A Review on Artificial Intelligence for Grid Stability Assessment

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***Abstract*— Artificial intelligence provides a convenient route for power grid stability assessment. Compared with simulation-based approaches, artificial intelligence can potentially save time on model development and numerical computation in stability assessment. This paper first reviewed existing literature on using artificial intelligence for power grid stability assessment. Then a machine-leaning-based tool is presented and developed to assess power grid transient stability, frequency stability, and small signals stability. Test results verified the accuracy and effectiveness of the AI tool for power grid stability assessment.**

***Index Terms*— Artificial intelligence, stability assessment, power grid.**

I. Introduction

Power grid stability consists of transient stability, frequency stability, small signal stability, and voltage stability (Fig. 1) [1-2]. Fast assessment of system stability is useful in many places, including day-ahead scheduling, real-time operation, and long-term planning. Traditional methods for power system stability assessment are based on time-domain simulation, which heavily relies on the availability of real-time power system dynamic models and requires significant simulation computational resources [3-7].

Beside model simulation, another category of methods for stability assessment is data-driven methods, as shown in Fig. 2. Data-driven methods for stability assessment consists of measurement-based methods and artificial-intelligence-based methods. Measurement-based methods use measurement data to develop simplified models (such as transfer functions or reduced models) for stability assessment, which require less computation time compared with time-domain simulation based on detailed models [10-13]. However, the development of measurement-based simplified models is a non-trivial task [16]. In contrast, artificial intelligence based stability assessment is data-driven and not directly based on physical principles [17-19]. After trained using simulation or measurement data, artificial intelligence models can perform stability assessment based on system feature inputs.

A number of studies have already tried applying artificial intelligence into power system stability assessment [16-20]. This paper provides a literature review on existing studies. Most existing machine learning based approaches can only assess one type of stability. Input features are usually selected based on trial and error on a specific machine learning model. This work proposed an artificial intelligence tool using the same set of input data to assess power system transient stability, small signal stability, and frequency stability, simultaneously. The accuracy and efficiency of the proposed approach in stability assessment is verified on an 18-bus system.

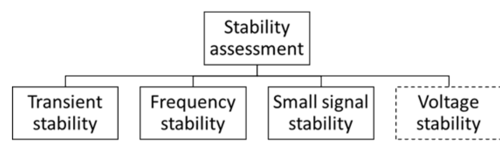

Fig. 1. Stability topics in power grids

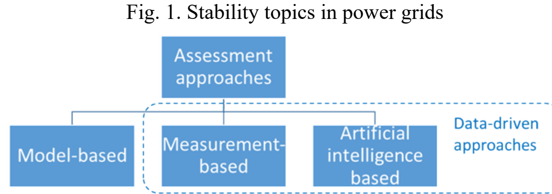

Fig. 2. Power grid stability assessment approach categorization

II. Literature Review on Using Artificial Intelligence for Stability Assessment

A. AI-based Transient Stability Assessment

Transient stability is the power system ability to maintain synchronism when subjected to a severe disturbance, such as a short circuit on a transmission line [23]. Existing literature that applies artificial intelligence to assess transient stability mainly uses three categories of methods: neural network, support vector machine [24-26], and decision tree [1], as summarized In Table I, Table II, and Table III respectively. Most of these studies used the New England 10-machine system as the test system. These methods showed high accuracy in classifying stable and unstable cases: all methods achieved higher than 96% accuracy and some even reached 100% in accuracy. Additionally, a few studies tried considering the change of

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TABLE I.
NEURAL NETWORK (NN) BASED METHODS FOR TRANSIENT STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[2]	Extreme learning machines (ELM)	IEEE 50-bus system	6,345	5,076	1,269	50	100
[9]	Extreme learning machine (ELM) + trajectory fitting (TF)	New England 10-machine	10,000	N/A	N/A	100 (269)	99.1
[15]	Extreme learning machine (ELM) + a decision-making process	New England 10-machine	4,000	2,000	2,000	N/A	97.92 – 98.38
[21]	An array of neural networks (NN) + an interpreter	PSB4 system + New England 10-machine	248/300	208/250	40/50	N/A	99.85/100
[22]	Probabilistic neural network (PNN)	IEEE 68-bus, 16-generator system + three wind generation units	190 operation conditions and three-phase faults	N/A	N/A	244, 150,100,50	> 99
[27]	Recurrent neural network (RNN) + long short-term memory network (LSTM)	New England 10-machine	5,000	3,750	1,250	N/A	100
[29]	Long-short Term Memory (LSTM) ensemble neural network + decision machine	New England 10-machine	4,058	3,044	1,014	N/A	100
[31]	Extreme learning machine (ELM) + Boosting learning	New England 10-machine	68,640	N/A	N/A	50 (183)	100
[32]	Extreme learning machine(ELM)	New England 10-machine	1,240	864	376	62	98
[34]	Convolutional neural network (CNN) + stacked auto-encoders (SAEs)	New England 10-machine	4,014	2,689	1,325	22	96.78 – 98.68
[35]	Neural network (NN) + incremental learning	Shandong power system- 362 buses	945	540	405	N/A	96.6

TABLE II.
SUPPORT VECTOR MACHINE (SVM) BASED METHODS FOR TRANSIENT STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[36]	SVM + transient energy function (TEF)	New England 10-machine	700	500	200	36, 18	97.5 – 100
[39]	Ball vector machine (BVM)	New England 10-machine	5,500	4,000	1,500	200	97.1
[41]	SVM	Priba system: 2484 buses	1,242	994	248	224, 150, 100, 50	94.4
[26]	SVM + DT + rotor angles trajectory clustering	New England 10-machine and IEEE 145-bus	3,672	1,099	2,573	19	90.74 – 98.15 94.75 – 95.41
[42]	SVM, Naïve Bayes, decision tree	IEEE 14-bus	8000	N/A	N/A	23	88.2 – 98.8
[43]	SVM + Cost-sensitive ensemble learning classifier	New England 10-machine	4,290	4,000	290	23	96.4 – 99.4
[44]	Least Square Support Vector Machine (LS-SVM)	New England 10-machine	6,600	4,620	1,980	39	100
[45]	Reformed support vector machines + sequential minimal optimization (SMO)	New England 10-machine	20,000	16,000	4,000	15	96.9
[46]	Fuzzy C-means clustering algorithm + SVM	IEEE 39-bus system	726	556	170	10	100

topology in artificial intelligence models [2,29].

A summary of these methods considering topologies is shown in Table IV. The most commonly used methods include: using the current topology to build the dynamic model and then

TABLE III.
DECISION TREE (DT) BASED METHODS FOR TRANSIENT STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[1]	Decision tree (DT) + regression tree (RT)	Salt River Project (SRP) power system	41,412	33,130	82,82	N/A	99.13
[8]	Weighted random forest (WRF)	New England 10-machine	2,000	1,300	700	263	98.79
[14]	Random forest (RF)	New England 10-machine	2,000	1,300	700	45	99.1
[20]	Decision tree (DT)	9-bus dynamic network and 1,696-bus Iran national grid	513/1,080	N/A	N/A	5	79.92 – 100 94.91 – 99.91

TABLE IV.
LITERATURE CONSIDERING TOPOLOGY CHANGE IN ARTIFICIAL INTELLIGENCE BASED TRANSIENT STABILITY ASSESSMENT

Ref	Method to consider topology change
[2]	The network is trained based on the current system topology and the loading conditions
[29]	Small-height DTs are periodically updated by incorporating the possible changes of the system topology

TABLE V.
OTHER ARTIFICIAL INTELLIGENCE BASED METHODS FOR TRANSIENT STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[28]	Deep belief network (DBN)	A real regional power system in China, consisting of 1300 buses, 3215 transmission lines	10,000	8,330	1,670	1,762	98.02
[30]	Least Absolute Selection and Shrinkage Operator (LASSO)	A practical 470-bus system	1,199	800	399	939	99.75
[33]	Type-2 fuzzy neural network	New England 10-machine	2,000	1,500	500	56	97.51 – 98.31

TABLE VI.
ARTIFICIAL INTELLIGENCE BASED FREQUENCY STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[31]	Single-hidden layer feedforward network (SLFN)	IEEE 14-Bus System; New England 39-bus system	600	480	120	N/A	97.5%

TABLE VII.
ARTIFICIAL INTELLIGENCE BASED SMALL SIGNAL STABILITY ASSESSMENT

Ref	Model	Test System	Samples	Training	Testing	# Features	Accuracy (%)
[37]	Artificial neural network	Single machine infinite bus system	N/A	N/A	N/A	4	~90%
[40]	Decision tree	PST 16-machine test system	2,500	N/A	N/A	252	99.77%

generate the training dataset [2]; and generating a training dataset that covers all possible system topologies before training the artificial intelligence model [29]. Several other artificial intelligence methods other than the three categories in transient stability assessment are listed in TABLE V. These methods achieved similar accuracy levels in transient stability assessment.

B. AI-based Frequency Stability Assessment

According to the definition from IEEE and CIGRE, frequency stability refers to the ability of a power system to maintain a steady frequency following a severe system upset resulting in an imbalance between generation and load [23]. Frequency instability occurs in the form of sustained frequency swings or large frequency deviations that eventually lead to tripping of generating units and/or loads, and system losing stability [38]. However, very few studies focused on frequency stability assessment using AI. In [31] (Table VI), an artificial neural network and power flow information were used to predict the frequency stability. The accuracy reaches 97.5%.

C. AI-based Small-signal Stability Assessment

Small-disturbance (or small-signal) rotor angle stability is concerned with the ability of the power system to maintain synchronism under small disturbances [23]. The disturbances in the small signal stability domain are considered to be sufficiently small, so that stability analysis can be performed based on a linearized representation of the system. Reference [37] in TABLE VII used neural network to study the small-signal stability of a single-machine infinite-bus system under different power output and power factor conditions, as well as power system stabilizer settings. Reference [40] used a decision tree to predict the eigenvalue region of critical modes. These studies also reached satisfactory (higher than 90%) accuracy in small signal stability assessment.

In general, it can be seen that most AI-based stability assessment approaches achieved high accuracy already. Overall, neural network has the highest accuracy. decision tree and SVM have slightly lower accuracy (Fig. 3). However, in existing literature, most machine learning approaches focus on one type of stability and select input features based on trial and error on a specific machine learning model. Few studies can use the same set of input data to assess the system frequency, transient, and small signal stability simultaneously.

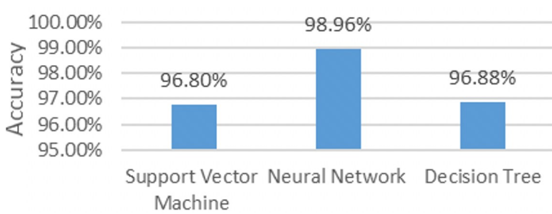

Fig. 3. Average accuracy comparison of different AI methods.

III. An Artificial Intelligence Tool for Frequency, Transient, and Small-signal Stability Assessment

This study proposed a convenient stability assessment tool to assess transient stability, frequency stability, and small signal stability simultaneously. The overall flow is shown in Fig. 4. First, dispatch data from the scheduling model are converted to AC power flow. Then multiple scenarios and their stability margins are obtained by running time-domain simulation. The stability indices are then used to train the artificial intelligence model. The trained artificial intelligence model can predict stability margin for new power flow scenarios. The inputs, outputs, and two artificial intelligence models used in this study are listed in Table VIII. The input features include generator dispatch levels and transmission network data. The outputs are the stability margin indices for different stability issues.

The stability assessment approach is implemented in an 18-bus test system. The system has four areas, each with one conventional generator. One additional PV power plant is in the east area, as shown in Fig. 5. The system has one power flow snapshot in every 5 minutes. The total number of power flow scenarios is 288 for 24 hours. The inputs for artificial intelligence based stability assessment are shown in TABLE VIII. Among all 288 power flow scenarios, 202 scenarios (70%) are randomly selected and used in training. The rest 82 scenarios are used for testing, The stability assessment accuracy is assessed by comparing the artificial intelligence outputs and the stability margin results from model simulation.

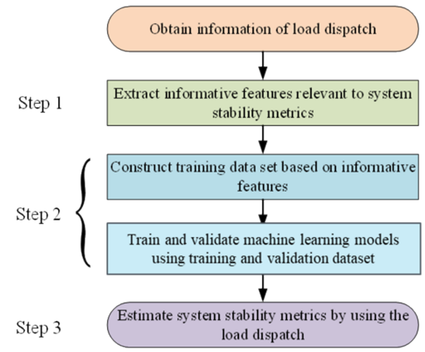

Fig. 4. Flowchart of artificial intelligence based stability assessment.

TABLE VIII. INPUTS AND OUTPUTS FOR ARTIFICIAL INTELLIGENCE BASED STABILITY ASSESSMENT

Stability	**Inputs**	**Outputs**	**Artificial intelligence method**
Frequency	• Generator dispatch levels; • Transmission network.	Frequency nadir after the largest contingency	• Neural network • Random forests
Transient		Critical clearing time (CCT)	
Small-Signal		Oscillation damping ratio + oscillation frequency	

A. Artificial Intelligence Based Transient Stability Assessment

The transient stability margin is measured by the minimum critical clearing time (CCT) of the whole system. The critical bus in each area are defined as the bus that results in the minimum CCT. The CCT values of the critical buses in each area are shown as the colored solid line in Fig. 6. The blue dash line shows the minimum CCT of the whole system, obtained by selecting the minimum CCT of the critical bus in each area.

The minimum CCT of the system is predicted using the artificial intelligence model. The comparison of the simulated CCT values with neural network and random forests results are shown in Fig. 7 and Fig. 8 respectively. Both artificial intelligence methods can achieve highly accurate CCT prediction.

B. Artificial Intelligence Based Small Signal Stability Assessment

In small signal stability assessment, the oscillation damping ratio and frequency predicted by artificial intelligence are compared with the results from eigenvalue analysis, as shown in Fig. 9 and Fig. 10, respectively. (For simplicity, following results only show neural network results.) It can be seen that both the damping ratio and the frequency can be assessed accurately using artificial intelligence.

C. Artificial Intelligence Based Frequency Stability Assessment

Similarly, the artificial intelligence based frequency stability assessment results are compared with the model simulation results. The change of frequency nadir when only inertia changes and when both inertia and governor status change are shown in Fig. 11 and Fig. 12, respectively. It can be seen that for both cases, the artificial intelligence can provide accurate estimation of the frequency nadir after a frequency event.

Table IX summarized the accuracy and computation time of stability assessment using artificial intelligence. It can be seen that both random forests and neural network reach high accuracy for the three stability assessment tasks using the same set of power flow input data. Neural network has higher accuracy than random forest except for small signal stability assessment. In addition, the artificial intelligence based method significantly reduces the computation time compared with conventional stability assessment methods. This result indicates that artificial intelligence has good capability in stability assessment. This approach can save the data preparation efforts and benefit multiple applications in which accurate and fast stability assessment is desired, such as real-time security margin assessment, short-term stability prediction for system adjustment, stability-related resource procurement and stability validation in day-ahead markets, and stability margin assessment of multiple power flow scenarios in long-term planning.

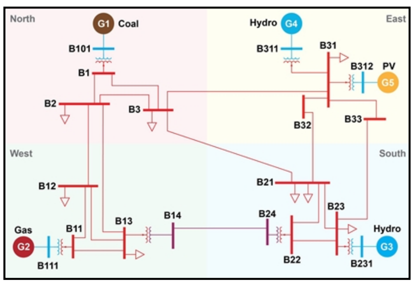

Fig. 5. 18-bus test system.

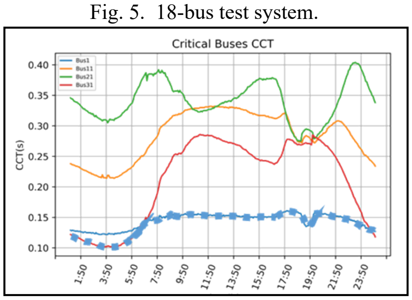

Fig. 6. CCT of critical buses in each area

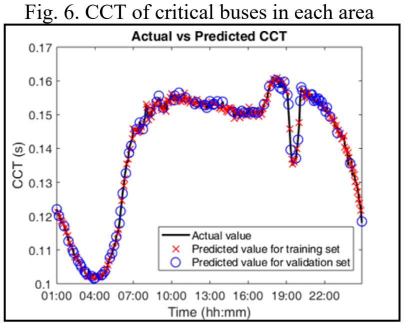

Fig. 7. Actual and predicted CCT (neural network).

TABLE IX. ACCURACY OF DIFFERENT TESTING OF ARTIFICIAL INTELLIGENCE BASED STABILITY ASSESSMENT

Stability	**Estimation accuracy**		**Time for stability assessment (86 dispatch scenarios)**	
	Random forests	Neural network	Time domain simulation	Artificial intelligence based
Frequency	98.30%	99.72%	~16 h	~0.18 ms (with trained model)
Transient	98.44%	99.29%	~1 h	
Small-Signal	98.61%	98.59%	~1 h	

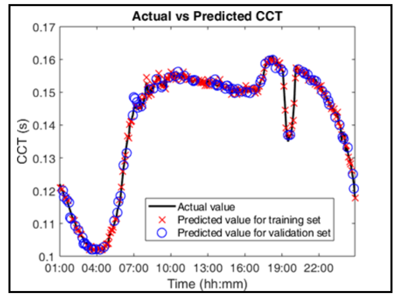

Fig. 8. Actual and predicted CCT (random forests).

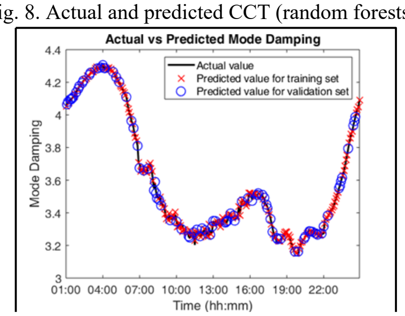

Fig. 9. Actual and predicted oscillation mode damping (neural network)

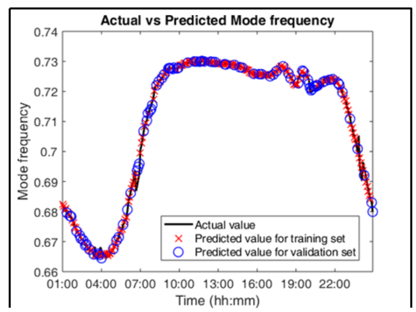

Fig. 10. Actual and predicted frequency of oscillation (neural network)

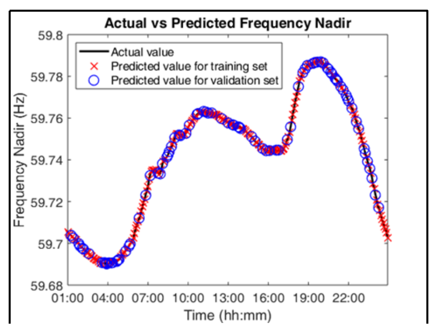

Fig. 11. Actual and predicted frequency nadir (inertia change)

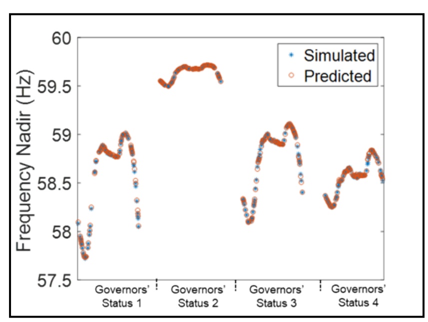

Fig. 12. Actual and predicted frequency nadir (inertia and governor change)

IV. Conclusions

Artificial intelligence based power grid stability assessment has achieved high accuracy on some test systems. Among existing studies, transient stability is the most common stability assessment problem studied by AI, while very few studies focused on small signal and frequency stabilities assessment using AI. Among all AI models, neural network in general has the highest accuracy on stability prediction. However, most existing studies focus on one stability problem and diverge largely on input features. In this work, a convenient tool is developed to use the same set of input features to assess transient stability, small signal stability, and frequency stability simultaneously. Test results show that the AI-based stability assessment tool can achieve accurate and fast assessment of frequency, transient, and small signal stability.

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