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Electrical Power and Energy Systems 77 (2016) 345–352

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Critical Clearing Time prediction within various loads for transient stability assessment by means of the Extreme Learning Machine method 18

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Hiroshima University, 1-4-1 Kagamiyama, Higashihiroshima 739-8527, Japan article info Article history: Received 15 November 2014 Received in revised form 1 October 2015 Accepted 13

17 November 2015 Keywords:

Critical Clearing Time (CCT) Transient Stability 50

Assessment (TSA) ELM (Extreme Learning Machine) Critical trajectory Load changing abstract

The Critical Clearing Time (CCT) is a key issue for Transient Stability 48

Assessment (TSA) in electrical power system operation, security, and maintenance. However, there are some difficulties in obtaining the CCT, which include the accuracy, fast computation, and robustness for TSA online. Therefore, obtaining the CCT is still an interesting topic for investigation.

This paper proposes a new technique for obtaining CCT based on 44

numerical calculations and artificial intelligence techniques. First, the CCT

is calculated by the critical trajectory method based on critical generation. Second, the 39

CCT is learned by

Extreme Learning Machine (ELM). This proposed method has the ability 6

to obtain the CCT with load changes, dif- ferent fault occurrences, accuracy, and fast computation, and considering the controller. This proposed method is tested by the IEEE 3-machine 9-bus system and Java-Bali 500 kV 54-machine 25-bus system. The proposed method can provide accurate CCTs with an average error of 0.33% for the Neural Network (NN) method and an average error of 0.06% for the ELM method. The simulation result also shows that this method is a robust algorithm that can address several load changes and different locations of faults occurring. There are 29 load changes used to obtain the CCT, with 20 load changes included for the training process and 9 load changes not included. Ó

2015 Elsevier Ltd. All rights reserved. Introduction Large disturbances in the 37

rotor angle or Transient Stability Assessment (TSA)

plays an important role for electrical power 7 sys- tem operations, security, and maintenance. Many researchers have developed methods

for obtaining the **Critical Clearing Time (CCT) for** the **transient stability**	12

assessment problem, but most of them have proposed direct methods, such as Single Machine Equivalent (SIME), energy function Boundary Controlling Unstable Equilib- rium Point (BCU), critical trajectory and artificial intelligence. However, a Time Domain Simulation (TDS) or conventional numer- ical simulation method are still used to validate the results. The method stated in references [1–8] can accurately provide results because the numerical integration of non linear differential equa- tions is used. However, this approach requires time and needs the detailed process of performing a calculation to guarantee the accuracy. Therefore, it is not suitable for highly dynamic changes, ⇑ Corresponding author at: Departement of Electrical Engineering,

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http://dx.doi.org/10.1016/j.ijepes.2015. 11.034 **0142-0615/** Ó 2015 **Elsevier Ltd. All rights reserved.**	4

especially for transient stability analysis with variations in the load changes and online assessments. There is a numerical method, among others, that can be used to calculate the potential energy and kinetic energy for transient sta- bility analysis; this approach is called the energy function method, as stated in reference [5]. This method can quickly provide a tran- sient stability assessment, but it does not guarantee the accuracy of the results. This circumstance means that the energy function method gives only approximate results. Another method that is believed to be fast in the calculation process and provides accurate results in terms of an exact solution is the critical trajectory method. This method calculates the CCT together with a critical trajectory, and it defines a trajectory that starts from the point of on-fault and ends at a critical condition, such as 16

losing synchronization. The critical trajectory method is a reliable method for analyzing the system stability, especially its transient stability.

This method requires a short time in the calculation process 23

and provides accurate results. A trajectory is a critical path that appears when a disturbance appears, and the system is in a critical condition shortly before losing synchronization [9]. This method is an exact method, which uses numerical integration calculations to solve differential equations; nevertheless, it is sufficiently fast to obtain the CCT. Some new fea- tures that modify the end point conditions and the use of a critical generator have been investigated in references [15,17]. The prelim- inary investigation, which considers the controller, i.e., the Auto- matic Voltage Regulator (AVR) and governor, has been published in references [18,19]. A transient stability assessment system

for determining the Critical Clearing Time (CCT) is developed with the use of 23

artificial intelligence [19–24]. Artificial Intelligence (AI) is used to predict the CCT for the on-line power system. An Artificial Neural Network (ANN) is an advanced calculation process that uses a specific pattern of neurons and weights to solve a problem. A learning or training technique is used in this method [20–22]. Artificial neural networks have the ability to learn the process- ing of information, such as how the human brain works to deter- mine the critical clearing time in transient stability assessment by changing the weights in neurons. The calculated process indi- cates that neural networks perform the process of learning or training on previous data, learning complex non linear mappings of the input samples. The result is provided by the mapping weights applied to the input data. In addition, not only can the arti- ficial neural network predict the result for learned data, but it can also provide a satisfactory result for the unlearned data. The

Extreme Learning Machine introduced by Huang et al. [23] is a promising new method of 21
learning compared with Single- Hidden-Layer Feed-forward

Network, which utilizes a classical learning approach. ELM not only can make the learning process faster than classical learning but also can provide a small value for the training error. Thus, the

performance of this method is superior to other classical methods	14

[23]. This research

paper proposes the ELM to obtain the	14

CCT for TSA on the first swing instability. However, the authors believe that this proposed method can also provide an accurate CCT for the multi-swing instability case. Therefore, further investigation is necessary

to check the superiority and ability of the proposed method in the	36

near future. In addition, this method is capable of predicting an accurate CCT and requires less calculation time than the other NN [23]. It can also be used for TSA online. The Fouad and Anderson or IEEE 3-machine 9-bus systems and Java-Bali 54- machine 25-bus systems are implemented to validate the proposed method. The various loads and point of faults are also observed

to check the superior capability of this proposed method for obtain- ing CCT.	16

In addition, the CCT is obtained by the critical trajectory method, as stated in references [9–19], for preliminary data. Basic theory The fundamental theory plays an important role for this pro- posed method to obtain the CCT. The proposed method refers to a previous method that is used for the preliminary calculation of obtaining the CCT, and it will also be explained in this section. This section also describes some assumptions that are used in this paper, to make them more easily understood. The previous theory and assumptions will be explained next [17].

Critical Clearing Time CCT is defined as the maximum time that	46

is allowed to remove the disturbance without interrupting the system's performance. The system will be stable if the disturbance can be cleared before the time allowed. On the other hand, if the system becomes unsta- ble, then the maximum time allowable disturbance cannot be overcome. A power system must have a Critical Clearing Time that is longer than the operational circuit breaker in the system. Although the CCT is not the main criterion, it should be worked on first when a disturbance occurs. The Critical Clearing Time value is calculated based on the greatest disturbance or the worst case possibility that there is a three-phase short circuit. There are various methods used to calculate the CCT, such as the energy function, extended equal area criterion, Single Machine Equivalent (SIME), conventional numerical simulation, time domain simulation, and critical trajectory based on losing the synchronism and critical generator. Further development in obtaining the CCT has been performed by the artificial intelligence approach. Critical trajectory Based on references [9–19], it is explained that some trajecto- ries affect the behavior of the system before, during, and after a fault occurs. The stability limit of a power system can be explained by utilizing this trajectory. Fig. 1 shows the trajectory of a

power system for **a single machine** system that is **connected to an infinite bus** 31

with damping. Here, “1” indicates a fault on the trajectory, “2” indicates a stable condition after a system disturbance, and “4” indicates that the condition is not stable when the disturbance is late- disconnected; “3” is a critical trajectory that is a critical condition of electric power systems. The theoretical background for obtaining the CCT using the critical trajectory method is stated in references [9–19] and can be explained as follows. A transient stability condition begins when a disturbance occurs at t = 0 after the xpre stable condition. This condition dynamically changes during an interruption [0, s] according to the equation: Here, a “1” indicates a fault on trajectory, “2” indicates a stable condition after a system disturbance, and “4” indicates that the condition is not stable when the disturbance is late- disconnected; “3” is a critical trajectory, which is a critical condi- tion of electric power systems. The theoretical background for obtaining the CCT using the critical trajectory method is stated in reference [9–19] and can be explained as follows. A transient stability condition begins when a disturbance occurs at t = 0 after the xpre stable condition. This condition is dynamically changing during an interruption [0, s] according to the equation: x_ ¼ fFðxÞ; 0 6 t 6 s; xð0Þ ¼ xpre ð1Þ x 2 RN; t 2 R; fF : RN ! RN ð2Þ The curve “1” is formulated by the equation 382 381 380 379 1 ω rad/s 378 4 377 2 3 xu 376 375 374 373 372 -2 -1 0 1 2 3 4 δ

rad 1: Fault-on Trajectory, 3: Critical case, 4: Unstable case, 2: Stable case after fault clearing, xu: **Unstable Equilibrium Point (UEP)** Fig. **1.** 11

Trajectory of single machines connected to an infinite bus, with damping. I.B. Sulistiawati et al. / Electrical Power and Energy Systems 77 (2016) 345–352 347 xðtÞ ¼ XFðt;xpreÞ; 0 6 t 6 s ð3Þ XFð ;xpreÞ : R ! RN ð4Þ When the disturbance was disconnected at time s, the conditions will change based on the following equation: x_ ¼ f ðxÞ; s 6 t 6 1; f : RN ! RN The curve “2” and “4” are calculated by the equation xðtÞ ¼ Xðt; x0Þ; s 6 t 6 1; Xð ; x0 : RN ! RNÞ ð5Þ ð6Þ The curve “3” occurs when the disturbance was disconnected at time s = CCT, with a note that the initial point x0 for the critical tra- jectory is CCT on a fault-on trajectory and is given by the following equation: x0 ¼ XFðs;xpreÞ; s ¼ CCT ð7Þ Neural network A neural network can be described as the process of the human brain’s neural networks during the training and learning processes. A neural network is potentially applicable as a benchmark for com- puting nonlinear problems because this method can be used in the absence of a mathematical equation. Therefore, this method is suit- able for solving nonlinear problems, especially transient stability analysis in power systems. The neural network architecture consists of input units (x), weights (w), a hidden layer, and output units. These weights are a key issue for improving the output to attain a target. The output function can be expressed as follows: Fðx; wÞ ¼ f ðw1x1 þ þ wnxnÞ ð8Þ Fig. 2 shows that the standard back-propagation neural networks consist of the inputs, weight, two hidden layers and output. The learning process for this method calculates the weights to obtain the output target. If errors exist, then the weights are updated to improve the solution to make the error of the target small enough. This method is used for comparison of the proposed method. Proposed method for obtaining CCT This research paper proposes

the Extreme Learning Machine (ELM) method to obtain **the** predicted Critical Clearing **Time.**	42

This method is one type of neural network method that has the capabil- ity of obtaining the Critical Clearing Time. Therefore, it can provide a timely solution. The performance of this method has also been compared with the single learning algorithm

Hidden Layer Feed forward Network (SLFN), which **is** described **in**	43

reference [20]. The procedure of the proposed method will be explained as follows: Fig. 3 shows architecture of the proposed method, which was used to obtain the predicted Critical Clearing Time. This proposed method is derived from SLFN and is called

the Extreme Learning Machine (ELM) [22]. **For**	6

N samples, ðxi; tiÞ ð9Þ

where xi ¼ ½xi1; xi2; . . . ; xinŠT **2 Rn and ti ¼ ½ti1; ti2;** . . . ; timŠT **2 Rm** The standard SLFN **with N hidden** nodes **and** activating **function** gðxÞ **can**	1

be formulated as follows: XN~ XN~ bigiðxjÞ ¼

bigðwi xj þ biÞ ¼ oj i **¼1 i¼1**	20

j ¼ 1;...;N; ð10Þ **where wi ¼ ½wi1; wi2;** . . . ; winŠT **is the weight vector** that connects **the ith** input to **the** ith hidden node. **bi ¼ ½bi1; bi2;** . . . ; bimŠT **is the weight vector** that connects	2

the ith hidden node to the output. bi is the threshold of the ith hidden node. wixj = the inner product between wi and xj.

Based on

the standard SLFN with N~ hidden nodes and an activation function, gðxÞ can predict the N samples with zero 28

errors. PN~ This outcome means that j¼1koj tjk ¼ 0, and thus, XN~ bigðwi xj þ biÞ ¼ tj; j ¼ 1; . . . ;

N i¼1 This equation can be written in a simpler way, as 5

follows:

Hb ¼ T with Hðw1; . . . ; wN~; b1; . . . ; bN~; x1; . . . ; xNÞ 2 gðw1 x1 þ b1Þ gðwN~ x1 þ 1

bN~Þ 3 ¼ 64 . . . . 5 7

gðw1 xN þ b1Þ gðwN~ xN þ 1

bN~Þ NN~ ð11Þ ð12Þ ð13Þ ð14Þ x1 w1 x2 w2 y x3 w3 . . xṅ wn input weight Hidden layer output Fig. 2. Neural network architecture with two hidden layers. Fig. 3. Architecture of the Extreme Learning Machine. 2 bT1 3 2 tT1 3 b ¼ 64 . 7 5 and T ¼ 46 .. 5 7 bTN~ N~ m tTN nm H

is the hidden layer output matrix of the neural network, and x1, x2, . . ., xN is the ith hidden node output with respect to the 24

inputs.

T is the target or output. The 9

proposed method does not require a bias

for the hidden layer (bi) **and** tuning for the **input weights** (wi). **The** weights on **the** 9

hidden layer output matrix are obtained at random without any training iterations. The output weights are determined by the formula Hb = T, and this relation- ship is linearized by least-squares for the linear systems, with b^ HyT ¼ ð15Þ Problem formulation Power system model Multi-machine system A multi-machine system is defined as a model xd' with genera- tors that are indicated by two differential equations. This model is called a classical swing equation and can be represented as follows: Mix_i ¼ Pmi Peiðdiþ Dixi d_i ¼ x ð16Þ i The multi-machine systems used centre of angle (COA) swing equations that can be written as follows: Mix~_i ¼ Pmi Peiðhiþ Mi PCOA Diðx~iþ MT h_i ¼ x~i where MT ¼ Mi; x0 ¼ Xn 1 XnMixi; d0 ¼ 1Xn Midi;

i¼1 MT i¼1 MT i¼1 41

hi ¼ di d0; x~i ¼ xi x0; Xn PCOA ¼ ðPmi Peiðhiþþ; Peiðhiþ ¼ YijEiEj sinðhi hj þ aijþ Xn i¼1 j¼i

Pmi is the ith **mechanical power** input; xi **is the** ith generator **rotor** speed; di **is the** 32

ith generator angle deviation;

Mi is the ith **moment of inertia; Di is the** ith **damping** 30

coefficient;

Ei is ith **voltage behind the transient** reactance; Pei **is** 7

the ith electric power. AVR and Governor are represented as follows: E_i ¼ TAVRi 1 ðE0i Eiþ þ KAVRiðVrefi Vtiþ P_mi ¼ TGOV1 1 ðPmrefi Pmiþ þ KGOVðx~iþ with Peiðdiþ ¼ YijEiEj cosð di þ dj þ aijþ Xn j¼i ð17Þ ð18Þ ð19Þ ð20Þ ð21Þ The CCT obtained by the Critical Trajectory method has been pub- lished before and can be explained with the following formulation: ( ) min Xm lk 0ðlkþ þ lmþ1 0Wðlmþ1Þ ð22Þ x0;x1;...;xmþ1;e;s k¼0 where xk 2 RN; ðk ¼ 0; . . . ; mþ; e 2 R; s 2 R lk ¼ xkþ1 xk jxx__kkþþ11 þþ xx__kkj e ð23Þ x_k ¼ f ðxkÞ ð24Þ with the following boundary conditions: x0 ¼ XFðs; xpreÞ ð25Þ lmþ1 ¼ xmþ1 x u with f ðxuÞ ¼ 0 ð26Þ This minimizing problem

is solved by The Newton–Raphson method to obtain	7

the critical trajectory together with the CCT. Then, this procedure is repeated to obtain the CCT for all of the points of the faults, when varying the load. This CCT is learned by the pro- posed method to speed up the calculation that will be applied online. However, not all of the obtained CCTs for varying the loads are learned by the proposed method; only some of them are, specif- ically, 31%. The aim is to provide robustness in

the proposed method. The proposed method The proposed method is called the	12

Extreme Learning Machine (ELM), and it has the ability to select random	14

hidden nodes and determine the output weights analytically	49

[22–24]. The proposed method is also capable of providing results in less time during the learning process. In this paper, the author rigorously proves that the

input weights and hidden layer biases of the SLFNs can be randomly assigned. If the activation functions for the hidden layer are infinitely differentiable after the input weights and hid- den layer biases are chosen randomly, then the SLFNs can be sim- ply considered to be a linear system. The output weights	3

(which link the hidden layer to the output layer) of the SLFNs can also be analytically determined through a simple generalized inverse operation.	17

This Process can still give good results in solving prob- lems that involve a large and complex system. In addition, the

Extreme Learning Machine (ELM) has a learning speed that can be thousands of times faster than the traditional feed forward net- work learning algorithms, such as the back-	15

propagation neural network (BPNN) algorithm, while

the obtained result is better in terms of the general performance. The algorithm of the training process of the

ELM is based on the Single Layer Feed forward Network (SLFN) and has an 5

efficient and simple algorithm that can be written as follows:

Find specific w^i; b^i; b^ ði ¼ 1; . . . ; N~ 34

Þ

Hðw^1; :::; w^N~; b^1 . . . ; b^~ NÞ ^b T 33

¼ mwibinib Hðw1;...;wN~;b1;...;bN~Þb T ð22Þ Minimizing the cost function given by XN XN~ ! 2 E ¼

bigðwi xj þ biÞ tj ð23Þ j¼1 i¼1 20

Gradient-based learning algorithms denoted as H are used to search for the minimum of kHb 27
Tk. The procedure

tends to be simpler because the

vector W becomes the set of weights (wi, bi) and bias (bi) parameters, and it is 10
iteratively adjusted as Wk ¼ Wk 1 g @EðWÞ @W ð24Þ Here, g is the learning rate.

 The

input weight wi and the hidden layer biases bi can be 9 fixed because, in fact, they both

are not necessarily tuned, and the hid- den layer output matrix H actually remains unchanged 5

when the learning process begins [24]. Thus, we find

solution ^b of the linear system Hb = T Hðw^1; . . . ; w^N~; b^1 . . . ; ^b~ NÞ ^b T 6

¼ mbin Hðw1;...;wN~;b1;...;bN~ Þb T ð25Þ Simulation results Simulation procedure The proposed method is tested to obtain the CCT using the IEEE3-machine 9-bus system and the Java-Bali 500 kV 54- machine 25

-bus system, as shown in Figs. 4 and 5, respectively. The 29

first simulation is

on the IEEE 3 -machine 9 -bus system, as shown in Fig. 19

4, and it can be explained as follows: bus 6 is assumed to have changing loads. Generator 1 is a hydro electric plant, while 2 and 3 are the steam generators. Simulation is accom- plished by performing

a three-phase short circuit at points A, B, and 47

G. In addition, the transmission line is assumed to have double circuits and a point of fault that occurs

close to the bus. A three-phase short circuit fault is given at 38

one point, and then, CCT is calculated on this condition. The obtained CCT is repeated at each changing load at bus 6. In addition, the calculation of the CCT is repeated by three-phase short circuit faults at different points. The fault points A, B, and G are investigated. These three points of the fault can be explained below: (a) Fault “1”or fault point A is the point of fault between bus 1 and 4 and is close to bus 1. (b) Fault “2”or fault point B is the point of fault between bus 2 and 7 and is close to bus 2. (c) Fault "3"or fault point G is the point of fault between bus 7 and 8 and is close to bus7. The second simulation is the Java-Bali 54-machine 25-bus sys- tem, as shown in Fig. 5. Bus 15 is a bus that gradually changes load. At each change in the load, a three-phase

short circuit simulation is performed to obtain the	26

same Critical Clearing Time as before.

It is assumed that a three-phase short circuit occurs at	19

the fault points B, C, and G. Fault point B is the bus between Cibinong and Bekasi, fault point C is the bus between Saguling and Cirata, and fault point G is the bus between Cirata and Cibatu. Other assumptions are the same as the previous simulation of the power system model. Fig. 4. IEEE 3-machine 9-bus system. Fig. 5. Java Bali 500 kV 54-machine 25-bus system. Obtaining CCT A numerical simulation is performed by the critical trajectory method, which is performed using Eqs. (6), (7) and stated in the references [9]. The simple AVR and governor models are used for both power system models, as stated in references [18,19]. A fur- ther feature is used to obtain the CCT with load variations. This approach is to determine the daily load profile in the electric power system.

The conventional numerical simulation method is used to validate obtaining the	45

CCT. The next step is the learning process while using the proposed method. The obtaining

of the CCT is calculated by the proposed method	26

and is performed approximately 200 times, to validate the robustness and accuracy. Figs. 6 and 7 illustrate the obtaining of the CCT using the two methods: the NN method and the proposed method called ELM. These iterations are run 200 times.

It is shown that the proposed method can provide	7

a similar CCT in a number of iterations, which is not the case in other methods. This finding proves that the pro- posed method can provide a robust result although it is a statistical method. Tables 1-6 show the simulation results that were performed by the critical trajectory (CT), back-propagation

IEEE 3-machine 9-bus system and Java Bali 500 kV 54-machine 25-bus system. The load variations are also listed in the tables. Tables 1 and 2 show obtain- ing the CCT in seconds using CT, NN, and ELM. Fault variations are also listed. The obtained CCT numbers using the proposed method are similar to using the critical trajectory method. It is observed IEEE 3 Generator 9 Bus 0.375 0.37 0.365 0.36 CCT 0.355 0.35 0.345 0.34 NN ELM 0.335 0.33 0 50 100 150 200 Number of Simulation 250 Fig. 6. CCT for IEEE 3-machine 9-bus system simulated 200 times. Table 2a Obtaining CCT Fault-1 for the Java Bali 500 kV 54-machine 25-bus system. Load variations P (MW) Q (MVar) Obtaining CCT for Fault-1 CT (s) NN (s) ELM (s) 1162 355 1187 340 1207 360 1232 385 1252 405 1272 425 1277 430 1297 450 1302 455 0.6653 0.6678 0.6904 0.6936 0.7135 0.7159 0.7473 0.7402 0.7785 0.7839 0.8128 0.8076 0.8219 0.8128 0.861 0.8388 0.8716 0.8319 0.6542 0.6862 0.7170 0.7537 0.7769 0.8043 0.8128 0.8528 0.8634 CCT 0.258 0.256 NN ELM 1187 1207 1232 340 360 385 0.2557 0.2563 0.2571 0.2554 0.2564 0.2570 0.2556 0.2561 0.2570 Table 2b 0.266 Jawa Bali 500 KV Obtaining CCT Fault-2 for the Java Bali 500 kV 54-machine 25-bus system. 0.264 Load variations Obtaining CCT for Fault-2 0.262 P (MW) Q (MVar) CT (s) NN (s) ELM (s) 0.26 1162 355 0.2546 0.2545 0.2546 0.254 1252 405 0.2579 0.2580 0.2572 0.252 1272 425 0.2587 0.2587 0.2577 1277 430 0.2589 0.2588 0.2579 0 50 100 150 200 250 Number of Simulation 1302 455 0.2598 0.2591 0.2601 1297 450 0.2596 0.2592 0.2596 Fig. 7. CCT for Java Bali 500kV54-machine 25-bus system simulated 200 times. Table 1a Obtaining CCT for IEEE 3-machine 9-bus system for Fault-1. Load variations P (MW) Q (MVar) Obtaining CCT for Fault-1 CT (s) NN (s) ELM (s) 95 35 105 45 115 55 125 65 135 75 145 85 155 95 0.3485 0.3512 0.3635 0.3631 0.3805 0.3884 0.3995 0.4050 0.4205 0.4213 0.4445 0.4425 0.4715 0.4815 0.3487 0.3633 0.3802 0.3979 0.4197 0.4441 0.4735 Table 2c Obtaining CCT Fault-3 for the Java Bali 500 kV 54-machine 25-bus system. Load variations P (MW) Q (MVar) Obtaining CCT for Fault-3 CT (s) NN (s) ELM (s) 1162 355 1187 340 1207 360 1232 385 1252 405 1272 425 1277 430 1297 450 1302 455 0.1918 0.1906 0.1918 0.1914 0.1921 0.1917 0.1925 0.1926 0.1923 0.1921 0.193 0.1934 0.193 0.1937 0.1929 0.1928 0.1931 0.1931 0.1923 0.1924 0.1922 0.1933 0.1938 0.1938 0.1938 0.1946 0.1951 Table 1b Obtaining CCT for IEEE 3-machine 9-bus system for Fault-2. Load variations Obtaining CCT for Fault-2 Table 3a Error of CCT Fault-1 for IEEE 3-machine 9-bus system. P (MW) Q (MVar) CT (s) NN (s) ELM (s) Load variations Obtaining CCT for Fault-1 95 105 115 125 135 145 155 35 45 55 65 75 85 95 0.2145 0.2165 0.2195 0.2215 0.2245 0.2265 0.2295 0.2148 0.2166 0.2199 0.2217 0.2234 0.2270 0.2293 0.2151 0.2163 0.2194 0.2215 0.2245 0.2265 0.2289 P (MW) 95 105 115 125 135 145 Q (MVar) 35 45 55 65 75 85 Neural Network (s) 0.0027 0.0004 0.0079 0.0055 0.0008 0.002 Extreme Learning Machine (s) 0.0002 0.0002 0.0003 0.0016 0.0008 0.0004 155 95 0.01 0.002 Table 1c Obtaining CCT for IEEE 3-machine 9-bus system for Fault-3. Load variations Obtaining CCT for Fault-3 that the proposed method can provide an acceptable CCT com- P (MW) Q (MVar) CT (s) NN (s) ELM (s) pared to other methods. This finding means that the proposed method has the potential to become an alternative method for 95 35 0.2335 0.2347 0.2341 105 45 0.2375 0.2373 0.2368 obtaining the CCT. 115 55 0.2405 0.2418 0.2406 Tables 3 and 4 show the error in CCT in seconds, for the pro- 125 65 0.2435 0.2447 0.2439 posed method and NN compared with the critical trajectory 135 75 0.2475 0.2483 0.2470 method. The maximum error is 0.0238 in seconds. It is observed 145 85 0.2505 0.2495 0.2509 155 95 0.2535 0.2535 0.2533 that the proposed method can obtain an accurate CCT for all of the load variations and fault points in both systems.

345–352 351 Table 3b Error of CCT Fault-2 for the IEEE 3-machine 9-bus system. Load variations P (MW) Q (MVar) Obtaining CCT for Fault-2 Neural Network (s) Extreme Learning Machine (s) 95 35 105 45 115 55 125 65 135 75 145 85 155 95 0.0003 0.0196 0.00001 0.0203 0.0004 0.0211 0.0002 0.0224 0.0011 0.0225 0.0005 0.0244 0.0002 0.0238 Table 5 CPU calculation time for the ieee 3-machine 9-bus system. Load variations P (MW) Q (MVar) Calculation time CT (s) NN (s) ELM (s) 95 35 105 45 115 55 125 65 135 75 145 85 155 95 Average 0.7584 0.3588 0.8154 0.3008 0.8133 0.3120 0.8034 0.3276 0.7931 0.3187 0.7975 0.3299 0.7995 0.3120 0.7972 0.3228 0.0022 0.0022 0.0044 0.0044 0.0044 0.0067 0.0044 0.0033 Table 3c Error of CCT Fault-3 for the IEEE 3-machine 9-bus system. Table 6 Load variations Obtaining CCT for Fault-3 CPU calculation time for the Java Bali 500 kV 54-machine 25-bus system. P (MW) Q (MVar) Neural Network (s) Extreme Learning Machine (s) Load variations Calculation time 95 35 0.0012 0.0006 P (MW) Q (MVar) CT (s) NN (s) ELM (s) 105 45 0.0002 0.0007 115 55 0.0013 0.0001 1162 355 0.9385 0.6708 0.1699 125 65 0.0012 0.0004 1187 340 0.9422 0.3114 0.1681 1207 360 0.9214 0.2045 0.1664 135 75 0.0008 0.0005 145 85 0.001 0.0004 1232 385 0.9354 0.2392 0.1595 1252 405 0.9337 0.2333 0.1768 155 95 0.002 0.0002 1272 425 0.9374 0.2111 0.1681 1277 430 0.9304 0.2333 0.1837 1297 350 0.9483 0.2778 0.1629 Table 4a 1302 455 0.9482 0.2333 0.1681 Error of CCT Fault-1 for the Java Bali 500 kV 54-machine 25-bus system. Average 0.9373 0.2905 0.1692 Load variations Obtaining CCT for Fault-1 Tables 5 and 6 show the calculation time for the CT, NN, and P (MW) Q (MVar) Neural Network (s)

Extreme Learning Machine	(s)	ELM	methods	in	seconds.	The	average	of the	40

calculation time is 1162 355 0.0025 0.0111 also shown. The proposed method is 1.72 times faster than NN 1187 340 0.0032 0.0042 and 5.54 times faster than CT. This finding means that the pro- 1207 360 0.0024 0.0035 1232 385 0.0071 0.0064 posed method is fast enough to obtain the CCT and be potentially 1252 405 0.0054 0.0016 applicable for online transient stability assessment. 1272 425 0.0052 0.0085 1277 430 0.0091 0.0091 1297 450 0.0222 0.0082 Conclusions 1302 455 0.0397 0.0082 The proposed method is one type of intelligent technique that can obtain an accurate and robust CCT. The maximum error is Table 4b 0.0238 in seconds for both systems tested. Error of CCT Fault-2 for the Java Bali 500 kV 54-machine 25-bus system. The proposed method can also quickly calculate the CCTs, Load variations Obtaining CCT for Fault-2 which are 5.54 and 1.72 times faster compared to the CT and NN method, respectively. Therefore, the proposed method is poten- P (MW) Q (MVar) Neural Network (s) Extreme Learning Machine (s) tially applicable for online transient stability assessment. As an 1162 355 0.0001 0 additional feature, it can obtain the CCT while considering the con- 1187 340 0.0003 0.0001 1207 360 0.0001 0.0002 troller (governor) and AVR. 1232 385 0.0001 0.0001 1252 405 0.0001 0.0007 Acknowledgements 1272 425 0 0.001 1277 430 0.0001 0.001 1297 450 0.0004 0 The authors gratefully acknowledge the contributions of the 1302 455 0.0007 0.0003

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