Prediction of Critical Clearing Time of Java-Bali 500 kv Power System Under Multiple Bus Load Changes Using Neural Network Based Transient Stability Model

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Abstract: A transient stability model based on back propagation neural network is used to analyze transient stability of Java-Bali electricity system, especially in calculating the critical clearing time. The real and the active load changes on each bus that shows the real load pattern of the system used as neural network input, while the target is the Critical Clearing Time (CCT). By using the load pattern as input, it is hoped that the robustness of the proposed method against load changes at multiple bus can be achieved. Data of target critical clearing time used for the training was calculated from the concept of One Machine Infinite Bus (OMIB), by reducing the multi-machine system using a combination of methods of Equal Area Criterion (EAC) through the Trapezoidal method and the Runge-Kutta 4th order method. To analyze transient stability, a three phase ground fault was conducted at one bus and assumed not changed during the simulation. The proposed method will be implemented at Java-Bali 500 kv power system. The simulation results show the calculation of critical clearing time from the proposed method has a minimum error of 0.0016% and a maximum error of 0.0419% compared with CCT by OMIB.

Keywords: transient stability, multimachine, one machine infinitive bus, equal area criterion, neural network, critical clearing time.

1. Introduction

In recent years, research on the transient stability problem revolves around the identification of critical machine, critical clearing time and system transient stability modelling. However, solving non linear calculations on transient stability requires a long time, in contrast with the necessity to overcome the problem quickly and accurately [1].

A transient stability study with random variables is performed in [2], with linear approach involving the calculation of sensitivity derived from the CCT system. The study uses a complex reduction equation to determine the possibility of the system experiencing transient conditions. Determination of conditions of transient stability using multilayer perceptron artificial neural network studied in [3]. However, some weakness occurred in the determination of transient conditions of the system grouped by high and low class such that it did not accurately give a prediction value of CCT

Recent issues on the transient stability are how to calculate the CCT quickly and accurately, and has been approached using artificial intelligent, especially neural network because it can be applied online. Using neural networks the non linear characteristic of the system can be modelled easily. The advantages of using artificial neural network is a quick identification

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process, high accuracy and can solve non linearity problem [8]. Changes in the dynamic condition of the system can be modelled easily by neural netwok and therefore the robustness of the method based on neural network against load changes at multiple bus is guaranteed. In addition, the result of training of the neural network can applied on line, so that the condition of transient stability of the system is able to be known in a short time.

Critical clearing time prediction using neural networks has been published in many papers. Reference [9] determine the critical clearing time with the fault distance as an input applied on a single machine system using neural network. In this paper, neural network is able to assess the stability of the system with accurate transient for symmetric fault along the line. Some papers on critical clearing time related with a contingency on the system have been published at [10,11,12]. Reference [10] presented a neural network based approach for online implementation through estimation of a normalized transient stability margin for a particular contingency under different operating conditions. This method with a time-domain simulation technique is used to obtain the training set of the neural network. Reference [11] describes the procedures for reasoning CCT by means of rules extracted from a multilayer perceptron (MLP) artificial neural network. However, this reference still has weaknesses, the lack of consistency in force. Reference [12] discuss about prediction of CCT on the system caused by a fault on a bus from the generator. Some improvement could be achieved by increasing the number of hidden neurons and the number of training examples.

This study is trying to implement back propagation neural network to calculate critical clearing time of the system transient stability. The real and the active load changes on each bus that shows the real load pattern of the system used as neural network input, while the target is the Critical Clearing Time (CCT). By using the load pattern as input, it is hoped that the robustness of the proposed method against load changes at multiple bus can be achieved. Data of target critical clearing time used for the training was calculated from the concept of One Machine Infinite Bus (OMIB), by reducing the multi-machine system using a combination of methods of Equal Area Criterion (EAC) through the Trapezoidal method and the Runge-Kutta 4th order method. To guarantee the robustness of the proposed method against load changes in multiple bus, several certain load patterns are chosen to calculate the critical clearing time. It is expected that calculations can be carried out online and in less amount of time.

2. Methodology

A. General Methodology

The general methodology can be seen in figure 1. It starts from reading the data. The necessary data are power system network, data of generators, and load data. All this data is required for power flow studies to determine the voltage and phase angle and the loading of each bus before the disturbance. So, the performance of initial system was knowable.

The next step is the modelling of transient stability. Modelling machines for transient stability condition is done by giving three phase short circuit on one bus. The Severely Disturbed Machine can be determined by observing the acceleration of the machine when the disturbance is happened.

It is necessary to reduce the modelling machine into one machine, because it can simplify to solve problems, and then classify the machines into two groups, the critical machine and non critical machine. Two machines groups, then, is reduced into one machine infinite bus and the Critical Clearing Time can be calculated with a combination of OMIB equal area criterion via the trapezoidal method and the 4^{th} Order Runge Kutta method.

Neural Network (NN) is trained using CCT of OMIB-EAC obtained from the previous step. After training, the NN model will be tested using new operation condition to compute CCT. The results of testing CCT-NN will be compared with CCT-OMIB-EAC.

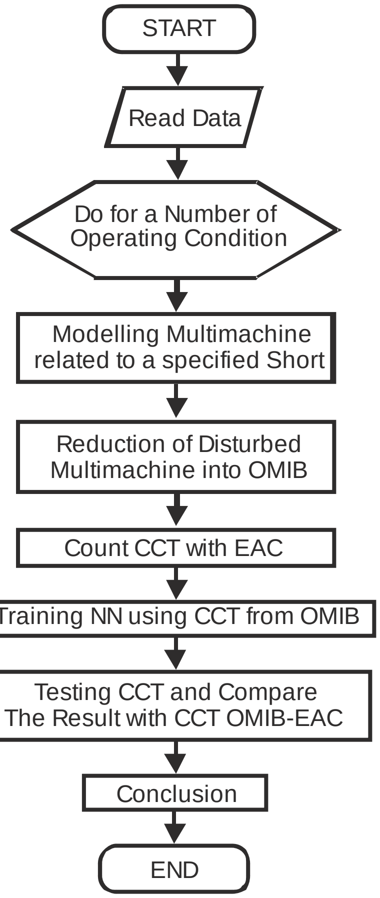

Figure 1. Determination Flowchart of CCT

B. Detail Methodology

B.1. Modelling Multimachine for Transient Stability

Transient stability in power systems is the system's ability to maintain operating conditions when large disturbances occur. Disturbance in the system can cause major changes in the angle rotor and systems. Failure to manage the interference will result in loss of synchronization between machines. Machine stability limit is different from one another.

By looking at the stability limit of the worst machines, then the system transient stability can be determined. Machines that have the lowest stability limit is the most critical machine that has a tendency to initiate instability and loss of synchronization on the system. As a result, other machines will be affected and lose synchronization also form a group of machines that are not stable in the system. Mathematical modelling of machine dynamics state-*i* with reference to the COA (Centre of Angle) is written as follows [7],

$$\frac{d\delta_i}{dt} = \omega_i \tag{1}$$

$$M_i \frac{d\omega_i}{dt} = P_i - P_{ei} - \frac{M_i}{M_T} \tag{2}$$

$$P_i = P_{mi} - E_i^2 G_{ii}$$

$$P_{ei} = \sum_{j=1}^{n} (C_{ij} \sin\delta_{ij} + D_{ij} \cos\delta_{ij})$$

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

where,

C_{ij} = $E_iE_jB_{ij}$
D_{ij} = $E_iE_jG_{ij}$
E_i = internal voltage generator
δ_i = rotor angle
δ_{ij} = δ_i - δ_j
ω_i = velocity
P_{mi} = prime mover
M_i = inertia constant
B_{ij} = conductance (of the matrix impedance already reduced)
G_{ij} = suseptance (of the matrix impedance already reduced)

The right hand side of equation (2) is called acceleration power machine (P_{ai}).

$$P_{ai} = P_i - P_{ei} - \frac{M_i}{M_T} P_{COA} \tag{3}$$

By eliminating the free variable *t* in equations 1 and 2, the differential equations between δ_i and ω_i can be written as follows,

$$M_i\omega_i \, d\omega_i = P_{ai} \, d\delta_i \tag{4}$$

2. Reducing into One Machine Infinite Bus (OMIB)

Conventional methods of analyzing the stability have some weakness such as computing time is longer, lack of information about the sensitivity and control. To cover the weakness above, researchers developed several methods such as Lyapunov in the early 1960s. Then the method of EAC (Equal Area Criterion) which was updated in 1980, with multi-machine system is converted into One Machine Infinite Bus (OMIB).

In this research, a better method decomposing the multimachine system into two machine and then combined two machines into One Machine Infinite Bus (OMIB) will be used. This method will generally divide the generators into two groups, namely group of critical machines (generators are responsible for the loss of synchronization) and non-critical group of generators (power remaining) and finally combined both resulted groups into one machine to infinite bus. Several stages of this method is as follows,

1. Perform short circuit simulation to obtain the stability condition of machinery and machine grouping into two groups namely the critical machines and non-critical machines
2. Modeling group of critical machines into one machine model and non-critical machines into one machine model also
3. Two models of machines were reduced back to one model of machine to infinite bus.

The method to divide the multimachines into two groups is based on machine acceleration power looked at the post fault condition. Machine *i* can be categorized into one of the Severe Disturbed Machine (SDM) group if it satisfies the following equation

$$\frac{|a_i^f|}{a_{\max}^f} > a \tag{5}$$

a^f_i is the acceleration of the *i*-th machine at the time of disturbance, a^f_{max} is the maximum acceleration value of machinery and α is the tolerance allowed (the value of 0.7 is sufficient to provide satisfactory results) [7]. Acceleration of the machine can be obtained by dividing power with the constant inertia machine acceleration.

Procedures for determining the critical machine is,

a. Calculate the acceleration of post-fault power of all SDM using equation 3.
b. Machine with SDM acceleration power through the zero line was considered as a critical machine.

Equations to form OMIB are given as follows. Centre of Angle (COA) for critical machine rotor angle (δ_c) is defined by the following equation,

$$\delta_C = \frac{1}{M_C} \sum_{k \in C} M_k \delta_k \tag{6}$$

Centre of Angle (COA) for the rotor angle (δ_N) of non-critical machine is defined by,

$$\delta_N = \frac{1}{M_N} \sum_{j \in N} M_N \delta_N \tag{7}$$

Rotor angle of OMIB (δ_{OMIB}) is given by the equation,

$$\delta_{OMIB} = \delta_C - \delta_N \tag{8}$$

Electrical (P_e) and mechanical (P_m) power output of generator at OMIB system given by the following equation,

$$P_e = M\left(\frac{1}{M_C} \sum_{k \in C} P_{ek} - \frac{1}{M_N} \sum_{j \in N} P_{ej}\right) \tag{9}$$

$$P_m = M\left(\frac{1}{M_C} \sum_{k \in C} P_{mk} - \frac{1}{M_N} \sum_{j \in N} P_{mj}\right) \tag{10}$$

Power acceleration (P_a) at OMIB system was defined by the following equation,

$$P_a = P_m - P_e \tag{11}$$

Moment inertia of the critical engine (M_c) is defined by,

$$M_C = \sum_{k \in C} M_k \tag{12}$$

Moment inertia of non-critical machine (M_N)is determined as follows,

$$M_N = \sum_{j \in N} M_j \tag{13}$$

Moment of inertia of OMIB system (M_{OMIB})is as follows,

$$M_{OMIB} = \frac{M_C M_N}{M_C + M_N} \tag{14}$$

3. Computing Critical Clearing Time (CCT) using Equal Area Criterion (EAC) via The Trapezoidal Method and The 4th Order Runge-Kutta Method

A. Trapezoidal Method

Trapezoidal method is used to determine the critical angle (δ_{cr}) of the OMIB by using an integral approach to numerical methods with first order polynomial equation. In this method arches curve of the function *f(x)* is replaced by a straight line. As shown in Figure 3 the area under the function *f(x)* between $x = a$ and $x = b$ is approached by a trapezoidal area formed by straight lines connecting the *f(a)* and *f(b)* and the *x*-axis and between $x = a$ and $x = b$. Approach is done with one parts (trapezoidal). According to the formula geometry, area trapezoid is [16]:

$$I \approx (b-a)\frac{f(a)+f(b)}{2} \tag{15}$$

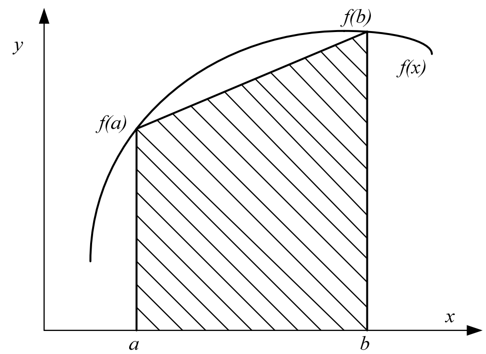

Figure 3. Trapezoidal Method

As shown in figure 3, the use of straight lines to approximate the curved lines caused the error of area that are not shaded. The amount of errors that occur can be estimated from the following equation:

$$E = -\frac{1}{12}f''(€)(b-a) \tag{16}$$

with € is a point which is located in the interval a and b. The equation above shows that if the integrated function is linear, then the trapezoid method will give exact values for the second derivative of the linear function is zero. Instead for the function with the degree of two or more, using the trapezoidal method will give an error.

Trapezoidal method is used to determine the critical angle (δ_{cr}) of the equivalent OMIB generator. In this method, to minimize error the curve is approached by a number of straight lines, form in many layers as in Figure 4.

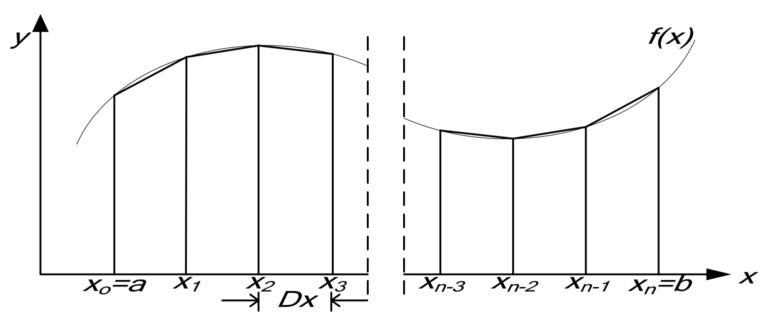

Figure 4. Trapezoidal Method with Many Layers

Total area is the sum of the layers area. The smaller divisions of the trapezoid area, more accurate results are obtained. If there are *n* layers, mean of layers is:

$$\Delta x = \frac{b-a}{n} \tag{17}$$

Δx is length of each layer.
The area limits given notation:

$$x_0 = a, x_1, x_2,......, x_n = b \quad (18)$$

Total integral can be written in the form:

$$I = \int_{x_0}^{x_1} f(x)\,dx + \int_{x_1}^{x_2} f(x)\,dx + \cdots + \int_{x_{n-1}}^{x_n} f(x)\,dx \quad (19)$$

Substitution of equation 15 to 19 will be obtained:

$$= \Delta x \frac{f(x_1)-f(x_0)}{2} + \Delta x \frac{f(x_2)-f(x_1)}{2} + \cdots + \Delta x \frac{f(x_n)-f(x_{n-1})}{2} \quad (20)$$

or

$$I = \frac{\Delta x}{2}\left[f(x_0) + 2\sum_{i=1}^{n-1} f(x_i) + f(x_n)\right] \quad (21)$$

or

$$I = \frac{\Delta x}{2}\left[f(a) + f(b) + 2\sum_{i=1}^{n-1} f(x_i)\right] \quad (22)$$

error that occur because using many areas are:

$$E_t = -\frac{\Delta x}{12}(b-a)f''(x_i) \quad (23)$$

When applied to the equal criteria criteria are as follows. Initial power angle (δ_0) is the angle of internal voltage generator ($E'\prec\delta$) while the maximum power angle (δ_{max}) can be obtained by fulfilling the equation 3 for $P_a^p = 0$. When a very small $\Delta\delta$ taken to reduce cutting error, then the acceleration area and deceleration area as follows:

$$A_a = \int_{\delta_i^0}^{\delta_i^{cr}} P_{ai}^f d\delta_i \quad (24)$$

$$A_d = -\int_{\delta_i^{cr}}^{\delta_i^m} P_{ai}^p d\delta_i \quad (25)$$

$$A_d = \frac{\Delta\delta}{2}\left[P_{ai}^p(\delta_i^{cr}) + P_{ai}^p(\delta_i^m) + 2\sum_{i=1}^{n-1} P_{ai}^p(\delta_i)\right] \quad (26)$$

with

$$n = \frac{\delta_i^m - \delta_i^{cr}}{\Delta\delta} \quad (27)$$

By making δ^{cr} increased by $\Delta\delta$ from 0 to δ^{max} and evaluate margin stability each iteration, then we will get δ^{cr}. Stability margins of course can not be exactly equal to zero, and therefore used a small error tolerance.

A three phase short circuit fault occurs at the sending end, caused no power is deliver to the infinite bus. Electrical power Pe is zero, and the power angle curves same with the horizontal axis. Machine is accelerated by total input power and same with power acceleration thus increasing the speed, storing kinetic energy and raises the angle δ_o.

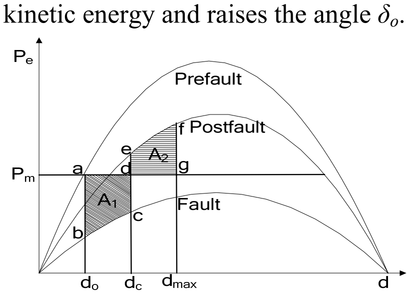

Figure 5. Equal Area Criterion for 3 Phase Fault Short Circuit

When the disturbance is removed at the point of δ_c, which shifts the operating point to the initial power angle curve at point *e*. Net power is now declining, and its kinetic energy will reach a zero value at the point *f*, when the shaded area (*defg*), characterized by A_2, same with the shaded area (abcd), characterized by A_1. Since P_e is greater than P_m, the rotor will continue to slow in line-power angle curve past the point of *e* and *a*. Because the effects of damping, the oscillations slowed and the operating point back to the point of initial power angle δ_0. So the equation will be obtained for termination of the critical angle is achieved if the increase δ_1 cause the area A_1, which shows the deceleration area, smaller than the area that shows the acceleration energy. This occurs when δ_{max}, or point of *f*, is at an intersection between the lines P_m and curves P_e, as shown in Figure 3. By using the equal area criteria, it was found,

$$\int_{\delta_o}^{\delta_c} P_m d\delta = \int_{\delta_c}^{\delta_{\max}} (P_{\max}\sin\delta - P_m) d\delta \quad (28)$$

be integrated equation , then obtained ,

$$P_m\left(\delta_c - \delta_o\right) = P_{\max}(\cos\delta_c - \cos\delta_{\max}) - P_m\left(\delta_{\max} - \delta_c\right)$$

$$\cos\delta_c = \frac{P_m}{P_{\max}}\left(\delta_{\max} - \delta_o\right) + \cos\delta_{\max} \quad (29)$$

B. The 4th RUNGE KUTTA

The 4th Order Runge Kutta is used to determine the critical clearing time (t^{cr}) of OMIB based on δ_c which has been established in previous processes. To determine the value of x_t using 4th Order Runge Kutta first, determine the following four constants [16],

$$k_1 = f(t_i,x_i)\Delta t \quad (30)$$
$$k_2 = f(t_i+(0.5)\Delta t,x_i+(0.5)k_1)\Delta t \quad (31)$$
$$k_3 = f(t_i+(0.5)\Delta t,x_i+(0.5)k_2)\Delta t \quad (32)$$
$$k_4 = f(t_i+\Delta t,x_i+k_3)\Delta t \quad (33)$$

then the value of x can be determined as follows:

$$x_{i+1} = x_i + (1/6)*(k_1+2k_2+2k_3+k_4)$$

When applied to find the critical clearing time (t_{cr}) are as follows:

$$k_1 = f(\delta_i,\omega_i)\Delta t = \omega_i\Delta t$$
$$l_1 = g(\delta_i,\omega_i)\Delta t = (\pi f/H_i)*P_a^f(\delta_i)*\Delta t$$
$$k_2 = f(\delta_i+0.5k_1,\omega_i+0.5l_1)\Delta t = (\omega_i+0.5l_1)*\Delta t$$
$$l_2 = g(\delta_i+0.5k_1,\omega_i+0.5l_1)\Delta t = (\pi f/H_i)*P_a^f(\delta_i+0.5k_1)*\Delta t$$
$$k_3 = f(\delta_i+0.5k_2,\omega_i+0.5l_2)\Delta t = (\omega_i+0.5l_2)*\Delta t$$
$$l_3 = g(\delta_i+0.5k_2,\omega_i+0.5l_2)\Delta t = (\pi f/H_i)*P_a^f(\delta_i+0.5k_2)*\Delta t$$
$$k_4 = f(\delta_i+k_3,\omega_i+l_3)\Delta t = (\omega_i+l_3)*\Delta t$$
$$l_4 = g(\delta_i+k_3,\omega_i+l_3)\Delta t = (\pi f/H_i)*P_a^f(\delta_i+k_3)*\Delta t$$

then, the value of δ and ω is,

$$\delta_{i+1} = \delta_i + (1/6)*(k_1+2k_2+2k_3+k_4)$$
$$\omega_{i+1} = \omega_i + (1/6)*(l_1+2l_2+2l_3+l_4)$$

where, $\delta_1 = \delta^0$ and $\omega_1 = 0$

By increasing t from 0 to 1 second using a small Δt it will be found CCT (t^{cr}). Iteration will stop if $\delta_n = \delta^{max}$

4. Neural Network

Neural network method is artificial neural networks that can work like the workings of the human brain uses a lot of nodes (neurons) to doing processes that transform inputs (x) multiplied by the weights (w) to getting the output (y) [15]. Neural network capable of learning processes through changes in the weights based on history data. From history data, a neural network can obtain the output $F(x, w)$ of the data that has never been teach before. For example there a network of neural network have the input signal (n) and weights (n), then the output function of neurons is:

$$F(x,w) = f(w_1 x_1 + ... + w_n x_n) \tag{34}$$

The weights and biases at each neuron in the learning process is obtained with an activation function. The learning process is done when the training data suitable with the target data. The learning process starts from the input to the hidden layer, and last to the output layer. The output obtained from this layer. At the time of the output is not equal to the target, then the output will be redirected back to the hidden layer back toward the input layer. This process is called back propagation.

Learning with back propagation algorithm using two stages feed forward and back forward. The process begins with the feed forward input unit (x_i) at the input layer are forwarded to each hidden layer ($z_1 ... z_J$). Each hidden unit (z_J) will compute the activation value and sends it to the output layer. Each unit calculates the output layer activation (y_k) and compare it with the target value (t_k) to determine the error factor (δ_k) is used to return output (y_k) to the previous layer. Next, a layer of hidden units will recalculate each layers (z_J). Error factor is not returned to the input layer, but the factor (δ_j) and activation (x_i) will update the weights between input layer and hidden layer. While the weighting factor of the hidden units to output units based on the factors (δ_k) and activation z_J

Backpropagation Learning Neural Network performed using Matlab software. Network architecture of the neural network consists of several inputs that are the incremental of active and reactive load that can be added to the system as long as does not exceed the capacity of the system.

The output of the neural network is CCT as the target. From the overall 96 existing data, only 86 data will be used to train the NN, while the rest 10 data will be used as testing data. Momentum backpropagation will be used for neural network training process which is composed of 86 inputs, two hidden layers and one output layer. Inputs consist of 2 neurons, each of which represents active and reactive load system. The hidden layers consist of two layers. The first layer of hidden layer consists of 43 neurons with activation function tansig. The second layer consists of 14 neurons with activation function logsig. Output layer consists of a single neuron with activation function purelin.

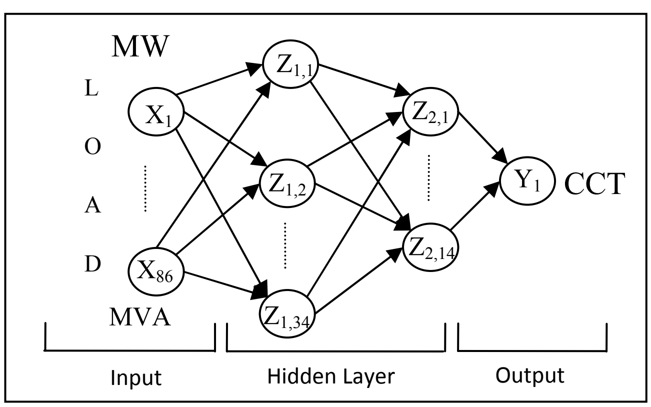

Figure 6. Backpropagation Neural Network Architecture Network

3. Implementation

The system used in this study is the Java-Bali interconnection 500kV. This system consists of 23 buses with 28 mesh transmission and 8 generators as can be seen in figure 7.

The generators are Suralaya, Muaratawar, Cirata, Saguling, Tanjungjati, Gresik, Paiton, and Grati. Among these eight plants, power plants Saguling Cirata are water power plants, while others are steam power plants. In this study Suralaya power plant act as a slack generator.
The load data obtained from PT PLN (Persero) [17]. The kV base is 500 kV, MVA base is 1000 MVA, and the system frequency is 50 Hz. Generator data used are shown in Tables 1.

Table . Generator Data

Generator Number	Generator Name	Xd' (pu)	H
1	Suralaya	0.297	5.19
2	Muaratawar	0.297	1.82
3	Cirata	0.274	2.86
4	Saguling	0.302	1.64
5	Tanjung Jati	0.2588	3.2
6	Gresik	0.297	2.54
7	Paiton	0.297	4.42
8	Grati	0.297	3.5

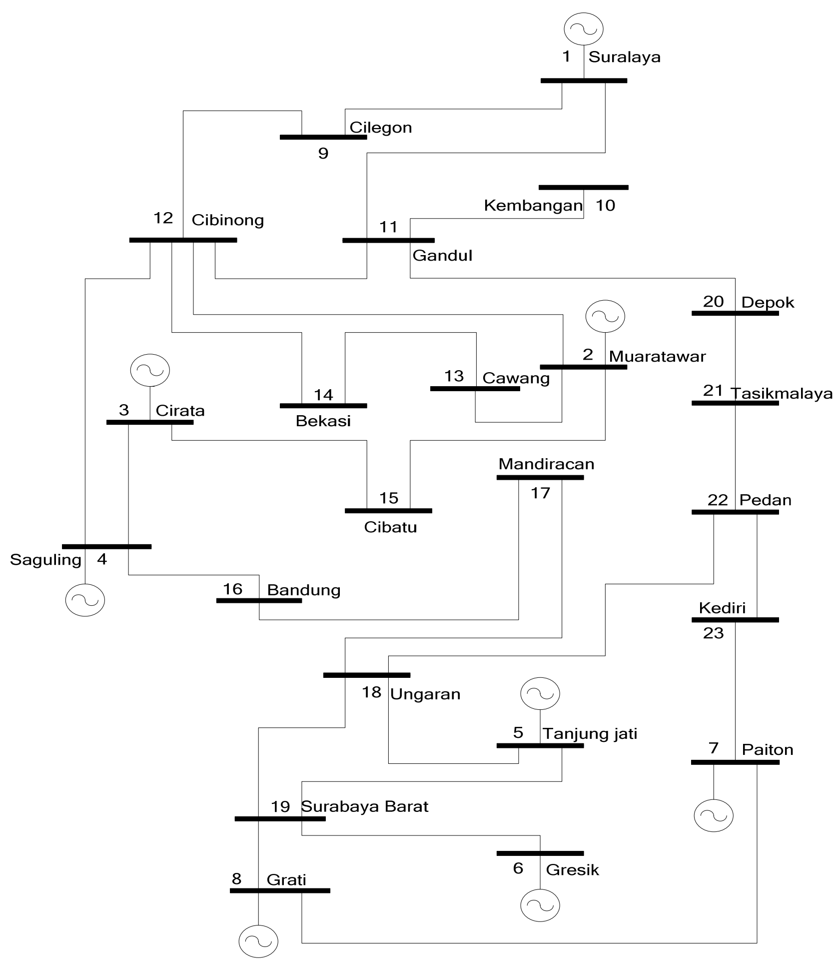

Figure 7. Diagram of the Java-Bali Interconnection System Lines 500 kV

Step of implementation are as follows,

1. Java-Bali initialization data consisting of 500 kV active and reactive generator power, load power,nreactance and admittance of transmission, the angle and voltage of the system.
2. Run Load Flow Program. Calculate the admittance matrix reduction prefault (before disturbance), the prime mover, voltage generator, and the initial angle generator.
3. Test the system using 3 phase ground fault disturbance on the bus load.
4. Calculate the admittance matrix reduction during interruption.
5. Open CB in network transmission to eliminate interference.
6. Calculate the admittance matrix reduction after disturbance.
7. Calculate the *i*-th machine acceleration during disturbances, and the maximum value of acceleration machine. If the ratio between the value of the *i*-th machine acceleration and maximum acceleration is larger than α (eq. 5), those values machines are categorized critical, if not then there is no critical machine and end the program.
8. Check the maximum electrical power and mechanical power of critical machine. If the maximum electrical power is greater than the mechanical power than the critical machine is stable and end the program, otherwise then analyzed using OMIB.
9. Calculate the Critical Clearing Angle (CCA) using the Equal Area Criterion (EAC) via the trapezoidal method.
10. Calculate the critical clearing time (CCT) of OMIB using Runge-Kutta 4th order.
11. Repeat the above steps for other load operation condition
12. Training Neural Networks using load change data as input and CCT as output
13. Test the proposed method and compare the result
14. Comparing CCT OMIB-EAC with the CCT-NN

4. Result Analysis

Using real data Java Bali on the 12th of April 2011, simulation was done by conducting three phase ground fault at bus Gandul and the line between bus Gandul and bus Cibinong was terminated momentarily. Load changes are given on each bus load occurs every fifteen minutes. Some of the results of CCT calculation using OMIB-EAC can be referred to table 2.

The next step is training of back propagation neural network. In this paper, the learning process converges when the value of the minimum MSE is achieved by 0.001

Next, is comparing the value of critical clearing time obtained from the calculation method OMIB-EAC, with results obtained by training using the method of BP Neural Network. Some of the comparison CCT can be seen in table 3.

Table 2. CCT OMIB-EAC for Training NN

TIME	BUS NUMBER						CCT OMIB-EAC (s)
	9		10		11		
	MW	MVAR	MW	MVAR	MW	MVAR	
19:00	140	87	251	155	655	405	0.2820
19:15	137	84	251	155	653	404	0.2880
19:30	133	82	251	155	651	403	0.2860
20:00	127	79	254	157	633	392	0.2840
20:15	127	79	256	158	624	386	0.2870
20:45	114	70	256	158	596	369	0.2780
21:00	100	62	254	157	577	357	0.2750
21:15	87	54	254	157	561	347	0.2710
21:30	73	45	254	157	544	337	0.2680
21:45	93	58	250	155	572	319	0.2640
22:00	113	70	246	152	488	302	0.2570
22:15	130	80	242	150	485	300	0.2550
22:30	147	91	238	147	482	298	0.2530

Table 3. Comparison Training CCT using OMIB-EAC and Neural Network Method

NO	TIME	TRAINING CCT (s)	CCT OMIB-EAC (s)	ERROR (%)
1	18:00	0.2801	0.2800	0.0002
2	18:15	0.2839	0.2840	0.0004
3	18:30	0.2882	0.2880	0.0005
4	18:45	0.2848	0.2850	0.0005
5	19:00	0.2826	0.2820	0.0020
6	19:15	0.2869	0.2880	0.0037
7	19:30	0.2866	0.2860	0.0021
8	20:00	0.2820	0.2840	0.0002
9	20:15	0.2870	0.2870	0.0000
10	20:45	0.2779	0.2780	0.0003
11	21:00	0.2750	0.2750	0.0002
12	21:15	0.2711	0.2710	0.0004
13	21:30	0.2680	0.2680	0.0001
14	21:45	0.2640	0.2640	0.0000
15	22:00	0.2570	0.2570	0.0000
16	22:15	0.2550	0.2550	0.0000
17	22:30	0.2530	0.2530	0.0000
18	22:45	0.2470	0.2470	0.0000

From training result, we obtain that the minimum error was 0%, and maximum error is 0.0084%. The average error of neural network training to OMIB-EAC method is 0.0005186. The comparison accuracy of the output value of the CCT using the method OMIB-EAC and Neural Network can be seen in Figure 8.

Table 4. CCT OMIB-EAC For Testing NN

TIME	BUS NUMBER						CCT OMIB-EAC (s)
	9		10		11		
	MW	MVAR	MW	MVAR	MW	MVAR	
00:45	337	208	198	122	326	202	0.2220
04:15	299	185	176	109	278	172	0.2270
04:45	313	194	179	110	289	179	0.2310
05:45	339	210	190	117	352	218	0.2420
10:00	386	239	235	145	669	414	0.2640
10:45	363	224	234	144	739	457	0.2680
12:45	323	200	229	142	744	460	0.2740
13:00	286	177	193	119	764	473	0.2770
19:45	130	80	253	156	642	397	0.2810
20:30	127	79	257	159	615	381	0.2840

Table 5. Comparison CCT Testing and CCT OMIB-EAC

NO	TIME	TESTING CCT (s)	CCT OMIB-EAC (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

In Figure 8 it appears that the estimation value of CCT resulted using BP neural network is very similar with the CCT values calculated using the method OMIB-EAC with a very small difference.

Next, testing is conducted to compute the CCT using data which are not trained. Severe distributed load conditions was chosen in testing and evaluating the accuracy and robustness of the proposed method. Severe example of the load changes data can be seen in table 4 and the result of this testing step can be seen in table 5.

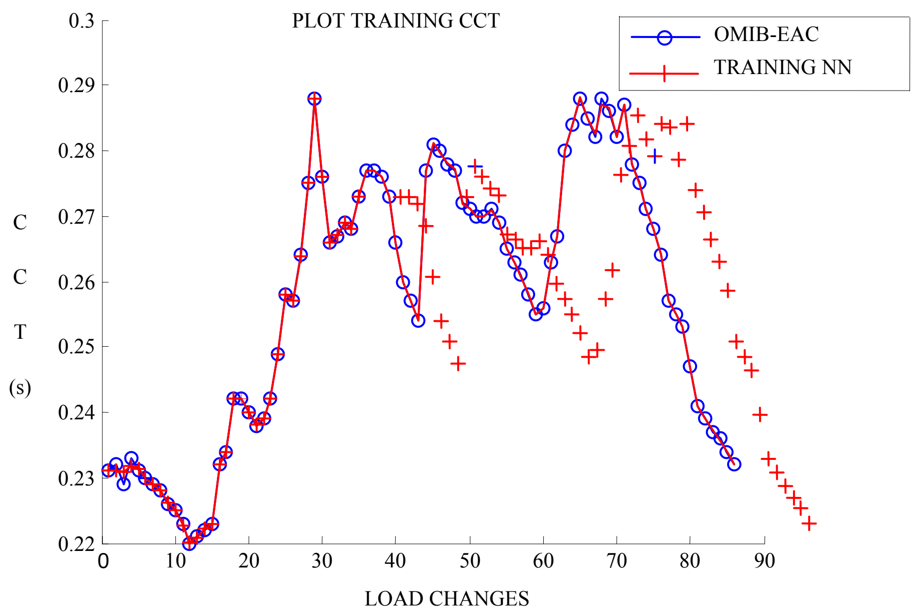

Figure 8. Comparison of CCT OMIB-EAC and Training CCT-NN

From the CCT-NN testing simulation, the minimum error obtained is 0.0042 and a maximum error is 0.0376. The average of error testing is 0.0204. Simulation results can be seen in the figure 9 below.

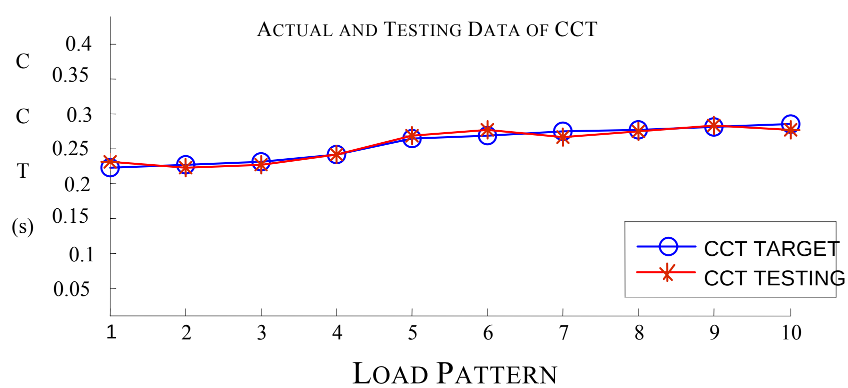

Figure 9. Comparison of CCT-NN and CCT OMIB-EAC

Comparing the value of CCT-OMIB-EAC with CCT- NN at figure 9, it can be concluded that both values are mostly located in the same position. The best results are shown with error 0.0042

Conclusion

Transient stability is the most important in the operation of electric power system. From simulation of Java Bali system, we have presented back propagation neural network based approach for online estimation critical clearing time under real operating condition. The simulation results show that bp neural network could be estimated accurately and computational efficiency the critical clearing time with the minimum error 0.0042. The conclusion is the proposed approach is suitable for online critical clearing time estimation.

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