Estimation Of Critical Clearing Time Using Artificial Neural Network For Based Transient Stability Mode

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Abstract. This study represents simulations for estimating transient stability using a neural multi-layer perceptron (MLP) network to obtain the neural network training set to evaluate the transient stability of the Iraqi Super Grid (400 KV) to measure the critical clearing time. Whether the actual and active load varies on each bus when the system fails, it will show the actual loading sequence of the system to use as an input to the neural network, while the critical clearing time (CCT) is the basis for calculating the critical clearance time target data used in the neural network from the Rate of Change Kinetic Energy (RACKE) principle, Multimachine power system using the Runge-Kutta fourth-order combination of methods. A three-phase ground error was conducted for transient stability analysis and was not altered during simulation. In the result of the test, The proposed approach applied to Iraq super grid 400KV system has been shown to be more appropriate for estimating transient stability when actual and active loads shift over critical clearing time. With a minimum 0.0016% error and a maximum 0.0419% error relative to multimachine CCT (RACKE).

Keywords. Transient stability, Update rate of kinetic energy, multimachine, neural network, critical clearing time.

1. Introduction

An important requirement for the safe operation of power systems is the transient stability evaluation. The transient stability is measured taking into account the impact of large disruptions such as faults, load or generator failure, line switching, etc. on the network. For a particular stable operating condition and for a particular major disturbance, a power system is transiently stable if this is followed by a disruption [1]. The Critical Clearing Time (CCT) is the maximum time interval by which the fault has to be resolved to preserve the stability of the system. The CCT is measured and compared with the real fault clearing time in direct stability estimation methods. The system is determined to be transiently stable if the former is greater than the latter.

To measure the degree of system stability, the difference between these two values can be used as an index. This index's higher value suggests a more stable system. The gap in the fault clearing time between the critical energy value and the energy is also sometimes used as an index.

One way to calculate the critical clearing time is through brute force numerical differentiation [2],[3]. In other words, the critical clearing time is recalculated by changing the parameter to assess the change in the critical clearing time. For instance, the paper [4] analyzes the effect on the critical clearing time of a multi-machine bus system by direct simulation of a number of parameter adjustments.

Recently, a lot of attention has been paid to applying ANN to the transient stability assessment of the power systems. The advantages of qualified ANN are quick assessment, high precision to solve the
problem of transient stability and parallel data processing power. There are essentially two assessment processes, measurement and prediction. Evaluation of power systems focuses on critical clearing time while prediction of power systems, critical clearing time is not significant, but classification into stable and unstable states using stability indexes such as CCT, difference in rotor angle between generator and reference generator [5], [6].

Optimize CCT faster and more accurately one of the newly transient stability problems and a smart artificial network has been used to address this issue, certainly as it can be applied to the Internet. The system's non-linear feature can be conveniently modeled using neural networks. The rapid recognition of the process is evident in the use of artificial neural networks and is distinguished by high precision and can solve non-linear problems. The neural network can easily alter the dynamic state of the network, so that the durability of the neural network-based method faces changes in load in the multiple vector. The product of neural network training can also be extended to the Internet, so we can see if the system is stable or not fast and accurate. This study attempts to implement a neural network to calculate the transient system stability's critical clearing time. The real and active load varies on each bus showing the actual load sequence of the system used as the neural network input, whereas the goal is the Critical Clearing Time (CCT). By using the load sequence as data, multiple bus changes are expected to achieve the robustness against load changes of the proposed solution. Using the 4th order process Rate Of Change Kinetic Energy (RACKE), the data of the target critical clearance time used for the training was measured. Many different load patterns are chosen to estimate the critical clearing time to ensure that the proposed method is resilient to load changes in multiple buses.

2. Analysis standard
The method of integration used to solve system differential equations is the fourth order method of Rung-Kutta and is considered a standard for comparison. The flow charts used by the RACKE to measure the Critical Clearing Time (CCT) As shown in figure 1. It begins with network and system data processing. These data required for the power flow for each bus before the disturbance, measure the initial state of the second step using the routine for Transient stability, solve differential equations of system in the failed state and obtain inertia rotor angles and speeds. Calculate the values (RACKE) after the clearance of the fault, assuming that the fault is cleared at this new time. Critical clearing time CCT varies from t1 to t2. Neural Network (NN) is equipped using CCT From the last stage. The NN strategy is going to be checked for CCT calculation after practicing using a new operating environment. The results of the CCT-NN test will be compared with the CCT –RACKE test results.

3. Mathematical Model For Stability Power System
The dynamics swing equation for the ith machine of an n- machine system can be represented by the following 2nd –order differential equation:

\[
M \frac{d^2 \delta_i}{dt^2} = P_m - P_e
\]  

Most of the direct methods for determining transient stability are based on the Center-Of-Angle (COA) or Center-Of Inertia (COI) reference frame classic model of a power system. The dynamic eqn (1) can be represented in this reference frame by the following two differential equations in the 1st-order [7].
\[
\frac{d\Theta_i}{dt} = \omega_i
\]
\[
M_i \frac{d\omega_i}{dt} = P_i - P_{sl} - \frac{M_i}{M_T} P_{COA}
\]
\[
M_T = \sum_{i=1}^{n} M_i
\]
\[
P_{COA} = \sum_{i=1}^{n} P_{COA} - \sum_{i=1}^{n} P_{g_i}
\]

\[\text{Start} \]

- Read in network and machine initial condition
- Calculate Network and Machine Initial Condition
- Calculate Y matrix for the faulted system
- List CCT with method RACKE
- Prep NN with RACKE CCT
- Testing CCT and comparing CCT- RACKE results
- Print the results

\[\text{End}\]

**Figure 1.** Flow chart procedure.
4. Change rate of the kinetic energy calculation for transient stability

Through observing the different energy sources of the power system and their interaction when there is a fault, devices close to fault accelerate and increase their kinetic energy, while the rest decelerate until a new interaction starts. The rate at which each machine is consumed or given up kinetic energy plays an important role in determining the final behavior of the system. There will be at least one computer pulling out of synchronism when the mechanism loses stability. This concept was used to develop a new criterion for rapidly transient stability evaluation, called the Kinetic Energy Change Rate (RACKE) criterion. [8]. In this process, the differential equations are solved so that the RACKE can be determined immediately after the clearance of the fault. This RACKE has a zero value at stable points of equilibrium and increases to a negative limit at the time of error clearance [9]. The system differential equations solution method explaining the system dynamics rotor speeds and rotor angles are given at the end of each integration stage. Such values are Used when applying this criterion to assess the Critical Clearing Time (CCT) [10].

The power output expression is based on the assumptions of I voltage behind the transient reaction, constant mechanical input for the system, negligible saliency and negligible transfer conductivity:

\[ P_{elec} = E_i^2 G_{ii} + \sum_{j=1}^{n} E_i E_j B_{ij} \sin (\delta_i - \delta_j) \]  

(4)

Where: \( E_i \) is the internal voltage of machine, \( G_{ii} \) is the short circuit conductance of machine (I), and \( B_{ij} \) is the transfer susceptance between machine I and j. The machine i's kinetic energy \((KE)_i\):

\[ (KE)_i = \frac{1}{2} M_i \omega_i^2 \]  

(5)

\( M_i \): is the angular momentum of the ith machine randomly; is the ith machine's speed deviation. Likewise, as in a single infinite bus system, ith machine RACKE will be [11],

\[ (RACKE)_i = M_i \omega_i \frac{d\omega_i}{dt} \]  

(6)

Or \( (RACKE)_i = \omega_i (P_{mech} - P_{elec}) \) \( \text{ (for } i = 1, 2 \ldots n \)  

(7)

A machine absorbs kinetic energy in a multi-machine power system due to the inconsistency of the power input and the power output when the device is disrupted. The system will then continue to be stable or otherwise based on the ability of the post-fault mechanism to absorb and transform this kinetic energy from all devices. In the appropriate form. At the moment when the process is about to lose control, during least one device is about to disconnect from the rest of the synchronization. This is the main machine and is therefore concerned about its dynamics. Which machine or group of machines behaves in this manner depends on the properties of the machine and the rate at which the kinetic energy (RACKE) given by eq. (7) is released for conversion into potential form. It is, therefore, logical to use this RACKE as a criterion for the stability assessment of n multi-machine power system [12].

5. ARTIFICIAL NEURAL NETWORKS

Neural networks use learning algorithms to determine the input and output data relationships. The multi-layer perceptron (MLP) model is one of the simplest and yet most competent models proposed for modeling actual neurons. Fig. 2 shows an MLP neural network with a hidden layer[6].
Using neural networks, this defines the complex relationship between the variables of input and output. Often referred to as a multilayer perceptron is a multilayered neural feed forward network. A neural network consists of an input layer, an output layer, and one or more hidden layers. Basically, one hidden layer is sufficient to create a complex input-output relationship. The number of neurons in the input layer and output layer is dependent on the specific problem, but the number of neurons in the hidden layers is arbitrary and usually determined by method of trial and error [13,14].

MLP Neural Network was using Matlab's software. The network architecture of the neural network consists of several inputs that are the cumulative active and reactive load that can be added to the system so long as it does not surpass the ability of the system. The neural network's performance is CCT as the goal. Together with the time domain simulation method, the training data Rate Of Change Kinetic Energy (RACKE) approach is used.

6. THE PROPERTY APPROACH

The network being considered consists of an Iraqi electrical network consisting of a network of 400 kV and 132 kV. This work is limited to the 400 kV bus and transmission lines network. There are 33 busses on the Iraqi Super Grid (400 KV), 18 as generation busses and 15 as load busses. This network configuration is shown in Fig.2[15]. The station (KUTP) atbus-19is selected as a slack bus for the load flow solution. In normal circumstances, the total system capacity (10851.43 MW) and (3269.67 MVR) is 50 Hz. The data machine used is shown in Appendix A.

7. Step of proposed approach

1- Iraq super grid initialization data consisting of 400 kV active and reactive power generator, load control, reaction and input transmission, angle and voltage of the network.
2- Run the program to load the stream. Calculate the pre-fault (before disturbance) admission matrix reduction, Primary mover, generator of voltage, and initial generator of angle.
3- Calculate the decrease of the admission matrix during interruption.
4- Using the transient stability process, solve the system differential equations in the failed state and obtain the rotor angles and speeds at the end of the iteration stage; Assume the fault to be cleared at the end of the step; measure (RACKE)i for i=1,2,......,n after the fault clearance; let these be (xi); store these values.
5- Advance time by one integration stage and repeat process 2 procedures; allow time to be \( t_2 \) \((t_2=t_1+t)\), where the size of the stage is allocated.

6- Calculate the (RACKE) \( i \) values after clearance of the fault, assuming at this new time the fault is to be cleared, let them be given \( Y_i \).

7- If \( Y_i > X_i \) magnitude is set to \( X_i = Y_i \) and time is set to \( t_1 \), then return to phase 7. If for any \( I \) \( Y_i < X_i \), proceed to the next phase. Notice that \( Y_i \) is expected to be pessimistic.

8- Stop the differential equations integration. The critical time for clearance is between \( t_1 \) and \( t_2 \) seconds. If the stage is sufficiently small. At the CCT, \( T_1 \) can be obtained

9- Repeat the above steps for other conditions of load service

10- Use input and output load shift data and CCT research of neural networks.

11- Check the approach proposed and compare the results

12- Trying to compare CCT - RACKE with the CCT-NN.

8. Implementation results

Three phase ground fault on the MMDH bus and the 4KUT bus line was temporarily terminated using real data from the Iraqi Super Grid. Changes in load occur every 15 minutes on each bus load. Some of the CCT calculation results using the RACKE method. Tabulate the findings in table 1. The next step is multi-layer neural network preparation. The learning cycle converges in this paper when the Mean Square Error (MSE) minimum value is reached by 0.001. First, the meaning of the critical clearing time obtained from the RACKE Method of measurement is compared to the results obtained from the Neural Network training. You can see the outcome of the analysis in the table 2.

![Diagram](image_url)  
**Figure 3.** Iraqi super Grid network, 400KV.

| Table 1. NN Training CCT RACKE |
|--------------------------------|
| **MMGH** | **4ME** | **K300G** | **4KX** | **4BC** | **4BCV** | **4BE** | **4KBB** | **4BE** |
| **K300G** | **4KX** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** |
| **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** |
| **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** |
| **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** | **4BE** | **4KBB** |

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Table 2. Calculation CCT using RACKE and Neural Network Method.

| NO | TIME  | TRAINING CCT (S) | CCT-RACKE (S) | ERROR % |
|----|-------|------------------|---------------|---------|
| 1  | 18:00 | 0.2501           | 0.2500        | 0.0002  |
| 2  | 18:15 | 0.2539           | 0.2840        | 0.0004  |
| 3  | 18:30 | 0.2582           | 0.2580        | 0.0005  |
| 4  | 18:45 | 0.2548           | 0.2550        | 0.0005  |
| 5  | 19:00 | 0.2526           | 0.2520        | 0.0020  |
| 6  | 19:15 | 0.2569           | 0.2580        | 0.0037  |
| 7  | 19:30 | 0.2566           | 0.2560        | 0.0021  |
| 8  | 20:00 | 0.2520           | 0.2540        | 0.0002  |
| 9  | 20:15 | 0.2570           | 0.2570        | 0.0000  |
| 10 | 20:45 | 0.2479           | 0.2480        | 0.0003  |
| 11 | 21:00 | 0.2450           | 0.2450        | 0.0002  |
| 12 | 21:15 | 0.2411           | 0.2410        | 0.0004  |
| 13 | 21:30 | 0.2380           | 0.2380        | 0.0001  |
| 14 | 21:45 | 0.2340           | 0.2340        | 0.0000  |
| 15 | 22:00 | 0.2270           | 0.2240        | 0.0000  |
| 16 | 22:15 | 0.2250           | 0.2250        | 0.0000  |
| 17 | 22:30 | 0.2230           | 0.2230        | 0.0000  |
| 18 | 22:45 | 0.2170           | 0.2170        | 0.0000  |

The results obtained for both methods showed the low error was 0% and the max error was 0.0084% In your RACKE scheme, the average error in neural network training is 0.0005186.
Table 3. CCT - RACKE For Testing NN.

| TIME   | BUSBUE NUMBER | MW (MW) | MVAR (MVAR) | CCT-RACKE (S) | TIME   | BUSBUE NUMBER | MW (MW) | MVAR (MVAR) | CCT-RACKE (S) |
|--------|----------------|---------|-------------|---------------|--------|----------------|---------|-------------|---------------|
| 00:45  | 18             | 175     | 75          | 0.2220        | 04:15  | 19             | 101     | 72          | 0.2270        |
| 04:45  |                | 127     | 94          | 0.2310        | 05:45  |                | 102     | 79          | 0.2420        |
| 05:45  |                | 229     | 102         | 0.2640        | 10:00  |                | 245     | 107         | 0.2680        |
| 10:45  |                | 209     | 110         | 0.2740        | 12:45  |                | 224     | 104         | 0.2770        |
| 13:00  |                | 150     | 90          | 0.2810        | 19:45  |                | 257     | 122         | 0.2840        |
| 20:30  |                | 128     | 65          | 0.2840        |

Table 4. CCT Evaluation Contrast and CCT- RACKE.

| NO | TIME   | TESTING CCT (s) | CCT-RACKE (s) | ERROR (%) |
|----|--------|-----------------|---------------|-----------|
| 1  | 00:45  | 0.2303          | 0.2220        | 0.0376    |
| 2  | 04:15  | 0.2221          | 0.2270        | 0.0215    |
| 3  | 04:45  | 0.2272          | 0.2310        | 0.0164    |
| 4  | 05:45  | 0.2404          | 0.2420        | 0.0068    |
| 5  | 10:00  | 0.2689          | 0.2640        | 0.0187    |
| 6  | 10:45  | 0.2769          | 0.2680        | 0.0332    |
| 7  | 12:45  | 0.2657          | 0.2740        | 0.0303    |
| 8  | 13:00  | 0.2736          | 0.2770        | 0.0123    |
| 9  | 19:45  | 0.2822          | 0.2810        | 0.0042    |
| 10 | 20:30  | 0.2776          | 0.2840        | 0.0227    |

From the case of research to measure CCT using untrained data. To check and evaluate the accuracy and strength of the proposed idea, extreme distributed load conditions were chosen. Table 3 offers a sharp example of the load change data and the test stage outcome can be seen in Table 4. The minimum error resulting from the CCT-NN test simulation is 0.0042 and 0.0376 is a maximum error. The maximum error test is 0.0204.

9. Conclusion
MATLAB was used to develop a complete model for the transient stability study of the multimachine power system. From the simulation of the Iraqi Super Grid (400 KV) we presented the results of this study showing that Neural Network is efficient in analyzing transient power system stability and characterizing critical clearing time with a minimum error of 0.0042. Similar to the SBS approach, the RACKE method achieves a significant reduction in processing time. Because these approaches do not allow machine equation solution beyond error clearing time the inference is that The suggested solution is sufficient for the online critical clearing time measurement.

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### Appendix A

**Machines data**

| Unit name | Bus number | Capacity of generating MW | moment of inertia H (sec) | The Speed drop Ra |
|-----------|------------|---------------------------|--------------------------|-------------------|
| MMDH      | 1          | 240                       | 14.1                     | 0.05              |
| KRMG      | 4          | 360                       | 10.281                   | 0.05              |
| 4KRK      | 6          | 304.4                     | 12                       | 0.04              |
| QDSG      | 11         | 690.7                     | 55.5                     | 0.04              |
| BSMG-1    | 14         | 980                       | 24                       | 0.05              |
| BSMG-2    | 15         | 490                       | 12                       | 0.05              |
| MNSG      | 16         | 325                       | 12                       | 0.04              |
| KUTP      | 19         | 2443.33                   | 48                       | 0.04              |
| MUSP      | 20         | 800                       | 20                       | 0.05              |
| MUSG      | 21         | 166.3                     | 3                        | 0.05              |
| KHRG      | 23         | 746                       | 54                       | 0.04              |
| DEWG      | 24         | 345.8                     | 24                       | 0.04              |
| NSRP      | 26         | 524.2                     | 38                       | 0.05              |
| 4AMR      | 27         | 345.8                     | 24                       | 0.05              |
| HRTP      | 29         | 1165                      | 9.5                      | 0.04              |
| KAZG      | 30         | 758.7                     | 10                       | 0.04              |
| RMLG      | 31         | 980.4                     | 24                       | 0.04              |
| STBG      | 32         | 769                       | 48                       | 0.04              |