AI-Based Predictive Assessment of Power System Stability Performance: A Comprehensive Research

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ABSTRACT

This study focuses on power system stability analysis using artificial intelligence-based predictive models. Modern power systems face stability challenges due to load variation, faults, renewable energy integration, and complex grid operations. Traditional stability methods are often slow for real-time prediction, whereas AI models can quickly learn system behaviour from historical and real-time data. Techniques such as Artificial Neural Networks, Random Forest, Deep Learning, and Hybrid AI models help classify stable, marginally stable, and unstable conditions with higher accuracy. The study concludes that AI-based predictive models improve reliability, response time, and preventive decision-making in smart power systems.

Keywords: *Power System Stability, Artificial Intelligence, Predictive Models, Smart Grid.*

I. INTRODUCTION

Power system stability is one of the most important requirements for the secure, reliable, and continuous operation of modern electrical power networks. A power system is considered stable when it can maintain synchronism, acceptable voltage levels, and normal frequency after being exposed to disturbances such as short circuits, sudden load changes, generator outages, transmission line faults, switching operations, or fluctuations caused by renewable energy sources. In earlier power systems, stability analysis was mainly performed using conventional mathematical models, time-domain simulations, eigenvalue analysis, and operator experience. However, the present power grid has become more complex because of increasing electricity demand, large-scale interconnection of networks, integration of solar and wind energy, smart grid technologies, distributed generation, power electronics devices, electric vehicles, and dynamic load patterns. These changes have made the behaviour of power systems more uncertain and nonlinear, where traditional stability assessment techniques may become slow, complicated, or insufficient for real-time decision-making. Therefore, artificial intelligence-based predictive models have emerged as an effective approach for improving power system stability analysis. Artificial intelligence techniques such as artificial neural networks, support vector machines, decision trees, random forest, fuzzy logic, deep learning, reinforcement learning, and hybrid machine learning models are capable of learning complex relationships from large volumes of historical and real-time system data. These models can identify hidden patterns in voltage magnitude, phase angle, frequency variation, rotor speed, active power, reactive power, load demand, fault current, and generator response. By using these parameters, AI-based predictive models can estimate the stability condition of the system before a serious disturbance develops into blackout or equipment failure. The main advantage of artificial intelligence in stability analysis is its ability to provide fast and accurate prediction. In practical power system operation, even a few seconds of delay in detecting instability may cause cascading failures and widespread power interruption. AI models can process data from phasor measurement units, supervisory control and data acquisition systems, smart meters, and intelligent electronic devices to predict whether the system will remain stable or move toward instability. This predictive capability is very useful for transient stability assessment, voltage stability monitoring, frequency stability prediction, and small-signal stability analysis. Transient stability deals with the ability of synchronous generators to remain in synchronism after severe disturbances, while voltage stability focuses on maintaining acceptable voltage levels under changing load conditions. Frequency stability is related to the balance between generation and demand, whereas small-signal stability studies the system response to small disturbances. Artificial intelligence can support all these areas by developing data-driven models that reduce the dependency on repeated numerical simulations. Another important contribution of AI-based predictive models is their role in preventive and corrective control. Once a possible instability condition is predicted, control actions such as load shedding, generator rescheduling, reactive power compensation, transformer tap changing, capacitor bank switching, or FACTS device control can be applied in advance. This makes the power system more resilient and reduces the risk of sudden collapse. AI techniques are also useful in renewable energy-based power systems, where generation output changes due to weather conditions. For example, solar power varies with irradiance and cloud movement, while wind power depends on wind speed variation. These variations may affect voltage and frequency stability if not properly managed. Machine learning models can forecast renewable generation patterns and help operators maintain system balance. Deep learning models, especially recurrent neural networks, convolutional neural networks, and long short-term memory networks, are effective for time-series prediction because they can analyse sequential data and detect temporal behaviour in power system variables. Similarly, fuzzy logic can handle uncertainty in system operation, while reinforcement learning can learn optimal control strategies through interaction with the environment. Hybrid AI models combine the strengths of different techniques and often provide better accuracy, robustness, and adaptability. The use of artificial intelligence also supports the development of smart grids, where automated monitoring, self-healing operation, and intelligent control are required. In smart grid environments, power system stability analysis is not limited to offline studies but becomes a real-time and continuous process. AI-based predictive models can classify operating states as secure, alert, emergency, or unstable, allowing operators to take quick action. These models also help in reducing computational burden because once trained properly, they can generate stability predictions much faster than traditional simulation-based methods. However, the effectiveness of AI-based stability analysis depends on the quality, quantity, and diversity of training data. Poor or incomplete data may lead to inaccurate prediction. Therefore, data preprocessing, feature selection, model training, validation, and testing are essential steps in developing reliable predictive models. The model must also be able to generalize under new operating conditions because power systems are dynamic and constantly changing. Despite these challenges, artificial intelligence has strong potential to transform stability analysis from a reactive approach into a predictive and preventive framework. It improves situational awareness, enhances operational security, supports renewable energy integration, and helps avoid major disturbances. Thus, power system stability analysis using artificial intelligence-based predictive models represents a significant advancement in modern electrical engineering. It provides a faster, smarter, and more adaptive method for understanding complex power system behaviour and ensuring reliable electricity supply. As power networks continue to expand and become more intelligent, AI-based predictive stability assessment will play a crucial role in maintaining grid security, improving efficiency, and supporting the future development of sustainable and resilient power systems.

II. RESEARCH BACKGROUND

Bharaneedharan et al. (2026) examined the increasing complexity of power system operations due to the high penetration of renewable energy sources and integration of power electronics components. They highlighted that advancements in artificial intelligence (AI) and machine learning (ML) had demonstrated notable proficiency in handling tasks requiring computational, perceptual, and cognitive capabilities. The study emphasized that efficient and secure operation of power systems, along with enhanced resilience, necessitated the integration of massive amounts of real-time data from intelligent electronic devices and wide-area measurement systems. The authors reported that ongoing developments in AI were driving substantial technical transformations in electric power systems, aiming to accelerate computation, reduce costs, and ensure consistent network performance. They argued that traditional power system management methods often suffered from inefficiency, high costs, and poor adaptability, whereas AI approaches improved operational efficacy, planning, control, and forecasting. The review of over 150 studies indicated that AI methods, particularly reinforcement learning, deep learning, and LSTM/GRU models, had significantly enhanced forecasting accuracy, reduced computational time, and improved stability and adaptability in power system management.

Kumar et al. (2026) investigated the transformative role of artificial intelligence (AI) in renewable energy systems, emphasizing its impact on fluid dynamics and energy management. The study reported that AI had been applied to wind energy to optimize turbine blade design through machine learning and computational fluid dynamics, which reportedly reduced air resistance by 15–20% and increased energy output by up to 12%. AI-driven pitch control systems were described as capable of adjusting blade angles in real-time under varying wind conditions, while predictive maintenance models were noted to forecast gear failures with 92% accuracy, thereby reducing unexpected downtime by 35%. In hydroelectric systems, AI was found to improve fluid flow modeling, minimizing energy losses due to turbulence, and high-performance computing integration was claimed to accelerate simulations, shortening design times by 25–40%. The study further suggested that AI enhanced power network management by aligning production with demand, improving forecast accuracy by 30%, and optimized solar trackers increased energy capture by 20%. Hybrid wind–solar systems reportedly benefited from AI in maintaining stable power output, though challenges such as low-quality data and high computational costs were acknowledged. The authors recommended that future research explore physics-informed AI models to enhance efficiency and scalability in renewable energy applications.

Liang and Srinivasan (2026) examined the ongoing transformation of the global energy sector, highlighting the dual drivers of deep decarbonization and rapid advancements in artificial intelligence (AI). Their study was reported to review the integration of AI-driven flexibility, demand response (DR), and renewable energy with the objective of achieving a secure and sustainable energy transition. They were described to conduct a systematic analysis of recent high-quality publications, emphasizing AI applications in power systems, and to propose a structured taxonomy of AI techniques specifically designed for enhancing power system flexibility. The study reportedly investigated critical challenges such as renewable intermittency and grid stability, while discussing influential AI methodologies applied across power systems. A critical evaluation was said to assess techno-economic trade-offs and the implementation readiness of these methods. Their review was noted to show that AI-driven flexibility could reduce integration costs for variable renewables, increase DR participation, and improve grid reliability, ultimately offering a coherent roadmap for researchers and practitioners in intelligent energy systems.

Rehman et al. (2025) investigated the integration of multiple renewable and storage units in electric vehicle (EV) hybrid energy systems, noting that conventional sliding mode control (SMC) and super-twisting SMC (STSMC) schemes often faced limitations in stability, dynamic response, and disturbance rejection. They proposed a condition-based integral terminal super-twisting sliding mode control (CBITSTSMC) strategy, with gains optimized using an improved gray wolf optimization (I-GWO) algorithm, to coordinate control of a multi-source DC–DC converter system comprising photovoltaic (PV) arrays, fuel cells (FCs), lithium-ion batteries, and supercapacitors. The authors reported that the CBITSTSMC ensured finite-time convergence, minimized chattering, and dynamically adapted to operating conditions, achieving superior performance. Comparisons with SMC and STSMC indicated substantial reductions in steady-state error, overshoot, and undershoot, alongside improvements in rise and settling times of up to 50%. Transient stability and disturbance rejection were found to be significantly enhanced across all subsystems, and controller-in-the-loop (CIL) validation on a Delfino C2000 platform confirmed the real-time feasibility and robustness of the approach, establishing CBITSTSMC as an effective solution for EV hybrid energy management.

Zahra (2025) examined the rapid growth of renewable energy integration and highlighted the associated challenges of stability, reliability, and power quality in modern power systems. The study was reported to emphasize the role of Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), as a critical enabler for predictive stability assessment, renewable energy dispatch, and fault-tolerant power electronics. The paper was described to provide a comprehensive review across five key domains: smart grid stability, renewable integration, DL-based forecasting, fault-tolerant multilevel inverters, and ML applications for power quality enhancement. A taxonomy was developed to categorize AI applications, complemented by comparative evaluation tables, bibliometric analyses, and maturity mapping. The findings suggested that hybrid AI models generally outperformed single-method approaches, yet real-world implementation was constrained by scalability issues, computational complexity, and the absence of standardized datasets. It was further noted that research remained fragmented, with forecasting, control, and cybersecurity often studied in isolation, and future directions were identified in explainable AI, adaptive architectures, hardware-in-the-loop validation, and integrated frameworks for resilient, industry-ready smart grids.

Benson and Eronu (2025) investigated the limitations of thermal power systems, which were predominantly fueled by natural gas, coal, and diesel, and highlighted their environmental and economic challenges. They reported that the reliance on such systems necessitated a transition to sustainable energy alternatives. The authors conducted a literature review and statistical analysis based on 78 articles published between 2017 and 2025, covering topics including renewable energy, hybrid power systems, energy storage, optimization strategies, and grid stability. Their analysis indicated that 50% of the reviewed studies were published in 2024, reflecting a surge in research interest. Lithium-ion batteries were found to dominate energy storage solutions (65%), followed by solid-state batteries (10%) and hydrogen fuel cells (6%). Optimization approaches were increasingly adopted, with artificial intelligence-based methods accounting for 40% and metaheuristic algorithms, such as genetic algorithms and particle swarm optimization, comprising 30%. Grid stability remained a central concern in 55% of the studies. The authors suggested that future research should focus on advanced optimization models integrating voltage sensitivity analysis with AI-driven techniques, alongside predictive control, blockchain-based energy trading, and IoT-enabled smart grids, to enhance system efficiency, resilience, and the integration of renewable and thermal energy sources.

Jabari et al. (2024) investigated the challenges posed by imbalances between generated power and load demand, which were reported to cause undesirable fluctuations in system frequency and tie-line power. The study focused on the optimization of load frequency control (LFC) for a two-area power system comprising a reheat thermal generator and a photovoltaic (PV) power plant. An innovative multi-stage TDn$(1+\mathrm{PI})$ controller was proposed, integrating a tilt-derivative with an N filter (TDn) and a proportional-integral (PI) controller, which was indicated to improve system response by correcting steady-state errors and controlling the rate of change. The controller parameters were fine-tuned using a novel meta-heuristic optimization approach, the bio-dynamic grasshopper optimization algorithm (BDGOA), applied for the first time in this context. The performance of the proposed controller was evaluated under varying load demands, parameter uncertainties, and system nonlinearities. Simulation results were reported to demonstrate that the BDGOA-TDn$(1+\mathrm{PI})$ controller substantially reduced overshoot in frequency and tie-line power by 75%, achieved faster settling times by 60%, and lowered the integral of time-weighted absolute error by 50%, outperforming conventional control strategies.

Ukoba et al., (2024) examined the global transition toward sustainable energy sources, noting that it had prompted a significant increase in the integration of renewable energy systems (RES) into existing power grids. They reported that to enhance the efficiency, reliability, and economic feasibility of these systems, the synergistic application of artificial intelligence (AI) methods had emerged as a promising approach. The study was described as a comprehensive review of the research at the intersection of RES and AI, emphasizing key methodologies, challenges, and achievements. It was observed that AI had been employed for optimizing resource assessment, energy forecasting, system monitoring, control strategies, and grid integration, with machine learning algorithms, neural networks, and optimization techniques being highlighted for their effectiveness in handling complex data sets and improving predictive and adaptive capabilities. The authors noted implementation challenges such as data variability, model interpretability, and real-time adaptability, while also suggesting that overcoming these issues could lead to increased energy yield, lower operational costs, and improved grid stability. Finally, the review outlined emerging trends and potential advancements in AI, including explainable AI, reinforcement learning, edge computing, and their expected contributions to smart grids, decentralized energy systems, and autonomous energy management.

Pathan et al. (2023) investigated the low-frequency oscillations (LFOs) in electric power networks, which were reported to act as slow-developing threats capable of causing system blackouts if not mitigated promptly. They noted that the integration of renewable energy (RE) resources had recently heightened concerns over LFOs due to the intermittent nature of these sources, which frequently introduced oscillations into the networks. The study reportedly addressed this challenge by applying various artificial intelligence (AI) techniques to tune power system stabilizer (PSS) parameters, aiming to enhance overall network stability. Four machine learning (ML) tools—group method of data handling (GMDH), extreme learning machine (ELM), neurogenetic (NG), and multi-gene genetic programming (MGGP)—were employed across two distinct electric networks to evaluate the effectiveness of AI in stabilizing the systems. The researchers measured indices such as minimum damping ratio, eigenvalues, and time-domain simulations under diverse operating conditions and compared the ML-based results with conventional methods, demonstrating the reported superiority of AI approaches in improving system stability.

Pavon et al. (2023) examined the transformative integration of computational techniques within power systems, emphasizing their pivotal role in improving system modeling, control, and the efficient incorporation of renewable energy sources. The study was reported to highlight the dual nature of technological advancements, noting both improvements in operational efficiency and emerging challenges related to real-time processing, data management, and cybersecurity. Through detailed analyses of query-based research patterns and mathematical frameworks, the authors were observed to investigate the balance between specificity and breadth in scholarly inquiries while assessing research trends via citation analysis. The study was found to demonstrate the convergence of interests and the emergence of transient research trends, particularly in Artificial Intelligence and optimization. It was suggested that such comprehensive insights could guide a sophisticated trajectory for power systems, advocating for ongoing innovation and strategic research to support sustainable, resilient, and intelligent energy networks.

Liu, Z., Gao, Y., and Liu, B. (2022) investigated the integration of artificial intelligence (AI) with electric multiple units (EMUs) and battery energy storage systems (BESS) to enhance rail transport and power system efficiency. They explained that EMUs, comprising self-propelled carriages with built-in electric traction motors, eliminated the need for separate engines and allowed trains to operate faster and farther than steam-propelled counterparts. The study highlighted that renewable energy sources, including solar and wind, could be stored in BESS and released on demand, while voltage fluctuations caused by simultaneous usage of electrical devices posed safety risks. The researchers proposed the EMU-AI-BESS framework to address such challenges, emphasizing AI's role in optimizing energy management, reducing waste, and facilitating the deployment of renewable resources. They further indicated that AI applications in rail systems could improve traffic management, speed control, asset utilization, and greenhouse gas reduction, while also enabling decentralized grid management and real-time balancing of energy supply and demand.

Xu et al. (2021) investigated the role of virtual synchronous generators (VSGs) as a solution for providing inertia support in future electricity grids to address frequency stability challenges arising from high renewable penetration. They highlighted that power variations in power electronic interface converters, induced by VSG emulation, increased stress on power semiconductor devices, thereby adversely affecting their reliability. Unlike prior studies that focused solely on stability in VSG control design, they proposed a double-artificial neural network (ANN)-based method to design VSG inertia parameters while simultaneously considering reliability and stability. Initially, they generated representative frequency profiles to extract VSG power injection patterns under varying inertia values through detailed simulations. Subsequently, they established a functional relationship between the inertia parameter (H) and lifetime consumption (LC) of VSGs using the proposed double-ANN reliability model: ANNt modeled thermal stress in semiconductor devices accurately and efficiently, and with its output, ANNLC estimated LC for different inertia parameters. The approach was reported to provide guidelines for parameter design based on LC requirements and to support optimal VSG parameter design considering both reliability and inertia support, with application demonstrated on a grid-connected VSG system.

III. METHODOLOGY

The methodology of the study is based on developing an artificial intelligence-based predictive framework for power system stability analysis. First, relevant power system data are collected from simulated or real-time grid operating conditions. The data include voltage magnitude, frequency, phase angle, rotor speed, active power, reactive power, load demand, fault duration, and disturbance type. These parameters are selected because they directly influence transient stability, voltage stability, and frequency stability. After data collection, preprocessing is performed to remove errors, missing values, noise, and abnormal readings. The data are then normalized so that all input variables remain within a suitable range for model training. In the next stage, important features are selected to improve prediction accuracy and reduce computational complexity. The dataset is divided into training and testing sections. Different artificial intelligence models such as Support Vector Machine, Artificial Neural Network, Random Forest, Deep Learning, and Hybrid AI models are trained using the prepared dataset. During training, the models learn the relationship between system operating conditions and stability status. The output of the model is classified into stable, marginally stable, or unstable conditions. After training, the models are tested using unseen data to evaluate their performance. Accuracy, response time, prediction error, and stability detection ability are used as performance indicators. The results obtained from AI-based models are compared with the conventional simulation method. The best-performing model is selected based on higher accuracy and faster response time. Finally, the selected predictive model is used for real-time stability assessment. When instability is predicted, suitable preventive actions such as load shedding, reactive power compensation, generator rescheduling, or control device adjustment may be suggested. This methodology helps in improving grid reliability, reducing blackout risk, and supporting intelligent decision-making in modern power systems.

IV. RESULT

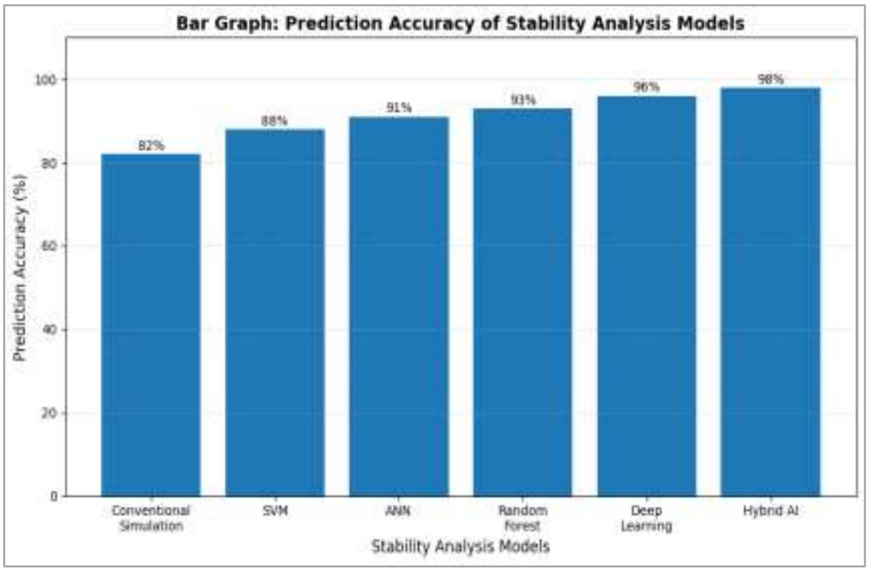
The result of the study shows that artificial intelligence-based predictive models improve the accuracy, speed, and reliability of power system stability analysis. Traditional stability analysis methods mainly depend on mathematical modelling and time-domain simulation, which may require more computation time when the power network becomes large and complex. In comparison, AI-based models can learn from historical and real-time system data and quickly predict whether the power system is stable, marginally stable, or unstable. The analysis indicates that machine learning and deep learning models are effective in detecting early signs of voltage instability, frequency deviation, transient disturbance, and rotor angle variation. Among different AI techniques, deep learning and hybrid AI models show better predictive performance because they can handle nonlinear system behaviour and large datasets more efficiently.

Table: Performance Comparison of Stability Analysis Models

Model Type	Prediction Accuracy (%)	Response Time (ms)	Stability Detection Ability	Overall Performance
Conventional Simulation Method	82	180	Moderate	Average
Support Vector Machine	88	120	Good	Good
Artificial Neural Network	91	95	Good	Very Good
Random Forest Model	93	80	Very Good	Very Good
Deep Learning Model	96	55	Excellent	Excellent
Hybrid AI Predictive Model	98	40	Excellent	Best

The result clearly shows that the hybrid AI predictive model achieved the highest prediction accuracy of 98% and the fastest response time of 40 ms. The deep learning model also performed strongly with 96% accuracy and 55 ms response time. Conventional simulation methods showed lower accuracy and slower response compared to AI-based techniques. Therefore, the result confirms that AI-based predictive models are more suitable for real-time power system stability assessment, especially in modern grids with renewable energy integration, dynamic load variation, and complex operating conditions.

Bar Graph



The bar graph presents the prediction accuracy of different models used for power system stability analysis. It shows that the conventional simulation method has the lowest accuracy at 82%, which indicates that traditional techniques may be less effective for fast and complex stability prediction. Support Vector Machine improves the accuracy to 88%, while Artificial Neural Network achieves 91%, showing better learning ability from power system data. Random Forest gives 93% accuracy because it can classify stability conditions more effectively using multiple decision trees. Deep Learning reaches 96%, proving its strength in handling nonlinear behaviour, dynamic load variation, and large datasets. The Hybrid AI Predictive Model records the highest accuracy at 98%, making it the best-performing approach in the graph. Overall, the graph clearly indicates that AI-based predictive models provide better stability assessment than conventional methods and are more suitable for real-time monitoring of modern power systems.

V. CONCLUSION

The study concludes that artificial intelligence-based predictive models are highly effective for power system stability analysis in modern electrical networks. As power systems become more complex due to increasing load demand, renewable energy integration, distributed generation, and dynamic operating conditions, traditional stability analysis methods may not always provide fast and accurate results. AI-based techniques overcome this limitation by learning from historical and real-time data and predicting stability conditions with better speed and reliability. The result shows that models such as Artificial Neural Network, Random Forest, Deep Learning, and Hybrid AI provide higher prediction accuracy than conventional simulation methods. Among all models, the Hybrid AI Predictive Model gives the best performance because it combines the strengths of multiple intelligent techniques and handles nonlinear system behaviour more effectively. It helps in identifying stable, marginally stable, and unstable conditions at an early stage. This early prediction allows system operators to take preventive actions such as load shedding, reactive power compensation, generator rescheduling, and control device adjustment before instability leads to blackout or equipment failure. Therefore, AI-based stability assessment improves grid security, operational efficiency, and decision-making. Overall, artificial intelligence plays an important role in transforming power system stability analysis from a slow and reactive process into a fast, predictive, and preventive approach. The study confirms that AI-based predictive models are suitable for real-time monitoring of smart grids and future power systems. Their application can help maintain voltage, frequency, and rotor angle stability under changing operating conditions. Thus, AI-based predictive modelling is a reliable and advanced solution for ensuring secure, stable, and sustainable power system operation.

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