produce an output with a smaller error than the previous changes. The process of random changes continues until a solution is found. In backpropagation, the error between the actual and the desired outputs is fed back to the neuron to adjust its weights.

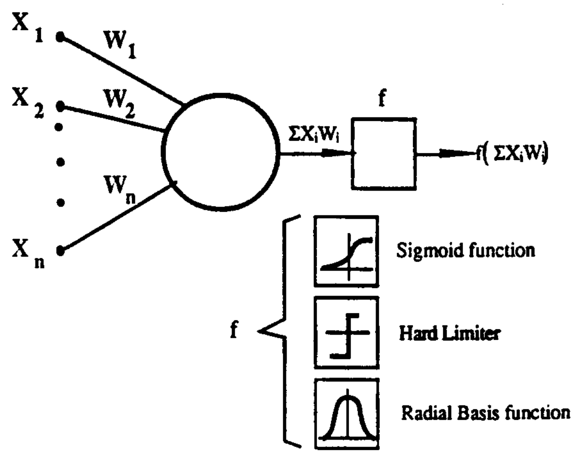

Fig. 2 An Artificial Neuron

4. STATIC SECURITY ASSESSMENT AND CONTROL USING AN ANN

Static security in power systems operation alludes to determination of the possible violations of bus voltage magnitude and branch flow limits due to potential faults in the system. It serves two purposes:

(i) It determines the security state of the present system under all contingencies and alerts the operator as to the violations.
(ii) It initiates preventive control to retain security and economy under all such contingencies.

The first purpose can be served by analyzing the system for every contingency using a fast ac power flow algorithm. However, repeated solutions of the power flow program incorporating every single contingency can be enormously time-consuming thus rendering the method inappropriate for use in real-time. A fast contingency screening and ranking method coupled with an ANN for determination of the "security vector" comprising of voltage magnitudes and branch flows can be use to improve the performance of static security assessment.

In static security assessment, one needs to investigate for a set of real and reactive powers on buses, the condition of line flows exceeding the maximum ratings and bus voltage deviations from their lower and upper limits. In alternate terms, for a given vector of bus powers, a vector of line flows and bus voltage magnitudes has to be determined and evaluated. This translates into modeling the ac power flow problem by a neural network. The approach is shown in Fig 3.

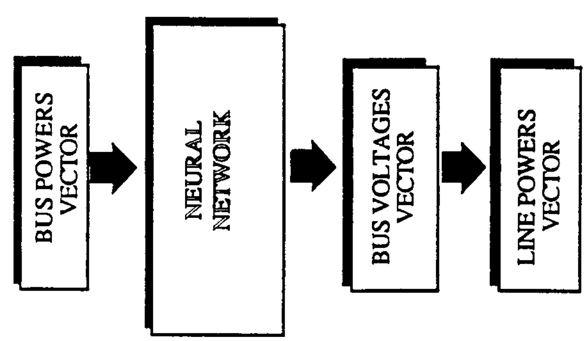

Fig. 3. Neural network for modeling power flow.

The set of power flow equations is modeled by one layer of the feedforward neural network shown in Fig. 4. The conventional methods of solving the power flow equations require significant computational effort and are therefore difficult to use in real time applications. With an ANN approach, the conventional tedious means of obtaining solutions of power flow by using numerical methods can be avoided.

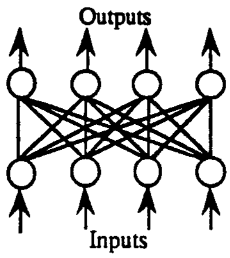

Fig. 4. One layer neural network.

Single layer neural networks represent linear relationships. A possible approach to incorporate the non-linearities of the power system network, is to use a feedback loop, as shown in Fig. 5. 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.

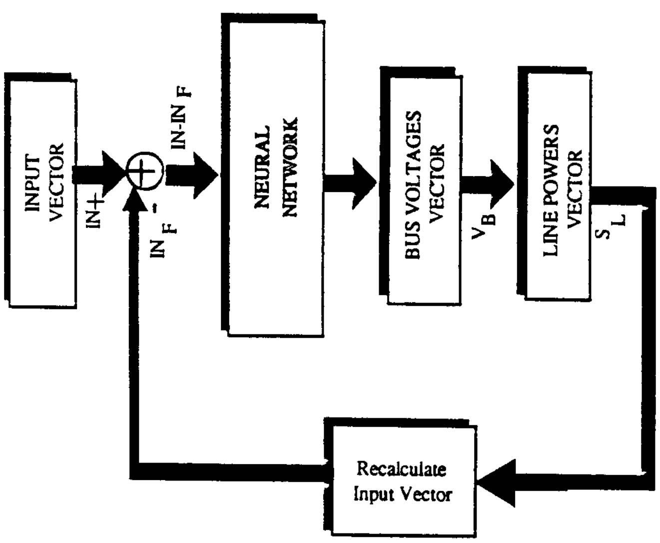

Fig. 5. Neural network with feedback for power flow Analysis.

Usually a few iterations of the feedback loop are enough to obtain convergence. The results are comparable with those from obtained from a fast decoupled method, but the computational effort is smaller in comparison.

4.1 Supervised Training for Security Monitoring

For a given power system, the ANN 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 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.

The training was validated on the IEEE 24-bus reliability test system [37] shown in Fig. 6. Relevant data for performing a power flow is shown in the appendix. After training was completed successfully, some comparisons of the performance of the ANN were done against that of a fast decoupled load flow.

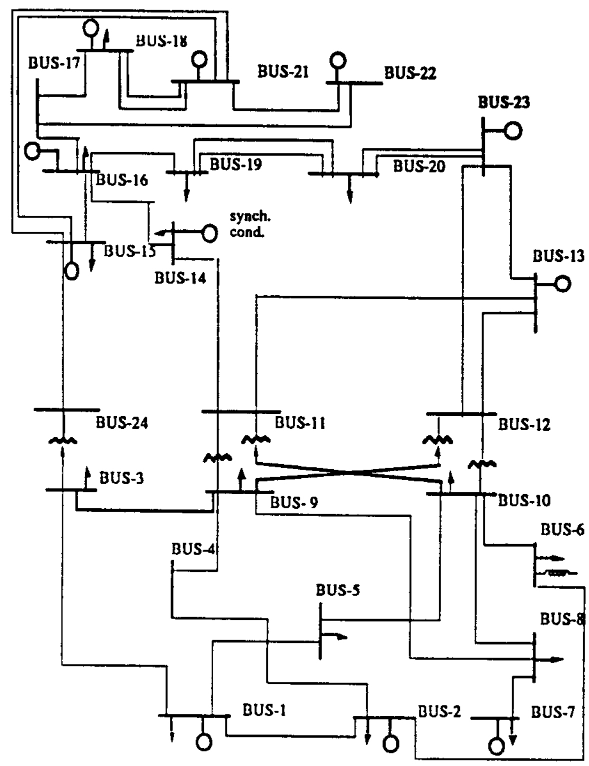

Fig. 6. The Modified IEEE 24-Bus Test System

Table 1 shows results of using the one-layer neural network with feedback for predicting power flow results for the test system. Results following only the second iteration are shown. This table should be compared with Table 2 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.

4.1 Corrective Control with the Trained Ann

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 3 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.

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 1. 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	|V| - 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	|V| - 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	|V| - cont	0.99000	7.1105	591.00	20.08
BUS- 14	|V| - cont	1.00000	4.9288	0.00	88.54
BUS- 15	|V| - cont	1.01000	8.6599	215.00	-4.82
BUS- 16	|V| - cont	1.01000	8.4001	155.00	100.26
BUS- 17	load	1.01562	10.3777	0.00	0.00
BUS- 18	|V| - 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	|V| - cont	1.02500	11.4018	386.42	165.48
BUS- 22	|V| - cont	1.04500	14.1829	296.09	81.30
BUS- 23	|V| - cont	1.01000	10.2304	660.00	75.71
BUS- 24	load	1.00386	5.5917	0.00	0.00

Table 2. 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	|V| - 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	|V| - 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	|V| - cont	0.99000	7.5685	591.00	20.52
BUS- 14	|V| - cont	1.00000	5.4819	0.00	88.65
BUS- 15	|V| - cont	1.01000	9.2781	215.00	-6.27
BUS- 16	|V| - cont	1.01000	8.9984	155.00	97.81
BUS- 17	load	1.01561	10.9951	0.00	0.00
BUS- 18	|V| - 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	|V| - cont	1.02500	11.9861	386.42	163.28
BUS- 22	|V| - cont	1.04500	14.7520	296.09	81.04
BUS- 23	|V| - cont	1.01000	10.7158	660.00	74.61
BUS- 24	load	1.00369	6.1056	0.00	0.00

Table 3. 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 4. 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

5. AN EXPERT SYSTEM FOR CORRECTIVE CONTROL

The preceding section discussed an artificial neural network that can be effectively used for developing corrective control strategies. An alternate approach that can be utilized for fast on-line implementation of corrective control, is by using an expert system. This section describes the issues behind the development of a rule-based expert system which can be used in combination with linear network sensitivities for recommending emergency and preventive control actions for both voltage and line flow corrections.

5.1 The Knowledge Base

The knowledge base for the expert system was determined by induction from results of off-line studies of the power system. The system behavior due to changes in parameters were studied extensively using the power flow technique in order to formulate most of the rules. Rule sets were developed for the following functions:

(i) diagnosis
   - voltage magnitude deviations
   - branch overloads

(ii) correcting low voltage
(iii) correcting high voltage
(iv) generating list of suitable control candidate for voltage control.
(v) recommending control for voltage correction
(vi) initiating branch flow control
(vi) locating control component for branch flow control
(vii) screening for partial control
(viii) recommending controls for branch overload relief.

The expert system has been developed on a "80486-based" IBM-PC using Prolog Development Center's PDC-PROLOG. The latter is based on the PROLOG language, a widely used tool in artificial intelligence applications. The power system network simulations for determining sensitivities are also done on the PC. A graphical front-end serves as the man-machine interface.

5.2 Network Sensitivities

The goal of the expert system is to expeditiously remediate voltage and branch overload problems in real power systems. Network sensitivities of voltage magnitudes and line flows to different control devices play important roles in the completion of the strategy. These sensitivities work in the same manner in terms of functionality, as the heuristics of an experienced operator. An important question when dealing with power system security is speed. Real time solutions are critical. In a very large power system, trying to solve a problem at one bus by systematically checking every control device would certainly be a waste of time. In this system the sensitivity matrices act as natural filters for selecting only those sensitivities which will have the greatest effect. When looking at a system one should realize that a change at one control element will have more effect on the bus to which it is directly connected, and little or no effect on buses farther down. The expert system is set up so as to disregard any control components with small effects on the controlled quantities.

The sensitivity analysis finds a relationship between a controlling quantity, such as the MVars injected by a capacitor, and a controlled quantity such as the corresponding voltage at a particular bus. For voltage control Eq.(1) is used to calculate the sensitivities of voltages at buses with respect to reactive power generated or consumed at a bus. Repeated power flow solutions using the fast-decoupled method yield an average sensitivity which is calculated as:

$$S_{ji}=\frac{\Delta|V_j|}{\Delta Q_{gi}} \qquad (1)$$

where
S_{ji} = Sensitivity at the j bus with respect to a change in the control element at bus i.

$\Delta|V_j|$ = Change in voltage magnitude at bus j

ΔQ_{gi} = The change in reactive power generated at bus i.

Capacitors, reactors, synchronous condensers and tap transformers are all control elements which when changed cause a change in the amount of reactive power generated and thus a change in voltage. This relationship allows for a simple replacement of the change in reactive power for a change in the given control element. Similar sensitivities can be developed for all control elements in the network. The ratio to be calculated is always the change in the controlled (dependent) quantity to the respective change in the controlling (independent) quantity. Sensitivity matrices can be formed for each control element. One of such matrices is shown in Fig. 7 for static capacitors placed on three buses in the IEEE 24-bus RTS.

Effect on Bus / Cap location	Bus-3	Bus-4	Bus-5	---	Bus-12	Bus-24
Bus-4		○		---		
Bus-8			○	---	○	
Bus-24	○			---		○

Fig. 7. A sensitivity matrix used for formulating control strategies

In the figure, circles show a high degree of correlation between the capacitor and voltages at load buses. The choice of a capacitor for correcting low voltages in the system will therefore be governed by the number of these circles associated with the element such that maximum benefit can be utilized by the least amount of control.

Table 5 shows the sensitivities of a partial set of elements to some of the control devices in the IEEE 24-bus system, under the two scenarios of (i) pre-contingency state or base case (to be used in emergency control strategy) and (ii) post-contingency state (to be used for preventive control). In the tables, two specific outages are shown.

Table 5a. Sensitivities for the Generator at Bus 16

Line	Base-Case	Outage (14 - 16)	Outage (15 - 24)
Bus 1-Bus 2	-0.40161	-0.36629	0.42347
Bus 1-Bus 3	0.18767	0.28298	-0.14992
Bus 15-Bus 16	-0.23097	0.30161	0.00000
Bus 16-Bus 17	-0.05411	-0.07072	0.00000
Bus 20-Bus 23	-0.16363	-0.30871	-0.22597

Table 5b. Sensitivities for the Phase Shifter at Bus 9 - Bus 11

Line	Base-Case	Outage (3 - 24)	Outage (11 - 14)
Bus 1-Bus 3	0.162500	-0.725002	0.406250
Bus 3-Bus 9	-2.093750	0.743771	-1.537499
Bus 9-Bus 11	9.524994	8.337498	8.612499
Bus 11-Bus 13	3.768711	3.500042	4.906158
Bus15-Bus21	-0.181255	0.00000	-0.124989

5.3 Formulating the Rules

The knowledge base consisting of the rules searches for the "best" control measure according to a pre-set criteria. In formulating the rules a number of criteria were strictly adhered to. Some of the criteria for branch overload relief are described below:

- Lesser overloaded circuits are allowed to increase their loading if it permits the decrease of the loading of other heavily overloaded lines.
- A control measure is optimal if it can correct the highest number of violations compared to others.
- For generator real power control, the most economic solution is desirable.
- Load curtailment will be the last control strategy selected when all possible controls have been exhausted.
- For line switching, select the line with the heaviest overload; however, switching of this line should not create more overloads than in the original case.
- Actual overloaded conditions have higher priority for elimination than in the contingency case.
- When only the contingency overloaded conditions exist, the generation shift is determined such that no additional overloads will result.

A number of important rules for solving the voltage violation problem are shown below:

Rules for diagnosis

If voltage magnitudes at some buses are outside the set limits, then there are voltage violations present in the system.

If voltage violations are present in the system, then find buses with violations in order of largest voltage violation to smallest.

Rules for correcting low voltage

If voltage violation is in the negative direction (i.e. voltage is below minimum), then
-find the capacitors with available adjustments in that direction.
-If there are no capacitors that will solve the voltage violation problem, find all transformer tap changers with available tap ratios.
- If there are no capacitors or transformer tap changers that will solve the voltage violation problem, find the available synchronous condensers.

Rules for correcting high voltage
If voltage violation is in the positive direction (i.e. voltage exceeds the maximum), then
- find the reactors with available adjustments.
-If there are no reactors that will solve the voltage violation problem, find the available transformer tap changers.
-If there are no reactors or transformer tap changers that will solve the voltage problem, find the available synchronous condensers.

Rules for finding suitable control candidate
If there is an available control component, then
- find the control element to which the affected bus has the highest sensitivity (best candidate) and find the amount of change required to bring the voltage violation within limits; (full correction).
- if the change desired is not fully available, then apply the amount possible. (partial correction).
- If a control element creates more voltage violations than were originally in the system, then find a control element corresponding to the next highest sensitivity (next best candidate) and find the amount of change required to bring the voltage violation within limits.

Rule for recommending control
If the newly found control component value does not create more voltage violations than were originally in the system, then assert the new control component value into the database and find the new voltage magnitudes for all load buses.

Some rules for relieving line overload problems are shown below:

Rules for initiating flow control
If voltage violations are present in the system, then first initiate voltage correction strategy and then return to the line relief strategy.
(The voltage correction scheme requires changes in reactive power flows and hence will likely have an effect on the line flows)

If line flow violations are present in the system, then list lines with violations in order of largest line overloads to smallest.

Rules for locating control component
If there are generators available with proper adjustments, then find those generators with the available adjustments.

If there are no generators with available adjustments, then find the phase shifters with available adjustments.

Rules for screening
If there is an available control component, then
- find the control element to which the overloaded line has the highest sensitivity and find the amount of change required to relieve the overload (full correction).
- if the change desired is not fully available, then apply the amount possible (partial correction).

Rule for recommending control
If the newly found control component value does not create more line overloads than were originally present in the system, then assert the new control component value into the database and find the new line flow values for all transmission lines.

Using the Sensitivities to Recalculate Network Conditions

The sensitivity factors are useful in fast identification by the expert system, of the control parameters available for corrective measures during security violations. A second useful aspect of the sensitivity analysis can be derived in the following scheme. Once the recommendations from the expert system are implemented in the system, it becomes a necessity to recalculate the voltages at buses and the branch flows. An AC power flow program is ideal for accomplishing the latter. However, speed is of utmost concern in such situations as repeated solutions will be required. Therefore, a reverse calculation using sensitivities gives acceptably accurate figures for these parameters. The following general equations give an indication of the nature of these calculations:

$$S_{ji}^{*}\ \Delta Q_{gi} = \Delta|V_j| \quad (2)$$

$$|V_{j,new}| = |V_{j,old}| + \Delta|V_j| \quad (3)$$

5.4 Results from the Expert System

Table 6 shows results of using the expert system for voltage correction on the lightly-loaded system. The minimum and maximum voltage magnitudes at all buses except the voltage-controlled buses were assumed to be respectively 0.95 per unit (p.u) and 1.05 p.u. The table contains the original voltage magnitudes as the expert system sees it. These values are obtained from a full ac power flow. The table also contains the voltage magnitudes after the recommendations from the expert system are implemented. Each adjustment requires a full "pass" over the relevant rules. Therefore multiple passes may be required for correction of all voltage problems in the system.

There were three serious under-voltage problems at Bus-3, Bus-4, Bus-8 and Bus-9 and a few other smaller problems. Following are the ES recommendations for this test case:
Pass #1: Adjust the capacitor at Bus-4 from 0 to 100 MVars.
Pass #2: Adjust the capacitor at Bus-8 from 0 to 100 MVar.
Pass #3: Adjust the tap on the transformer between Bus-3 and Bus-24 from 0.95 to 1.05.

Upon completion of the voltage magnitude corrections, the line flows were adjusted to account for changes in bus voltages as recommended by the the expert system. A separate program written in "C" recalculates the values for the adjusted reactive power generations at voltage-controlled buses and real and reactive power flows in all lines. Flow violations existed on the line between Bus-14 and Bus-16, and on the line between Bus-16 and Bus-17. Table 7 shows some important line flows before and after the expert system was tested on this system for relieving branch overloads. The expert system suggested the following:

- Change generator output at Bus-18 from 388 MW to 293 MW (Relieves overload on line from Bus-16 to Bus-17).
- Change generator output at Bus-15 from 215 MW to 66 MW. (Relieves overload on line from Bus-14 to Bus-16).

The final line flows are all below their line rating after the expert system recommendations were incorporated.

Table 6. Voltage Control by the Expert System

Bus	Orig. V (pu)	Pass 1	Pass 2	Pass 3
Bus 3	0.91591	0.92371	0.92741	0.972252
Bus 4	0.93048	0.99858	1.00338	1.00962
Bus 6	0.94898	0.95188	0.095888	0.960615
Bus 8	0.90993	0.91453	0.095463	0.957575
Bus 9	0.92636	0.94436	0.95376	0.963812
Bus 10	0.94609	0.94959	0.095959	0.960332
Expert System Recommendations:		Adjust capacitor at bus 4 from 0 to 100 MVar	Adjust capacitor at bus 8 from 0 to 100 MVar	Adjust tap transformer between busses 3 and from .95 to 1.05

Table 7. Branch Flow Control by the Expert System

Start	End	Rating (MVA)	Original Flow (MVA)	Pass 1 (MVA)	Pass 2 (MVA)
Bus 1	Bus 2	140	17.60	50.91	108.11
Bus 1	Bus 3	140	18.73	21.26	57.42
Bus 1	Bus 5	140	65.91	89.42	128.54
Bus 2	Bus 4	140	30.91	49.33	80.29
Bus 2	Bus 6	140	47.27	63.20	88.67
Bus 3	Bus 24	400	203.41	176.57	130.82
Bus 6	Bus 10	140	120.86	106.52	85.11
Bus 10	Bus 11	400	194.99	172.44	136.76
Bus 10	Bus 12	400	221.31	203.68	175.68
Bus 11	Bus 14	240	11.75	82.86	51.81
Bus 13	Bus 23	240	130.90	118.31	98.65
Bus 14	Bus 16	240	319.92	285.24	231.08
Bus 15	Bus 24	240	228.45	202.53	159.53
Bus 16	Bus 17	240	276.20	227.52	208.48
Bus 17	Bus 18	240	141.55	93.07	76.67
Bus 19	Bus 20	240	88.31	102.81	125.45
Expert System Recommends:		Pass 1: Reduce generation at Bus-18 by 95 MW. Pass 2: Reduce generation at Bus-15 by 149 MW.			

6. CONCLUSIONS

Artificial neural networks and expert systems have been used in a variety of power system applications. Problem diagnosis through feature or pattern recognition is a significant strength of trained ANNs. Expert systems can capture the expertise and experience of human operators to yield control measures under complex situations. This paper has provided an investigative look at the capabilities of ANNs and expert systems for recommending emergency and preventive measures. Experimental results prove that both paradigms are suitable for on-line use. Although, their performance on larger power systems cannot be extrapolated from the results presented in the paper, it is expected that the same configuration of the ANN will perform satisfactorily. However, the training process will require larger data sets and therefore longer time. For these large power networks, the expert system will require more efficient pruning methods to reduce the search space and thereby eliminate unnecessary delays in obtaining the solution.

7. REFERENCE

[1] J.C. Kaltenbach, L.P. Hajdu, "Optimal Corrective Rescheduling for Power System Security", IEEE Trans. on Power App. & Systems, Vol. PAS-90 (2), 843-851, Mar./Apr. 1971.

[2] W.O. Stadlin, D.L. Fletcher, "Voltage Versus Reactive Current Model for Dispatch and Control", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-101 (10), pp. 3751-3760, Oct., 1982.

[3] A.A. Mazi, B.F. Wollenberg, M.H. Hesse, "Corrective Control of Power System Flows by Line and Bus-Bar Switching", IEEE Trans. on Power Systems, Vol. PWRS-1 (3), 258-265, Aug. 1986.

[4] A.G. Bakirtzis, A.P.S. Meliopoulos, "Incorporation of Switching Operations in Power System Corrective Control Computations", IEEE Trans. on Power Systems, Vol. PWRS-2 (3), 669-676, Aug. 1987.

[5] D.S. Kirschen, H.P. Van Meeteren, "MW/Voltage Control in a Linear Programming Based Optimal Power Flow", IEEE Trans. on Power Systems, Vol. 3 (2), 481-489, May 1988.

[6] A.P.S. Meliopoulos, G. Contaxis, R.R. Kovacs, N.D. Reppen, N. Balu, "Power System Remedial Action Methodology", IEEE Trans. on Power Systems, Vol. 3 (2), 500-509, May 1988.

[7] R.E. Palmer, R.C. Burchett, H.H. Happ, D.R. Vierath, "Reactive Power Dispatching for Power System Voltage Security", IEEE Trans. on Power App. & Systems, Vol. PAS-102 (12), 3905-3910, Dec. 1983.

[8] D.T. Sun, R.R. Shoults, "A Preventive Strategy Method for Voltage and Reactive Power Dispatch", IEEE Trans. on Power App. & Systems, Vol. PAS-104 (7), 1670-1676, July 1985.

[9] G. Schnyder, H. Glavitsch, "Integrated Security Control Using an Optimal Power Flow and Switching Concepts", IEEE Trans. on Power Systems, Vol. 3 (2), 782-790, May 1988.

[10] S.K. Chang, F. Albuyeh. M.L. Gilles, G.E. Marks, K. Kato, "Optimal Real-Time Voltage Control", IEEE Trans. on Power Systems, Vol. 5 (3), 750-758, Aug. 1990.

[11] A. Thanikachalam, J.R. Tudor, "Optimal Rescheduling of Power for System Reliability", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-90 (5), pp. 2186-2192, Sept./Oct., 1971.

[12] K.R.C. Mamandur, R.D. Chenoweth, "Optimal Control of Reactive Power flow for Improvements in Voltage Profiles and for Real Power Loss Minimization", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-100 (7), pp. 3185-3194, July, 1981.

[13] E. Housos, G. Irisarri, "Security Assessment and Control System: Corrective Strategies", IEEE Trans. on Power App. & Systems, Vol. PAS-104 (5), 1075-1083, May 1985.

[14] C.C. Liu, K. Tomsovic, "An Expert System Assisting Decision-Making of Reactive Power/Voltage Control," IEEE Trans. on Power Systems, Vol. PWRS-1 (3), 195-201, Aug. 1986.

[15] S. J. Cheng, O. P. Malik, G. S. Hope, "An Expert System for Voltage and Reactive Power Control of a Power System," IEEE Trans. on Power Systems, Vol. 3 (4), 1449-1455, Nov. 1988.

[16] H. Sasaki, N. Yorino. R. Yokoyama, "An Expert System for Power System Security Control", Proc. 1989 PICA Conf., 259-266.

[17] W.R. Wagner, A. Keyhani, S. Hao, T.C. Wong, "A Rule-Based Approach to Decentralized Voltage Control", IEEE Trans. on Power Systems, Vol. 5 (2), 643-651, May 1990.

[18] S. Shah, S.M. Shahidehpour, "A Heuristic Approach to Load Shedding Scheme", IEEE Trans. on Power Systems, Vol. 4 (4), 1421-1429, Nov. 1990.

[19] E.B. Makram, K.P. Thornton, H.E. Brown, "Selection of Lines to be Switched to Eliminate Overloaded Lines Using a Z-Matrix Method", IEEE Trans. on Power Systems, Vol. 4 (2), 653-661, May 1989.

[20] B. F. Wollenberg, T. Sakaguchi, "Artificial Intelligence in Power System Operations," Proceedings of the IEEE, Vol. 75, No. 12, 1678-1685, Dec. 1987.

[21] T. Sakaguchi, H. Tanaka, K. Uenishi, T. Gotoh, Y. Sekine, "Prospects of Expert Systems in Power System Operation", Int. Journal of Electrical Power & Energy Systems, Vol. 10 (2), 71-82, Apr. 1988.

[22] T. Sakaguchi, K. Matsumoto, "Development of a Knowledge-Based System for Power System Restoration", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-102 (2), 320-326, Feb. 1983.

[23] R. Fujiwara, T. Sakaguchi, T. Kohno, H. Suzuki, "An Intelligent Load Flow Engine for Power System Planning," IEEE Trans. on Power Systems, Vol. PWRS-1 (3), 302-307, Aug. 1986.

[24] C.C. Liu, S. Lee, S. Venkata, "An Expert System Operational Aid for Restoration and Loss Reduction of Distribution Systems," IEEE Trans. on Power Systems, Vol. 3 (2), 619-626, May 1988.

[25] C.C. Liu, M.J. Damborg, "CRAFT: On-Line Expert System for Customer Restoration and Fault Testing", Electric Power Research Institute, EPRI EL-6680, Vol. 1, Final Report, March 1990.

[26] Y.H. Pao, "Application of Neural Net Computing to Power Systems", Proc. NSF Workshop on App. of Art. Neural Network Methodology in Power System Engg., Clemson SC, Apr. 1990.

[27] H. Mori, "Artificial Neural Net Applications in Power Systems in Japan", Proc. NSF Workshop on App. of Art. Neural Network Methodology in Power System Engg., Clemson SC, Apr. 1990.

[28] T.S. Dillon, "Artificial Neural Networks Applications to Power Systems and Their Relationship to Symbolic Methods", Int. Journal of Electrical Power & Energy Systems, Vol. 13 (2), 66-72, Apr. 1991.

[29] D.J. Sobajic, Y.H. Pao, "Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems", IEEE Trans. on Power Systems, Vol. 4 (1), 220-228, Feb. 1989.

[30] M. Agounne, M. A. El-Sharkawi, D. C. Parks, M. J. Damborg, R. J. Marks II, "Preliminary Results on Using Artificial Neural Networks for Security Assessment," Proc. 1989 PICA Conf., 252-258.

[31] E.H.P. Chan, "Application of Neural Network Computing in Intelligent Alarm Processing", Proc. 1989 PICA Conf., 246-250.

[32] H. Mori, Y. Tamaru, S. Tsuzuki, "An Artificial Neural Net Based Technique for Power System Dynamic Stability with the Kohonen Model", Proc. 1991 PICA Conf., May 1991.

[33] B.H. Chowdhury,Bogdan. M. Willamowski, "Security Assessment Using Neural Computing",1st Forum on Artificial Neural Network App. to Power Systems, Seattle, WA. July 1991.

[34] S. Weerasooriya, M.A. El-Sharkawi, M.Damborg, R.J. Marks II, "Towards Static-Security Assessment of a Large-Scale Power System Using Neural Networks", IEE Proceedings-C, 64-70, Jan. 1992.

[35] P.D. Wassermann, Neural Computing, Van Nostrand, 1989.

[36] R.P. Lippmann, "An Introduction to Computing With Neural Nets", IEEE ASSP Magazine, 4-22, April 1987.

[37] IEEE Committee Report, "IEEE Reliability Test System", *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-98(3): 2047-2054, 1979.

APPENDIX

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

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