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SURAT KETERANGAN

No. : 077497 /IT2.VII.4.2/TU.00.08/2018

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Judul	:	Critical Trajectory – ELM Technique For Computing Critical Clearing Time
Penulis	:	Irrine Budi Sulistiawati, Ardyono Priyadi, Adi Soepriyanto
Jurnal /Prosiding/Buku	:	Jurnal Kursor (2015)
Nomer Pemeriksaan	:	2018.1843

dengan hasil

1. Tingkat kesamaan keseluruhan : 13%
2. Tingkat kesamaan individual maximum : 1%

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Critical Trajectory – ELM Technique For Computing Critical Clearing Time Irrine Budi Sulistiawati1,2,a, Ardyono Priyadi1,b , Adi Soepriyanto1,c, 1Department

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Abstract –Electric power system is called reliable if the system is able to provide power supply without interrupted. However, in large systems changing on the system or disturbance may affect the power supply.

Critical clearing time is the time for 7

deciding the system is

a stable or an unstable condition. 34

Critical clearing time has also relationship with setting relay protection to keep the system in the stable condition. Prediction of critical real time for online assessment is expected to be used for preventive action

system. Extreme learning machine is able to perform faster prediction of neural network. With the greatest prediction error rate is 0.0091 percent. Keywords:

critical clearing time, neural network, extreme learning machine **I. Introduction The**

Analysis development of electric power system is growing rapidly by entering the use of artificial intelligent in it. The use of conventional method is being abandoned because this kind of method takes a lot of time in the computation process, especially on transient stability analysis with its complicated non linear models, as well as the more complex problem that demand fast and accurate assessment results which is use for controlling system can be easily solved by artificial intelligent. The ability of artificial intelligent in terms of fast analysis, estimate even prediction made artificial intelligent as a main tools to execute electric power system assessment rather than another traditional method that was used previously. The use of neural network as tools that is used in transient stability assessment becomes the attractiveness of many research [1-4]. From several research that are used as reference, according to A.L. Bettiol, the use of Neural Network gives satisfactory performance results to judge system performance if we compare it with transient stability evaluation that need complicated calculation process and a lot of time to gain non linear solution. According to Sharefean Amir, the use of artificial intelligent in transient stability assessment has a weakness in terms of input measurement. But, still according to Amir, the solution of this problem is using neural network that has capability and knowledge in terms of learning and input processing process. Neural Network was widely used and recognized excellence to perform non linear mapping estimate from several inputs. Besides that, neural network can model artificial system as natural as possible. However, with the development of artificial intelligent science, the use of neural network was regarded as the old method because of its learning algorithm process that is getting slower than required. The learning process that require more than couple hours, even several days, make this neural network is classified as a conventional method. Therefore, the development of neural network that rely on learning and calculating rate becomes the focus of several research recently. According to Guang-Bin Huang, et all, several research recently investigate the capability of feed forward neural network with many layer. This research conclude that continue activation function can gives better result than before. In fact, neural network perform a research that is called training by using several data that has been defined before. When perform forecasting for specific number of data, still according to Huang and Babri, it appears that the result of feed forward neural network with single layer and some specific hidden N node and the using activation function non linear indicate that the observation is fixed or unchanged at some specific hidden N node. This means that input weight which is the layer between input layer and first hidden layer and hidden bias layer 24

need arrangement so that the result is as good as the learning algorithm result of feed forward neural network. Old algorithm of neural network indicate that the parameter of feed forward neural network has to be determined first and depend on weight and bias layer. This research will perform analysis of time estimate of critical severance by using Neural Network and fa1 XP1,Q1 w(x1)a1 w(x3)a1 x1 w(x2)a1 fa2 XP2,Q2 x2 fa3 fa4 fb1 fb2 fb3 y CCT XP9,Q9 x 9 fb24 fa54 Fig 1. Neural Network Architecture Extreme Learning Machine and the result from both method will be compared. To examine the effectiveness from the method that has been used, IEEE 3-machine 9-bus system and Java-Bali 500 kV 54-machine 25-bus system will be tested. II. Methodology This research contains the use of artificial intelligent to calculation technique of critical clearing time.

Neural Network and Extreme Learning Machine are used for performing big estimation of 20

critical clearing time in appraisal of transient stability of electric power system. 7

II.1. Neural Network When neural network was introduced for the first time at 1948 by McCulloch and Pitts, it attract the researches attention because the neural network can adopt the working process of human brain and can be used for solve the problem by model system linear function to gain desired result. . This research use back propagation with several layer that capable to arrange weight from input to hidden layer by error way from hidden layer more than by error way from output layer. Besides that, the capability of BP Neural Network that can be used for non linear activation function and network with many parallel calculation and can model linear function make this neural network become option to solve the problem rather than another method. The steps from the neural network stages are starts with input unit that accept input xi that is passed down to hidden layer in front of them [6]. Input unit (x) is through several weight (w) and interconnected for output (y). In every hidden layer, input unit will be multiplied by weight and will be summed and bias will be added to the equation In this research, input are consist of two neurons, each represents active power and reactive power of system. Hidden layer are consist of two layer, the first layer use tan-sig activation function and second layer use log-sig activation function. The weight of hidden layer can be calculate use this equation below : Z _ in j = w(x1)a1x1 + w(x2)a1x2 + ... + w(x9)a54x9 Z _ in j = V0 j + ∑ wij + xi n i =1 (1) Every neuron weight and bias of learning process are obtained by activation function : Z j = f (Z _ in j) (2) The activator that is used are sigmoid function that follow the equation below : Z j =1+exp(−z_inj) 1 (3) Next step is output unit that can be achieved by multiply weight and sum the result as well as add bias at calculation process. Output layer use one neuron with purelin activation function : Y_ ink = W0k + ∑ Z jW jk p j =1 (4) When the result of feed forward learning process was not the same with the target output, then algorithm process of back propagation was started. In fa1 XP1,Q1 x1 fa2 this back propagation algorithm, output that is different with target

will be sent back to hidden layer toward the input layer. 1

fb1 fb2 δ XP2,Q2 x fa3 2 fb3 y CCT fa4 XP9,Q9 x9 fb24 fa54 Figure 2. Architecture Back Forward This process will be called as back propagation that can be seen at figure 2 . Learning process of back propagation neural network are supervised learning form, which is by seeing the suitability between output and target. Back propagation is started by compare output and target. If output not suitable with target, then the error that has been appeared will be use to improve weight so that the desired compatible output will be obtained. This weight improvement process is performed by set back the unsuitable output to hidden layer to be forwarded to input layer and then fix the weight by equation : Wkj (t + 1) = Wkj (t) + α .δ k .Z j (5) Every hidden unit (zJ) will calculate

activation value and send it to outer layer. Each unit that calculate output layer activation (yk) and compare it with target value (tk) to determine error factor (δk) will be used to return output (yk) to the next layer. 1

II.2. Extreme Learning Machine The use of tuning process at

input weight and hidden bias make algorithm of 33

neural network require time at the learning process

(Huang, G.B., Zhu, Q.Y and Siew, C.K 2006). Learning 10

process with gradient descent at neural network algorithm that use many iteration make this algorithm of neural network require much computation time. Calculation process that use algorithm of neural network is growing with the discovery of new algorithm which is Extreme Learning Machine. First discovered by Guang-Bin Huang (2004), this method can choose input weight and bias at hidden layer randomly. Therefore, this method does not require much time to calculation process like algorithm of neural network. Besides that, this method can achieve small training error and weight and capable to give a good and fast generalization performance. The architecture of

extreme learning machine can be described **as**	2

figure 3. The architecture of

extreme learning machine above **can be** explained **as**	2

: ai = the vector of input weight that connect hidden node to i and input node or center from hidden node to i. bi = threshold from

hidden node to **i** βi = **the weight vector** that connect **hidden node** with **output node.**	19

II.3. Normalization Initial normalization was performed at extreme learning machine to make activation function to produce output between [0,1] or [1,1]. In accordance with reference (Huang, G.B., et. all 2004), it was formulated as : X n = 2 x (

X p – min { X p }) / (max { X p } – min { X p	15

}) – 1 (6) With : Xn = the value of normalization result that goes between [-1,1] Xp = the value of real data that is not normalized yet. min {Xp} = minimum value at data set. Mathematically,

Extreme learning machine can be translated **as follows.**	2

Refer to N sample that can be expressed as

(xi,ti) with : xi =[xi1,xi2,...,xin]T ∈Rn (7) ti =[ti1,ti2,...,tim]T ∈Rm 3

(8) Determine

activation function g and number of node at hidden layer L. 30

For

N hidden layer and activation function in g(x) then : N? 29

N? ∑βigi(xj) = ∑βig

(wi.xj +bi) = oj i =1 i=1 2

XP1,Q1 x 1 XP3,Q3 x 1 3 β 1 XP4,Q4 x 4 XP5,Q5 x 5 i β i XP6,Q6 x o j cct 6 XP7,Q7 x (ai,bi) 7 XP8,Q8 x 8 L β L XP9,Q9 x 9 n 9 500 XP2,Q2 x 2 n input neuron L hidden neuron Output neuron Figure 3. Architecture Extreme Learning Machine

j =1,...,N (9) With wi =[wi1,wi2,...,win]T = weight vector 3

that connect i hiddennodeandinputnode.

βi =[βi1,βi2,...,βim]T = weight vector that 28

connect i hiddennodeandoutputnode wixj =multiplyfromweightvectorandinput bi=thresholdfromhiddennodetoi

From standard

SLFN with N? hidden node with activation function g(x), it can predict N sample with zero error which is mean that ∑ Nj ?=1 6

o j − t j = 0 which is mean o j = t j then : N?

∑βig(wi.xj +bi) = tj, j =1,...,N i =1 Hβ =T (10) Can be 16

explained below : = (

1,..., N? , 1,..., N? , 1,..., N 11

)

⌈g(w1.x1+b1) ? g(wN?.x1+bN?)⌉ = | | ? ? ? | | |⌊g(w1.xN +b1) ? g(wN?.xN +bN?) |⌋NxN? | (11) 5
⌈β1T ⌉ β= | ? || | T = ⌈| | t?

1T ⌉| | |⌊βNT? ⌋|N?xm | |⌊tTN |⌋nxm (12)

H is hidden layer of matrix output from neural network; ith column from H is 12
hidden output of ith

that connect with input x1, x2,...,xN . g(w1x1 + b1) is output of hidden neuron that connect with input xi,

β is the matrix of input weight and T is 21

desired target or output. UMnalcikheinec,oinnvpeunttiwoneaiglhmt(ewthi)

oda,ndathiEddxternembeiasLoefarlnaiynegr (bi)

do not need tuning and hidden layer of matrix output (H) can	22

be obtained without iteration. Output weight can be determined from H β = T from the solution by using Least-Square (LS) with β̂ for linear system : β̂ = H †T (13) II.4. Denormalization After output had been obtained from learning process, denormalization was performed, in accordance with (Zhu, Q.Y., dkk 2005), it can be formulated as : X d = 0.5 (X n +

1) (max { X p } − min { X p }) + min { X p	25

} (14) With : Xd = data value after denormalization Xn = output data after denormalization min {Xp}=

minimum value of set data max {Xp}= maximum value of set data	17

After learning that use extreme learning machine gave result, then extreme learning machine testing was performed with data that has never been taught before.

Weight, bias and number of hidden	14

were using

weight, bias and number of hidden	14

that had been used at learning process. To see the effectiveness of extreme learning machine method, error percentage calculation that occurred was also performed, and was formulated by : MSE = N1 ∑iN=1 (yi − ti) 2 (15) where N= number of data yi= estimate data output ti= actual weight data MAPE = 1 N N i=1 ∑ y prediction − yt arg et yt arg et 100% (16) where yprediction = prediction value JST ytarget= actual value that occurred N = number of data that has been processed II.5. Compare the result of Extreme Learning Machine and Neural Network From the simulation of proposed method, then calculate the speed of the simulation predictions using neural network and extreme learning machine. From the result, we can see that extreme learning machine can predict CCT faster thanNN. Plotting picture from both method will show in the result. III. Simulation To examine the effectiveness of the method that has been used, simulation was perform at 3 Generator 9 Bus system that can be seen at this picture below. The second simulation was done with Java Bali 500 kV 54-machine 25-bus system. Simulations done by giving disturbance at some point and calculate the critical clearing time. Neural network method has been tested to perform prediction from critical clearing time above, and then prediction was performed again by extreme learning machine method. The result from both method above will be compare to see the effectiveness of them by calculating the speed of both of these methods in predicting the critical clearing time 2 7 B G I9 C 3 G2 F H G3 5 6 4 D E 1 A G1 Figure 4. Fouad Anderson 3 Generator 9 Bus System IV. Result Analysis IV.1. System Fouad

Anderson 3 Mesin 9 Bus On the system of Fouad and Anderson 3 Machine 13
9 Bus system,

simulation was done by perform three phase short circuit interference at 32

several point in point A, B and C that we call as Fault 1, 2 and 3. We change one load bus with various capacity then give three phase short circuit in every load changes. From the simulation that has been run, the prediction critical clearing time was obtained as below : Table 1. Prediction CCT Using Neural Network on System 1 INPUT CCT ON (s) P Q FAULT 1 FAULT 2 FAULT 3 95 105 115 125 135 145 155 35 45 55 65 75 85 95 0.3485 0.3635 0.3805 0.3995 0.4205 0.4445 0.4715 0.2145 0.2165 0.2195 0.2215 0.2245 0.2265 0.2295 0.2335 0.2375 0.2405 0.2435 0.2475 0.2505 0.2535 The following table is the result prediction critical clearing time

using extreme learning machine Table 2. Prediction CCT Using Extreme Learning 23
Machine

on System 1 INPUT CCT ON (s) P Q FAULT 1 FAULT 2 FAULT 3 95 105 115 125 135 145 155 35 45 55 65 75 85 95 0.3487 0.3633 0.3802 0.3979 0.4197 0.4441 0.4735 0.2151 0.2163 0.2194 0.2215 0.2245 0.2265 0.2289 0.2341 0.2368 0.2406 0.2439 0.2470 0.2509 0.2533 The next step is to compare the speed of artificial intelligent in predicting cct. By changing

26

the number of neurons in the hidden layer neural network, the

simulation was doing to see the speed neural network in predicting cct and compared with the speed of

extreme learning machine in predicting cct. The results of the 11

comparison of the speed predictions can be seen in the following plot picture 5. Figure 5. Prediction of critical clearing time between neural network and extreme learning machine for system 1 From figure 5 we can see that the time required to predict

the critical clearing time shows that the extreme learning machine is 9

able to provide faster predictions than neural network. The next step is calculating

the critical clearing time for the 9

second system Java Bali 500 kV 54- machine 25-bus system. Figure 6 is the second system interconnected in Java Bali island. The system have 54 machine and 25 bus to supply electric demand in Java Bali island. Three phase short circuit is given on three points, on point B, C and G are referred to Fault 1, Fault 2 and Fault 3. The simulation results are to be obtained critical clearing time as follows on table 3. Table 3. Prediction CCT Using Neural Network on System 2 INPUT CCT ON (s) P Q FAULT 1 FAULT 2 FAULT 3 1162 1187 1207 1232 1252 1272 1277 355 340 360 385 405 425 430 0.6678 0.6936 0.7159 0.7402 0.7839 0.8076 0.8128 0.2545 0.2554 0.2564 0.2570 0.2580 0.2587 0.2588 0.1906 0.1914 0.1917 0.1926 0.1921 0.1934 0.1937 1297 450 0.8388 0.2592 0.1928 1302 455 0.8319 0.2591 0.1931 Table 4. Prediction CCT Using Extreme Learning Machine on System 2 INPUT CCT ON (s) P Q FAULT 1 FAULT 2 FAULT 3 1162 1187 1207 1232 1252 1272 1277 1297 1302 355 340 360 385 405 425 430 450 455 0.6542 0.6862 0.7170 0.7537 0.7769 0.8043 0.8128 0.8528 0.8634 0.2546 0.2556 0.2561 0.2570 0.2572 0.2577 0.2579 0.2596 0.2601 0.1923 0.1924 0.1922 0.1933 0.1938 0.1938 0.1938 0.1946 0.1951 9 Cilegon 12 Cibinong 1 24 Suralaya Balaraja 10 Kembangan Gandul 11 Cawang 13 2 Muaratawar Depok 20 15 Cibatu 4 Saguling Bekasi 14 3 Tasikmalaya 21 Cirata 16 Mandiracan 17 5 Pedan Bandung Selatan Tanjung jati 22 19 Surabaya Barat Ngimbang 25 18 Ungaran Kediri 23 6 8 7 Paiton Figure 6. Java Bali 500 kV 54-machine 25-bus system

To see the effectiveness of the proposed method, the 27

calculation speed of both methods

in predicting the critical clearing time obtained the 8

following results in figure 7. V. Conclusion From the

simulation results show that the prediction of critical clearing time 1

using extreme learning machine method proven faster and more accurate when compared with neural network method. Therefore, when

used to predict critical clearing time in real time, the 8

proposed method can be used. References Figure 7. Prediction of critical clearing time between neural network and extreme learning machine for system 2 From the simulation results shown in figure 5 and figure 7 shows that the extreme learning machine is [1] Yorino N, Sasaki H, Tamura Y, Yokoyoma YR. able to predict critical clearing time faster than neural Generalized analysis method of auto-parametric resonances in power systems. IEEE Transaction on Power Systems network. By changing the number of hidden layers in 1989; A 4(3):1057-1064 neural network, results obtained showed extreme [2] Vega DR, Erns D, Fereira CM, Pavella M. A Contingency learning machine fixed faster and gives accurate filtering ranking and assessment technique for on-line results. transient stability studies. International conference on electric utility deregulation and restructuring and power Calculation error of prediction using neural technologies. 2000 network gives the greatest error result is 0.0079. [3] Fuji W, Wakisaka J, Iwamoto S. Transient stability analysis While extreme learning machine method gives a based on dynamic single machine equivalent. 39th North prediction error of 0.0244 for system 1. American Power Symposium. 2007. [4] Haque MH. Further developments of the equal-area criterion The graphic of critical prediction error can be seen on for multi-machine power system. Electric Power Systems figure 8. Research.1995. [5] Chiang HD, Wu FF, Varaiya P. A BCU Method for Direct Analysis of Power System Transient Stability. IEEE Transaction on Power Systems 1994; Vol 9 No. P 1194- 1208 [6] IEEE Power

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