EFFECTIVENESS OF ARTIFICIAL NEURAL NETWORKS FOR FIRST SWING STABILITY DETERMINATION OF PRACTICAL SYSTEMS.

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Abstract - **The paper presents an evaluation of the effectiveness of Artificial Neural Networks for rapid determination of critical clearing times for practical networks with varying line outages and load patterns. Studies are reported on the performance of Artificial Neural Networks which have been trained using previously-proposed and new training items. It is concluded that Artificial Neural Networks have difficulty in returning consistently accurate answers under varying network conditions.**

INTRODUCTION

Considerable activity has centred in recent times on the practical application of Artificial Neural Networks (ANN) to power systems. Candidate application areas include voltage control [1,2], system security [3,4,7,8], dynamic stability [5,12], steady state stability [14,19,34], short-term load forecasting [6,9,10,11], machine control [13], harmonic monitoring [15], and protection [16]. However, despite major research efforts the literature suggests that there have been very few practical applications for ANN in the field of power systems engineering. The situation with respect to practical applications of ANN contrasts with the adoption of other artificial intelligence techniques such as expert systems [18] and fuzzy technology [36]. This contrast could be a due to the current imperfect state of knowledge of ANN, despite its long history [17], or it could be due to attempts to apply ANN to inappropriate problems.

The authors have explored the effectiveness of ANN in one of its potential applications, that of the on-line determination of first swing stability of electrical power systems. Investigations have included currently proposed techniques [19] and enhancements which are discussed here. After exhaustive testing of the techniques on two practical systems of small to medium size it is concluded that at present there are inherent limitations of ANN which inhibit its use in this application.

Essentially the problem is the apparent inability of ANN to accommodate relatively minor deviations in power system operating conditions and topology.

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FIRST SWING STABILITY

The degree of modelling required for stability studies depends largely on the purposes for which the proposed stability studies are required [27].

Short-term studies of the first swing type approximate the behaviour of the system up to the first second after a major disturbance. Governor and boiler time constants are too long to significantly influence such short time outcomes and are therefore ignored. It is further assumed that fast acting excitation will hold the machine internal voltage constant. These are the classical assumptions used in the derivation of the equal area criterion for first swing stability [35] and are adopted for studies with ANN reported here.

For studies which must cover a period of more than 1 second, detailed modelling of machines and their control systems may be required. For studies in the mid-term range of up to about 5 minutes, a detailed boiler model will be required [20]. For long-term studies other factors need to be considered such as thermal overloading of lines and load shedding [21].

CRITICAL CLEARING TIME

The concept of Critical Clearing Time (CTT) is well known [35]. It represents the maximum time that a particular fault can be allowed to persist on a system before instability will inevitably arise. The most consistently reliable method for obtaining the CCT is to apply a fault and to analyse the system behaviour in the time domain. This method of obtaining the CCT is very time consuming and is most suitable for off-line design or planning work rather than for on-line operational purposes.

The problem of on-line determination of CCT associated with first swing stability is considered here, and a simple machine model is adopted comprising a fixed mechanical power input and a constant internal voltage behind the transient reactance. This model is consistent with that used for the equal area criterion.

METHODS OF FAST ASSESSMENT OF CRITICAL CLEARING TIME

Several attempts have been made to develop fast methods for assessing the CCT of a system.

One method is to explore the stability of non-linear differential equations using techniques developed by Liapunov in the 1890's. [22,23,31,32]. In this approach an attempt is made to establish a stability region within which the system is stable.

Several problems arise in the application of the Lyapunov method, and to date it appears to have had only limited practical application [33]. A major problem is the choice of an appropriate Liapunov Function [24].

Another method for rapid transient stability assessment is the use of Pattern Recognition [25,26]. There are some similarities to the use of a trained ANN as described below.

Application of ANN to the determination of CCT removes the necessity for on-line time domain solutions since the trained ANN is simply presented with data on the current system operating state and the CCT is provided as output.

In order to ensure adequate training of an ANN it is necessary to use a sufficiently large number of CCT's assembled with other information into sets of training facts. A useful ANN should be trained under a range of different system loading conditions and pre-existing line out conditions

USE OF ARTIFICIAL NEURAL NETWORKS

There are many readily available publications on the subject of ANN [17,28,29,30]. Consequently only a brief outline of ANN will be given here.

Neural networks fall into two separate types. The first is where the network is not given the required answer during training. An example is the Kohonen network. The second is the directed training type where the network is provided with the answer during training and adjustments are made to the 'weights' associated with the connections between layers of the neural network by a process of back propagation.

A Back Propagation ANN consists of a number of neurons arranged in a series of layers. Each of the neurons in each layer is connected to each neuron in the preceding and succeeding layers by connections of variable strengths or adjustable 'weights'. There are no connections between neurons occupying the same layer. The values of the inter-layer weights are adjusted by repeatedly presenting training data in cycles. When the network is able to give the correct output within prescribed limits on presentation of the corresponding input data the network is said to be trained.

In the case of the Back Propagation ANN there will always be an input layer and an output layer and one or more hidden layers. Each item of input data will have an associated input neuron and each item of output data will have an associated output neuron. In the case of first swing stability the only output is the CCT.

The optimum number of neurons in the hidden layer, and the number of hidden layers, is determined on a heuristic basis, although it has been shown that one hidden layer can approximate arbitrarily well any continuous function. [31].

Training Facts

A number of items relating to the system conditions are assembled into sets, each of which is known as a training fact. As many training facts as necessary to ensure adequate training are presented to the ANN during the training phase. The selection of the training items used to form the training facts is of critical importance to the success of operating an ANN.

Since the intention is to provide fast, on-line assessment of CCT, it is necessary to ensure that the input data required for interrogating the ANN is readily available. Steady state power system network solutions can be obtained very rapidly, and provide a rich source of information for ANN training and interrogation.

Training Items

Training items comprise useful information obtained from a series of steady-state network solutions in the intact, faulted and fault-cleared states. Constant data, such as machine inertias, is not useful data for the ANN since there is no pattern to identify. As indicated earlier, the CCT obtained from dynamic time-domain analysis is also included as a training item .

For steady-state solutions the network is reduced to the internal machine buses and their equivalent interconnections. The internal voltages and mechanical power inputs on the individual machines are held constant. The items comprising a training fact were then chosen as follows:

Item 1

Accelerating power for each machine immediately following the application of a fault

$$P_{ai} = P_{mi} - P_{ei} \tag{1}$$

where

P_{ai} is the accelerating power available, machine 'i'

P_{mi} is the mechanical input power, machine 'i' (mechanical power is equal to the initial steady state electrical load on the machine plus machine losses)

P_{ei} is the electrical output power, machine 'i' (electrical power output is calculated under the specified network conditions)

Dividing the accelerating power by the machine inertia M_i as proposed in [19] was investigated. Such a variation is equivalent to scaling, since this item in all training facts is modified in the same way. No improvement in the performance of the ANN was observed.

Item 2

Accelerating power squared for each machine immediately following the application of a fault. In [19] this item was scaled by dividing by the machine inertia and is claimed to give information on individual machine accelerating energy.

Item 3

Rotor angle for each machine relative to the centre of inertia [32], with the faulty line removed.

$$\delta_{di} = \delta_{mi} - \delta_{coi} \quad (2)$$

where

δ_{di} is equal to the angular deviation of rotor 'i' with respect to the system centre of inertia [32]

δ_{mi} is the rotor angle, machine 'i'

δ_{coi} is the system centre of inertia

Item 4

Driving point susceptance B_{ii} for each machine internal bus following removal of the faulted line. This represents the post-fault strength of the connection of the machine to the rest of the network.

Item 5

Total system "energy adjustments"

$$EN = \sum_{i=1}^{n} (P_{ai} \cdot \delta_{di}) \quad (3)$$

where

EN is defined as the energy adjustments in the system

n is the number of machines in the study

Item 6

Critical Clearing Time (CCT)

The maximum set of training items for each training fact therefore comprises four items per machine and two items relating to the system.

Table I: Items Used in Each Training Fact

Machine Items	P_{ai} fault on	P_{ai}^2 / M_i fault on	δ_{di} post fault	Bii post fault
System Items	EN	CCT		

The training items were tried in all possible combinations from the use of two items per training fact up to the maximum of six, one of which was always the CCT.

It is important to ensure that the range of the training data in the training facts presented to the ANN is adequate for the problem being posed. A neural network may be thought of as a very good interpolator but its powers of extrapolation are limited, if indeed they exist at all. It is essential that interrogation of the neural network is within the range of the set of training facts on which the network has been trained.

Pre-Conditioning of Training Items

When the training items are first assembled as training facts they may not be in the most effective form for training. Pre-conditioning of the training data, such as scaling, is generally necessary, and an approach similar to that used for pattern recognition [38] was applied. Various ways of pre-conditioning data were used in attempts to improve training including dividing each item of the raw data by the maximum value in the set, dividing through by the average and dividing through by the variance. This is an interesting area for future research since training was found to be significantly influenced by pre-conditioning. No general rule is proposed here, although dividing each set of items by the average appeared to be a useful first step.

When training a neural network it is a matter of chance whether a satisfactory ANN is obtained. Should the neural network not train satisfactorily, or show signs of becoming unstable after a few thousand training cycles, it may be necessary to randomise the weights or to try a variation of the pre-conditioning and hope that the next training solution is more satisfactory.

PERFORMANCE OF THE ANN

Studies were performed on two small to medium capacity Australian systems.

Table II: System Parameters

	System 1 [34]	System 2
Total load	2000 MW	7000 MW
Generating stations	4	20
Buses	12	106
Lines	16	156
ANN		
Number of Layers	3	3
Number of input neurons	17	81
Number of hidden neurons	17	68
Number of output neurons	1	1

A four layer ANN with various numbers of neurons in the two hidden layers was tried on the first system but there appeared to be little improvement in performance. By some criteria the number of neurons in the hidden layer of the three layer ANN's appears excessive but fewer numbers of neurons resulted in diminished performance. Increasing the number of neurons in the single hidden layer of the three layer ANN defined above did not appear to improve performance.

Training

To obtain training facts the first system was solved at five load levels and generation patterns. In addition, solutions were obtained at each of the five load levels under three different topological conditions. In the first condition all lines were in service. In the second condition a significant line was removed. In the third condition a different significant line was removed.

For each of the fifteen system operating conditions referred to above, a fault was applied to a bus to simulate a line fault close to that bus. The faulted line was then removed and the CCT for this location and condition was obtained. This process was repeated until every line in the system had been faulted in turn at each end. When the training facts had been assembled, the ANN was subjected to 20,000 training cycles.

Extensive testing was carried out to determine the relative training effectiveness of the various items. It appeared that none of the items was effective individually for training the neural network but that all contributed to some extent in producing a trained neural network when used together. All items were used for the results which follow.

Table III: Training Performance - Test System No. 1
Small Variations in Network Conditions

Study	Load Pattern	System Conditions	Maximum Seconds	Error Per Unit
a1	1	intact	0.14	0.25
a4	2	intact	0.02	0.07
a7	3	intact	0.02	0.08
a10	4	intact	0.03	0.07
a13	5	intact	0.12	0.20
a2	1	'a' line out	0.13	0.27
a5	2	'a' line out	0.03	0.07
a8	3	'a' line out	0.01	0.04
a11	4	'a' line out	0.01	0.03
a14	5	'a' line out	0.07	0.16
a3	1	'b' line out	0.10	0.22
a6	2	'b' line out	0.02	0.05
a9	3	'b' line out	0.03	0.10
a12	4	'b' line out	0.02	0.09
a15	5	'b' line out	0.10	0.19

The training performance of the ANN was assessed by examining the maximum per unit error of the presented CCT's. If the maximum error was less than 0.1 per unit the ANN was considered to be satisfactorily trained.

In Table III the performance of the network is acceptable for load patterns 2, 3, and 4 but the results are poor for patterns 1 and 5

When more variable conditions were included, the error occasionally rose to an unacceptable level of up to 0.5 per unit. Table IV presents the maximum error obtained from many sets of training facts devised from the first test system.

Table IV: Training Performance - Test System No 1
Large Variations in Network Conditions

Study	Maximum Seconds	Error Per Unit
aint	0.13	0.35
aalo	0.13	0.32
ablo	0.12	0.31
all	0.23	0.40

aint system intact with five load patterns
(Includes studies a1, a4, a7, a10, a13)

aalo line 'a' out with same five load patterns
(Includes studies a2, a5, a8, a11, a14)

ablo line 'b' out with same five load patterns
(Includes studies a3, a6, a9, a12, a15)

all Combined above three studies
(Includes all studies a1 to a15)

The second system was considerably larger than the first system and additional difficulties were encountered. Much more time was required to calculate the many CCT's need for the training facts and the times for training the ANN also increased sharply. Although a number of attempts were made to apply ANN techniques to this system it proved to be intractable.

Interrogation

The trained ANN, when presented with previously unseen facts, produces a series of CCT's which ideally should closely approximate the CCT's determined by the traditional time domain method.

In the course of this investigation many of the presented facts did result in very low errors, but there were also many which resulted in unacceptably large errors. Table V presents the largest error obtained from interrogations on the trained ANN.

Table V: Interrogation Performance - Test System No 1
Large Variations in Network Conditions

Study	Maximum Seconds	Error Per Unit
aint	0.13	0.26
aalo	0.05	0.18
ablo	0.05	0.18
all	0.11	0.36

DISCUSSION

Considerable difficulties were experienced in training the ANN, The ANN could produce good results towards the middle of the CCT training range but values at the extremities tended to become unacceptable as can be seen in Table III. Various subterfuges were adopted in attempts to emphasise the end values. The obvious method of increasing the number of training facts present at the extremities did not have the desired effect and this remains a problem.

Increasing the training from 20,000 to 120,000 and 220,000 cycles did not improve the performance significantly. The technique of polling a number of ANN's trained on differently randomised untrained networks [37] also failed to improve performance.

As could be expected, the ANN generally trained better when all data came from a network with conditions which varied very little. Under these conditions the maximum training error of a collection of data could easily be below 0.1 per unit.

An ANN which is generally well trained will nevertheless occasionally produce erratic and erroneous results when interrogated with new facts. This unpredictable behaviour would generally be unacceptable in practice.

Despite extensive training using many different sets of training facts and various methods of pre-conditioning it was not possible to obtain a satisfactorily trained ANN under significantly varying network conditions.

The reason for the poor performance of the ANN on this particular problem is open for conjecture. It seems likely that the difficulty stems from widely varying network conditions and fault locations leading to very similar CCT's, whereas quite different CCT's can arise from relatively small variations in network conditions such as choice of fault location. Under such circumstances no pattern may be able to be found, even by an ANN.

CONCLUSION

The range of CCT errors from the ANN on interrogation by previously unseen facts, and in some cases facts which have been used in the training process, is at present too large for use of this method on a practical system.

REFERENCES

[1] T.Haida and T.Akimoto, "Genetic Algorithms Approach to Voltage Optimisation," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 139-143

[2] S.V.Vadari, "A Hybrid Artificial Neural Network/Artificial Intelligence Approach for Voltage Stability Enhancement," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 154-160

[3] V.S.S.Vanakalaya, "Power System Security Enhancement Using a Coupled ANN-ES Scheme," *Expert System Application to Power Systems 4,* Melbourne January 1993, pp. 275-284

[4] M.Aggoune, M.A.El-Sharkawi, D.C.Park, M.J.Damborg and R.J.Marks, "Preliminary Results Using Artificial Neural Networks for Security Assessment," *IEEE Transactions on Power Systems,* Volume 6, May 1991, pp. 890-896

[5] H.Mori, Y.Tamaru, and S.Tsuzuki, "An Artificial Neural-Net Based Technique for Power System Dynamic Stability with the Kohonen Model," *IEEE Transactions on Power Systems,* Volume 7, May 1992, pp. 856-864

[6] D.C.Park, M.A.El-Sharkawi, R.J.Marks, L.E.Atlas, and M.J.Damborg, "Electric Load Forecasting Using an Artificial Neural Network," *IEEE Transactions on Power Systems,* Volume 6, May 1991, pp. 442-449

[7] M.Aggoune, M.A.El-Sharkawi, D.C.Park, M.J.Damborg, and R.J.Marks, "Preliminary Results Using Artificial Neural Networks for Security Assessment, discussion," *IEEE Transactions on Power Systems,* Volume 6, August 1991, pp. 1324-1325

[8] A.B.R.Kumar, A.Ipakchi, and V.Brandwajn, "Neural Networks for Dynamic Security Assessment of Large Scale power Systems:" Requirements Overview, *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 65-71

[9] D.C.Park, O.Mohammed, M.A.El-Sharkawa, and R.J.Marks, "An Adaptably Trainable Neural Network Algorithm and its Application to Electric Load Forecasting," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 7-11

[10] K.Y.Lee, Y.T.Cha, and C.C.Ku, "A Study on Neural networks for Short-Term Load forecasting," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 26-30

[11] G.Lambert-Torres, C.O.Traore, F.G.Mandolesi, and D.Mukhedkar, "Short Term Load Forecasting Using a Fuzzy Engineering Tool," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 36-40

[12] H.Mori, "An Artificial Neural-Net Based Method for Estimating Power system Dynamic Stability Index," *Proceedings of the First International Forum on Applications of Neural Networks to Power Systems,* Seattle, July 1991, pp. 127-133

[13] Q.H.Wu, B.W.Hogg, and G.W.Irwin, "A Neural Network Regulator for Turbo Generators," *IEEE Transaction on Neural Networks,* Volume 3, January 1992, pp. 95-100

[14] Chao-Rong Chen and Yuan-Yih Hsu, "Synchronous Machine Steady State Stability analysis Using an Artificial Neural Network," *IEEE Transactions on Energy Conversion,* Volume 6, No 1, March 1991, pp. 12-20

[15] R.K.Hartana and G.G.Richards, "Harmonic Source Monitoring and Identification Using Neural Networks," *IEEE Transactions on Power Systems,* Volume 5, November 1990, pp. 1098-1104

[16] S.Ebron, D.L.Lubkeman, and M.White, "A Neural Network Approach to the Detection of Incipient faults on Power Distribution Feeders," *IEEE Transactions on Power Delivery,* Volume 5, April 1990, pp. 905-914

[17] Igor Aleksander, *"Neural Computing Architectures, The Design Of Brain-Like Machines,"* MIT Press, Cambridge, Massachusetts, 1989

[18] Z.Z.Zhang, G.S.Hope, and O.P.Malik, "Expert Systems in Electrical Power Systems - A Bibliographical Survey," *IEEE Transactions on Power Systems,* Volume 4, November 1989, pp. 1355-1362

[19] D.J.Sobajic and Y.H.Pao, "Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems," *IEEE Transactions on Power Systems,* Volume 4, February 1989, pp. 220-228

[20] *"Mid Term Simulation of Electric Power Systems,"* EL 596, Project 745, Electric Power Research Institute, June 1974

[21] *"Long Term Power System Dynamics,"* Research Project 90-7, Electric Power research Institute, April 1974

[22] S.Lefschetz, *"Differential Equations: Geometric Theory,"* Dover Reprint, New York, 1977, p. 381

[23] B.Toumi, R.Dhifaoui, Th.Van Cutsem, and Ribbens-Pavella, "Fast Transient Stability Assessment Revisited," *IEEE Transactions on Power Systems,* Volume PWRS-1, May 1986, pp. 211-220

[24] O.Gurel and L.Lapidus, *"A Guide to Methods for the Generation of Liapunov Functions,"* International Business Machines Corporation, New York, March 1968

[25] D.R.Ostojic and G.T.Heydt, "Transient Stability Assessment by Pattern Recognition in the Frequency Domain," *IEEE Transactions on Power Systems,* Volume 6, February 1991, pp. 231-237

[26] C.K.Pang, F.S.Prabhakara, A.H.El-Abiad, and A.J.Koivo, "Security Evaluation in power Systems Using Pattern Recognition," *IEEE Transactions on Power Systems,* Volume PAS 93, May/June 1974, pp. 969-976

[27] B.Stott, "Power System dynamic Response Calculations," *IEEE Proceedings,* Volume 67, February 1979, pp. 219-241

[28] D.Waltz and J.A.Feldman (eds.), *"Connectionalist Models and Their Applications,"* Ablex Publishing, New Jersey, 1988

[29] M.Caudel and C.Butler, *"Naturally Intelligent systems,"* MIT Press, Cambridge Massachusetts, 1989

[30] J.E.Dayhoff, *"Neural Networks and Architecture,"* Van Nostrand Reinhold, 1990

[31] T.Poggio and F.Girosi, *"A Theory of Networks for Approximation and Learning,"* Massachusetts Institute of Technology, July 1989

[32] M.A.Pai, *"Power System Stability,"* North Holland Systems and Control Service, Volume 3, North Holland Publishing Co., Amsterdam, 1981

[33] O.Saito, et.al., "Security Monitoring Systems Including Fast Transient Stability Studies," *IEEE Trans Power Apparatus and Systems* 94, pp. 1989, 1975

[34] G.N.Allen, E.Hobson and L.Jain, "Investigation of the Transient Stability Problem Using Artificial Neural Networks," *Australian Universities Power and Control Engineering Conference,* October 1992, pp. 279-284

[35] W.D.Stevenson, *"Elements of Power System Analysis,"* McGraw Hill, 1975

[36] D.G.Schwartz, "Fuzzy Logic Flowers in Japan," *IEEE Spectrum,* Volume 29, July 1992, pp. 32-35

[37] L.K.Hansen, and P.Salamon, "Neural Network Ensembles," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Volume 12, October 1990, pp. 993-1001

[38] P.T.Moseley, J.Morris, and D.Williams (eds.), *"Techniques and Mechanisms in Gas Sensing,"* Adam Hilger Series on Sensors, 1991, pp. 345-381

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Discussion

L.L. LAI and F. NDEH-CHE, (Energy Systems Research Group, City University, London EC1V 0HB, England, UK): The authors are to be commended for presenting an interesting paper. The discusser offers the following comments on the paper:

Neural Networks (NNs) have recently attracted a great deal of attention owing to their ability to learn most classes of nonlinear continuous functions with bounded inputs and outputs to arbitrary precision. This learning and versatile inupt-output mapping capabilities together with parallel and collective processing abilities lead to applying NN to identification and controlling of nonlinear dynamical systems.

As the authors used the back-propagation neural networks which could be useful when applying to test patterns that have a high correlation with the training patterns because back-propagation networks are, in general, not self-learning; it is not surprised to see that the authors are not able to obtain a satisfactory result when testing the network with different system conditions.

It will be helpful if the authors could identify the different input used in the two systems as described in the paper so as to account for the number of input neurons used.

The finding from the discussers as reported in reference [A] is that the learning rate, momentum factor, number of neurons in the hidden layer are important to the stability and performance of the neural network, if the authors have also carried out this investigation, the discussers would be pleased to know about the results.

Reference

[A] L.L. Lai et al., 'Fault diagnosis in HVDC systems with neural networks', Preprints of Papers, 12th IFAC World Congress, Sydney, Australia, International Federation of Automatic Control, Vol 9, July 1993, 179-182.

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E.HOBSON, G.N.ALLEN (University of South Australia): The authors wish to thank Dr L.L.Lai and F.Ndeh-Che for their encouraging remarks. In answer to the various matters raised by the discussers the following comments are made.

The authors have experimented extensively with all available ANN factors such as training rates, momentum factor, number of hidden layers and number of neurons per hidden layer. Each ANN application appears highly idiosynchratic, and generalised conclusions are hard to draw. In our case no advantage couid be found for increasing the number of hidden layers above one, and having more neurons per hidden layer than contained in the input layer.

The items used in constructing the training facts used for the two sample power systems were identical. That is in both cases there were 4 items relating to each machine and one system energy function. The specification of these items is described in the paper under the heading "Training Items".

Since publishing the paper a considerable amount of work has been carried out and some of the most recent results are promising. Instead of using the critical clearing time as the target value, the ANN is now trained to a single system stable or unstable criterion. Using this amended training target, and after making appropriate adjustments to the output of the ANN, it has been found possible to obtain the correct answer in all cases studied. The previous limitations on the degree of difference in network structure remain, and it is still not possible to mix system topologies or generating conditions.

It has also been found that the application of coherency techniques to power systems has the potential to greatly reduce the size of the ANN without any apparent loss in performance. The stable/unstable training criterion has been applied to 3 power systems having 4, 5, and 10 power stations using a coherency reduction program and errorless results have been obtained.

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