

ANN Based Critical Clearing Time Determination for IEEE 9 Bus System

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Abstract— This paper presents Artificial Neural Network based critical clearing time (CCT) calculation for IEEE-9 bus system. The critical clearing time (CCT) at the critical contingency is considered as an index for transient stability. By selecting loads and generators active and reactive power as a input neurons critical clearing time is determined. The modeling and simulation results for load flow and CCT calculations are accomplished using the simulation package ETAP. The ANN training and testing is implemented in MATLAB software

Keywords—component, formatting, style, styling, insert (key words)

I. INTRODUCTION

The transient stability plays an important role in power system stability assessment. It deals with electromechanical oscillation of synchronous generators, created by a disturbance in the power system. It is determined by observing the variation of the rotor angle as a function of time in the fault period. The stability analysis of power system may involve the calculation of Critical Clearing time (CCT) for a given fault which is nothing but, the maximum allowable value of the clearing time for which the system remains to be stable. If the fault is cleared within this time, the power system remains stable. However, if the fault is cleared after the CCT, the power system is most likely to become unstable. Thus, the estimation of CCT is an important task in the transient stability analysis for a given contingency. In this paper, an IEEE 9 Bus system is considered for the Transient Stability Analysis.

Critical clearing time (CCT) is a measurement of power systems Transient stability. It denotes the secure time for clearing the contingency, usually three-phase ground-fault. A large value of CCT indicates that the power system has ample time to clear the contingency. CCT depends on generator inertias, line impedances, grid topology, and power systems operating conditions, fault type and location. For a single machine infinite bus power system, CCT calculations are straight forward. While for the case of multi-machine power systems, CCT is always obtained by time-domain simulations, and hence the evaluation of CCT can only be done off-line [1, 2].

Fast and efficient methods for transient stability analysis have been sought due to the increase in size and complexity of power systems. A variety of methods for transient

stability assessment have been proposed in the power systems literature. These are numerical integration, direct methods, probabilistic methods and pattern recognition methods. To reduce the computation burden and implement on-line assessment, a number of studies have applied artificial neural networks (ANN) to calculate the CCT for multi-machine power systems [3–10].

This paper presents a feasibility study of artificial neural networks (ANNs) for transient stability assessment for power systems. The ANNs use the system operating variables such as generator's output power and load demand as inputs. Section II describes the simulation of the IEEE 9-bus test system in ETAP. Section III gives a brief description of the extended equal area criteria and its use in the calculation of the critical clearing time of a test power network. The training and the application of the neural network for transient stability assessment are described in Section IV. The presentation and discussion of the results are given in Section V. The paper's conclusions are presented in Section VI.

II. SIMULATION OF THE IEEE 9 BUS SYSTEM

The IEEE 9-bus test system is simulated on ETAP 7.5.1. The single line diagram (SLD) of the simulated test system on ETAP is shown in Fig 1. For this test system generator and line parameters are given in appendix. The total generation is 519.5 MW and total load is 315 MW. The test system contains 6 lines connecting the bus bars in the system. The generator is connected to network through step-up transformer at 230 kV transmission voltage. The results of load flow analysis when all generators and loads are operating at rated power are given in Table.1

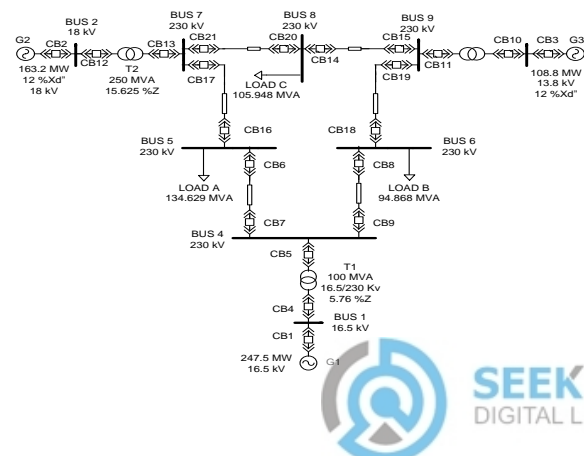


FIG. 1 SINGLE LINE DIAGRAM OF IEEE-9 BUS TEST SYSTEM

TABLE.1 LOAD FLOW REPORT

Bus No.	Bus KV	Voltage Mag. (%)	Voltage Angle	Gen. (MW)	Gen. (MVAR)	Load (MW)	Load (MVAR)
Bus 1	16.5	104.0	0.0	70.074	36.848	0	0
Bus 2	18.0	102.5	9.5	163.00	21.017	0	0
Bus 3	13.8	102.5	4.7	85.00	-5.165	0	0
Bus 4	230	101.918	-2.1	0	0	0	0
Bus 5	230	98.088	-3.8	0	0	120.70	48.099
Bus 6	230	100.615	-3.7	0	0	91.112	30.365
Bus 7	230	101.505	3.9	0	0	0	0
Bus 8	230	100.722	0.8	0	0	101.454	35.494
Bus 9	230	102.795	2.0	0	0	0	0

III. CALCULATION OF CRITICAL CLEARING TIME USING EEAC

A great interest has been raised on EEAC, since it was proposed in literature [12-16], because it is able to yield fast and accurate transient stability analysis. In order to determine the stability of the power system as a response to a certain disturbance, the extended equal area criterion (EEAC) method described in [16] decomposes the multi-machine system into a set of critical machine(s) and a set of the 'remaining' generators. The machines in the two groups are aggregated and then transformed into two equivalent machines to form a One-machine-Infinite-Bus (OMIB) system. Some basic assumptions for EEAC are : (i) The disturbed system separation depends upon the angular deviation between the following two equivalent clusters the critical machine group (cmg) and the remaining machine group (rmg), (ii) The partial centre of angles (PCOA) of the critical machine group (δ_{cmg}) and The partial centre of angles (PCOA) of the remaining machine group (δ_{rmg}):

$$\delta_{cmg} = \frac{\sum_{i \in cmg} M_i \delta_i}{M_{cmg}} \quad (1)$$

$$M_{cmg} = \sum_{i \in cmg} M_i \quad (2)$$

$$\delta_{rmg} = \frac{\sum_{j \in rmg} M_j \delta_j}{M_{rmg}} \quad (3)$$

$$M_{rmg} = \sum_{j \in rmg} M_j \quad (4)$$

Based on the above assumption, a multi-machine system can be transformed into equivalent two-machine system. Then the two machine equivalent is reduced to a single machine infinite bus system. The equivalent OMIB system model is given by the following equation:

$$M \frac{d^2 \delta}{dt^2} = P_m - P_e = P_m - [P_c + P_{max} \sin(-\gamma)] \quad (5)$$

Where,

$$M = \frac{M_{cmg} M_{rmg}}{M_T}$$

$$M_T = \sum_{i=1}^n M_i$$

$$\delta = \delta_{cmg} - \delta_{rmg}$$

$$P_c = \frac{M_{rmg} \sum_{i,k \in cmg} E_i E_k G_{ik} - M_{cmg} \sum_{j,l \in rmg} E_j E_l G_{jl}}{M_T}$$

$$P_m = \frac{M_{rmg} \sum_{i \in cmg} P_{mi} - M_{cmg} \sum_{j \in rmg} P_{mj}}{M_T}$$

$$P_{max} = \sqrt{C^2 + D^2}$$

$$\gamma = \tan^{-1} \left(\frac{C}{D} \right)$$

$$C = \frac{M_{rmg} - M_{cmg}}{M_T} \sum_{i \in cmg, j \in rmg} E_i E_j G_{ij}$$

$$D = \frac{M_{rmg} - M_{cmg}}{M_T} \sum_{i \in cmg, j \in rmg} E_i E_j B_{ij}$$

The accelerating and decelerating areas are given by [17], [18]:

$$A_{acc} = (P_m - P_{CD})(\delta_{cr} - \delta_0) + P_{maxD} [\cos(\delta_{cr} - \gamma_D) - \cos(\delta_0 - \gamma_D)] \quad (6)$$

$$A_{dec} = (P_{CP} - P_m)(\pi - \delta_{cr} - \delta_P + 2\gamma_P) + P_{maxP} [\cos(\delta_{cr} - \gamma_P) + \cos(\delta_P - \gamma_P)] \quad (7)$$

Where 0 denotes original (pre-fault), D during fault, and P post-fault, δ_{cr} is the critical clearing time.

The transient stability margin: $\mu = A_{acc} - A_{dec}$, at the critical clearing time t_{cr} , $\mu = A_{acc} - A_{dec} = 0$

Solving the equations (6) & (7), the critical clearing angle δ_{cr} can be computed. The value of critical clearing time (CCT) can be computed [18] by following formula:

$$t_{cr} = \sqrt{\frac{2M}{P_m} (\delta_{cr} - \delta_0)} \quad (8)$$

Where,
 P_m = generator output before fault
 δ_0 = pre-fault angle

IV. USE OF ARTIFICIAL NEURAL NETWORKS FOR

ESTIMATING CRITICAL CLEARING TIME

The neural network was inspired by its inception by the recognition that the human brain computes differently than that of a conventional digital computer. The brain acts as a highly complex, non-linear and parallel computer. An artificial neural network (ANN) is a flexible mathematical structure which is capable of identifying complex nonlinear relationships between input and output data sets. A neural network is a parallel-distributed processor made up of simple processing units, is known as neurons, which has a tendency for storing, and making easily available, experimental information.

A three-layer feed-forward network with back-propagation algorithm has been applied for the ANN training of the system under study. The data is propagated from the input layer to the hidden layers before reaching the final output layer. The error signals at the output layer are then propagated back to the hidden and input layers. The sum of square error is then minimized by adjusting the synaptic weights and bias in any layers during the training process of ANN models as shown in Fig. 2.

Where,

u_{ii} : Weight between the i^{th} neuron of input and i^{th} neuron of first hidden layer

v_{ii} : Weight between the i^{th} neurons of two hidden layers

w_i : Weight between the i^{th} neuron of second hidden layer and output layer

b_i^1 : Bias Input

For a multi-layer network, the net input $n^{k+1}(i)$ and output $a^{k+1}(i)$ of neuron i in the $k+1$ layer can be expressed as:

$$n^{k+1}(i) = \sum_{j=1}^{sk} w^{k+1}(i, j) y^k(j) + b^{k+1}(i) \quad (9)$$

$$a^{k+1}(i) = f^{k+1}(n^{k+1}(i)) \quad (10)$$

By representing the sum of the output square error as the performance index for the ANN, the error function is given by

$$E = \frac{1}{2} \sum_{r=1}^R (q_r - a_r^k)^T (q_r - a_r^k) = \frac{1}{2} \sum_{r=1}^R (e_r)^T e_r \quad (11)$$

Where $e_r = q_r - a_r^k$ is the output error and a_r^k is the final output of the r^{th} input. The Levenberg–Marquardt algorithm is used to minimize the mean square error function in equation (11).

When fault is occurred at the end of line 7-5 nearby bus 7, the real generator power (P_{G1} , P_{G2} and P_{G3}), reactive generator power (Q_{G1} , Q_{G2} and Q_{G3}), load real power (P_{LA} , P_{LB} and P_{LC}) and load reactive power (Q_{LA} , Q_{LB} and Q_{LC}), are selected as the input neurons of the ANN model, while the output neuron defines the critical clearing time t_{cr} . The number of neurons in input layer is equal to the number of inputs i.e. 12 while the output layer has one neuron. The selection of number of neurons for the two hidden layer is made on hit and trial method basis, comparing the regression plot of each and choosing the best among them. The best performance is obtained with 20 neurons in 1st hidden layer and 10 neurons in 2nd hidden layer. The transient stability analysis for 100 cases have been carried out with the values of P_{G1} , P_{G2} , P_{G3} , Q_{G1} , Q_{G2} , Q_{G3} , P_{LA} , P_{LB} , P_{LC} , Q_{LA} , Q_{LB} and Q_{LC} . The 80% of the total cases is selected for the ANN training, 10% for testing and 10% for validation. The corresponding critical clearing time as calculated by ANN with LMBP algorithm (t_{cr}) for different load-generation scenarios and fault is occurred on the end of line 7-5 at near bus 7 is shown in Table.2.

The Table 2 summarizes the results of training the ANN. It illustrates the outputs of the ANN and the actual CCT computed with the EEAC method. The table shows randomly selected samples of the inputs and outputs of the ANN and the actual CCT. The results show a close agreement between the output of the ANN and the calculated CCT. It also shows the RMS values of the error and the difference between the ANN outputs and the CCT values for a fault at end of line 5-7 nearby bus 7, obtained by the EEAC method. This table indicates that the CCT value outputs of the ANN match the CCT obtained by the EEAC method with unacceptable level of accuracy.

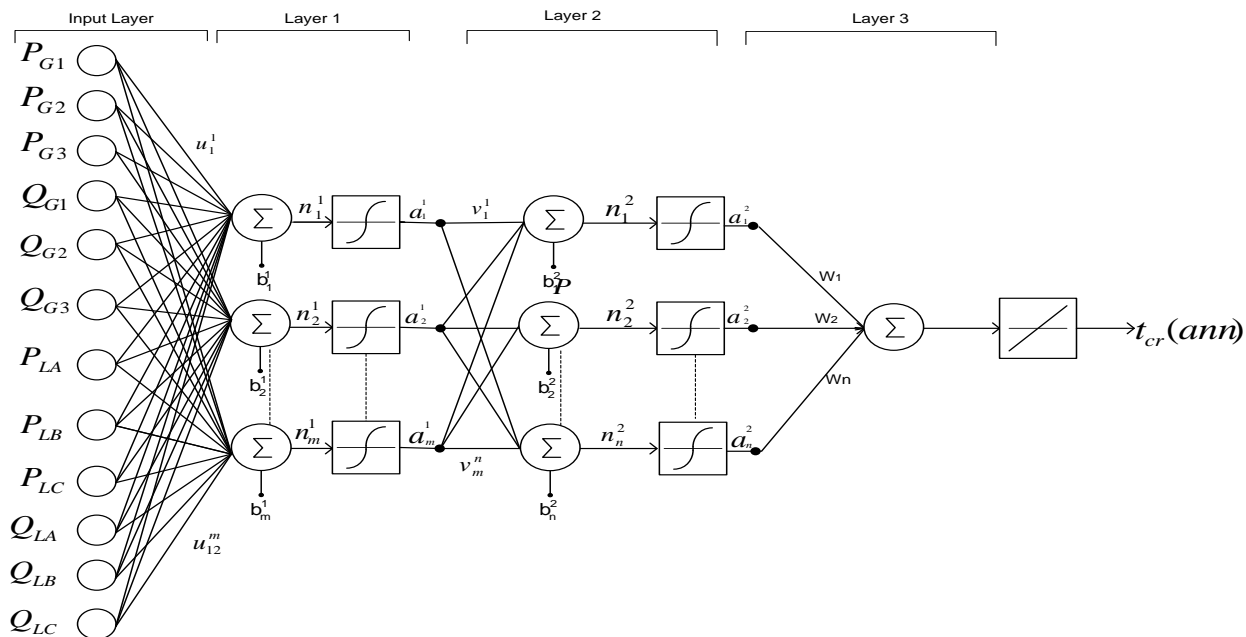


Fig. 2 Three-layer feed forward neural network

TABLE 2: ANN-BASED CCT CALCULATION

P_{G1}	P_{G2}	P_{G3}	Q_{G1}	Q_{G2}	Q_{G3}	P_{LA}	P_{LB}	P_{LC}	Q_{LA}	Q_{LB}	Q_{LC}	Actual CCT	ANN Output	Error (%)
0.701	1.63	0.851	0.368	0.210	-0.052	1.25	0.90	1.00	0.50	0.30	0.35	0.31	0.33	-0.0175
0.325	1.62	0.81	-0.356	0.047	0.181	0.12	0.73	1.69	0.15	0.21	0.24	0.31	0.34	-0.0303
0.283	1.58	0.63	0.174	0.185	-0.036	0.25	0.70	0.82	0.34	0.20	0.19	0.27	0.29	-0.0218
0.345	1.47	0.63	-0.070	-0.060	-0.299	0.75	0.67	0.92	0.28	0.12	0.08	0.31	0.31	0.0044
0.806	1.25	0.81	0.181	-0.029	-0.198	1.03	0.67	1.18	0.10	0.64	0.04	0.43	0.42	0.0153
0.153	1.11	0.78	-0.050	0.429	-0.394	0.46	0.94	0.69	0.25	0.03	0.52	0.39	0.38	0.0065
0.131	1.41	0.68	0.267	0.316	-0.539	0.68	0.76	0.76	0.34	0.16	0.25	0.30	0.36	-0.05717
1.302	1.58	0.74	0.564	0.403	-0.234	1.09	0.67	1.84	0.22	0.94	0.14	0.41	0.39	0.0160
0.788	1.58	0.89	-0.308	0.343	0.028	0.92	0.91	1.34	0.17	0.12	0.43	0.35	0.36	-0.0031
1.082	1.64	0.67	0.399	0.250	0.063	0.71	1.08	1.60	0.33	0.25	0.74	0.34	0.34	0.0023
0.685	0.98	1.00	-0.090	-0.280	-0.082	1.11	0.69	0.80	0.09	0.34	0.08	0.54	0.52	0.0261
1.106	1.28	0.80	0.317	-0.011	-0.020	1.20	0.89	1.04	0.47	0.22	0.33	0.45	0.46	-0.0050
0.955	1.38	0.79	0.037	-0.303	-0.163	1.06	0.75	1.37	0.21	0.21	0.14	0.39	0.39	0.0056
0.441	1.68	0.71	0.114	-0.152	-0.050	1.28	0.66	0.87	0.24	0.17	0.12	0.26	0.27	0.00084
0.578	1.39	0.69	0.057	-0.279	0.146	0.64	1.00	0.85	0.13	0.33	0.23	0.34	0.33	0.0072
0.518	1.57	0.82	0.333	0.219	-0.292	0.85	1.31	0.71	0.40	0.46	0.03	0.31	0.33	-0.0189
0.917	1.49	0.71	0.226	0.361	-0.139	0.74	1.57	0.74	0.25	0.87	0.02	0.37	0.35	0.0158
0.200	1.92	0.59	-0.149	0.372	-0.158	0.87	0.69	0.71	0.47	0.20	0.24	0.21	0.20	0.0094

0.396	1.29	0.53	0.191	0.417	-0.127	0.84	0.69	0.71	0.89	0.27	0.19	0.36	0.35	0.0149
1.719	1.00	0.50	-0.202	0.561	-0.360	0.92	1.04	1.07	0.23	0.17	0.23	0.12	0.13	-0.0033
0.710	1.80	0.47	0	0.165	0.129	0.96	1.06	1.10	0.46	0.36	0.09	0.27	0.26	0.0109
0.680	2.28	0.49	0	0.397	0.020	1.05	1.28	1.08	0.11	0.38	0.31	0.21	0.22	-0.0165
0.728	1.21	0.49	-0.112	0.203	-0.118	0.74	0.64	0.97	0.24	0.20	0.39	0.42	0.36	0.0581

V. Conclusion

ANN is a very fast tool for CCT estimation compared to other methods but should be trained carefully over a wide hyperspace in order to avoid over-fitting. The ANN is trained once for a given power system for any expected situation and then used for any load condition in the system. Results obtained using an artificial neural network to predict critical clearing times for a specific fault and clearing modes in power system. The pre fault active and reactive powers of all generators and loads are used as ANN inputs. For IEEE-9 bus system it is found that for most testing examples the CCT was predicted with good accuracy.

Bus to Bus (Line)	R (pu)	X(pu)	Half Line Charging /2(pu)
1-4	0.0000	0.0576	0.0000
4-5	0.010	0.085	0.088
5-7	0.032	0.161	0.0153
4-6	0.017	0.092	0.079
6-9	0.039	0.170	0.179
7-2	0.0000	0.0625	0.0000
7-8	0.0085	0.072	0.0745
8-9	0.0119	0.1008	0.1045
9-3	0.0000	0.0586	0.0000

APPENDIX

Generator Data at 100MVA Base

Generator	G1	G2	G3
Rated MVA (G)	247.5	192	128
kV	16.5	18.0	13.8
Power Factor	1.0	0.85	0.85
Speed(rpm)	150	3000	3000
Type	Hydro	Steam	Steam
X_d (pu)	0.1460	0.8958	1.3125
X_d' (pu)	0.0608	0.1198	0.1813
X_q' (pu)	0.0969	0.8645	1.2578
X_q'' (pu)	0.0969	0.1969	0.25

X_l (leakage) (pu)	0.0336	0.0521	0.0742
t_{d0}'	8.96	6.00	5.89
t_{q0}'	0	0.535	0.600
Inertia constant (H)	23.64 MJ/MVA	6.40 MJ/MVA	3.01 MJ/MVA

Line Data at 230kV, 100MVA Base

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