# Transient Stability Assessment Using Neural Networks


## ABSTRACT

This paper deals with the application of artificial neural network to the transient stability assessment of a power system. The backpropagation technique is used to train the neural networks. The use of artificial neural network for computing critical clearing time and transient energy margin for a machine infinite bus system has been illustrated. In our enthusiastic investigations we found the ideas here proposed for a single machine will be the pioneer for extension of the same to the assessment of multi machine stability.


## Introduction

A high degree of security for normal operation of larger inter connected power system is required one of the requirements of reliable service in electrical power system is to maintain the synchronous machines running in parallel with adequate capacity to meat the low demand with the growing stress on present days power systems, the potential impact of faults and other disturbances on their security is increasing. Protective relays in the power system detect faults and trigger the opening of circuit to isolate the fault. The power system can be considered to go through changes in configuration in three stages, from a prefault, faulted to a post faults system. The analysis required knowing whether following a contingency, the power system will "survive" the transients and moving to a stable operating condition is referred to as dynamic security assessment. The transient stability assessment of power system is done to appraise the system capability to with stand major contingencies and to suggest remedial actions i.e., means to enhance this capability.

## Conventional methods for transient stability assessment.

Several approaches for transient stability assessment of power systems such as numerical integration second method of Lyapunov, pattern recognition.

## Numerical integration :

In this approach transient stability analysis if performed by simulation. For given operating condition and special and specified large disturbance a time solution obtained for the generator rotor angles, speeds, terminal voltages etc., by examining the swing curves, separation of one or more generators from the rest of the system indicating loss of synchronism is detected. Even for small power network and simple mathematical model possible this method is slow and cumbersome.

## The second method of Lyapunov:

In this method, the integration off post fall system equation is replaced by stability criterion. The value of a suitably designed lyapunov function v is calculated at the instant of last switching in the system and compared with the previously determined critical value Vcr of this function if V is smaller than Vcr the system will reach a stable equilibrium point.

## Pattern recognition :

The main objective of the pattern recognition method is transient stability assessment is to reduce computational requirements to minimum this is done at the expense of elaborate off line computations. The methodology of pattern recognition consists of defining a pattern vector x whose components contain all significant variables of the system. This vector is evaluated at many representative-operating conditions to generate "training set". If some component of the pattern vector or strongly correlated with one another a process of dimensionality reduction is performing to identified significant and hopefully uncorrelated set of components. This is process is called feature extraction. The final step is to determine a function s (x) such that

s(x) = { >=0 for a secure x)

{<=0 for an insecure x)

this function is called a classifier, at once the classifier obtained, for sample x one can classify the sample as stable or unstable very rapidly. The most important task in the application of pattern recognition is the selection of primary variables because the lower limit for the classification error depends on the primary variables.

## Draw backs of conventional methods

1. The online transient stability assessment of the electrical power systems is an extremely difficult task with the available techniques.
2. Each contingency (fault) must be treated separately.
3. Smaller time step intervals are needed to ensure numerical stability.
4. Electro motive force and mechanical power inputs are assumed constant during the transient.
5. Very elaborate off line computations give scope to errors.

## Advantages of ANN over conventional methods

In order to ever come the above draw backs recently, there has been some interest in the application of ANN in the assessment of transient stability an integrated approach, compressing neural networks and conventional methods has the potential to meet the on line requirements. The application of ANN for computing critical clearing time and transient energy margin with respect to a specific contingency.

The advantages:

1. this technique has the potential of faster transient stability assessment than the other other conventional methods.
2. This technique provides the online transient stability assessment.

# About artificial neural networks

## Artificial Neural Networks

Neural-networks is one of those words that is getting *fashionable* in the new era of technology. Most people have heard of them, but very few actually know what they are. This essay is designed to introduce you to all the basics of neural networks - their function, generic structure, terminology, types and uses.

The term *'neural network'* is in fact a biological term, and what we refer to as neural networks should really be called Artificial Neural Networks (ANNs). I will use the two terms interchangeable throughout the essay, though. A real neural network is a collection of neurons, the tiny cells our brains are comprised of. A network can consist of a few to a few billion neurons connected in an array of different methods. ANNs attempt to model these biological structures both in architecture and operation. There is a small problem: we don't quite know how biological NNs work! Therefore, the architecture of neural networks changes greatly from type to type. What we do know is the structure of the basic neuron

## The Artificial Neuron

Just as there is a basic biological neuron, there is basic artificial neuron. Each neuron has a certain number of inputs, each of which have a *weight* assigned to them. The weights simply are an indication of how 'important' the incoming signal for that input is. The *net value* of the neuron is then calculated - the *net* is simply the weighted sum, the sum of all the inputs multiplied by their specific weight. Each neuron has its own unique threshold value, and it the *net* is greater than the threshold, the neuron fires (or outputs a 1), otherwise it stays quiet (outputs a 0). The output is then fed into all the neurons it is connected to.

## Design

The developer must go through a period of trial and error in the design decisions before coming up with a satisfactory design. The design issues in neural networks are complex and are the major concerns of system developers.

### Designing a neural network consist of :

- Arranging neurons in various layers.
- Deciding the type of connections among neurons for different layers, as well as among the neurons within a layer.
- Deciding the way a neuron receives input and produces output.
- Determining the strength of connection within the network by allowing the network learn the appropriate values of connection weights by using a training data set.

## Learning

The brain basically learns from experience. Neural networks are sometimes called machine learning algorithms, because changing of its connection weights (training) causes the network to learn the solution to a problem. The strength of connection between the neurons is stored as a weight-value for the specific connection. The system learns new knowledge by adjusting these connection weights.

The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training.

The training method usually consists of one of three schemes:

### 1. Unsupervised learning

The hidden neurons must find a way to organize themselves without help from the outside. In this approach, no sample outputs are provided to the network against which it can measure its predictive performance for a given vector of inputs. This is learning by doing.

## 2. Reinforcement learning

This method works on reinforcement from the outside. The connections among the neurons in the hidden layer are randomly arranged, then reshuffled as the network is told how close it is to solving the problem. Reinforcement learning is also called supervised learning, because it requires a teacher. The teacher may be a training set of data or an observer who grades the performance of the network results.

Both unsupervised and reinforcement suffer from relative slowness and inefficiency relying on a random shuffling to find the proper connection weights.

## 3. Back propagation

This method is proven highly successful in training of multilayered neural nets. The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connections between the layers, thus improving performance. A form of supervised learning.

## Off-line or On-line

One can categorize the learning methods into yet another group, off-line or on-line. When the system uses input data to change its weights to learn the domain knowledge, the system could be in training mode or learning mode. When the system is being used as a decision aid to make recommendations, it is in the operation mode, this is also sometimes called recall.

## Backpropagation training algorithm:

It is systematic method of training the ANN in this algorithm weights and thresholds are adjusted in the following manner.

$$\phi R = \sum \Delta W jk (n+1) \eta \delta k OUTj + \Delta Wjk (n)$$

$$W jk (n+1) = W jk (n) + \Delta Wjk (n+1)$$

$$\Delta\theta k (n+1) = \eta\delta\kappa + \Delta\theta k (n)$$

$$\theta k (n+1) = \theta k (n) + \Delta\theta k (n+1)$$

Where, $\delta\kappa$ = (TARGET k- OUT k ) (1-OUT k ) OUT k

$\lambda$= Gain Scale factor.

$\eta$= Learning rate, typically less than 10 used to limit the rate of change of weights.

$\delta$= Momentum co-efficient which determines the inertia of the weight adjustment these training parameters can be varied to make training more efficient. The optimum values of these parameters depend on the nature of the problem.

# TRANSIENT STABILITY ASSESSMENT (TSA) OF A MACHINE - INFINITE BUS SYSTEM

A Single machine connected to a infinite bus through double circuit line has been considered for TSA using ANN.

In this approach critical clearing time is computed for a given net work topology and loading conditions for certain contingency. If critical clearing time is greater than the actual fault clearing time then the system is stable otherwise it is unstable. The transient stability assessment can also be done with the use of transient energy margin as stability index.

## Computation of critical clearing time :

For each operating condition in the training set, the CCT has been determined using the following steps.

1. Using well known equal area criterion the critical angle is computed

   $\delta c = \cos^{-1} \{\delta m - \delta o) \sin \delta o - r1 \cos \delta o + r2 \cos\delta m) / (r2-r1)$

   where $\delta o$ is the prefault rotor angle.

   $\delta m$ is maximum power angle for stability

   $\delta m = \Pi - \sin^{-1} (\sin \delta o/r2)$

   $r2 = P\ max\ 3 / P\ max1$

   $r1 = P\ max2 / P\ max1$

where P max1, P max2 , P max3 are the maximum power transferred in prefault , during fault and post fault conditions respectively.

## 2. The Swing Equation:

$$M \frac{d\delta}{dt2} = Pm - P\,max \sin \delta$$

Is solved using “step by step method” up to critical clearing angle to obtain critical clearing time for a given fault clearing time Tcl .

the system is stable if Tcl < CCT
the system unstable if Tcl > CCT

## Input parameters:

The input vector of the training pair consists of :

1. Rotor angle at the instant of fault initiation i.e., I1 = δo
2. initial acceleration parameter I2 = (Pm - Pe ) /M
3. III input is : I3 = (Pm - Pe ) 2 /M

With assumption of the constant mechanical power during the fault and almost constant generator output Pe .The second parameter gives a measure of rotor angle deviation at the instant of fault clearing relative to their pre fault values under the same assumption the third input parameter provides information and the kinetic energy of the generator accumulated fault during fault on period.

## Transient stability assessment based on Transient energy margin as stability index

The transient energy margin (TEM) is defined as the difference between the potential energy at un stable equilibrium point (UEP) and the sum of the potential energy and the kinetic energy at the fault clearing time. The potential energy is associated with the machine torque angle the potential energy between any two transient states is the net area between the post fault power out put curve and the turbine power out put, de limited by the torque angle at the two transient states The figure illustrates the use of equal area criterion. This may interpreted using the transient kinetic energy and potential energy concepts. Area A1 is a measure of the energy delivered by the turbine during the fault. This area may be considered as the kinetic energy stored in the machine due to differences between instantaneous frequency and that of the rest of power system. The kinetic energy at the fault clearing is equal area A1. Area A3 gives the potential energy with respective post fault stable equilibrium point, accumulated during the fault on period. The area A2 + A3 represents the potential energy at unstable equilibrium point which is also known as “Critical Energy” .

According to the definition:

Transient Energy Margin = (A2+A3) - (A1+A3) = A2-A1

= Decelerating area - Accelerating area

The positive energy margin indicates a stable system. A small energy margin indicates that the power system is very close to instability and power system operator can initiate preventive control actions to widen the energy margin.

### Computation of Transient Energy Margin:

For machine infinite bus system the energy margin is computed by calculating the accelerating and decelerating areas. Fault clearing angle is obtained by integrating the swing equation up to fault clearing time.

Area A2 = $P_{max3}(\cos\delta_{cl} - \cos\delta_{\upsilon}) - P_m(\delta_{\upsilon} - \delta_{cl})$

Area A2 = $P_{max2}(\cos\delta_{cl} - \cos\delta_{o}) - P_m(\delta_{cl} - \delta_{s})$

Where $\delta_{cl}$ is fault clearing angle. $\delta_{\upsilon}$ is unstable equilibrium angle.

### Input parameters

The input parameters which are fed to ANN are the following:

1. Pm -mechanical power input to generated.
2. T ke - Total kinetic energy at the fault clearing time given by area A1
3. T pe - Total potential energy at the fault clearing it is given by the area A3 which is computed as

   Area A3 = Pmax3 (cos $\delta$s- cos $\delta$cl )- Pm($\delta$cl $-\delta$s)
4. V m -Terminal Voltage of the Generator
5. $\delta$cl - Rotor angle at fault clearing time
6. $\Delta$ Wcl - change in the speed of the generator at fault clearing time obtained by integrating the swing equation up to fault clearing time

## Training of ARTIFICIAL NEURAL NETWORK:

For the input parameters provided above are computed. For each operating point corresponding transient energy margin has been computed. The training set consisted of six dimensional patterns labeled with their corresponding transient energy margin value.

The training set has been normalized before applying it to the artificial neural network. This normalizing set is applied to the neural network which consists of four units in the single hidden layer.

The least square error which is defined as :

$$E = \frac{1}{2} \sum_{P} (\text{Target - out})^2$$

Where P = 1 to N patterns. After the network is trained its performance is evaluated using data which are nor part of training set it can be seen that TEM computed using ANN agree with the TEM computed by EAC the difference between the two can be eliminated using more number of training pairs so that training is complete.

**CONCLUSIONS**

A neural network approach for fast assessment of the transient stability of a machine infinite bus system has been developed. The proposed method can be used to a develop a comprehensive on-line dynamic security package for energy management system thus enhancing the overall security of the power systems. Studies need be carried out using ANN for TSA of a multimachine system considering change in network topology, fault clearing time and different loading conditions

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