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Research Article

The Use of Artificial Intelligence in Assessing the Reliability of Electric Power Systems and Networks

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Abstract

Improving the reliability of power networks is a critical challenge, especially with the rise of renewable energy sources and the continuous growth in electricity demand. This article explores the use of artificial intelligence, specifically dynamic Bayesian networks (DBNs), to evaluate the reliability of electric power systems and networks, focusing on the IEEE 9-bus and IEEE 14-bus networks as case studies. To achieve this, a comprehensive study was conducted by simulating various operating scenarios using these networks as models. These networks were modeled using the simulation and analysis software PyAgrum. Key system variables, including nodes, lines, generators, and transformers, were integrated into the analysis, enabling the construction of conditional probability tables (CPTs) for each component. These tables accounted for both interdependencies and state transitions to reflect real-world dynamics accurately. Simulations performed using MATLAB enabled an in-depth analysis of reliability levels, revealing critical information on the availability rates of nodes, transformers, and generators. The analysis identified specific vulnerabilities within the network, such as node 2 in the IEEE 9-bus network achieving an availability rate of 65%, which indicates robust performance. Conversely, nodes 7 and 9 exhibited significantly lower availability rates of 20% and 40%, respectively, highlighting critical areas requiring immediate attention. Similarly, transformer 1 displayed a relatively high availability rate of 70%, indicating strong performance, whereas transformer 3 showed a notably low availability rate of 30%, suggesting an urgent need for upgrades or replacements. For generators, generator 1 had the lowest availability at 25%, representing a critical vulnerability, while generator 2, with a 55% availability rate, stood out as the most efficient and could serve as a benchmark for performance improvement efforts.

Keywords

Power Network Reliability, Artificial Intelligence, Dynamic Bayesian Networks, IEEE 9-bus Network, IEEE 14-bus Network, Reliability Assessment

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1. Introduction

The increasing complexity of modern electrical systems, such as smart grids and wireless sensor networks, requires advanced methodologies for evaluating and enhancing their reliability. The reliability of power networks is a critical concern, as it ensures not only continuous and high-quality electricity supply but also reduces the risk of failures that could significantly impact essential infrastructures and society as a whole. Traditional reliability modeling techniques, such as reliability block diagrams, fault tree analysis, and event tree analysis, have significantly contributed to the field [1]. However, they exhibit limitations when addressing dynamic interdependencies and state transitions of network components. In response to these challenges, the integration of artificial intelligence, particularly dynamic Bayesian networks (DBNs), has emerged as a transformative approach. DBNs allow for modeling the dynamic behaviors and complex dependencies within network components, enabling a more precise and detailed analysis. The use of artificial intelligence to assess the reliability of electric power systems and networks is a growing field that increasingly attracts the interest of electrical engineering professionals. In particular, reliability and availability assessments are areas where Bayesian networks (BNs) have proven to be highly effective. From the work of [2], which introduced time series modeling for dynamic Bayesian networks (DBNs), to J. B. Dugan's research on dynamic fault tree models for fault-tolerant computing systems, numerous studies have been published on the reliability of electrical systems and their components. For instance, [3] conducted an assessment of wind turbine reliability based on wind speed using Bayesian networks. Their methodology employed an approximate inference algorithm combined with dynamic discretization of continuous variables to calculate the reliability index of wind turbines and their components. Additionally, the proposal of a new method to evaluate the reliability of distribution systems with decentralized generation using BNs was introduced by [4]. This innovative approach enabled the calculation of reliability indices for a distribution system and evaluated the contribution of each component to overall system reliability.

In his master's thesis, [5] developed two groups of models with multi-state nodes to compare Bayesian networks with the traditional fault tree method. The extended model allowed for the discretization of continuous variables and provided a probability distribution linked to failure over time. Similarly, [6] utilized belief networks to assess nodal energy quality and availability based on correlation factor analysis between renewable sources, such as solar and wind. They also developed a Bayesian model structure to evaluate nodal energy supply quality, incorporating renewable sources alongside the main components of the electrical network. Meanwhile, [7] presented a methodology for applying Bayesian networks to the reevaluation of structural system reliability, integrating multiple failure sequences and correlations between component limit states. The proposed approach integrates dynamic Bayesian networks (DBNs) to model temporal interactions and conditional dependencies between components in an electrical network. It addresses the critical question of whether artificial intelligence, particularly DBNs, can effectively improve or assess the reliability of power systems and networks. By capturing complex dynamics and uncertainties, this method offers a more precise and robust reliability assessment, particularly for networks such as the IEEE 9-bus and IEEE 14-bus systems. Unlike traditional methods, this technique adapts to variations in component performance over time, contributing directly to enhancing network resilience and overall availability.

2. Materials and Methods

In this approach, dynamic Bayesian networks model the interactions and temporal dependencies between the network nodes. Component failure probabilities are estimated by integrating empirical and historical data (availability rates), enabling Bayesian inference to assess the impact of failures on network reliability.

The different steps involved in developing the reliability assessment method are as follows:

(1) Modeling the network with a DBN
(2) Model parameterization
(3) Simulations
(4) Performance criteria calculations

2.1. Modeling Power Network Components with Random Variables

The modeling of power network components utilizes random variables to represent the characteristics of various elements. Each network component such as transmission lines, transformers, and generators is represented as a random variable, with its possible states corresponding to different operational conditions (e.g., operational or failure) [8-10]. Reliability parameters, including failure rates, are defined for each component based on historical data and previous studies [12].

In the case of the IEEE 9-bus and IEEE 14-bus networks, which are widely recognized as benchmarks for analyzing small to medium-scale electrical systems, the primary components consist of generators, nodes, transformers, and loads. Each of these components is modeled using random variables that capture their performance characteristics and operational states [11].

(1) Generators are modeled using random variables representing their availability [14-16].
(2) Nodes and transmission lines are modeled considering random variables describing their transport capacity, resistance, reactance, conductance, and losses [16].
(3) Transformers are also modeled with random variables representing their capacity, efficiency, impedance, and

power losses [16].

2.2. Defining Dependencies Between Power Network Components

Probabilistic dependencies emerge when the values of random variables associated with different components are linked through joint distributions. These dependencies are modeled within the DBN framework using dependency graphs that capture both causal and temporal relationships between the states of various components [14]. In a DBN, the graph's nodes represent the random variables corresponding to network components, while the arcs between nodes illustrate the causal or probabilistic dependencies [14, 15, 17].

2.3. Estimating Conditional Failure Probability Distributions

The conditional failure probability distributions are computed for each component while accounting for the defined dependencies. These distributions form the basis for constructing the conditional probability tables (CPTs) required in DBN modeling. Statistical learning techniques are employed to estimate CPTs efficiently [15-18]. Once these conditional distributions are established, the failure probabilities and unavailability rates of the power network can be accurately calculated.

2.4. Constructing the Dynamic Bayesian Network

Representing a power network model as a DBN involves identifying the network's key variables and their interactions. Each variable is represented as a node in the DBN, and cause-and-effect relationships between the variables are represented as directional arcs between the nodes [14-16]. The conditional probabilities associated with these relationships are also specified to account for uncertainty.

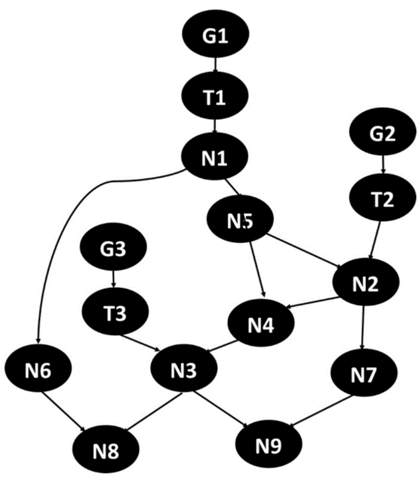

Figure 1. *Dynamic Bayesian Networks IEEE 09 Nodes.*

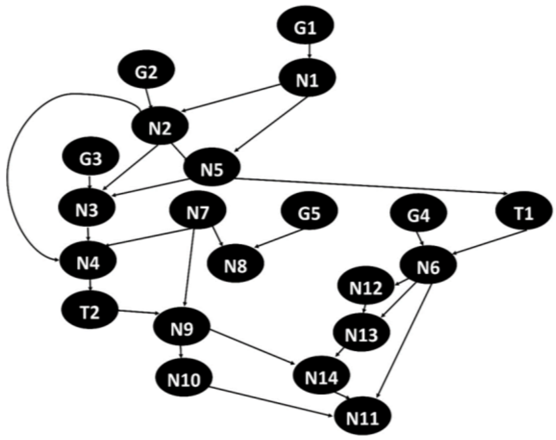

Figure 2. *Dynamic Bayesian Networks IEEE 14 Nodes.*

2.5. Simulation and Bayesian Inference

Simulations using the DBN model are performed to estimate the failure and unavailability probabilities of network components over time. Bayesian inference is applied to update these probabilities dynamically based on new data or observations [14, 19]. This approach enables predictive insights into potential failures and provides a comprehensive assessment of the network's overall reliability. Figures 3 and 4 illustrate dynamic Bayesian networks that visualize the dependencies and reliability of the network components through availability indicators and conditional probabilities. Each component is represented as a rectangle displaying its availability (green bar), statistics (mean and standard deviation), and dependency relationships, depicted through arrows that signify conditional probabilities between components.

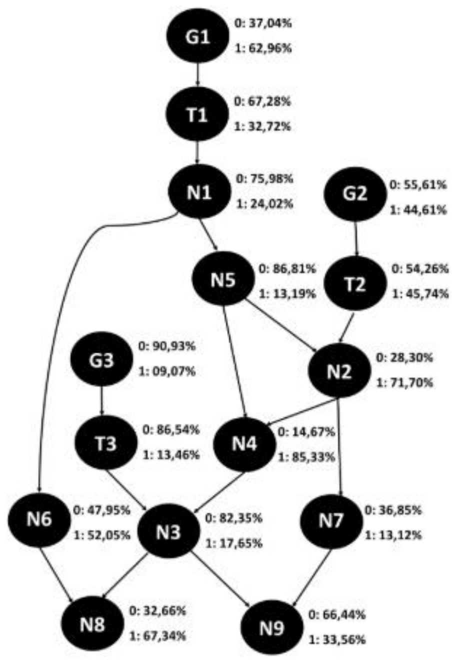

Figure 3. *Dynamic Bayesian Network with Evidence for IEEE 09 Nodes.*

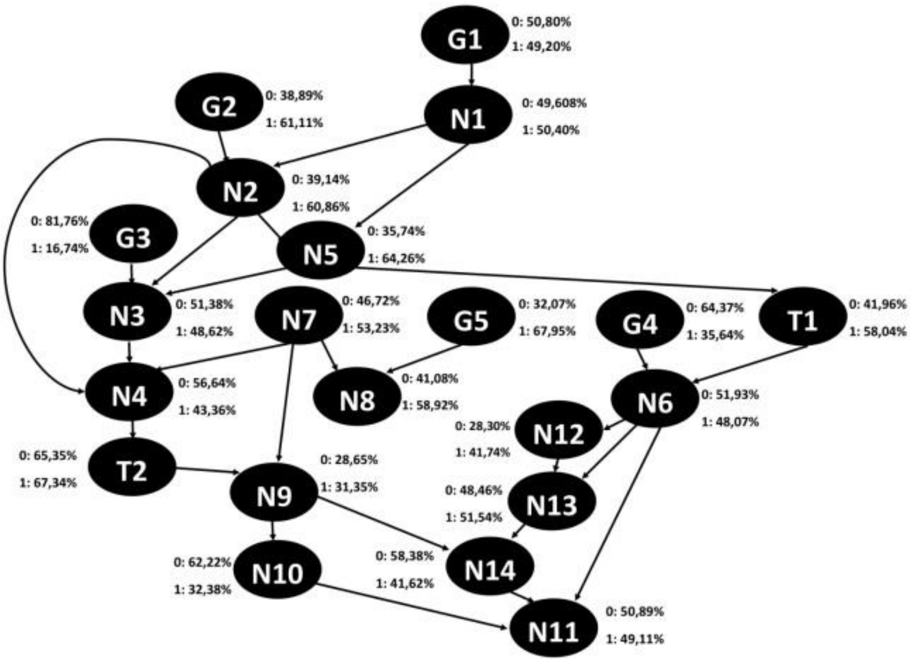

Figure 4. *Dynamic Bayesian Network with Evidence for IEEE 14 Nodes.*

3. Results and Comments

3.1. Availability Rate of Different Nodes

The application of the methodology produced the following graphs:

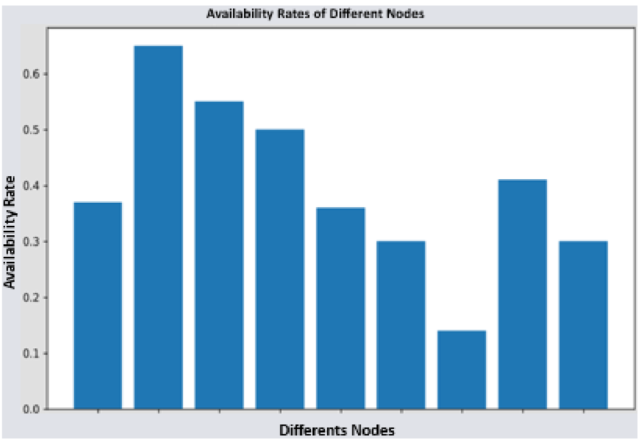

Figure 5. *Availability Rates of Different Nodes for IEEE 09-Node Network.*

Figure 5 illustrates the availability rates of nodes in the IEEE 9-bus network, reflecting the proportion of operational time for each node. Among them, Node 2 demonstrates the highest availability, reaching approximately 65%. This high availability rate is attributed to the presence of a transformer and a generator with relatively high reliability rates that support Node 2. The reliability of these components reduces failure occurrences, thereby enhancing overall node availability. In contrast, Nodes 7 and 9 exhibit significantly lower availability levels, at 20% and 40%, respectively. These reduced rates are primarily due to their strategic positions within the network and the heightened stress caused by heavy load demands.

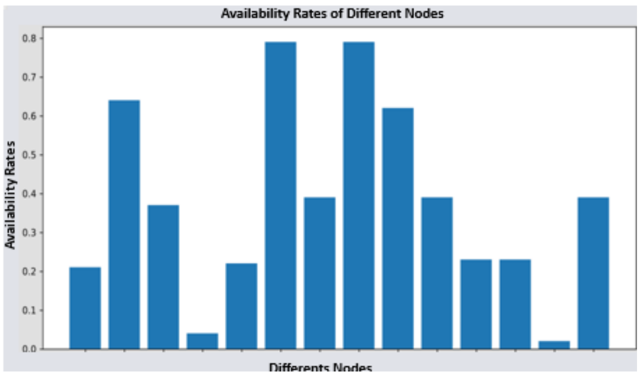

Figure 6. *Availability Rates of Different Nodes for IEEE 14-Node Network.*

Figure 6 highlights substantial differences in availability rates among the network nodes. Notably, Nodes 3, 6, and 8 exhibit high availability rates, attributed to the presence of Static VAR Compensators (SVCs), which enhance network stability. These nodes also benefit from multiple interconnections and alternative pathways, which bolster their resilience against failures. Conversely, Nodes 4, 11, and 12 show markedly low availability rates, primarily due to the lack of sufficient alternative pathways at these critical points in the network. According to IEC 61508 standards, node availability should range between 94% and 96%, with an average of 95%. The observed deviations from these standards underscore the need for targeted interventions to enhance the reliability of underperforming nodes and ensure the network meets or surpasses these thresholds.

3.2. Availability Rates of Generators

Figure 7 showcases stark differences in the performance of generators within the network. Generator 1, exhibiting a low availability rate of 25%, performs poorly, likely due to excessive workload and insufficient redundancy, which exacerbate its vulnerability to failures. In contrast, Generator 2 achieves the highest availability rate at 55%, attributed to a well-balanced load distribution with other components, effectively mitigating its failure risk. Generator 3, with an availability rate of 50%, demonstrates reasonable reliability but requires optimization to reach performance levels comparable to Generator 2. Nonetheless, the current availability rates for all generators are significantly below the NERC standards, which recommend an average availability of 94%.

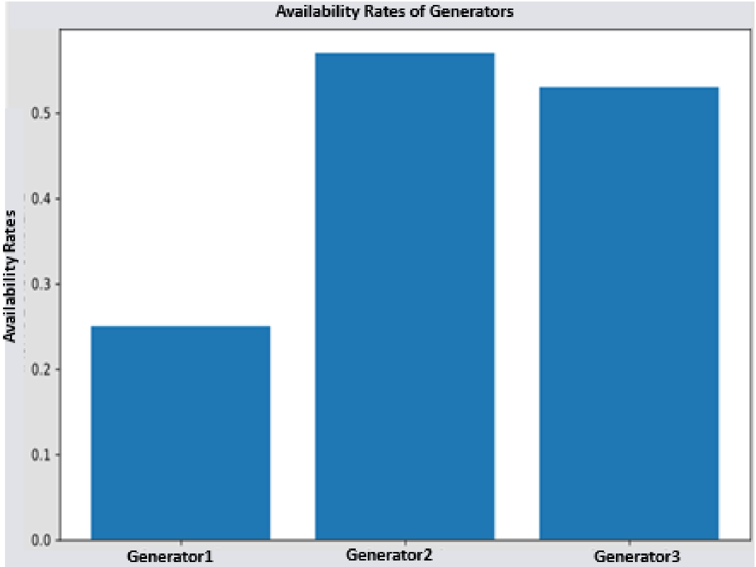

Figure 7. *Availability Rates of Generators for IEEE 09-Node Network.*

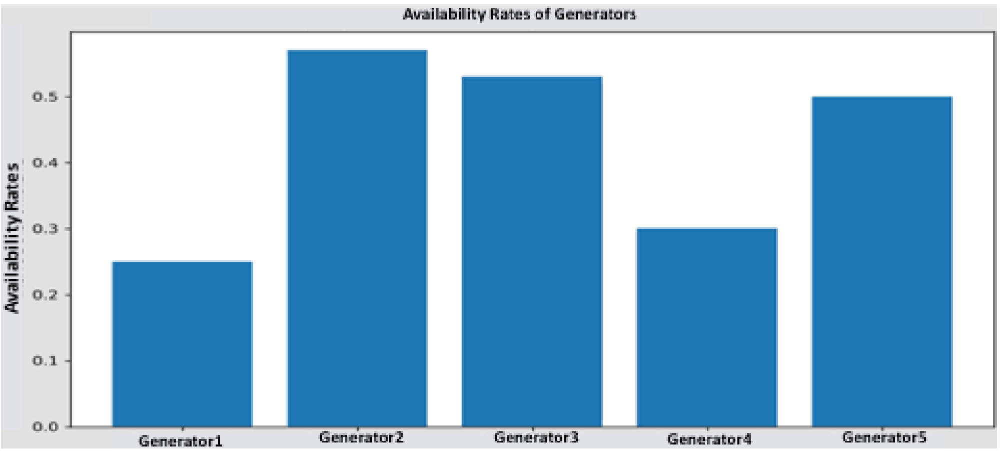

Figure 8. *Availability Rates of Generators for IEEE 14-Node Network.*

The generators in the network exhibit varying availability rates influenced by their location and strategic role. Generators 2 and 3, located on main buses, demonstrate higher availability rates of 57% and 53%, respectively. Their central positioning in electricity distribution enhances their significance for network stability, enabling better performance. In contrast, Generators 1 and 4, which show lower availability rates of 25% and 30%, are significantly impacted by their reliance on critical components with higher failure probabilities, adversely affecting their overall performance. Despite these efforts, the current availability rates fall significantly short of the North American Electric Reliability Corporation (NERC) standards, which recommend rates between 90% and 98%. Addressing this shortfall requires improving generator reliability by increasing redundancy in critical components and implementing more effective management strategies to achieve compliance with international performance benchmarks.

3.3. Availability Rates of Transformers

Figure 9 shows that Transformer 1 has a notably high availability rate, indicating its robust performance. This high rate suggests that Transformer 1 is less susceptible to failures of other components, likely due to its strategic position within the network or its more resilient interconnections. In contrast, Transformers 2 and 3 exhibit comparatively lower availability rates, which could result from higher operational loads or more frequent failure incidents. The availability range for the transformers is between 97% and 99%, with an average of 98%. However, according to the IEEE 493 standard, this current availability rates fall below the recommended levels, emphasizing the need for further improvements in transformer reliability.

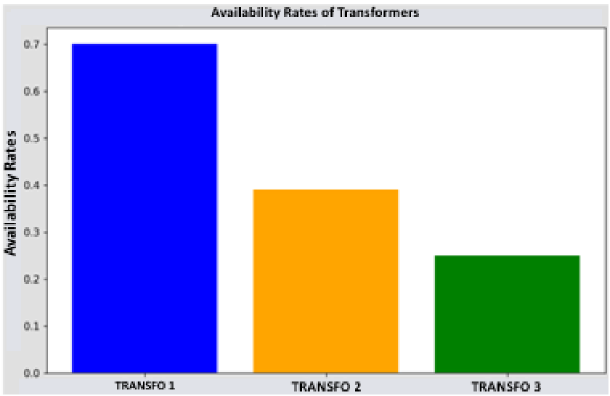

Figure 9. *Availability Rates of Transformers for IEEE 09-Node Network.*

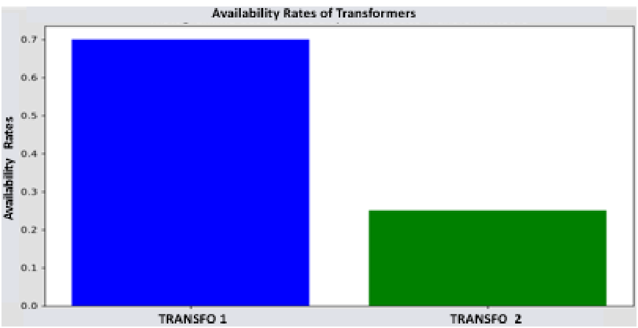

Figure 10. *Availability Rates of Transformers for IEEE 14-Node Network.*

Figure 10 highlights a significant disparity in the availability rates of the two transformers. Transformer 1, with an availability rate of 70%, demonstrates greater reliability, attributed to the meshed network configuration that facilitates energy flow rerouting through alternative pathways during failures. In contrast, Transformer 2, with an availability rate of only 27%, is frequently subjected to overloads, making it significantly more prone to failures. These performance levels are well below the IEEE 493 recommended availability standards of 97% to 99%, underscoring a considerable need for improvement to enhance the reliability of these critical components.

3.4. Reliability Curves

Figure 12 illustrates how the reliability of the network diminishes as the number of non-functional nodes increases, highlighting the modeled conditional dependencies between interconnected nodes. Each failing node elevates the failure probability of connected nodes, triggering a cascading effect. This dynamic emphasizes how the initial failure of certain critical nodes (key components) progressively erodes the overall reliability of the network.

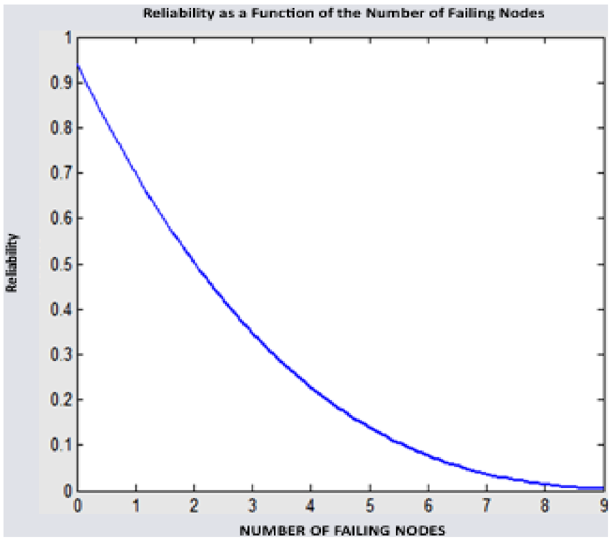

Figure 11. *Reliability as a Function of the Number of Failing Nodes in the IEEE 9-Node Network.*

Figure 11 demonstrates that network reliability declines as the number of failing nodes increases. The observed peaks highlight significant fluctuations in reliability corresponding to changes in the number of failing nodes. These variations arise from the random failure of nodes within the network and the differing impacts these failures exert on the overall system. Peaks represent moments when critical nodes—those with substantial influence on network stability—fail, causing a pronounced drop in reliability. Despite these fluctuations, the reliability remains within a specific range, indicating a baseline level of network stability. This relative stability is attributed to the inherent resilience and redundancy in the network's design. Even with multiple node failures, the network compensates for these losses to some degree through redundancy mechanisms. As a highly redundant meshed network, each node is connected to several others, enabling multiple pathways for energy transmission and alternative routes for power flow.

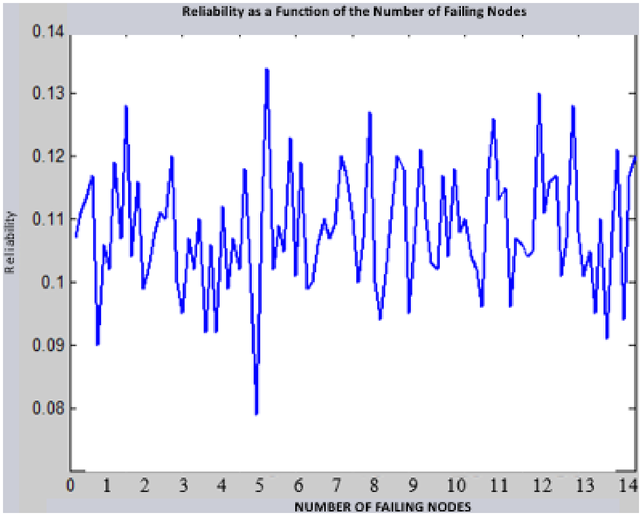

__Figure 12__. Reliability as a Function of the Number of Failing Nodes in the IEEE 14-Node Network.

4. Discussion

Artificial Intelligence (AI) is revolutionizing the reliability assessment of electric power systems by outperforming traditional methods through advanced techniques such as machine learning (ML) and deep learning (DL). These innovations enable more accurate predictions and streamlined modeling of system complexities. For instance, neural networks consistently surpass traditional statistical models in failure prediction, while reinforcement learning optimizes maintenance scheduling to reduce costs without compromising reliability. Furthermore, AI's capacity to process large datasets and adapt to real-time conditions significantly enhances the accuracy and efficiency of reliability assessments. Unlike traditional approaches such as failure mode and effects analysis (FMEA), AI-based probabilistic models, including Bayesian networks, offer a more holistic understanding of system reliability by capturing interdependencies between components. Nevertheless, AI faces several challenges, including its reliance on high-quality data, the lack of interpretability in complex models like deep learning, and the substantial computational resources required for large-scale applications. To overcome these hurdles, hybrid methodologies have been introduced. For example, combining AI with Monte Carlo simulations enhances computational efficiency and accuracy, creating a balanced approach to reliability assessments. Looking ahead, integrating AI with IoT and edge computing could revolutionize real-time reliability analysis by utilizing the massive data generated by sensors in power systems. Additionally, the development of explainable AI (XAI) techniques could foster trust and usability by increasing transparency in AI decision-making processes. Moreover, the increasing penetration of renewable energy sources introduces variability and uncertainty, which AI can address by evaluating the reliability of systems with high renewable energy integration. Furthermore, AI could play a pivotal role in assessing cybersecurity vulnerabilities in increasingly digitalized power systems, thereby enhancing resilience. Future research should also quantify the economic and environmental impacts of AI, including cost reductions achieved through optimized maintenance strategies and lower carbon footprints enabled by operational efficiency. Ultimately, AI enables smarter grids and proactive system management, contributing to sustainability and energy security. However, ethical considerations, such as biases in AI models and the equitable distribution of technology, must be addressed to maximize its benefits. In conclusion, while certain obstacles remain, AI demonstrates unmatched accuracy and efficiency, signifying a paradigm shift in reliability assessment and paving the way for resilient, sustainable, and efficient power systems.

5. Conclusions

This research demonstrates the effectiveness of using artificial intelligence, particularly dynamic Bayesian networks (DBNs), as a robust tool to assess and enhance the reliability of power systems and networks. By applying this methodology to the IEEE 9-bus and 14-bus networks, it was possible to simulate various failure scenarios, evaluate node availability rates, and pinpoint critical vulnerabilities that significantly affect overall reliability. The primary goal of this research was to improve the availability of power systems and networks. This was achieved by systematically evaluating network availability through DBNs, which involved modeling network structures, parameterizing models, running simulations, and calculating key performance metrics. The results indicated that certain nodes, such as Node 2 in the IEEE 9-bus network (Figure 5), exhibited a relatively high availability rate of approximately 65%, attributed to its connection with highly reliable components such as transformers and generators. Conversely, Node 7, with an availability rate of around 20%, emerged as a significant weak point, indicating potential vulnerabilities in critical areas of the network. In the IEEE 14-bus network, Nodes 5 and 9 displayed availability rates nearing 80%, which reflects strong reliability and robustness. However, Nodes 12 and 14 demonstrated extremely low availability rates, around 10%, highlighting high-priority critical areas requiring immediate attention.

DBNs proved highly effective in identifying network vulnerabilities, optimizing maintenance strategies, and subsequently enhancing the overall reliability of the network.

By integrating a comprehensive range of availability rates, the research aimed to improve the availability of power systems and networks further. This integration enabled precise modeling of interactions between network components using DBNs, which were parameterized with availability rates to simulate various failure scenarios and provide an in-depth evaluation of overall network performance.

Abbreviations

IEEE	Institute of Electrical and Electronics Engineers
DBN	Dynamic Bayesian Network
CPT	Conditional Probability Table
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
FMEA	Failure Mode and Effects Analysis
IoT	Internet of Things

Author Contributions

Raymond Tachago is the principal author. The author read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Appendix

I. Probability of availability of the IEEE 9 and 14-node network.
II. Conditional probability of the IEEE 9 and 14-node network.
III. Excerpt of Matlab codes for reliability curves.
IV. Excerpt of Matlab codes for availability rates.
V. Parameter data for the IEEE 9 and 14-node networks.

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Biography

Raymond Tachago is a doctoral student at the National Advanced School of Engineering of Yaoundé 1 in the Department of Electrical and Telecommunications Engineering. He earned his degree in Electromechanical Engineer several years ago and is now recognized for his exceptional academic background. Raymond currently runs his own company, AE Consult, which he founded, where he manages numerous projects and actively participates in collaborations. He is a rising star in the civil engineering industry and has participated in various national and international conferences with the aim of promoting, creating, and encouraging young people to excel and build a solid foundation for the future.

Research Field

Raymond Tachago: Artificial intelligence in power systems, Reliability assessment of electric networks, Bayesian networks in power reliability, Optimization techniques in power systems, Smart grids and energy management.