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ML-Based Power System Stability Assessment Considering Network Topology Changes: WECC 20,000+ Bus System Case Study

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***Abstract*—Modern power grids are fast-changing and thus require real-time monitoring and online stability assessment. With the rapid development of machine learning (ML) techniques, using data-driven models to provide fast and accurate estimations of power system stability marginal information, such as frequency nadir for frequency stability and critical clearing time (CCT) for transient stability, have become possible. However, despite the numerous research on ML-based methods for frequency nadir and CCT prediction, there is limited work on the impact of different network topology changes. Furthermore, most previous studies only focused on small or synthetic systems, and there is a lack of research on actual large power system models. In this paper, the above issues are addressed by studying the actual U.S. Western Electricity Coordinating Council (WECC) system model with more than 20,000 buses. Massive simulations are conducted in PowerWorld Simulator to study the impact of various topology change scenarios on both frequency stability and transient stability. System operating information is extracted from the success dispatch cases of various network topologies to generate a comprehensive dataset for ML-based models. Two ML methods, random forest (RF) and multilayer perceptron (MLP) neural network, are trained and tested for both frequency nadir prediction and CCT prediction. Test results have proven the models are capable of online stability assessment for large power networks such as the WECC system with sufficient accuracy.**

Keywords—Power system stability assessment, frequency nadir, critical clearing time, network topology change, machine learning.

I. INTRODUCTION

Power system stability assessment has great significance in power system operation and control because it can provide insight into the system's stability index under severe faults. Traditionally, power system stability is assessed by using the time-domain simulation method [1] [2] or the direct method [3] [4]. However, both methods are not suitable for large-scale power system analysis or fast online stability assessment of modern fast-changing power grids.

The recent development in data-driven methods has shown potential in addressing the shortcomings of traditional methods. Many researches have been done in both frequency nadir prediction for system frequency stability and CCT prediction for system transient stability. To list a few examples, a comprehensive study has been done to compare several ML-based methods on predicting frequency nadir, and both gradient boosting and XGBoost have shown promising accuracy [5]. Another study using convolutional long short-term memory network also shown high accuracy in frequency nadir prediction [6]. A stacking model based on random forest and XGBoost is proposed for CCT prediction [7]. Ensemble extreme learning machine regression model technique has been applied on CCT prediction in [8]. The above methods' performance have been tested and validated on various small power systems. Despite this, the existing literature on power system stability assessment for large actual power grid is very sparse. One recent research work using large actual WECC system has proposed two ML models for both frequency nadir and CCT prediction. By comparing the prediction time, the ML-based methods are capable of making faster-than-real-time prediction of online transient stability assessment for large-scale actual power system [9]. However, the impact of network topology on frequency nadir and CCT remains underexplored in the literature. An XGBoost based model is proposed in [10], which shows good generalization capability in case of noise interference and changed topology. Transfer learning technique has also been applied to transient stability assessment to accommodate network topology change impacts on prediction accuracy [11]. A graph convolutional neural network based model considering topology changes in small system has been proposed in [12]. One recent study has examined the impact of both N-1 and N-2 topologies and implemented large ML models using 13,000 dispatches for accurate CCT prediction [13]. Alternatively, there is still lack of research considering comprehensive topology changes impact on both frequency stability and transient stability in actual large-scale power systems.

In order to tackle the issue of limited research on power system stability assessment tools that can account for topology changes in large-scale power systems, this paper uses the actual WECC 20,000+ bus model to conduct comprehensive case studies on the impacts of different network topology on system stability. Two ML-based models for both frequency nadir and CCT prediction that take into account of various topology changes are also implemented and tested on the actual WECC 20,000+ bus system.

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II. Impact of Network Topology Changes on WECC Systems Transient Stability

A. Introduction of Case System

In this paper, 228 fine-tuned actual dispatch cases from the WECC 20,000+ bus full system model are used to study the impact of topology change on system stability. These real-world dispatch cases are converted based on the EMS data of the US WECC system and lack of robustness. Therefore, additional tuning and case selection are applied prior to the topology change studies in order to exclude the unstable cases. After selection, 138 dispatch cases are used to conduct further frequency stability study and 69 dispatch cases are used for further transient stability study. Frequency nadir and CCT are selected as the stability index for system frequency stability and transient stability respectively. Various topology change scenarios are simulated in PowerWorld Simulator to analyze the impact of different network topologies on system stability.

B. Topology Change Impact on Frequency Stability

A total 138 out of 228 dynamic dispatch cases were found suitable for the frequency stability study. After carefully examining the topology data of the 20,000+ bus system, three 345kV level tie-lines and three large generators in Arizona and NEW Mexico area, shown in Fig.1, were selected for generating various topology changes. Massive dynamic simulations under selected disturbances, large generator drop event that lose two 1.37GW generators, have been ran in PowerWorld Simulator in batches on both original WECC system with no topology change and the modified WECC system of six different topology change scenarios. Frequency nadir and system operating information such as generator active power and inertia were extracted from each case for later ML dataset construction. The detailed topology change scenarios and the number of succeed dispatch case can be found in Table 1 below.

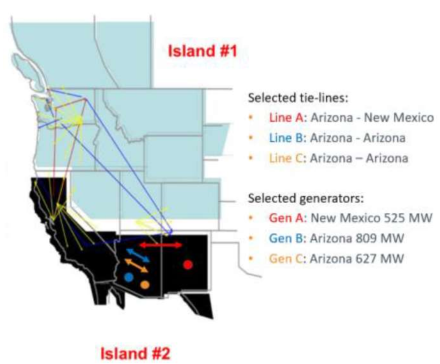

Fig. 1. Selected tie-lines and generators for study the impact of topology change on frequency nadir.

TABLE I. Topology Scenarios of the Frequency Stability

Topology Scenarios	Outage Tie-lines or Generators	Success Dispatch Cases
Original case	No topology change	128
Trip 1 tie-line	Line A	129
Trip 2 tie-lines	Line B + C	129
Trip 3 tie-lines	Line A + B + C	128
Trip 1 genertaor	Gen A	129
Trip 2 genertaors	Gen A + B	132
Trip 3 genertaors	Gen A + B + C	133

The comparisons of frequency nadir before and after topology changes are shown in Fig. 2. After tripping one or more tie-lines, the frequency nadir does not change much. This is due to tripping tie-lines does not lose any generators, and thus total generation MW showed no obvious change resulted in no obvious change in frequency nadir. After tripping generators, generation MW decreases, and a lower frequency nadir can be observed as more generators were lost.

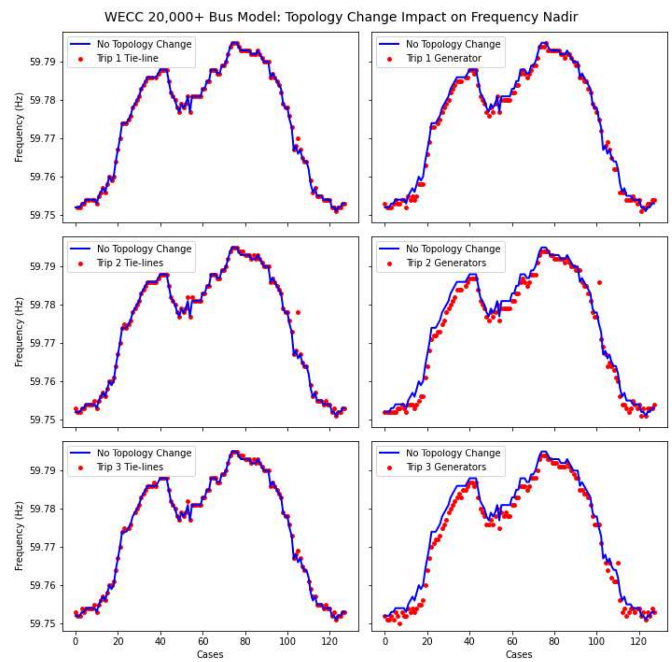

Fig. 2. Network topology change impact on frequency nadir.

C. Topology Change Impact on Transient Stability

A total 69 out of 228 dynamic dispatch cases were found suitable for the transient stability study. After carefully examining the topology data of the 20,000+ bus system, six 500kV tie-lines in the Northwest area of the WECC system have been selected to perform N-1 to N-6 topology change study. Similar to frequency stability study, massive dynamic simulations with branch fault contingencies have been done in PowerWorld Simulator on both original WECC system and the modified WECC system after N-1 to N-6 network topology scenarios. The operating information and CCT values of the success dispatch cases were extracted for later ML dataset construction. The detailed topology changes scenarios and the number of succeed dispatch case can be found in Table 2 below.

TABLE II. Topology Scenarios of the Angle Stability

Topology Scenarios	Outage Tie-lines	Success Dispatch Cases
Original case	No topology change	69
N-1	Trip 1 500kV tie-line	66
N-2	Trip 2 500kV tie-lines	65
N-3	Trip 3 500kV tie-lines	62
N-4	Trip 4 500kV tie-lines	64
N-5	Trip 5 500kV tie-lines	69
N-6	Trip 6 500kV tie-lines	69

The comparison of CCT before and after topology changes are shown in Fig.3. Considering the full WECC model is a large-scale system that contains over 20,000 buses, tripping one or two 500kV tie-lines had no significant impact on the CCT values. However, when three or more 500kV tie-lines were tripped, a decrease in CCT values can be observed. Note that the system already became unstable after tripping more than three 500kV tie-lines., Therefore; tripping five or six 500kV tie-lines do not have significant impact on the CCT values compared to tripping three or four 500kV tie-lines.

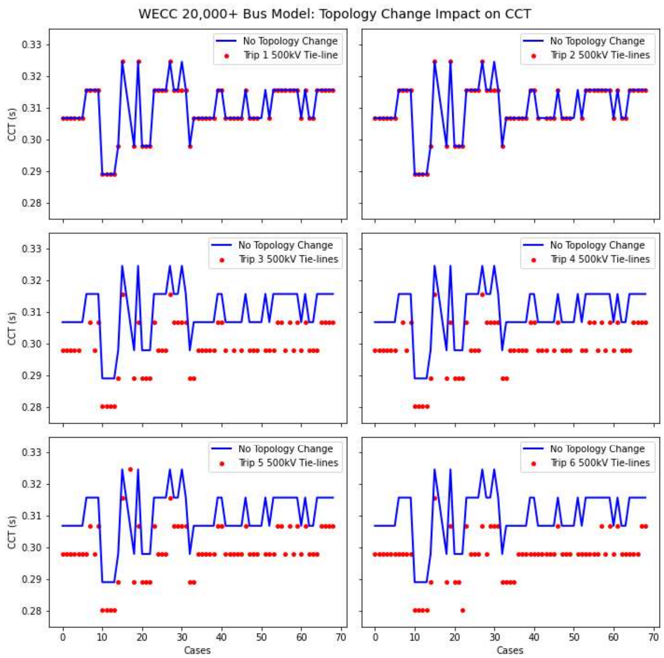

Fig. 3. Network topology change impact on CCT.

III. ML-BASED METHODS FOR TRANSIENT STABILITY ASSESSMENT CONSIDERING TOPOLOGY CHANGES

In this paper, two machine learning models, i.e. a random forest (RF) model and a multilayer perceptron (MLP) neural network model are used are both frequency nadir and CCT prediction. The flowchart of the ML-based power system stability assessment process is shown in Fig. 4 below.

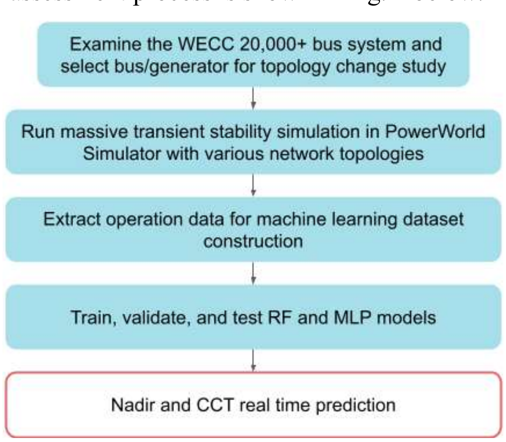

Fig. 4. Overall structure of the proposed ML-based power system stability assessment.

A. Machine Learning Models for Frequency Nadir Prediction

To generate the machine learning dataset for frequency stability assessment, we conducted time-domain simulations of the full WECC system model to obtain frequency stability margin information. The frequency nadir was computed by identifying the minimum frequency value in the median frequency response across all buses. A total of 908 successful dispatch cases were obtained, including both no topology change and six different network topology scenarios. For each successful dispatch case, we extracted the active power output of the system's 4270 generators as input features for the machine learning models. The frequency nadir was used as the prediction target for the ML models. The data are mixed and randomly split into 80% training set and 20% testing set, the split is stratified by cases.

When training the RF model, 5-fold cross validation is used. The optimal parameters selected after fine-tuning are Max_depth = 9 and n_estimator = 50. The prediction and actual frequency nadir comparison is shown in Fig. 5. We randomly selected 75 test cases (sorted by frequency nadir value from low to high) to plot for better visualization purpose. The relative error of the same 75 cases are shown in Fig 6 below.

For the MLP model, the data was normalized to 0-1 range referencing the training split. When training the MLP model, 2 hidden layers is used and the learning rate is 1E-4. The prediction and actual frequency nadir comparison of the MLP model is shown in Fig. 7 and only 75 randomly selected test cases are plotted. The relative error of the same 75 test cases is shown in Fig. 8.

According to Fig. 6 and Fig. 8, the majority of the relative error for both models is within 0.004%, which demonstrates very good nadir prediction performance.

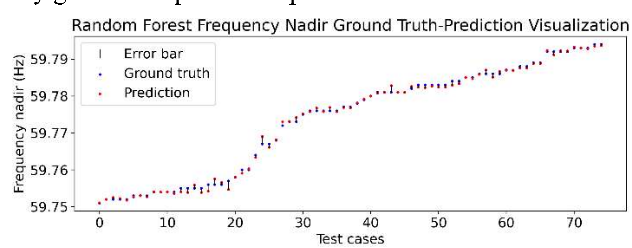

Fig. 5. RF model frequency nadir prediction on randomly selected 75 test cases sorted by nadir from low to high..

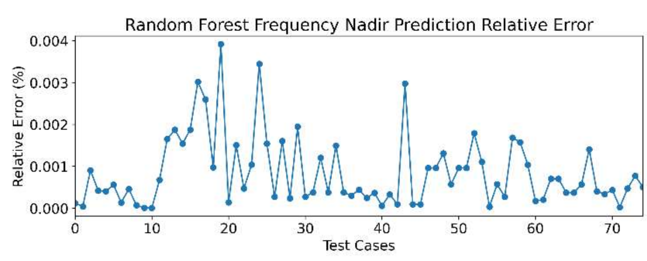

Fig. 6. RF model frequency nadir prediction relative error on the randomly selected 75 test cases sort by nadir from low to high.

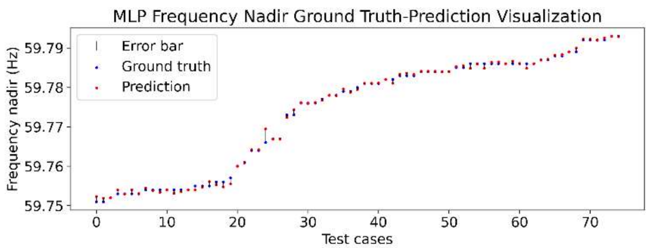

Fig. 7. MLP model frequency nadir prediction on randomly selected 75 test cases sorted by nadir from low to high.

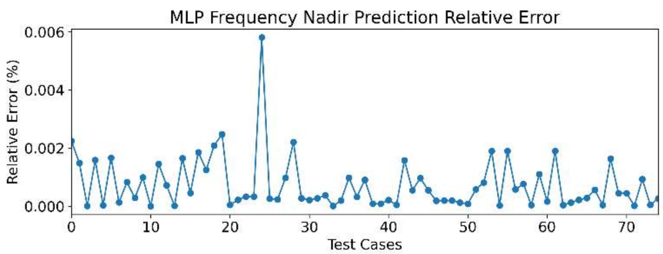

Fig. 8. MLP model frequency nadir prediction relative error on the randomly selected 75 test cases sort by nadir from low to high.

The frequency nadir prediction performance matrix for both models is summarized in Table 3 below. Both RF and MLP models are capable of making accurate frequency nadir predictions. The majority of the absolute prediction errors are within 0.001Hz. The MLP model performs better than the random forest model by 24.23% when comparing the prediction root-mean-square-error (RMSE).

TABLE III. ML-BASED METHODS FREQUENCY STABILITY ASSESSMENT PERFORMANCE

Performance Matrix		**ML Models**	
		Random Forest	***MLP***
Absolute Error	Mean	0.00055	0.00043
	Max	0.00852	0.00743
	Min	7.1E-15	6.7E-7
	90th Percentile	0.00107	0.00105
RMSE		0.001077	0.000816

B. *Machine Learning Models for CCT Prediction*

The machine learning dataset for transient stability assessment is also obtained by conducting time-domain simulations of the full WECC system model. The CCT value of each success dispatch case is obtained by varying the fault clearing time until the transient instability occurs. A total of 464 successful dispatch cases were obtained, including both no topology change and six different network topology scenarios. For each successful dispatch case, there are 1405 generators with both active power and inertia information. We extract this information and used as input features for the machine learning models. The CCT value of each dispatch case was used as the prediction target for the ML models. The data are mixed and randomly split into 85% training set and 15% testing set due to the insufficient number of success cases, the split is stratified by cases.

When training the RF model, 5-fold cross validation was used. The optimal parameters selected after fine-tuning are Max_depth = 3 and n_estimator = 100. The prediction and actual CCT comparison of the total 73 test cases is shown in Fig. 9. The prediction relative error of the test cases are shown in Fig. 10 below.

For the MLP model, the data was again normalized to 0-1 range referencing the training split. When training the MLP model, 5 hidden layers is used and the learning rate is 1E-3. The MLP model prediction and actual CCT comparison is shown in Fig. 11. The prediction relative error is shown in Fig. 12.

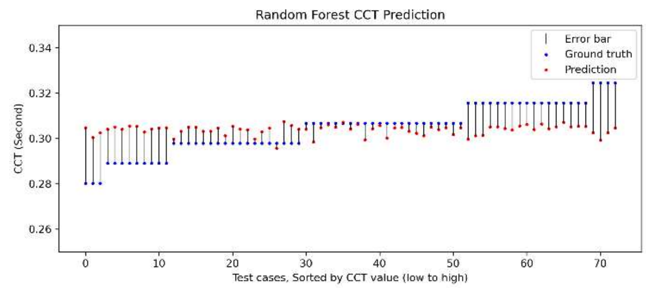

Fig. 9. RF model CCT prediction sorted by CCT from low to high.

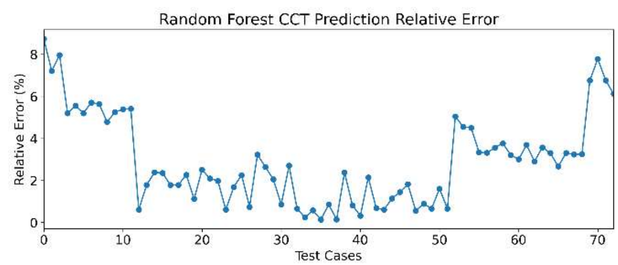

Fig. 10. RF model CCT prediction relative error sorted by CCT from low to high.

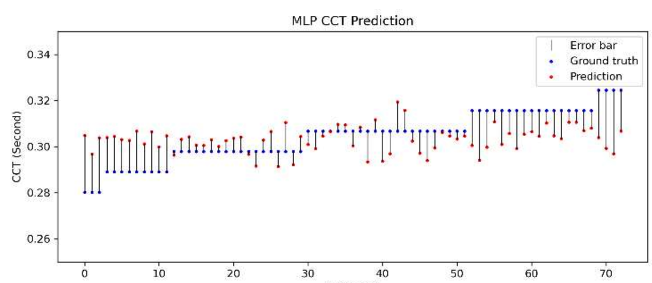

Fig. 11. MLP model CCT prediction sorted by CCT from low to high.

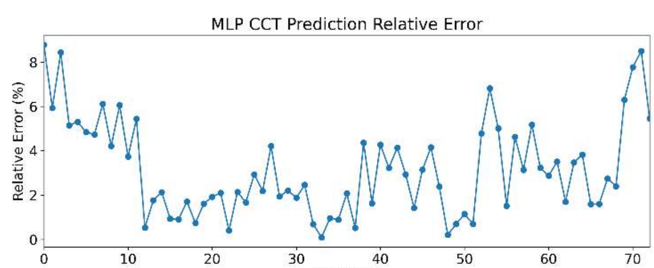

Fig. 12. MLP model CCT prediction relative error sorted by CCT from low to high.

According to Fig. 10 and Fig. 12, the majority of the CCT relative prediction error for both models is within 6%, which indicates acceptable prediction accuracy. The CCT prediction performance matrix for both models is summarized in Table 4 below. Both RF and MLP models are capable of making fast CCT predictions with acceptable accuracy. The majority of the absolute prediction errors are within 0.017s for both models. Both methods demonstrate comparable performance without a clear advantage of one over the other.

TABLE IV. ML-BASED METHODS ANGLE STABILITY ASSESSMENT PERFORMANCE

Performance Matrix		ML Models	
		Random Forest	***MLP***
Absolute Error	Mean	0.00896	0.00959
	Max	0.02526	0.02759
	Min	0.00043	0.00026
	90th Percentile	0.01646	0.01765
RMSE		0.01098	0.01154

IV. CONCLUSION

This paper presents a case study that explores the effects of different topology changes on system frequency stability and transient stability of the actual 20,000+ bus WECC system model. The frequency nadir and the CCT are used as the stability indices for the system's frequency and transient stability, respectively. To assess the impact of each network topology on these stability indices, we conducted time-domain simulations and provide a detailed analysis of the results. Then, the system operation information are extracted from successful dispatch cases, and employed as input features for two machine learning models: random forest and MLP. The models were trained and evaluated using frequency nadir and CCT as prediction targets to assess frequency stability and transient stability, respectively. The test results indicate that both ML models have demonstrated strong performance in predicting frequency nadir. However, the MLP model has a clear advantage over the random forest model in terms of prediction accuracy by comparing the RMSE performance matrix. As for CCT prediction, although the accuracy is not as high as that of frequency nadir prediction, both absolute error and relative error remain within an acceptable range. This less accuracy is due to the limited dynamic dispatch cases were found suitable for conduct transient stability study. To further improve the accuracy of CCT prediction, future research should aim at examining a larger number of actual dispatch cases in the WECC full model and implementing more advanced machine learning models. Additionally, incorporating additional features such system topology network, voltage and load information could also be considered.

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