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Review Article

Comparative Study on Various Smart Grid Stability Predictions with Deep Learning and Machine Learning

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Abstract

Smart grids are electrical transmission systems that enable economical electricity use without harming the environment. Driven primarily by the concept of demand responsiveness, a smart grid is a contemporary power system that enables bidirectional communication. To increase the smart grid's reliability and optimize the effectiveness and regularity of electricity transmission, it is essential to forecast its stability. Because of the many factors that affect it, such as producer and consumer participation, which may influence smart grid stability, it is challenging to predict its stability. The stability of smart grids has been predicted using a variety of machine learning and deep learning techniques in this study.

Keywords: *Artificial Intelligence (AI), Internet of Things (IoT), Machine learning, Smart Grid Stability, Electricity, Deep Learning.*

I. INTRODUCTION

Electricity is an essential source of energy that comes from various sources such as airstreams, water, solar cells, thermal, fossil fuels (natural gas, coal, and petroleum), tidal, biomass, and nuclear plants. In the extreme growth of people, the consumption of electricity is increasing day by day. Energy consumption is expected to increase significantly over the next several decades due to factors such as the world's increasing population and industrialization, as well as the expansion of the global economy. As a result of its versatility as an energy source and its widespread availability, electricity has risen to prominence in recent years. Electricity generation stems from a multitude of sources, encompassing thermal energy, solar power, hydroelectricity, nuclear reactors, wind turbines, and the extraction of fossil fuels. This diversity underscores its status as a pivotal energy source. Furthermore, as populations expand and societies progress, the associated surge in power requirements sets higher standards for energy generation. Smart grids have the capability to amalgamate consumer data to establish an efficient electricity distribution system. Smart grids harness renewable energy resources, rendering them a secure addition to the power grid. These grids evaluate real-time supply data through the collection of consumer demand information. Subsequently, they compute the electricity cost and convey this pricing data to customers, enabling them to make informed decisions regarding usage. Given the time-sensitive character of this process, ensuring the stability of a smart grid emerges as one of its principal imperatives. In a smart grid, information about how much power people want is collected, compared centrally to how much power is available now, and then the suggested price information is sent back to users so they can decide how much power to use. Since the whole process depends on time, predicting grid stability dynamically is not only a worry but also a big need. The goal is to comprehend and prepare for changes and disruptions in energy production and/or usage that are caused by people in the system. This should be done in a dynamic way, taking into account not only technical factors but also how participants react to changes in the energy price.

II. LITERATURE REVIEW

Applying machine learning (ML) and deep learning (DL) techniques to smart grid applications is not new. Alsirhani et al. [1] used a novel MLP-ELM strategy to predict the reliability of smart grid networks by standardizing the results using a Z-score. Non-numeric values were transformed during preprocessing, and patterns were discovered via exploration. The results demonstrated that MLP-ELM outperformed conventional techniques, with 95.5% accuracy, 90% precision, 88% recall, and 89% F-measure, all of which point to its potential in improving smart grid dependability. Breviglieri et al. [2], the authors used a suite of optimized deep learning (DL) models to investigate the distributed smart grid control (DSGC) system across a broad input value range, with the goal of predicting the smart grid's stability without the use of limiting assumptions. The proposed DL models achieved good accuracy. The authors demonstrated that DL models provided novel insights into the simulated environment, and it showed rapid adaptation that improves system stability. The technique suggested in [3] aimed to address the difficulty of stability prediction in the presence of missing data. The loss of a sensor, network link, or other system might account for this missing variable. This work proposed a unique feedforward neural network (FFNN) model that can deal with missing inputs, which proved to be an effective solution to the problem. A star network with just four nodes was used to test the model's accuracy. Four different scenarios with missing input data were used in this analysis. For each scenario, a secondary neural network was trained to forecast the missing variables; these results were then used as input by the main neural network to make stability predictions. During training and testing, the sub-neural network performed the best, with a mean squared error (MSE) of 0.0001 and an R^2 of 0.99. During training, the principal network's R^2 was 0.9, while it was 0.97 during testing. The MSE for this network was 0.008. The models performed quite well across all four scenarios, with MSEs around zero and R-squared values close to one. A novel upgraded stacked GRU-RNN for univariate and multivariate scenarios was used to anticipate renewable energy (RE) production and electricity demand [4]. Multiple sensitive monitoring metrics or historical power consumption data are selected for the input dataset using correlation analysis. A simpler GRU, AdaGrad, and configurable momentum are then built into a stacked GRU-RNN. The revised training approach and redesigned GRU-RNN structure improve training efficiency and robustness. Using its self-feedback connections and better training mechanism, the stacked GRU-RNN maps the specified variables to RE generation or electricity load. Two studies verify the suggested method: predicting wind power production using meteorological characteristics and modeling electricity demand using historical energy usage data. The experimental findings indicated that the suggested technique can provide accurate energy estimates needed for smart grid operations. Naz et al. [5], the authors used the UMass Electric Dataset and two different ways to predict how much power would be used and how much it would cost. The suggested ELR method is better at making predictions than both CNN and LR. This has been proven using measures like MAPE, MAE, MSE, and RMSE on both the UMass Electric and UCI datasets. The dataset, which is multiple, is normalized and then split into a training set and a testing set. Recursive feature elimination (RFE), CART, and Relief-F are all used in feature engineering. ELR, which was made to make accurate predictions, does better than existing models, which is a big step forward for the accuracy of estimates for smart grid operations. Singh and Yassine [6] predicted the energy demand with the help of CNNs. But CNN requires setting a number of levels, which makes it complicated in both space and time. Two improved ways are suggested to make the load and price of energy more accurate. Both methods use samples that have one variable or more than one. Also, both home data and data from utilities are analyzed together. Massaoudi et al. [7] automatically tuned hyperparameters using simulated annealing to improve the forecasting model. Simulations revealed that the suggested model made accurate predictions on a simulated electrical grid stability dataset. Comparisons show its advantages over cutting-edge solutions. Bingi and Prusty [8], the authors, proposed neural network models trained with the damped least-squares technique for predicting the stability of smart grids. The results demonstrate the superior performance of the feed-forward neural network in terms of minimal error and highest R^2 values for the considered system. Tiwari et al. [9], the authors used a range of ML methods to guess the grid's security and keep it from breaking down. A Kaggle dataset was used in the tests. With 98% accuracy, the suggested model could predict load using the bagging classifier method. Accurate predictions of how much power will be used are a key part of keeping the grid from going down, which makes the grid more stable and stronger overall. Ahmed et al. [10], the authors discussed how smart grids and green energy may be utilized in combination to meet rising energy demand. They discussed the challenges of designing a smart grid with green energy. The authors also noted the importance of ML models over statistical models for nonlinear data. Mohsen et al. [11], the authors recommended employing a neural network to forecast the reliability of a smart grid. The dataset used is derived from DSGC system simulations. Testing the suggested neural network's efficacy yielded a loss rate of 0.06, an accuracy of 97%, and a loss rate of 0.06 during training. Hong et al. [12], the authors introduced a short-term residence load forecasting system that uses DL to exploit the spatiotemporal correlation found in load data from appliances. Paragraphs are used to explain the way in which a particular activity or set of actions is related to one another inside the same sequence of words. To learn the association among various power consumption habits for short-term load forecasting, a deep neural network and iterative ResBlock-based technique are developed. The effectiveness of the suggested forecasting method has been tested via experiments using real-world observations. The outcomes demonstrate that load data from appliances and iterative ResBlocks may both contribute to better predicting results. Alazab et al. [13], a unique multidirectional long short-term memory (LSTM) approach is being developed to forecast the stability of the smart grid network. Results are compared to those achieved using other well-known DL methods, such as GRU and conventional LSTM and RNN. The experimental findings demonstrate that MLSTM performs better than the competing ML methods. Bose et al. [14], the authors addressed innovative smart grid AI applications. Automation of current wind-generating system design and health monitoring in operation, fault pattern detection of an SG subsystem, and real-time simulator-based SG control are these applications. Many additional applications may be created from these examples. The article begins with a quick overview of AI basics relevant to these applications. Jindal et al. [15] used DT and support vector machine (SVM) classifiers to analyze power use data rigorously. Since the SVM classifier receives DT-processed data, the suggested technique is a two-level data processing and analysis strategy. Furthermore, the findings show that the suggested approach greatly lowers false positives and is feasible for real-time use. Önder et al. [16], the authors applied cascading of ML algorithms and achieved good results. The results showed that cascade methods outperformed conventional ML methods. Sallam [17] applied the DL technique for smart grid stability prediction and achieved good results. A case study of ML models used to anticipate smart grid stability and difficulties that may arise when renewable energy is employed was described in [18]. The authors in [19] applied various ML techniques for smart grid stability prediction and achieved good results. They used ML models to predict power-grid synchronization stability [20]. The algorithms used in experiments are RF, SVM, and artificial neural networks (ANN). Neelakandan et al. [21] are creating a stability prediction system using MHSA-LSTM. SOS optimization was used to optimize MHSA-LSTM model hyperparameters. The AHBFS and SOS algorithms greatly affect the MHSA-LSTM models for stability prediction. Several simulations illustrate AHBFS-ODLSP model adjustments and analyze their results. The AHBFS-ODLSP approach performs best with a 99% F score. Reddy et al. [22] utilized neural networks, decision trees (DTs), and SVM in smart grid management systems and performed well. Maizana et al. [23] carried out a stability investigation of the smart grid management system on the campus building. The authors observed that the battery is acting as a source while the PLN and solar cells are providing the energy, or vice versa, and just one bus at the load is in an unstable or dangerous state. Aziz and Lawi [24] proposed ensemble ML methods for electrical grid stability and achieved good accuracy. The authors experimented with C4.5 and CART algorithms and reported good results. Merza et al. [25] describe AI strategies built on DL algorithms that can use real-time measurement data to detect foreign direct investment (FDI) assaults on smart grids. Untraceable FDI assaults that bypass SVE defenses are countered with the help of the convolutional deep belief network (CDBN) design. Most of the existing works proposed conventional ML models or DL models for stability prediction in smart grids. In this paper, the authors proposed a novel fusion method of ML and DL algorithms for smart grid stability prediction. The rest of the paper is organized as follows: Section 2 explains the proposed method. Section 3 consists of results and discussion. Section 4 has a conclusion [26]. The present work proposed five different cascade methods with pre-processing, training and testing division, and the classification stages of the classification procedure for estimating SG stability [27]. This study [28] proposes a machine learning model to identify smart grid stability more efficiently. To accomplish this, we collected the electrical grid stability dataset from a public machine learning repository and analyzed the correlation of individual features. In [29], this paper discusses a comprehensive review of AI-based modeling, an AI-enabled smart grid for demand forecasting that leverages machine learning (ML) and artificial intelligence (AI) techniques to predict electricity demand with high accuracy and efficiency. It integrates advanced data analytics with the grid's operational systems to enable better decision-making, enhance grid management, and improve energy efficiency. This paper [30] intends to predict stability from the smart grid stability prediction dataset using machine learning algorithms. This research [31] presents a hybrid deep learning model (Convolutional Neural Network [CNN] with Bi-LSTM) with a two-way attention method and a multi-objective particle swarm optimization method (MPSO) for short-term load prediction from a smart grid. This study addresses this challenge by leveraging machine learning (ML) models and explainable artificial intelligence (XAI) techniques to predict the stability of a decentralized smart grid [32]. This paper presents an optimized Long Short-Term Memory model for predicting smart grid stability, leveraging the Novel Guide-Waterwheel Plant Algorithm (Guide-WWPA) for enhanced performance. Traditional methods often struggle with the complexity and dynamic nature of smart grids, necessitating advanced approaches for accurate predictions. The proposed LSTM model, optimized using Guide-WWPA, addresses these challenges by effectively capturing temporal dependencies and nonlinear relationships in the data [33]. This paper compares machine learning-based traditional and ensemble techniques for predicting smart grid stability, utilizing an augmented dataset from Kaggle. For optimization, various classifiers and ensemble techniques, including bagging, boosting, stacking, and voting, were implemented with hyperparameter tuning [34]. This study explores the performance of various machine learning classifiers in predicting the stability of smart grid systems. Utilizing a smart grid dataset obtained from the University of California's machine learning repository, classifiers such as logistic regression (LR), XGBoost, linear support vector machine (linear SVM), and SVM with radial basis function (SVM-RBF) were evaluated [35].

III. THE ADVANTAGES OF THE SMART GRIDS

Improved energy efficiency, increased dependability, better integration of renewable energy, and reduced utility operating costs are just a few benefits of smart grids. They also make it possible for more precise billing, lower peak demand, and give customers access to real-time energy usage data, which promotes energy saving and better decision-making.

Here's a more detailed breakdown of the benefits of smart grids:

1. Efficiency and Reliability:
   i) Reduced energy losses:
   Smart grids can identify and reduce energy losses throughout the system, leading to cost savings for both utilities and consumers.
   ii) Improved grid reliability:
   By enabling faster fault detection and automated restoration processes, smart grids can reduce the frequency and duration of power outages.
   iii) Optimized energy flow:
   They can balance the flow of power more efficiently, reducing waste and improving overall grid performance.
   iv) Reduced peak demand:
   By enabling better demand management and peak load reduction, smart grids can help utilities avoid costly investments in new generation infrastructure.
2. Renewable Energy Integration:
   i) Seamless integration of renewable sources:
   Smart grids are well-suited to integrate renewable energy sources like solar and wind power into the grid, making the system more sustainable and environmentally friendly.
   ii) Facilitates distributed energy resources:
   They can support the connection of distributed energy resources (DERs), such as solar panels on homes, to the grid.
3. Cost and Efficiency:
   i) Lower operational costs for utilities:
   By automating tasks and optimizing energy flow, smart grids can reduce the operational costs for utilities.
   ii) Accurate billing:
   They provide real-time data on electricity usage, enabling more accurate and fair billing for consumers.
   iii) Cost savings for consumers:
   Reduced energy losses and the ability to participate in demand response programs can lead to cost savings for consumers.
4. Other Benefits:
   i) Enhanced environmental sustainability:
   By promoting energy efficiency and renewable energy integration, smart grids contribute to a more sustainable energy future.
   ii) Improved security:
   They offer enhanced security measures to protect against cyberattacks and other threats.
   iii) Real-time data and analytics:
   Smart grids provide real-time data on energy usage, allowing utilities and consumers to monitor and optimize their energy consumption.
   iv) Support for electric vehicles:
   They can facilitate the integration of electric vehicles into the grid, supporting the transition to a cleaner transportation system [36].

IV. CONCLUSION

We have reviewed a number of smart grid-related publications and conferences for this study. We have observed the range of techniques they have employed to forecast the stability of the smart grid. The effects of the smart grid technology have also been discussed.

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