FAST PREDICTION OF SYSTEM VOLTAGE INSTABILITY USING ARTIFICIAL NEURAL NETWORKS

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Abstract: Even though system voltage instability is the slowest cause of breakdown it is a major cause of collapses on power systems throughout the world. An early indication of the on-coming problem would enable quick security assessment and responses for controlling the danger to stability. Indicators or indices have been developed for this purpose but most involve complicated mathematical calculations and are not suitable for on-line use, nor prediction and prevention of voltage problems following severe disturbances beyond their scope. A new approach to voltage instability problems is presented by using artificial neural network techniques for their fast indication and it can also quantify the severity of the disturbances.

Keywords: Artificial Neural Network, Voltage Collapse, Voltage Instability, Reactive Power Control, Transient Stability.

1. INTRODUCTION

Voltage instability is becoming an increasingly serious problem in many modern power systems because of the progressively increasing loadings on the transmission grid. Environmental constraints and economic uncertainty have inhibited the construction and commissioning of new power stations. This has led to growing amounts of power being transmitted over extensive interconnected transmission networks at a time when it is becoming increasingly difficult to provide additional lines to augment the grid. This has resulted in much more heavily loaded lines than had been envisaged when planning the power systems and has resulted in progressively increasing series reactive power losses that have seriously impaired on system voltage control. In the last decade voltage instability problems have been experienced in many countries throughout the world, including Japan, Canada, Sweden, France, United States.

Voltage instability is due to inadequate reactive power support at critical points of the power system network. In most reported incidents of collapse there has been an extremely severe disturbance which created operating configurations much more unfavourable than those considered by planning or operating criteria. However, unlike other causes of collapse, there has been a first period of apparent stability which had persisted for a matter of minutes. As most protective devices are devised to handle fast changes, they have not been able to identify nor function during the first phase of system voltage instability. In the second fast phase, when protections such as transmission line and rotor overcurrent do function, their actions only serve to speed the demise of the power system. With the complexity of dynamic phenomena in modern power systems, operators have become increasingly dependent on automatic devices for the control of dangerous operating situations. System voltage instability, in spite of its disastrous consequences, is one phenomenon against which no such support is provided for the operators. Even during the first slow phase, abnormal conditions indicated over a widespread area cannot be identified quickly enough for operators to be able to implement effective measures.

Fast prediction of system voltage instability after the disturbances would be very helpful as system operators would have time to take action before the system enters the catastrophic phase. If nothing is done during the first phase of system voltage instability, collapse is unlikely to be avoided.

Many voltage instability indices have been developed in recent years, but they are usually complex and involve a lot of elaboration computation. Moreover, most of those indices do not take all dynamic factors into account and so are unable to make predictions of voltage collapse, or are so computationally complex that they are unsuitable for real-time, on-line use. This paper reports on research work that uses a neural network that would be capable of not only making fast predictions of impending system voltage instability but also of quantifying the severity of the situations.

2. PHYSICAL PHENOMENA - SYSTEM VOLTAGE INSTABILITY

The processes leading to system voltage instability involve two distinct phases, the first slow and the second fast. Although much of the power network is affected by the fast phase, initially the disturbance only has localised effects. Invariably the triggering event leads to a sudden, large increase of loading on some transmission lines, usually the loss of transmission lines or generators. Fig. 1 shows how the increase of transmission line loading causes a marked increase of series reactive power losses, the main factor that raises the system reactive power demand [1]. A numerical example is provided with a 120km 330kV line having 60MVar charging. When its load is increased from 2 to 3 surge impedance loading (SIL), 700MVA to 1050MVA, series losses would increase from 180MVar to 480MVar. Should the voltage also fall to 0.9 p.u., the
series losses would rise to 610MVAr. In this example a 350MVA (33%) line load increase causes a 430MVAr (140%) rise in series reactive losses.

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![Figure 1 Increase of line VAr loss with line load](image)

The first phase of system voltage instability commences with a sharp voltage reduction to the loads at the receiving ends of the affected lines. The power stations more or less hold voltage levels at the sending end of lines whose loading has suddenly been increased. The voltage reduction at the loads is primarily due to the additional voltage drop because of the increased power flow through the lines.

In the initial seconds two distinct effects occur:

Firstly at the generators whose automatic voltage regulators, in sustaining terminal voltages, sharply increase their reactive power outputs. Their higher output is primarily to supply much of the extra series reactive power losses caused by the sudden increase of transmission line loading.

Secondly, at the load centres, the sudden voltage reduction due to the lines' increased loadings, significantly reduces load magnitudes, as all loads respond to changes of voltage level. If there are synchronous condensers or static compensators at the load centre, their reactive power outputs would also suddenly increase in an effort to restore voltage levels.

In this event, static compensators would reach their limiting output and synchronous condensers would reach outputs greater than their continuous rating and yet be unable to regain previous voltages. Subsequently, during the first phase, transformer on-load tap changers would function automatically in an effort to restore voltage levels to consumers at the affected load centres. This slow acting tap changing would be the only dynamic changes during the first phase.

The large initial voltage reduction would cause simultaneous operation of transformer tap changers with identical timer settings. With each tapping operation, consumer voltages and load magnitudes would be raised, causing an extra loading on the transmission lines, a reduction of their receiving voltages a reduction of their line charging and an increase in their series reactive power losses. If no corrective measures are taken, the extra demand, particularly of reactive power, would need to be supplied by generators and synchronous condensers. Although each individual tap change would not produce large changes, cumulatively after some minutes, the increase would be substantial.

Progressively, rotating unit excitation would increase, above continuous rating on some units, until rotor temperature limits would be approached. Rotor overcurrent protection is provided to prevent generator rotor thermal damage to insulation. When functioning on one generator, its excitation and reactive power output is instantly reduced. All nearby units would have to pick up this reactive power, so raising their rotor temperatures and setting off a chain reaction of rotor overcurrent protections. This first rotor protection operation sets off the fast second phase, which has been reported to lead to steady state instability and power system collapse within seconds. The simulation of this process of system voltage instability has been described in Reference 2. It has been possible to make the simulation by replicating events described in reported incidents, requiring step changes in a number of parameters, such generator reactive power outputs and transformer tapping positions. Such a methodology is not conducive to real-time computation on the model of an extensive power system.

3. VOLTAGE INSTABILITY STUDY INDICES

There are two questions regarding voltage instability: How close is the current system operation to voltage instability? Secondly, if a disturbance occurs, will the system suffer voltage instability problems? Much of the research effort has been focussed on developing voltage instability indices to answer the first question, while the second question is generally neglected. There have been a number of indices proposed in 1980's. Most of them may fit into the following four categories:

1) \[ \frac{dV}{dQ} \]
   This is probably the first static index that was developed for voltage stability.[3]

   \[ \frac{d}{dQ} \sum Q_{Gi} \]

2) \[ VCPI = \frac{1}{dQ_{Lk}} \min \text{loss minimum} \]
   \[ \leq \text{preset threshold} \]
   This represents the sensitivity of total generation Var change with respect to Var demand change at a specific node k. This definition is of an algebraic nature.[4]
The actual causes of the voltage instability can be of two kinds: slow change such as gradually increase of loads and sudden change such as loss of major transmission lines. Slow change is easy to handle by existing indices such as those proposed in Reference 15. By confining the problem to sudden disturbances it can be expressed as: If a sudden disturbance occurs under the prevailing operating conditions will voltage instability occur? And if so, how much response will be needed?

4.2 The Neural Network

Imagine the problem of voltage instability as a black box, with the inputs for a given power system being those factors that reflect the system voltage stability level and the severity of the disturbance and the black box output giving the severity index. This black box model fits the neural network techniques perfectly. By simulating the system dynamic process with different operating conditions and disturbances on a given power system, a set of patterns can be produced sufficient to show the system inherent characteristics relating to voltage instability in response to system disturbances. A neural network properly trained by these patterns would be able to assess the possibility of voltage instability for other disturbances under different system operating conditions.

The information available would be the operating condition prior to the disturbance (which is usually available from SCADA), and subsequently to indicate if system can maintain stability or not. So the neural network's inputs will be this information, while its outputs could be chosen as any useful quantity e.g., the amount of load shedding to regain stability.

After any disturbance, almost all system static characteristics (such as system topology, load growth rate, generation distribution, transmission line impedance, line charging, generation reactive power limit, etc. and dynamic characteristics such as automatic tap changer timing, static compensator characteristics, load characteristics, etc.) remain unchanged with the exception of those directly involved in the disturbance. The fate of the system is only affected by the operating conditions immediately after the disturbance and the disturbance itself. Therefore factors that can represent the operating conditions and the disturbance attributes should be selected as the inputs of the neural network. Selection of instability indication for the neural network output may be more flexible and the amount of load shedding to prevent the voltage instability has been chosen as a good indicator.

5. PRACTICAL CONSIDERATIONS IN SIMULATION

The major work in building such an ANN index is to perform the dynamic simulation to produce training patterns. To demonstrate the usefulness of the method on practical power system, the New South Wales (NSW) state power system main grid has been chosen and the simulation was carried out by running multiple loadflow studies. A number of factors, described below, were considered in the simulation.

5.1 Generation VAR Limit

Most of the modern units are equipped with automatic excitation control. This enables the units to produce extra
reactive power to compensate the possible huge reactive power loss on the transmission network and maintain the system voltage level after a severe system disturbance such as loss of major transmission lines. But system operation cannot rely on the field forcing since the extra reactive power supply above the continuous rating is only available for a matter of minutes, until rotor protection curtails the reactive power output. The unit continuous rating can be regarded as the sustainable reactive power resource and is not a constant but slightly increases with lower real power output. However, in the simulation, the sustainable reactive power output for each unit was assumed constant.

5.2 Generation VAr Dispatch

NSW system major generators are all thermal units whose terminal voltage is kept at 1.0 p.u. in normal operation. Unit reactive power outputs are adjusted by operator push-button control of each generator transformer's tap changers as the tap changers are non-automatic. Following the loss of transmission lines, some units' reactive power outputs would increase substantially, perhaps above rated excitation while other units would have reactive power output less than their rating. It would be an advantage to off load the heavily excited units by the automatic action of generator tap changers but this is not the case in NSW system, nor are system operators and plant operators expected to take such action during the emergencies. Therefore, all generator transformer tap changers were locked during the entire simulation process.

5.3 Load Modelling

The loadflow package can model the loads in a variety of ways. NSW system load has been modelled as P=V, and Q=V², in effect real power as constant current load and reactive power as constant impedance load. These mixed load characteristics correspond reasonably well to test data.

The power system modelled in studies included the main grid (220kV, 330kV and 500kV), parts of 132kV network and all 330/132 kV transformers. Distribution transformers and loads at lower voltage levels were modelled as equivalent non-linear load connected to the 132kV buses. Therefore these equivalent loads include actual loads, distribution network losses, charging, etc.

5.4 Load Transformer Tap Changing

On the NSW power system 330/132kV substations are connected by 132kV circuits to 132/33kV substations. The timing for fast tap changing is 7 seconds per step on 330/132kV transformers whereas it is 60 seconds on 132/33kV transformer tap changers.

Although 132/33 kV transformers are not modelled, tap changing on these transformers will significantly affect the magnitudes of loads supplied by the 330/132kV substations. Fortunately, the fast tap changing on 330/132 kV largely overcomes this problem as there is scope for 17 tap movements in the 120 seconds before a second 132/33kV transformer tap movement. The fast response would allow 132kV voltages to recover, avoiding the need for more than one 132/33kV transformer tap change. Even if 330/132kV transformers did reach their top tap position without restoring 132kV voltage levels, the first 120 seconds after the disturbance could be simulated without losing the validity of the load models.

5.5 Generation Redistribution

Following any disturbance there would be a significant change of total load. In load flow studies of disturbances, as have been required for training the Neural Network, the results would be unsatisfactory if all demand changes were absorbed only by the swing generator.

The studies therefore used the distributed slack mode in the loadflows, by sharing the change of demand on all generators in proportion to each unit's rated output.

6. INPUTS FOR THE NEURAL NETWORK

Since an ANN with less inputs is easier to train and needs less training patterns, considerable effort was made to minimise the inputs by screening the information and selecting the most appropriate items. Two types of information are required by the neural network: information about system operating conditions immediately after the disturbance and information about the disturbance.

6.1 Information about System Conditions

An examination of system reactive power balance has identified just two parameters that are able to indicate system conditions immediately after the disturbance: total current system reactive power losses and each unit's reactive power margin. Total system reactive power losses approximately represent the prevailing operating point on the curve in Fig. 1 and so can show the trend of increase of reactive power losses. Unit reactive power margins are sufficient to represent the system's ability to cope with the oncoming increase of reactive power demand by subsequent dynamic events such as automatic transformer tap changing.

6.2 Information about the Disturbance

The disturbance itself does not cause the collapse but sets off the chain of events that lead to the reactive power shortage which produces system voltage instability. The reactive power shortage, locally or system wide, determines the severity of the voltage instability.

Therefore, instead of taking disturbance patterns such as the combinations of line outages as ANN inputs, voltage drops at key substations immediately after the disturbance have been chosen to provide a better representation for the impact of the disturbance. Total generation reactive power output change has also been selected as a supplementary indicator for describing the disturbance. Actual tests have shown that these inputs do offer sufficient information for the ANN to make correct predictions.
7. INDICATION OF VOLTAGE INSTABILITY

System voltage instability and then collapse are due to a deficiency of sustainable sources of reactive power supply. To prevent collapse and regain an acceptable voltage profile, timely load shedding in the affected regions is required if other control measures cannot restore the region's voltage levels. If there is no need to shed load the system can be considered voltage stable, otherwise the amount of load to be shed can provide a quantitative indicator of the severity of the incident.

The two criteria that determine the need for load shedding are: firstly to limit any generator reactive power to its rated output and secondly if any 330/132kV transformer tap changers is at its limiting position without regaining 132kV levels. In that event load shedding should ensure that 132kV levels meet the condition:

\[ V_{\text{schedule}} - V < 1.5\% \]

as 1.5% voltage drop is the threshold for activating an automatic tap change. If this condition is not corrected in 120 seconds after the disturbance, tap changers on 132/33kV and lower voltage transformers would continue to function and cause further reactive power losses and voltage reductions on the transmission grid. When the scheduled 132kV voltages are regained, the destabilising automatic transformer tap changing would be avoided.

There remain the question as to whether there is danger of voltage instability to the transmission grid should the 330kV bus voltage be as low as 0.92 p.u. after 132kV voltage levels have been restored. The danger only exists if overcurrent protection were to function on any one unit as this would trigger the second fast phase and subsequently system collapse.

When all generators and synchronous condensers are at or below their continuously rated excitation, this danger would be removed. By load shedding to meet these criteria, the risk to system voltage instability would be eliminated.

Ideally, an indicator should not only show the total amount of load shedding needed but also its location so as to guide operator or automatic load shedding. This could be achieved with a multiple output neural network for indicating the load shedding at each location. Though training a multiple output network is not an overwhelming problem, it was not attempted so as to minimise the work for this initial investigation. Only the total amount of necessary load shedding has been evaluated at this stage.

However in determining this total, the magnitude of load shedding at each location during the simulation process was chosen to be proportional to the local voltage drop:

\[ \Delta P = \Delta V \% \cdot P \]
\[ \Delta Q = \Delta V \% \cdot Q \]

This approach with load flow studies for the different disturbances has facilitated evaluation of the numerous cases.

8. SIMULATION PROCESS AND RESULTS

Studies have been undertaken to simulate the actual system voltage instability process following a critical disturbance by running multiple loadflows and monitoring the voltage decline at all major substations. One of the difficulties encountered with this full simulation is that the timing of generator rotor protection, which has a very large impact on the system reactive power balance which must be considered in the dynamic simulation, is unknown since it is affected by many factors such as rotor temperature prior to the disturbance, unit real power output, field forcing current during the dynamic process (which is affected by system line loss, tap changing, line charging, SVC operation, etc.), and so on. This approach would be much too time consuming for the hundreds of different cases required in determining the voltage and reactive power characteristics of the system for ANN training. Therefore a faster approach was undertaken with the following steps.

Step 1: . lock all transformer tap changers
  . set nonlinear load
  . free unit VAr limit
  . apply a fault
  . re-arrange generation when necessary.

Step 2: . release 330/132kV tap changers
  . reduce unit VAr outputs to their continuous ratings
  . shed load progressively according to above criteria
  . rearrange generation when needed
  . record results for ANN training

Step 3: . go to Step 1 to study another outage condition

Step 1 simulates the sudden disturbance occurring on the main grid. Voltage drop at major substations, total reactive power generation change, total transmission loss and reactive power margin of each unit after the disturbance are recorded.

Step 2 evaluates a stable system condition when all unit reactive power outputs are within their limits and tap changers have reached their correct positions following load shedding to meet the above criteria and regain acceptable conditions.

The NSW 330 kV main grid includes 90 buses, 9 major power stations (three of which are Snowy Mountain Council (SMC) hydro power stations), 144 lines and transformers and 30 major system load substations at different voltage levels. The generation capacity of the NSW system is 9560+j5000MVAr, and the generation capacity of the SMC is 2100+j7000MVA. Three different load profiles with total load of 10421+j2097MVA, 11463+j2306MVA and 12507+j2516MVA respectively are used in simulation for producing both training and testing patterns.

Disturbances applied to the system are single line, double line and triple line outages. For practical considerations, triple line outages are chosen from lines entering the
substation from the same side, connected to the same bus bar or in the same transmission corridor. Tests have shown that these disturbances are sufficient for an ANN to extract the voltage stability characteristics of the system.

The simulation is carried out on VAX-6000 main frame with a loadflow package. A total of 597 patterns are obtained from the simulation. A total of 32 inputs include key substation voltage drops, generating unit reactive power reserve, total generation reactive power changes and total transmission reactive power loss. The two outputs of ANN are the total active and reactive power shed as a percentage of the system generation capacity.

9. TESTS AND RESULTS

The results of the two groups of tests are shown in the tables.

9.1 Test on Line Outage

These tests examine the neural network performance when trained by line outage patterns. 548 patterns were used for training the neural network, and the remaining 49 patterns for testing the performance of ANN. Table I shows the results.

The LFS column indicates the loadflow simulation results and ANN column shows the neural network prediction. In some cases, ANN gives negative load shedding and this is due to computing error of the neural network, so the negative value can be regarded as zero load shedding or system stable.

Error column in the table shows the relative error of ANN output which is the actual error of P and Q shedding divided by the maximum amount of load shedding in the training patterns. In this simulation, the maximum load shedding in the training pattern is 1872 MW for P and 366 MVAr for Q.

The average error of ANN output is 1.11% for P and 1.18% for Q, or in actual values, 20.8 MW and 4.32 MVAr for P and Q respectively. This error is tolerable since it is only about 0.18-0.19% of total system load.

It is considered that neural network zero output (load shedding less than 0.2% or 20MW+j4MVAr can reasonably be regarded as zero) indicates that the system is stable and no control actions are needed.

On the other hand a positive non-zero output indicates the system is unstable so that load shedding is necessary. The results in the show that ANN can predict voltage instability for arbitrary line outages with a 94% accuracy.

9.2 Tests with Load Increases

The next test examined ANN performance for the effect of load increases at arbitrary locations.

System loads were divided into 10 groups at different locations with one group's loading increased to 50% and 100% above nominal, in sequence, to produce 58 cases of load increase.

Simulations are carried out on three different load levels, followed by the same line outage sequence. Two thirds of the results have been appended to the 597 line outage patterns for network training and one third of them have been used for testing the prediction performance.

The following data shows the results of the actual simulation and ANN output.

Table I Line outage test

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<th>P_shed (%)</th>
<th>Q_shed (%)</th>
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<td>LFS ANN Error</td>
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</table>

Table II shows that most of ANN output errors are below 5%, with only cases 10 and 16 having a large error. The
reason is that the pattern of voltage drop and reactive power shortage caused by the line outage may be very different from that caused by load changing at one or a group of locations. Consequently the line outage training patterns cannot adequately represent the characteristics of the voltage instability following large load changes. Should more load change patterns be produced for ANN training, a better accuracy would have been achieved.

Test 2 shows that the ANN trained mainly by line outage patterns also has the potential for predicting voltage instability caused by disturbances but the prediction accuracy was 85% because of the smaller number of load change cases.

One remarkable advantage of this ANN indicator is that when a sufficient number of patterns from various kinds of disturbances are obtained, the trained neural network can predict the voltage instability, no matter what other disturbances. The greater the number of training studies, the better will be its prediction accuracy. Creating a large number of training studies for a particular power system does not pose any great difficulties.

Another advantage is that the ANN indicator has the ability to correct bad system measurements, much as state estimators. In a mathematical sense, neural network computing is similar to curve or surface fitting of the available data, so allowing bad data to be screened out.

The investigation has shown that ANN can be used to produce an effective index for voltage instability. It is simple, fast, clear and flexible. It should be emphasised that the ANN is capable of making predictions of system voltage instability upon the system condition immediately after the disturbance. With more accurate or more comprehensive simulation of the post-disturbance dynamic process, better training patterns may be obtained to provide a better ANN performance. If required, it could be developed to indicate the quantity of load shedding at specific locations after a critical disturbance has occurred. The may well be incorporated into an automatic control to prevent system voltage instability.

Artificial neural networks will be able to provide the fast and effective indicator for the early warning of system voltage instability. This should prove a powerful weapon against the severe disturbances which have caused voltage instability and collapse on power systems throughout the world.

10. CONCLUSION

In spite of extremely unfavourable network dispositions produced by disturbances leading to system voltage instability, reported incidents describe delays of minutes before collapse had occurred.

Even though the disturbances have created far worse situations than considered by security assessments, the power system has demonstrated great resilience in withstanding their impact. This factor makes it all the more important to provide an early warning of the danger of system voltage instability and so capitalise on the stabilising forces to avoid a collapse. Artificial neural networks (ANN) offer such a facility as they could quickly recognise a dangerous situation when trained to identify system voltage instability.

By contrast, many of the indicators described in the literature show a margin to the voltage stability limit and are dependent on the computational assumptions of the complex system model. When operating beyond these limits, as has been the case after critical disturbances, the indicators cannot provide any guidance to the operators.

The paper has described the method of training an ANN to identify system voltage instability situations. By having sufficient training studies that considered a broad range of disturbance severity that a particular network, the ANN could identify a potentially stable or unstable situation with 94% accuracy. This training procedure was even able to provide a quantitative indication of the disturbance severity as the amount of load that would need to be shed to regain stable operation.

The unique feature of this proposal is that takes cognisance of the initially greater than rated unit excitation as well as the influence of automatic transformer tap changing in the initial dynamic events. In fact, it is this greater than rated excitation of rotating units which provides the power system's initial resilience to the severe disturbances, impeding collapse for a matter of minutes.

11. REFERENCES


