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Artificial Intelligence Based Transient Stability Detection of IEEE 9 Bus System

Authors: Arun Kumar Yadav; Imran Khan; Malik Rafi
AZAD Institute of Engineering & Technology, Lucknow
yadavarun896@gmail.com*, pe.imran@gmail.com** , mali_rafi@rediffmail.com

Abstract
The proposed approach focuses on developing an AI-based system utilizing event data to detect transient stability, with a specific emphasis on time-series measurements. The algorithm will be designed to account for various factors such as noise, measurement delays, line outages, and the integration of variable renewable energy sources (VREs). To facilitate high-fidelity data acquisition, phasor measurement units (PMUs) will be utilized to provide time-series information at a high sampling rate. Additionally, the impact of varying numbers of PMUs will be examined through simulation. The algorithm will be trained using a synthetic dataset generated by a MATLAB-based algorithm to simulate PMU measurement data. The IEEE bus test system will be employed to evaluate the algorithm's performance under different loading conditions.
The results of the study are expected to demonstrate the effectiveness of the proposed scheme in detecting stable and unstable transient stability conditions solely based on the magnitude and angle of bus voltages, without requiring detailed system parameter information. Furthermore, the proposed AI-based approach is anticipated to offer improved accuracy in transient stability detection across all scenarios. Importantly, the computational efficiency of the AI-based method will be compared to conventional approaches, highlighting potential advantages in terms of reduced computation time. Overall, this research aims to advance the field of transient stability assessment in power systems through the application of artificial intelligence techniques.
Key words: PMU, GSA, VSA, TSA, IEEE 9-Bus

1. Introduction:

Renewable-based power systems pose significant challenges due to their complexity and nonlinear behavior, exacerbated by the rapid fluctuations in electricity generation and consumption. As the penetration of variable sources like wind and solar increases, the stability and operating constraints of these systems are further stressed. Common constraints include bus voltages, system frequency, and rotor angles, while recognized stability indicators encompass transient stability, frequency stability, small-signal stability, and voltage stability. Ref. [2] introduced two new categories of grid stability, namely converter-driven stability and resonance stability, although these fall outside the scope of this review due to limited AI-based assessment studies in these areas.

Traditional time-domain simulation has long been the primary methodology for grid stability assessment (GSA) due to its flexibility in modeling. However, as grid scale expands and distributed resources proliferate, the computational burden of time-domain simulation restricts its online applicability. Simplified assessment methods based on measured data, such as the energy function method for transient stability assessment (TSA), the voltage index method for voltage stability assessment (VSA), and the system frequency response model for frequency stability assessment (FSA), have been explored. While these methods enhance assessment speed, their estimation accuracy may not be entirely satisfactory.

Artificial intelligence (AI) techniques have emerged as promising alternatives to traditional methods, offering accurate predictions with lower computational costs through trained models. Consequently, AI-based GSAs have gained traction in research. Various AI models, including Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN), have been implemented and compared, yielding favorable evaluation results. However, single AI models like SVM, DT, and ANN may exhibit limited adaptability to disturbances such as changes in grid topology and insufficient measurement data. To enhance the robustness of AI in GSA, numerous studies have explored improvements in AI model structure, input data preprocessing, multi-output results, and addressing non-ideal data acquisition.

2. IEEE 9-Bus Test Case

The utilization of the IEEE standard 9-bus system as the platform for this study offers several advantages. Firstly, it represents a microgrid and provides a significantly simplified model of an electric grid, making it suitable for testing new methods. Secondly, the 9-bus system has been widely adopted by researchers for studying both static and dynamic problems in power systems, ensuring compatibility and comparability with existing literature.

Using test systems like the IEEE 9-bus system offers convenience compared to employing models of real power systems. Real power systems often lack full documentation and can be exceedingly complex, making it challenging to identify general trends. Additionally, test systems facilitate reproducibility and enable researchers to validate their findings against established benchmarks.

Bus No.	Bus Code	Voltage	Generation		Load	
			MW	MVAR	MW	MVAR
1	3 (Slack)	1.04	0	0	0	0
2	2 (PV)	1.025	163	6.7	0	0
3	2 (PV)	1.025	85	-10.9	0	0
4	1 (PQ)	1	0	0	0	0
5	1 (PQ)	1	0	0	125	50
6	1 (PQ)	1	0	0	90	30
7	1 (PQ)	1	0	0	0	0
8	1 (PQ)	1	0	0	100	35
9	1 (PQ)	1	0	0	0	0

The IEEE 9-bus system comprises 3 generators, 3 loads, 10 transmission lines, and 3 transformers, as depicted in Figure 1. This configuration provides a balanced representation of key components found in power systems, allowing researchers to investigate various aspects of system behavior, stability, and performance. Overall, the IEEE 9-bus system serves as a reliable and widely recognized platform for conducting studies in the field of power systems analysis and optimization.

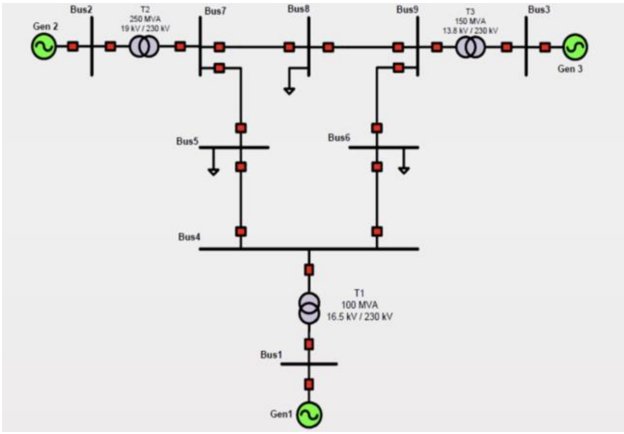

Figure 1 Diagram of the IEEE 9-bus system [31]

2.1 IEEE 9-Bus Case Data

The IEEE 9-bus system serves as the foundational platform for this research, representing a microgrid that offers a scaled-down yet comprehensive model of an electrical grid. Widely adopted by researchers, this system facilitates the exploration of both static and dynamic power system phenomena due to its well-documented nature and manageable size compared to real-world grids. Consisting of 3 generators, 3 loads, 10 transmission lines, and 3 transformers, as illustrated in Figure1, the IEEE 9-bus system's data, including bus data and transmission line data, have been extensively utilized throughout the study. While certain values have been adjusted to accommodate the six scenarios analyzed in this thesis, the loads and transmission line parameters have remained constant for consistency and comparison purposes. This ensures that any modifications made to the system align with the specific objectives and conditions outlined in each scenario, ensuring a robust and targeted analysis.

Table 1 Bus Data of IEEE 9-bus system

Table 2 Line or Branch Data of IEEE 9-bus System

Line From	Line To	R	X	½|Y|	Y
1	4	0	0.0576	0	0
4	5	0.01	0.085	0.088	0.176
4	6	0.017	0.092	0.079	0.158
6	9	0.039	0.17	0.179	0.358
5	7	0.032	0.161	0.153	0.306
9	3	0	0.0586	0	0

7	2	0	0.0625	0	0
9	8	0.0119	0.1008	0.1045	0.209
7	8	0.0085	0.072	0.0745	0.149

2.2 PMU

Phasor Measurement Units (PMUs) represent a significant advancement in real-time monitoring within power systems, offering instantaneous measurement of positive sequence voltages and currents at substations. Typically, these measurements occur over a single cycle of the fundamental frequency and are synchronized to a common GPS time signal. By aligning the time stamps of these measurements, a coherent depiction of the power system's state is obtained. Although various algorithms exist for estimating current and voltage magnitudes and phases, the Fourier filter stands out due to its harmonic rejection capabilities, speed of estimation, and recursive nature. However, while the underlying principles of synchronized phasor measurement remain consistent across PMU units, the specific implementation of measurement algorithms can vary significantly among manufacturers. Factors such as measurement window size, sampling rate, time stamping, and phasor computation rate may differ based on hardware requirements and limitations, impacting measurement precision. These differences in implementation can pose challenges for interoperability and compatibility between PMU units from different manufacturers. For instance, while precision can be improved with features like true 16-bit A/D converters and longer data windows, longer windows may lead to greater attenuation in off-nominal frequency conditions. Consequently, PMU units utilizing different data window sizes may yield divergent phasor magnitude readings under such conditions.

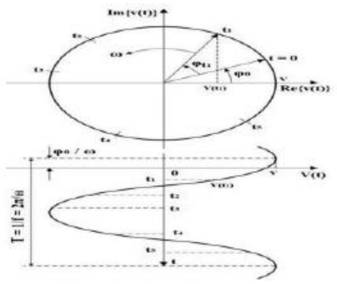

Figure 2. A sine wave vs. its phasor form [24].

The input data of a Phasor Measurement Unit (PMU) comprises voltage (V(t)) and current (I(t)), directly measured from the current transformer (CT) and potential transformer (PT).

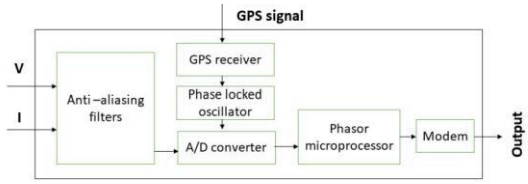

Figure 3. Phasor measurement units (PMU) block diagram

The IEEE Std. C37.118.1-2011 standard defines two performance classes for Phasor Measurement Unit (PMU) applications: the Measurement (M) class and the Protection (P) class. The M class prioritizes accuracy over response time, making it suitable for applications with stringent accuracy requirements, especially those involving higher frequencies. On the other hand, the P class emphasizes faster response times at the expense of some accuracy, making it more suitable for real-time protection and control applications that prioritize lower latency over absolute precision.

3. Results and Discussions

Analyzing the impact of faults occurring at different locations on bus 1 in the IEEE nine bus data involves assessing how variations in branch resistance and reactance affect the system's stability.

When a fault occurs at different locations on bus 1, it alters the impedance seen by the rest of the system, thereby influencing the system's overall behavior. The variations in branch resistance and reactance determine the fault's severity and its effect on the system's stability.

If the branch resistance increases due to the fault, it can lead to higher fault currents, potentially causing overheating and damage to the equipment. This increase in resistance may also result in voltage drops across the affected branches, affecting the system's overall voltage profile.

Similarly, variations in branch reactance can also impact the system's stability. An increase in reactance can lead to higher impedance, which may reduce fault currents but prolong fault clearing times. This can result in transient instability as the system struggles to return to a stable state after the fault is cleared.

Overall, the impact of variations in branch resistance and reactance on the stable or unstable condition of the system depends on factors such as fault location, fault duration, fault impedance, and the system's dynamic response to these variations. Analyzing these factors comprehensively can provide insights into how different fault scenarios affect the stability of the IEEE nine bus system.

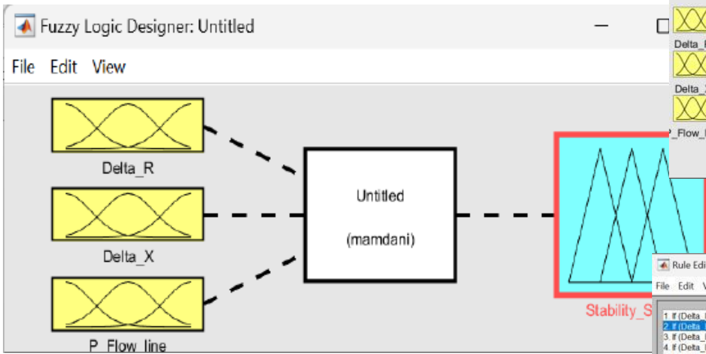

Figure 8: Fuzzy Logic Designer Fuzztestimator

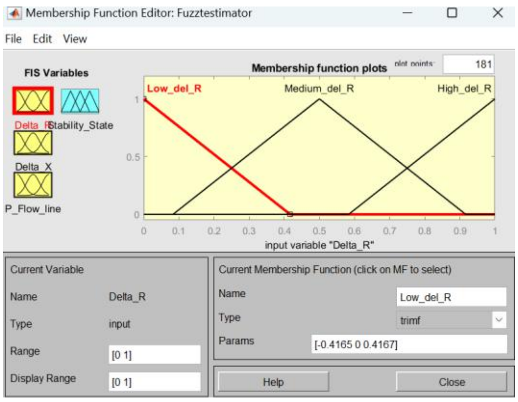

Figure 9: Membership Function Editor

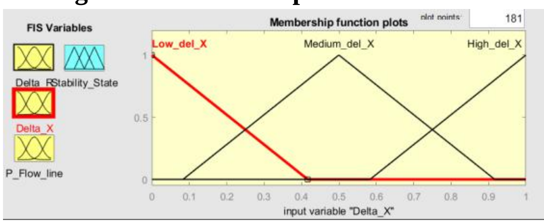

Figure 10: Membership Function Plots

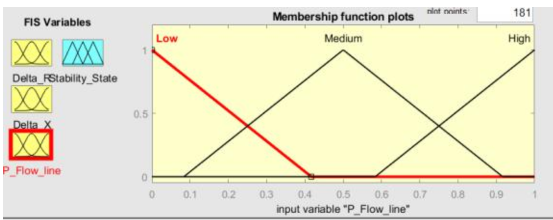

Figure 11: Membership Function Plots

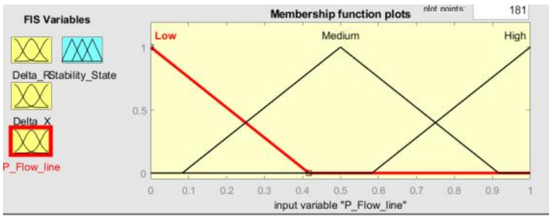

Figure 12: Membership Function Plots

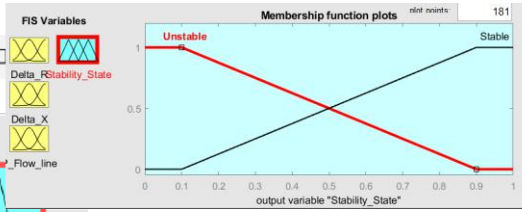

Figure 13: Membership Function Plots

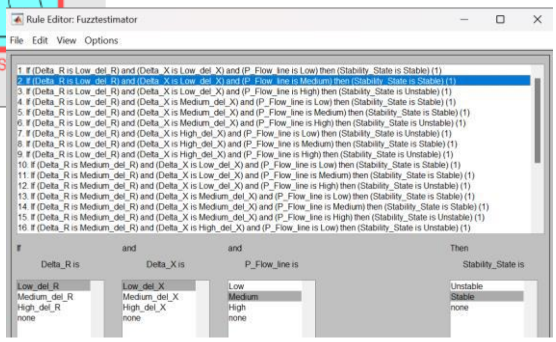

Figure 14:Rule Editor: Fuzztestimator

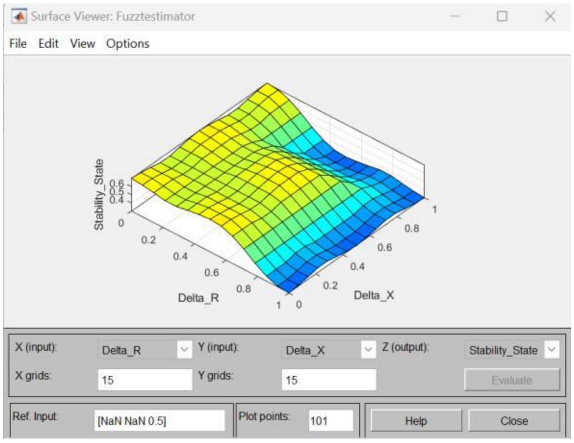

Figure 15: Surface Viewer: Fuzztestimator

4. Conclusions

Maintaining synchronous generators in parallel operation to meet load demands is crucial for ensuring a reliable power system. Transient stability, which refers to the ability of synchronous machines to remain synchronized following significant disturbances like three-phase failures, is a critical aspect of power system operation. While traditional methods such as time-domain simulation, Extended Equal Area Criterion

(EEAC), and Transient Energy Function (TEF) approach are commonly used to evaluate transient stability, they have limitations.

The time-domain simulation method is renowned for its accuracy and versatility but is unsuitable for real-time transient stability prediction due to its time-consuming nature. Meanwhile, approaches like EEAC and TEF offer alternative methods for assessing transient stability, but they also require intensive computations and may have modeling limitations.

Given these challenges, there is a need for more efficient and accurate methods for predicting transient stability in power systems, especially in real-time scenarios. Advanced techniques such as artificial intelligence-based models and synchrophasor-based methods have emerged as promising alternatives, offering the potential for faster and more reliable transient stability assessment. By harnessing the power of modern technology, the goal is to enhance the reliability and efficiency of power system operations while ensuring robust transient stability evaluation.

Given the aforementioned challenges in evaluating transient stability, it becomes crucial to explore novel avenues for assessment. Thus far, various machine learning (ML) techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees (DT), have been developed for this purpose. Among these strategies, Fuzzy logic stands out as a popular choice due to its simplicity in training, modular nature for parallel processing, and ability to map nonlinear relations between input and output data effectively.

The primary objective of this study is to investigate the application of fuzzy logic in transient stability assessment (TSA). By focusing on fuzzy logic, this work aims to provide researchers in the fields of machine learning and power system stability with a comprehensive understanding of the current research landscape and its ongoing challenges. Future research directions could involve conducting comparative studies across different machine learning techniques and exploring feature reduction strategies tailored for large-scale power systems. Additionally, integrating machine learning with edge computing in existing power systems could help minimize computing requirements and enhance the efficiency of smart equipment such as digital relays, PMUs, and smart meters by enabling local data analysis. Through such endeavors, advancements in transient stability assessment can be achieved, contributing to the overall reliability and resilience of power systems.

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