International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

A Review on Utilizing Artificial Intelligence Methods for Evaluating Transient Stability in Power Systems

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Abstract– The dynamics of the power system have significantly changed as a result of the integration of large-scale renewable energy sources and growing unpredictability, posing a number of issues. For precise power system planning and operation, a modern power system's transient stability assessment must be completed quickly. Conventional approaches are unable to meet this need. Thus, new strategies are needed in this area. Artificial neural networks and other machine learning techniques can be quite helpful in this respect. Thus, the purpose of this research is to review the use of artificial neural networks in power system transient stability assessment. It is anticipated that this work will give machine learning researchers a strong platform on which to build in order to power system stability and security.

Keywords-artificial neural network; machine learning; renewable energy; transient stability; uncertainty

1. Introduction:

Maintaining synchronous generators that are capable of meeting load demands while operating in parallel is one of the key prerequisites for a dependable power system. The aptitude of the synchronic machines to maintain synchrony through the short-term period that follows a significant trouble, like a three-phase failure, is referred to as transient stability in power systems [1-2]. While there are several traditional approaches to assess fleeting constancy, the time-domain imitation method is the most widely cast-off. This is widely used because of its great accuracy and universality, but it takes too long, so it is not appropriate for actual fleeting constancy prediction [3]. Control system transient stability has also been evaluated using the Extended Equal Area Criterion (EEAC) and the Transient Energy Function (TEF) method. However, the transient stability index must be computed using many computations, and all approaches have certain modelling limitations [4].

Given the aforementioned, it is imperative to investigate novel avenues for evaluating temporary stability. To far, a number of machine learning (ML) techniques based on computational intelligence, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees (DT), have been developed for this resolution. For a variety of reasons, ANN is the most widely used and well-liked of these strategies. Its training does not require any complex mathematical modelling, and its modular nature facilitates similar dispensation. Additionally, it has the aptitude to chart nonlinear relationships amid effort and harvest data instantaneously [1]. As a result, the purpose of this work is to examine particularly how ANN is applied to transient stability assessment (TSA).

2. Related Work:

Because ANNs can process and understand complex nonlinear relations, their application to power systems is gaining a lot of attention [47]. Additionally, they have the capacity to analyse data in parallel. Based on several offline simulations, an association mapping is created in ANN-based TSA amid the contribution features and the stability assessment's harvest outcomes. As a result, many studies have extensively used them to generate this relation mapping [48, 49–51].

ANNs were utilized in Reference [48] to forecast the critical clearing time (CCT) of a system with limited test control. Reference [49] predicted energy margin and stability using an individual TEF technique. For TSA, Reference [50] developed an integrated strategy using SL and unsupervised learning. A quick technique for pattern identification and classification for dynamic security situations was presented in reference [52]. ANNs were utilized in [53] to forecast the constancy of a scheme with 227 buses and 53 producers. Reference [54] used the Multi-Layer Perceptron Neural Network (MLPNN) and the recurrent Radial Basis Function (RBF) to estimate the angular velocities and rotor angles of synchronous machines ANN was utilized in Reference [55] to categorize the state of system stability for different scenarios. In [56], the multilayer Feedforward Neural Network (FNN) was utilized to start the nonlinear charting relation amid the fleeting liveliness margin and the producer control, at varied Fault Clearing times (FCT). The system dynamic equivalents-based Lyapunov's direct technique was employed as a quick way to get the ANN's training set. Reference [57] provided a special ANN-based global online fault detection, pattern classification, and relaying detection method for synchronous generators (SGs) in connected electric utility networks. The online ANN-based relaying method categorized the fault occurrence and nature as either transient stability or loss of excitation, and the allowable CCT and loss of excitation type as an open or short circuit.

A unique two-layer fuzzy hyperrectangular composite neural network was created in [58] to predict transient stability in real time. A study on improving transient stability through the use of auxiliary controls to regulate the flow of High Voltage Direct Current (HVDC) power was carried out in [59]. The stability analysis included both the line dynamics and the current controller model. A multi-machine system with a neural network controller was constructed in order to improve system stability. The subject of ANN input dimension reduction was discussed in reference [60]. The accuracy & effectiveness of two distinct TSA application techniques were examined and contrasted. Reference [61] provided details on an adaptive pattern recognition technique for CCT estimate based on neural networks. Reference [62] proposed the use of artificial neural networks (ANN) for power system contingency transient & screening stability evaluation. An ANN is used in the adaptive pattern recognition method of TSA proposed in reference [63]. Reference [64] examined the use of ANNs in analyzing the transient stability of a power system (calculation of CCT for short-circuit failures type, with transmission line interruption) using a supervised FNN. A multilayer feedforward ANN is employed in [65] to manage the online TSA of a power system. Reference [66] describes how the Unified Power Flow Controller (UPFC)'s control strategy, the RBF Neural Network (RBFNN), improved the transient stability performance of a multimachine power system. The primary objective of reference [67] was to validate the accuracy of ANN in evaluating the transient stability of a single machine infinite bus system. The findings acquired using the conventional Equal Area Criterion (EAC) approach were compared with the fault CCT produced by ANN. The test system was subjected to the multilayer FNN idea. Reference [68] provided a evaluation of two distinct machine learning procedures, ANN and SVM, for the forecast of online transient stability. considering several unknowns, such as load, fault type, location, fault clearing time, and network topology. Based on the superiority of ANN's classification metrics and computational time over SVM, the findings clearly demonstrated ANN's superior performance. Reference [69] offered ANN-based supervised machine learning to assess the transient stability of a power system while accounting for uncertainties related to load, faulted line, fault type, fault location, and fault clearance time. The neural network was trained using the appropriate system features as inputs and the probabilistic transient stability (PTS) status indicator as the output. Reference [70] looked at the PTS framework for power systems and the application of ANN to improve the assessment procedure. The research included a number of unknown variables, including the criticized line, fault kind, inaccurate location, and inaccurate clearance time. The obtained results proved the effectiveness of the suggested method, allowing it to be used to the transient stability prediction of any realistic large-scale power system. In [71], DT, SVM, and ANN were compared for two datasets. The findings indicated that TSA with ML is system-specific. It was also shown that there is a discernible difference in the two sets of algorithms' performance when the network's parameters are altered. A convolutional neural network-based TSA and instability mode assessment method was introduced in [72]. The method quickly generates a forecast result in terms of oscillatory instability, aperiodic instability, or stability using as input the bus voltage phasor recorded by Phasor Measurement Units (PMUs) within a brief observation window following disturbance. In [73], a novel hybrid intelligent system was created to predict transitory stability. An interpreter, a variety of neural networks, and a preprocessor made up the systemThe preprocessor divided the entire set of synchronous machines into groups of two generators apiece.

A novel method for power system TSA based on CNN (Convolution Neural Network) and voltage phasor was presented in [74]. Using the DL technique, a dynamic display of the power system transient process in the voltage phasor complex plane was first assembled. Second, a fast estimation prototype was put out, leveraging CNN and the voltage phasor complex plane image to achieve power system transient stability. A direct TSA method based on a Type-2 fuzzy neural network was presented in [75]. To overcome the uncertainty in the power system parameter measurement, Type-2 fuzzy logic was employed. On the other hand, a multilayer perceptron (MLP) neural network has the ability to learn and retain expert information. These two advantages were used in the hybrid technique that was created to provide an accurate computation of the TSA index, or CCT.

Reference [76] suggested TSA of a sizable 87-bus arrangement by combining feature extraction and selection techniques with a novel technique called the Probabilistic Neural Network (PNN). Transient stability was anticipated based on the generator relative rotor angles found using time domain simulations. It was determined that the PNN training time was shortened by incorporating feature reduction techniques, all while maintaining the accuracy of the classification outcomes. In [77], actual TSA was introduced inside a data-driven context by utilizing Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) elements to incorporate the temporal relations of the predictors. When the method was used to the IEEE 39-bus test system, it produced impressive test results when compared to an SVM benchmark..

In [78], a long short-term memory network-based TSA system was developed.. The described network attempted to achieve a trade-off balance amid valuation accurateness and reaction rapidity by suggesting a time-based self-adaptive strategy. Three power system case studies proved the usefulness of the proposed TSA methodology. A methodical approach to the construction and renovation of an accurate transient stability classifier was provided in Reference [79]. Initially, a CNN ensemble method was suggested to use these multi-dimensional data to develop the transient stability predictor by using the generators' time-series trajectories after disturbance as inputs. The efficiency of the system described was exposed by the simulation outcomes of two power systems. Reference [80] provided an explanation of how ANNs can be used to anticipate the power system's CCT. Selected features were used as input for the ANN's training, with CCT acting as the desired outcome. Time domain simulation was utilized to ascertain the target CCT, and a single contingency was employed. The simulation demonstrated that ANNs are suited for online applications since they can produce maps quickly and accurately.

An ANN application for tracking TSA including changes in system topology was given in Reference [81]. To offset the system instability, an offline trained artificial neural network (ANN) was utilized to provide the right corrective measure for online operation. According to the simulation results, the artificial neural network (ANN) can be a helpful tool for accurately assessing online transient stability. In [82], the Gated Graph Neural Network (GGNN) was utilized to predict transient stability and infer the kind of disturbance that precipitated the power system's instability. To create unstable samples, Conditional Generative Adversarial Networks (CGAN) were first used. Consequently, the power system's transient stability was assessed, and the real-time data was incorporated into the TSA model that had been trained. By using Graph Neural Networks (GNNs) to integrate topology

information into the model, Reference [83] achieved the integration of electrical and network topology information to develop a transient stability evaluation model. A simulated example validated the approach's viability in TSA and showed that the model can generalize to any grid layout.
In order to strengthen TSA, a convolutional neural network-based approach was developed in [84]. This method has the ability to overcome the shortcomings of traditional assessment techniques and meet TSA requirements with a high degree of evaluation precision. The features of the TSA problem were used to improve the training methods of convolutional neural networks, and the batch normalization process was used to produce the TSA model. In reference [85], a neural network-based adaptive pattern recognition approach was employed to conduct an extensive research on a power system for the estimation of the CCT. The weights were adjusted using the back propagation approach. The results from the neural network were compared with analytical computations.
A novel method for forecasting the online transient stability margin was introduced in [86]. The topology information and pre-fault power flow characteristics were extracted using 2D computer-vision based power flow images, transformation techniques, and a Geographic Information System (GIS). Additionally, under the anticipated set of circumstances, a complete network based on CNN was created to map the link between the generator stability indices and the steady-state power flow. The simulation results validated the usefulness of the provided method, and it is possible to examine the transient stability margin quantitatively and fast with the help of this offered methodology. Recurrent Graph Convolutional Network (RGCN)-based multi-task TSA was first presented in [87[The RGCN was created by combining the Graph Convolutional Network (GCN) and the LSTM unit. Test results on the IEEE 39 Bus system and the IEEE 300 Bus system showed that the suggested approach is more effective and resilient than the present models under a variety of conditions. Additional noteworthy research related to ANN application for TSA is available in [88-95].

3. Conclusion:

It is anticipated that this review will give scholars studying machine learning and power system stability a solid foundation, enabling them to comprehend the state of the field's research and its ongoing difficulties. Future research can involve comparing numerous reviews and case studies with different machine learning techniques. To further minimize the computing requirements, feature reduction strategies for extensive power structures must be developed. In order to diminish reliance on cloud networks, machine learning (ML) can be combined with superiority figuring in current power systems. This will enable keen equipment, such as digital relays, PMUs, and smart meters, to analyze data locally.

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International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

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