A Fast and Accurate Transient Stability Assessment Method Based on Deep Learning: WECC Case Study

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***Abstract*—Transient stability is one of the critical aspects of power system stability assessment. The increasing integration of inverter-based resources and the retirement of conventional synchronous generators result in the decreasing system inertia and growing complexity of system operating conditions. Using a few selected typical operating conditions cannot guarantee system transient stability in all operating conditions, and the time-domain simulation of all operating conditions requires tremendous time and is often infeasible. This paper proposes a more efficient transient stability assessment method based on deep learning. The binary search method is used to determine the critical clearing time (CCT) in creating training databased by time-domain simulation. This method is fast and accurate with 1 ms resolution. The buses whose CCTs are lower than 200 ms are considered critical buses. Buses close to each other are grouped based on their mutual admittance matrix to reduce the search space of the critical buses. This paper also proposes the generator feature normalization based on the physical model. Case study on the reduced 240-bus WECC system model demonstrates that the proposed method can predict CCT accurately and efficiently.**

***Index Terms*—Transient stability assessment, machine learning, deep learning, critical clearing time.**

I. Introduction

Transient stability is a critical aspect of power system stability, which refers to the ability of an AC power system to maintain its synchronism after a large disturbance. In current industry practices, transient stability is typically evaluated by time-domain simulation of selected representative operating scenarios, e.g., summer peak, winter peak, and spring light. Two direct methods are also used to assess power system transient stability: the extended equal area criterion (EEAC) [1]-[2] and the boundary controlling unstable (BCU) equilibrium point method [3]-[5].

Recent fundamental changes in power systems, e.g., replacement of conventional synchronous generators with inverter-based resources (IBRs), integration of large-scale distributed energy storages (electric vehicles), and integration of large amount of dispatchable loads, have resulted in more complex system dynamics. More importantly, due to the intermittence of renewables, power grids can experience more dramatic and frequent variations of operating conditions. This makes it infeasible to use traditional offline transient stability assessment methods, which only consider a few selected representative operating conditions. Thus, it is highly desirable to significantly improve its efficiency to achieve fast and accurate transient stability assessment based on real-time operating condition variations.

The critical clearing time (CCT) of a three-phase fault at each high-voltage bus can be used as the transient stability index. In [6]-[8], the CCT is estimated using a Lyapunov's type energy function or a transient energy function (TEF). This method has some limitations and does not guarantee accurate results all the time. Reference [9] proposes a combination of simulations and the CCT approximation method, which computes the approximated CCT using the energy function approach, starts the time-domain simulation with this approximated value, and finally obtains the accurate CCT. However, in a large power system, the accuracy of the energy function approach may not be guaranteed. As a result, the large error between the approximated CCT and actual CCT requires lots of repeated simulations to get the actual CCT. Also, extra calculation is needed to get the approximated CCT before the simulation.

Artificial Intelligence (AI) technologies, especially deep learning neural networks, have many successful applications in various areas, such as image recognition and language processing [10]. They also have great potential to fundamentally transform the way today's power industry monitors, analyzes, and controls power grids. Some researchers have investigated the application of AI in transient stability assessment. A deep imbalanced learning framework is proposed in [11], which can improve the effectiveness of transient instability recognition, since unstable cases are hard to see in an actual power grid. A convolutional neural network (CNN) transient stability classifier is developed in [12] to predict if the system is transient stable or not. A new transient stability assessment based on multi-branch stacked denoising autoencoder (MSDAE) is presented in [13]. MSDAE can achieve feature extraction and classification intrinsically and simultaneously in an end-to-end manner. However, their training dataset does not consider multiple operating

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conditions due to renewable generation variations. Moreover, reference [14] investigates the adaptive remedial action scheme based on deep learning.

This paper investigates the application of deep learning neural network in transient stability assessment. The reduced 240-bus WECC system model is used as the study system, which has 8,784 hourly dispatches in total in a year of 366 days [15]. CCT is used as the metric to assess the transient stability. The binary search algorithm is used to determine the CCT in time-domain simulations. Buses are grouped based on their mutual admittance matrix to identify the critical buses.

II. Study System and Training/Testing Dataset

A. Reduced 240-bus WECC System Model

The 240-bus WECC system model developed by the National Renewable Energy Laboratory (NREL) is a reduced model of the actual WECC system [16]. WECC system includes the provinces of Alberta and British Columbia in Canada, the northern portion of Baja California in Mexico, and all or portions of the 14 western states in the U.S. [17].

The 240-bus reduced WECC model has one year dispatch data obtained from the unit commitment and optimal power flow. The model reflects the generation resource mix of the WECC system as of 2018. Moreover, the developed dynamic model is validated against field frequency measurements by FNET/GridEye during actual events. The dynamic model preserves the dominant inter-area oscillation modes in the actual WECC system. Figure 1 shows the renewable penetration level in one year, which is varying between 0.20% to 49.19%.

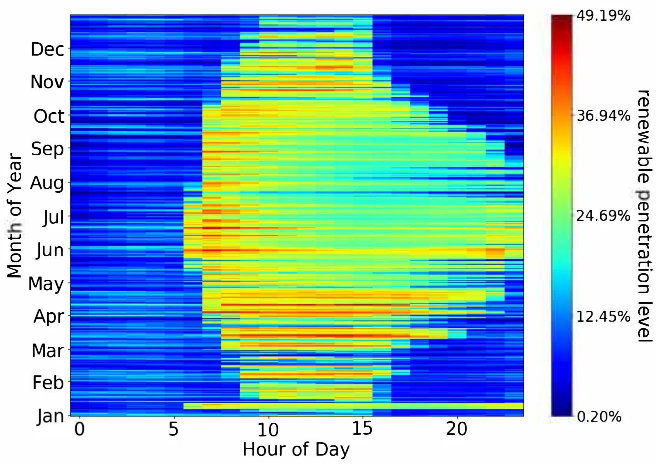


Figure 1. Renewable penetration of the study system.

B. Training/Testing Dataset Generation

1) System transient stability definition: In this study system, there are 187 high-voltage buses, and the rest are generator buses at lower voltage levels. The fault is applied on each of the 187 buses and is cleared after time t. Around 2 seconds after the fault is cleared, rotor angle signals are checked to see if any generators are out-of-step. To this end, generator's relative rotor angle is used, which is defined as (1)

$$\delta_i(t) = \Delta_i(t) - Ave\{\Delta(t)\} \quad (1)$$

where $\delta_i(t)$ is generator i's relative rotor angle at time t. $\Delta_i(t)$ is generator i's rotor angle at time t. $Ave\{\Delta(t)\}$ is the average rotor angle of all large generators at time t.

Generator i is deemed as out-of-step in (2) if the relative rotor angle deviation is larger than 180^0 around 2 seconds after fault clearance.

$$abs\{\delta_i(t_{pre-fault}) - \delta_i(t_{after-fault})\} > 180^0 \quad (2)$$

where $\mathrm{t_{pre-fault}}$ is time right before the fault, and $\mathrm{t_{after-fault}}$ is first swing (2 seconds in this case) after the fault.

In this study, CCT is used as the index of transient stability assessment. The CCT is defined as the maximum allowable time interval between the start and removal of the fault that maintains the system synchronized. However, the system will lose synchronization when fault is cleared after CCT.

2) Binary search algorithm for CCT: To get the CCT for a specific bus in one selected operating condition, multiple simulations are performed. The binary search algorithm is applied to reduce the number of simulations. The binary search algorithm can find the position of a target value within a sorted array. In this paper, 0 to 2000 ms is the range for the CCT search. If the CCT is in this range, the actual CCT can be found in 11 repeated simulations at most (log 2000 = 11). Also, multiple cores of CPUs are utilized to accelerate the simulations. If a PC is equipped with an 8-core CPU, multiple-core processing will speed up the simulation 2 to 3 times, considering the additional overhead time.

TABLE I shows one example of the binary search method. After 11 repeated simulations with different fault clearing time values, the program found the accurate CCT for one specific bus. In this example, the CCT is 232 ms.

TABLE I. Binary Search Algorithm for CCT

Simulation steps	Fault clearing time (ms)	Transient stability
1st	1,000	Unstable
2nd	500	Unstable
3rd	250	Unstable
4th	125	Stable
5th	188	Stable
6th	219	Stable
7th	234	Unstable
8th	227	Stable
9th	231	Stable
10th	233	Unstable
11th	232	Stable

3) Bus clustering: There are 187 buses in the system where faults can be applied to search for CCT. According to the NERC standard, backup relay is required to act in 12 cycles, which is 200 ms [18]. It is assumed that buses with a small mutual impedance will have similar CCTs because of a shorter electric distance. For example, applying a bus fault on two ends of a short line may have very similar impacts, and thus the CCTs will be close to each other. Therefore, all the buses are

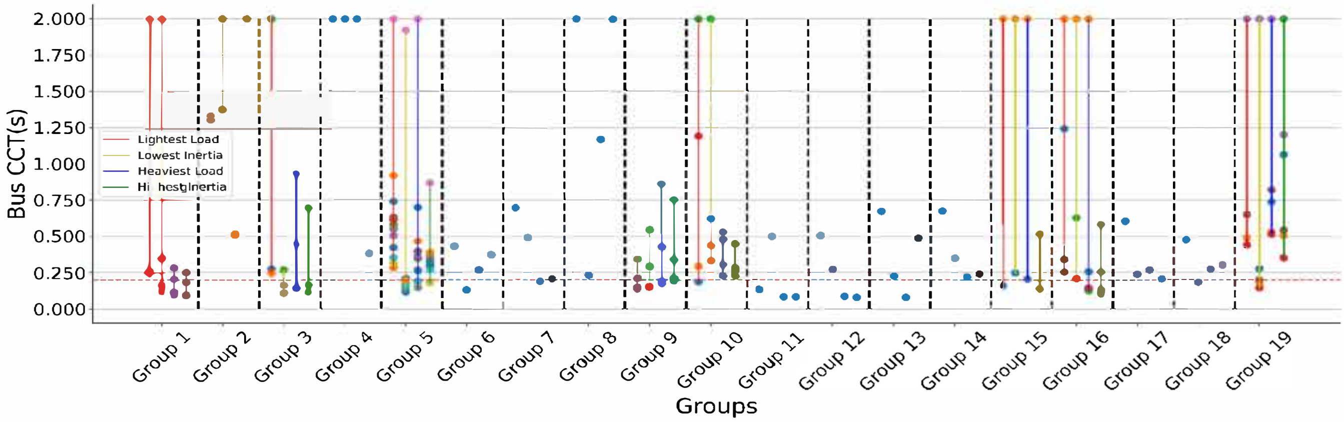


Figure 2. Grouped Buses' CCT in four typical scenarios (Group 1 to Group 19)

grouped according to their mutual admittance, and one representative bus from each group is chosen that has the lowest CCT in the group. Also, since different operating conditions will result in different CCTs for the same bus, four typical operating conditions representing the heaviest load case, lightest load case, lowest inertia case, and highest inertia case, are selected for simulations with the binary search algorithm to screen all buses' CCT.

In this study, buses whose mutual admittances are larger than 50 p.u. are grouped into one group. As a result, all 187 buses are grouped into 57 groups. Figure 2 shows Group 1 to Group 19 for illustration. The groups are separated by black dash lines. In each group, there are red, yellow, purple, and green lines connecting different color dots. The lines represent lightest load case, lowest inertia case, heaviest load case, and highest inertia case respectively. The colored dots on each line represent buses in that group, and the dots of the same color in each group across different line represents the same bus. For instance, in Group 15, there are two buses represented by blue and orange. The CCT of the orange bus is always larger than 200 ms in four scenarios, while the CCT of the blue bus is less than 200 ms in the lightest load case and highest inertia case. In most groups, the bus with the lowest CCT is always the same in the same group across four cases. Note that the buses with CCT less than 200 ms are of our interest. In some groups, none of these buses has a CCT less than 200 ms. By using this grouping method, around 30 critical buses with low CCT are identified for the transient stability assessment.

4) Flow chart: The overall flowchart of the transient stability assessment is given as follows.

Step 1: Pick four typical cases (lightest load, heaviest load, lowest inertia, and highest inertia,) for CCT scanning of all buses;

Step 2: Calculate 187 buses' CCT for each of these four cases using binary search algorithm;

Step 3: Group all 187 buses into different groups by the admittance matrix and select the critical buses for this system which always has CCT less than 200 ms in four different scenarios;

Step 4: Pick one or several buses from those critical buses for study. In this paper, only one bus (#6102) is selected for demonstration;

Step 5: Calculate 8784 different CCT values for the bus picked in Step 4 for all dispatches of a whole year;

Step 6: Build the machine learning model based on the results in Step 5, and train and test the machine learning model.

III. Deep Learning Model for Transient Stability Assessment

A. *Deep Learning Model*

In this study, the deep learning model is applied for transient stability assessment. The deep learning model is a neural network with more than one hidden layer. It can progressively abstract the input features from the previous layer to the next layer and results in better generalization. Generator dispatches and load flow results are the input of the neural network that are not sequential nor time dependent. The fully connected feed-forward neural network is a good fit for those features.

Figure 3 shows the neural network model for the transient stability assessment. The input features are the generators' dispatch and load flow results. The output of the model is the CCT of bus #6102.

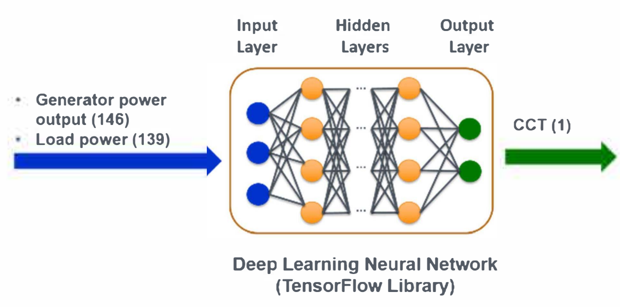


Figure 3. Neural network model for transient stability assessment.

B. *Feature Normalization*

Feature normalization is an important data processing step before training the machine learning model. Normalized features can have similar scales, so the model training efficiency can be improved. There are mainly two feature normalization methods: min-max normalization and standard normalization. Min-max normalization can scale the features into a range from 0 to 1, while standard normalization can scale features into Gaussian distribution with mean of 0 and standard deviation of 1.

Typically, the normalization scale is obtained from the training dataset, and applied to both the training dataset and the testing dataset. For image processing, this would not be a problem, since pixel value range is always from 0 to 255 for any samples in the training dataset and the testing dataset. For other types of applications, when the training dataset does not cover the full range of minimum and maximum of the whole dataset, the normalization scale based on the training dataset only may be biased. Considering the power system physical model, this study normalizes the generator's output according to the generator's Pmin and Pmax settings in the model for both the training dataset and the testing dataset, as shown in (3).

$$x' = \frac{x - Pmin(X)}{Pmax(X) - Pmin(X)} \quad (3)$$

where x' is a generator's normalized value. x is that generator's output. *Pmin(X)* and *Pmax(X)* are generator's Pmin value and Pmax value and in the simulation tool respectively.

Similarly, for the load features, the scale is obtained from the whole dataset, as given in (4).

$$x' = \frac{x - min(X)}{max(X) - min(X)} \quad (4)$$

where x' is a load's normalized value. x is that load's output. X is one feature in whole load dataset.

IV. SIMULATION

Based on the method introduced in Section II and Section II, the whole training dataset for one of the critical buses, Bus #6102, is generated. The binary search method is used during the CCT searching simulation, and the training dataset's CCT resolution is 1 ms. The deep learning neural network model defined in Figure 3 is built for transient stability assessment and trained based on the training dataset.

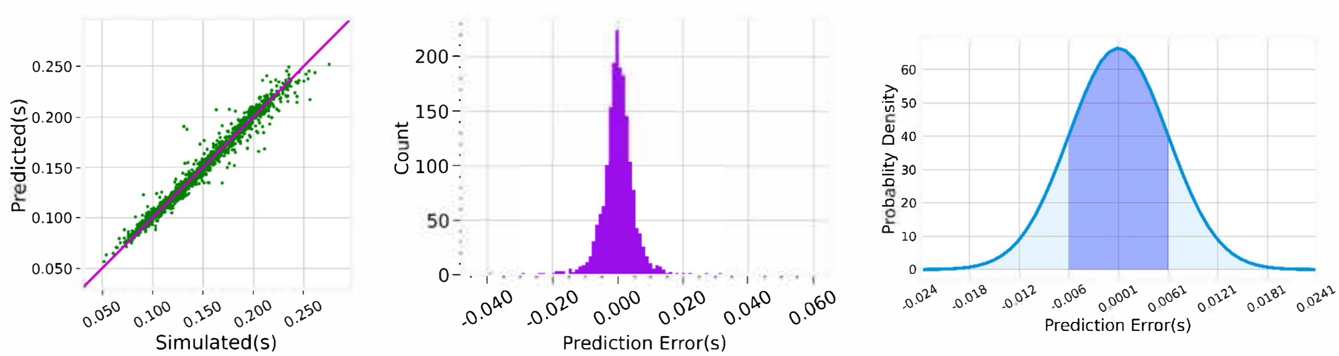
A model with too many layers and nodes tends to be over fitting, while one with insufficient layers and nodes tends to be under fitting. In this study, models with 3, 6, 8 and 9 hidden layers are built and tested. Different learning rates of 0.001, 0.005, 0.008, 0.01, 0.02 and 0.025 are attempted during model training. Dataset percentage for training also has an impact on the model's performance. Model's performance based on different percentages of training dataset is also compared. Validation is performed during the training process to prevent overfitting. The training process ends when the model stops improving on the validation dataset during training. TABLE II lists the best models' performance tested on the testing dataset when trained with different training dataset percentages. Root Mean Squared Error, Mean Absolute Error (MAE), and r-squared are used as the metrics.

From the table, when the training dataset reaches 70%, the model's performance does not improve anymore with the increasing training dataset percentage, e.g., the model's performance is very close when the training dataset is 70% and 80%.

TABLE II. MODEL PERFORMANCE COMPARISON.

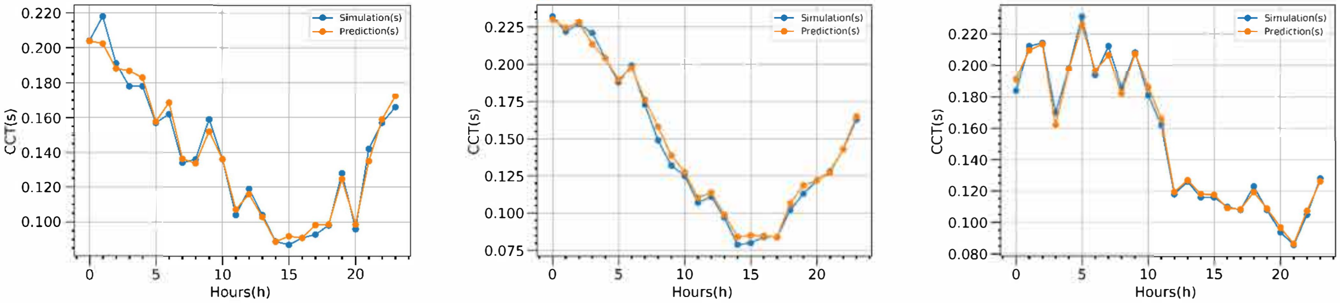
Training dataset Percentage	RMSE (ms)	MAE (ms)	R^2
10%	0.01636	0.011676	0.84093
20%	0.013938	0.009868	0.883444
30%	0.012441	0.008571	0.906948
40%	0.01119	0.007822	0.925682
50%	0.009527	0.006259	0.94582
60%	0.00932	0.005635	0.948318
70%	0.006019	0.003755	0.978561
80%	0.006067	0.003400	0.977657

Figure 4 shows the model's CCT prediction value, prediction error histogram, and Gaussian distribution on the testing dataset (1845 testing samples) when trained with 70% training dataset (4303 training samples). The MAE on the testing dataset is 3.75ms. The standard deviation of the error is 6.01 ms. According to the probability density function (PDF) in Figure 4(c), with 95% probability, the prediction error ranges from -12ms to 12.1 ms. Figure 5 shows the daily prediction of CCT value. The daily result shows the predicted CCTs match well with the simulated values.



(a) CCT prediction on testing dataset (b) CCT prediction error histogram (c) CCT prediction error Gaussian distribution

Figure 4. Testing result and error.



(a) Daily prediction on Apr. 27th (b) Daily prediction on Sep. 9th (c) Daily prediction on Sep. 23rd

Figure 5. Daily prediction results.

V. CONCLUSION

This paper proposes a deep learning-based transient stability assessment method that predicts the CCT values quickly and accurately under different operating conditions. In the training dataset generation, the binary search algorithm is used for CCT calculation, which can find the bus's CCT within 11 simulations at 1 ms resolution. This provides an accurate training database for training the deep learning model. This paper also proposes a bus grouping method based on the mutual admittance, so it can find critical buses in the system quickly. The simulation results show that the model trained with 70% training dataset has good performance, and the daily prediction results demonstrate that the model can accurately predict CCT values.

DISCLAIMER

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