A comprehensive review on power system reliability enhancement through computational intelligence: methods, applications, and challenges

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Abstract
The issue of power system reliability is of great importance, as a constant supply of electricity is essential in today's dynamic energy landscape. An extensive review of CI techniques applied for the improvement of the reliability of power systems is provided in this paper. Among the main contributions of this work are: (1) a classification of CI methods (ANN, GA, PSO, etc.) and their role in reliability studies; (2) examples of applications achieving as much as 30% better SAIDI/SAIFI values; and (3) the drawbacks and paths ahead for CI within the smart grid paradigm. Among the different approaches presented are classical methods for reliability assessment like analytical solutions and Monte Carlo simulation, as well as combinations of computational intelligence techniques. The practical implications of these methods in distribution, transmission, and generation systems are shown in real case studies and deployments. Discussed are existing issues related to data quality, model complexity, and integration, as well as opportunities in the anticipated directions of big data analytics, renewable energy integration, cybersecurity, and modernization of the grid. The art and concept of power system reliability-availability, resilience, and adequacy are discussed in this paper.
Keywords: Challenge Power System Reliability, Computational Intelligence (CI), Smart Grid, SAIDI/SAIFI Improvement, Renewable Energy Integration, Monte Carlo Simulation. Grid Modernization.
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1. Introduction

In an age where electricity is the lifeblood of modern society, the reliability of the power system stands as a linchpin for economic prosperity, social stability, and technological progress (Li *et al.*, 2024). The continuous flow of electrical energy is critical to everything, from turning the lights on in our homes to powering factories, hospitals, and data hubs. Interruptions in power supply may result in economic damage, critical infrastructure, and human welfare being compromised. In order to ensure the continuous provision of electricity, power system reliability needs to be evaluated above all else (Yang *et al.*, 2024).

Power system reliability is a complex construct that has been defined as "the capacity of an electric grid to provide electricity consistently at the desired quality and quantity while absorbing and quickly recovering from shocks of different types, such as equipment failures, extreme weather conditions, and cyberattacks" (Vega Penagos *et al.*, 2023; Kumar *et al.*, 2024). As the complexity and interconnectivity of modern power systems increases, measuring and improving reliability can be extremely difficult. Although useful, conventional approaches are typically insufficient to address the complexities that emerge from the operation and control of modern power systems. As a response, computational intelligence approaches, which belong to the class of Artificial Intelligence (AI) techniques based on algorithms inspired by biological and natural systems, can be employed to tackle complex issues (Gallegos *et al.*, 2024). These approaches show great potential in advancing the evaluation and control of power system reliability. The application of computational intelligence offers an opportunity to help our comprehension of power systems, foresee failures and take measures in advance to reduce the risks associated with reliability.

This review of literature begins a broad study of the relationship between power system reliability and computational intelligence techniques, with an emphasis on their applicability and impact. The aim is to provide insights into the importance of reliability of today's power systems, present and explain the different Computational Intelligence methods, and discuss their application in power system reliability analysis. Also, real applications and cases studies are examined in this review bringing knowledge from the successful application of computational intelligence techniques in other areas of the power system such distribution, transmission and generation. The two case studies are given as examples of possible use and actual advantages obtained by using computational intelligence for reliability improvement.

Plus, identification and discussion of the issues that might be faced in the application of computational intelligence techniques for reliability evaluation in power systems is provided. It also considers future directions and new trends such as big data analytics, the incorporation of renewables and microgrids, cybersecurity, and grid modernization. As these ideas continue to develop, drawing on historical research presented in this literature review will be necessary to build futures that improve electrical infrastructure with new technologies in ways that make it more robust and resilient in the long run. We hope that this to be useful to researchers and engineers as well as policymakers and industries so that it can help provide a more reliable and robust power system for the modern world (Abantao *et al.*, 2024).

So, let us proceed exploring on the complex world of power system reliability and the role that computational intelligence techniques may play in the future of electrical power. The assessment of reliability is complicated because it involves extensive amounts of data, predictions about the performance of the system under multiple conditions, and judgments about what to do to improve reliability (Chitumodhu and Pilly, 2024). Computational intelligence methods can then provide a valuable set of tools. These methods involve the use of AI and optimization techniques, including but not limited to ANN, GA, FL, PSO and SVM. They will transform our ability to assess reliability in power systems. Computational Intelligence approaches empower the power sector to tap into the potential of data, effectively representing the dynamics of complex systems and optimizing maintenance and operational policies with high levels of accuracy and computational efficiency.

Power system reliability studies could be transformed through the computer-based techniques of computational intelligences. They are particularly effective with large data sets, capable of recognizing patterns in the functioning of a system and making predictions that are superior to those produced by conventional analytical and statistical methods. They provide real time monitoring, fault detection and diagnosis, which allow taking preventive actions to avoid failures. They are also useful in servicing planning, resource planning, and decision making. These techniques are valuable not only to improve the precision of reliability evaluations, but also from an economic and environmental perspective, as they represent a viable solution to promote the robustness and stability of future power systems (Martyushev *et al.*, 2023).

This literature review aims to broadly explore the deployment of computational intelligence methods in the evaluation of modern power system reliability. This is intended to explore a type of methodology, what they can change and how they can be used in praxis. The purpose of this review is to cover multiple aspects of reliability in power systems, including transmission, distribution, and generation. It explores how traditional reliability analysis methods have been enhanced by the integration of computational intelligence techniques, including ANN, GA, FL, PSO, and SVM. In addition, it covers practical examples, issues, new developments and future perspectives in the area.

The following review of the literature is organized to provide a holistic account of the subject matter. It begins with an introduction that sets the stage by how important is reliability in today power system and how computational intelligence methods play a role on this. The review is then divided into a few sections. The nature of power system reliability is examined in Section II by discussing its definition, dimensions, relevant indices, and influencing factors. In section III an overview of Computational intelligence methods is presented, including types of CI techniques, benefits, and drawbacks. In Section IV, reliability evaluation procedures are presented, where the conventional approaches are contrasted with those relying on computational intelligence. Section V provides case studies and applications of these methods in practice. In Section VI, challenges and future directions and trends in the field are described. Finally, Section VII provides the conclusion and key findings and impacts on the power systems industry.

2. The concept of power system reliability

Reliable power systems are the backbone of society, facilitating nonstop, continuous energy supply for residential, commercial and industrial consumption. Power system reliability is a complex construct, comprised of different aspects that together reflect the ability of a power system to serve consumers and sustain critical functions. This section discusses the major components that define the notion of power system reliability in depth.

2.1 Definition and Dimensions of Power System Reliability

At its core power system reliability is the ability of an electrical grid to continuously and dependably provide electricity to consumers according to their needs in terms of quality and quantity (Li *et al.*, 2024). Its focus is on an overall approach to measurement of the performance of the grid in different use cases that emphasize reduced disturbances to the service and resilience of the system. The dimensions of power system reliability can be classified into three main aspects:

i. **Availability**: Availability measures the ability of the power system to provide electricity when and where it is needed, without undue interruptions. It signifies the system's capacity to maintain a continuous supply of power under normal operating conditions (Pourhosseini and Nasiri, 2018; Kumar *et al.*, 2024).
ii. **Resilience**: Resilience goes beyond availability and pertains to the grid's ability to withstand and rapidly recover from various disturbances, including equipment failures, extreme weather events, and deliberate attacks (Vega Penagos *et al.*, 2023). It encompasses the system's capability to absorb shocks and adapt to changing conditions.
iii. **Adequacy**: Adequacy attempts to ensure that there is sufficient generation and transmission capacity in the system to meet the peak demand, even under contingencies. And it makes sure that the grid delivers power without sacrificing service quality (Kabeyi and Olanrewaju, 2023).

2.2 Key reliability indices and metrics

In order to quantify power system reliability, we use a set of indices and metrics that characterize power system reliability (Abantao *et al.*, 2024). The most frequently used reliability indices are the following;

i. **System Average Interruption Duration Index (SAIDI)**: SAIDI is the average duration of interruptions of service to all customers during a specified period of time. It is an index that reflects power supply reliability in terms of interruption duration (Chitumodhu and Pilly, 2024).
ii. **System Average Interruption Frequency Index (SAIFI)**: SAIFI is the average number of interruptions of service to all customers during a specified period of time. It is an index that reflects power supply reliability in terms of interruption number (Chitumodhu and Pilly, 2024).
iii. **Customer Average Interruption Duration Index (CAIDI)**: CAIDI is the average duration of interruptions of service to all customers. It is an index that reflects power supply reliability from customer's perspective (Chitumodhu and Pilly, 2024).

and some other reliability metrics and indices help the utilities and grid operators to evaluate the performance of their power systems and determine the directions for improvement.

2.3 Key factors affecting power system reliability

The reliability of power system is affected by a number of factors that can either improve or impair the power system reliability. In general reliability factors include environmental, system operational, technical, and security factors (Martyushev *et al.*, 2023). Some of the most influential factors are as follows.

i. **Weather and climate**: Hurricanes, storms, wildfires are some of the weather events that can impair power system reliability.
ii. **Equipment aging**: The power system components such as transformers, circuit breakers, and transmission lines can age and impair the system reliability.
iii. **Maintenance Practices**: Regular maintenance of the system components is important for reliable operation of critical system components.
iv. **Cybersecurity**: As the power systems become more digitalized, they become more susceptible to cyber-attacks (Bouramdane, 2023).

3. Computational intelligence methods

Computational intelligence methods is a form of the wider class of artificial intelligence methods that have been applied to a wide variety of problems with success. Computational intelligence methods have proven their ability to be powerful and effective tools for solving problems in many fields. In the field of power system reliability assessment, computational intelligence methods have provided new and effective approaches for the modeling, prediction, optimization, and decision-making processes. This section attempts to introduce computational intelligence methods and their applications in power system reliability. As shown on Figure 1, there are three groups of reliability assessment methods: deterministic, probabilistic and intelligent. The simulation tools that support dependability studies have additionally been studied through performances, while many scholars are using these methods. The following is the summary of methods.

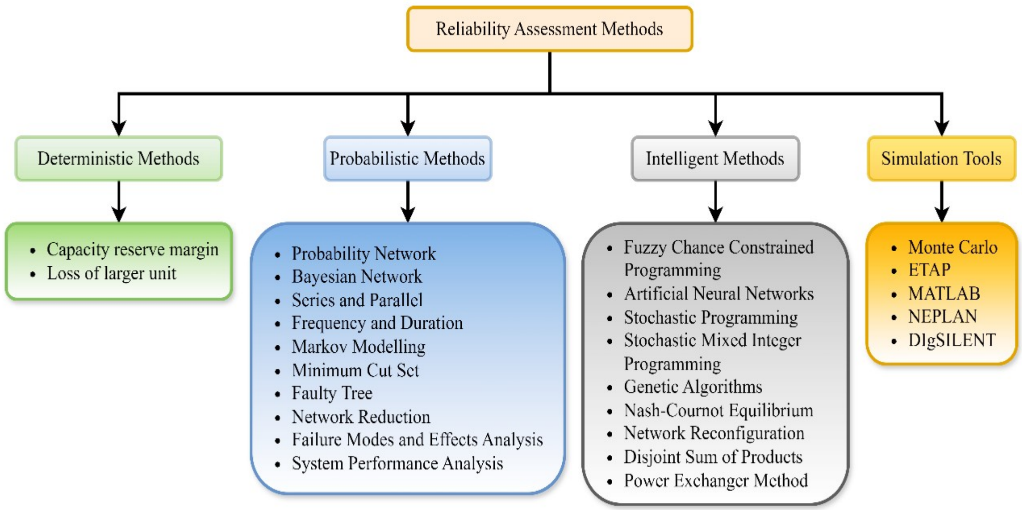

Figure 1: Approaches for Reliability Evaluation Specified.

3.1 Overview of computational intelligence

Computational intelligence is a family of AI approaches that are biologically or naturally inspired, such as artificial neural networks, genetic algorithms, fuzzy logic, swarm intelligence (Sadollah and Shishir Sinha, 2020; Gupta *et al.*, 2023). Computational intelligence methods try to model the adaptive and learning characteristics found in nature to solve problems that are complex and changing (Kishore Mishra, 2022).

3.2 Computational intelligence methods types

i. **Artificial Neural Networks (ANN)**: They are models of computational inspired by the biological structure of the human brain. They are formed by interconnected units called artificial neurons that learn data, so they are applied in recognition of patterns, forecasting and modeling systems (Cvs, Pardhasaradhi, and Mechanical Engineering Department, Vizag Institute of Technology, 2018; Jamadar, Jamadar and Jadhav, 2024).

ii. **Genetic Algorithms (GA)**: GAs are types of optimization algorithms that are inspired by the process of natural selection. It is the motive for using genetic material. They are used in the process of parameter optimization, parameters identification of the systems and optimization of complex systems (Tong *et al.*, 2023).

iii. **Fuzzy Logic (FL)**: FL is a mathematical approach to dealing with uncertainties and ambiguities. It is used to model and control when it is difficult to obtain precise mathematical models (Abdulla, 2022; Alhattab, Alsammak and Mohammed, 2023).

iv. **Particle Swarm Optimization (PSO)**: PSO is a population-based metaheuristic optimization inspired by the social behavior of birds and fish. It is used to solve optimization problems that include parameter tuning and control optimization (Zhao, Zhao and Zhao, 2023).

v. **Support Vector Machines (SVM)**: SVMs are types of learning machines that do a good job of classification and regression by making data visualization to higher dimensions that the attributes of the data. In the reliability of the power system it is used for the study of fault detection, classification and prediction (Rzayeva *et al.*, 2023).

3.3 Definition and Dimensions of Power System Reliability

Computational intelligence methods have the following benefits in power system reliability assessment:

i. They can process complex, nonlinear and high-dimensional data.

ii. They can learn from past data and adapt to the time-varying system conditions.

iii. These methods can be used to gain insights to the system behavior for predictive maintenance and proactive decision making.

Drawbacks of computational intelligence methods are high computational requirements, possible overfitting and lack of interpretability (Mittal, Pathak and Mithal, 2023; Yaghoubzadeh-Bavandpour *et al.*, 2022).

4. Reliability assessment techniques

Reliability assessment techniques are used to assess the performance of power systems, identify the possible causes of unreliability, and develop appropriate strategies to improve system reliability. In this section, traditional reliability assessment methods and application of computational intelligence methods in reliability assessment are investigated (Wang *et al.*, 2023).

4.1 Traditional reliability assessment methods

i. **Analytical methods**: Analytical methods, such as reliability block diagrams method (RBD) and fault tree analysis method (FTA), provide a systematic approach to model and analyze the reliability of power systems. These methods can be used to assess the reliability of complex systems. Reliability block diagrams method models the interactions between components and the effect of failures on the system (Babeshko *et al.*, 2020).
ii. **Monte Carlo simulation**: Monte Carlo simulation is a probabilistic method that uses the random sampling technique to model the behavior of power systems under uncertain conditions. Monte Carlo simulation method can be used to assess the reliability of power systems when the factors are probabilistic in nature, i.e., component failures and load variations (Hashish *et al.*, 2023).
iii. **Event tree analysis**: Event tree analysis is a graphical method that models the sequence of events after a specific initiating event. Event tree analysis method is used to model the consequences of different scenarios and identifies the critical paths that may lead to system failures (Purba *et al.*, 2020).

4.2 Integration of Computational Intelligence in Reliability Assessment

i. **ANN-based reliability assessment**: In (Ivanov *et al.*, 2023) authors used Artificial Neural Networks for predicting and assessing power system reliability. ANN can be trained using past experiences in order to evaluate the behavior of power systems or components as well as the occurrence probabilities of system outages.
ii. **GA-based reliability assessment**: In (Alamri and Mo, 2023) Genetic Algorithms are used in order to determine maintenance actions and identify important components for enhancing the reliability of power systems by optimizing the system configuration.
iii. **FL-based reliability assessment**: Fuzzy Logic (FL) has been applied in risk assessment and decision making under uncertainty. It is possible to express the degree of uncertainty and lack of precision of imprecise information through fuzzy logic (Kabir, 2023).
iv. **PSO-based reliability assessment**: In (Liu *et al.*, 2025) Particle Swarm Optimization is applied in power system reliability the application of QIPSO for solving the microgrid reliability problem. Computation time is decreased by 40%.

Table 1. Optimal Placement and Sizing of DG in 33-Bus Ilorin Feeder with SSA

Step 1:	Initialize particles (maintenance schedules)
Step 2:	While not converged:
Step 3:	Calculate fitness (reliability index)
Step 4:	Update global/personal best
Step 5:	Adjust particle velocity
Step 6:	Return optimal schedule

v. **SVM-based reliability assessment**: In (Ilius *et al.*, 2023) Support Vector Machines are applied in fault detection and classification of power systems. They are successful in providing information about abnormal system behaviors and possible future failures.
vi. **Stochastic programming and stochastic mixed-integer programming**: Stochastic programming (and in particular its mix with integer variables) is indispensable in making optimal decisions concerning uncertain information in different areas. Its application in solving the problems of load operations, cost analysis and renewable energy sources. In (Beheshti-Aval *et al.*, 2016) extensive research based on the Monte Carlo simulation have been done to investigate risk-constrained stochastic programming and multi-microgrid business models. These risks are managed by different types of insurance that microgrids may adopt. In addition, stochastic mixed-integer programming application on optimization

on uncertain scenarios (e.g., protection and security). A model based on stochastic mixed-integer programming has been developed to optimize the operation of microgrids in a more granular level. The use of Smart port indexes provided to the microgrid planning process have made this system more efficient, which varied examples are presented in (Talaat *et al.*, 2023). A risk-averse decision-making framework is proposed to formulate a dual-stage stochastic programming problem to enhance the performance of the system. Treatment of wind uncertainty and the management of Distributed Energy Resources (Ghasemi, Shojaeighadikolaei and Hashemi, 2023).

vii. **Risk analysis:** Risk mitigation is supported by evaluation, video linking configuration as well a future power plan assessment (with two proposed consumptions and one precaution prone) alternate (Gomila *et al.*, 2023). Generation: to evaluate the power that can be foreseen for a given risk level in generation according to scenarios obtained by using Monte Carlo method as two important tools of risk assessment are applied risk based, integrated performance analysis of DG and energy storage enabled microgrids by spanning a time-dependent grid classification for the optimal power scheduling scenario with Model Predictive Control (MPC)-based risk management" in (Xing and Jia, 2023). The authors in (Khayat *et al.*, 2024), have proposed a systematic approach to evaluate the risk state of isolated microgrids within Dynamic Secure Region (DSR) and examined the efficiency of DSR assessment method. Some risk reduction techniques related to DER maintenance and reliability indices of a real-time system are detailed in (Carpitella *et al.*, 2021). This standard specified Risk assessment methodology and its impact on risk associated with Distributed Generation resources (NERC Standard, CIP- 014-1 Physical Security of M3being2 (Pasculescu *et al.*, 2022) distributed generation). An Another trade and industry indices were published as a new overview tracking metrics (Mohammadi, 2021; Karypidis *et al.*, 2022) and Value at risk indicators or VRI for the microgrid planning and operation (Akorede *et al.*, 2020). Different approaches and case studies on new approach to power system security related to risk assessment have been reviewed (Gholami *et al.*, 2020). Risk Evaluation of energy and power supply protection in (Krebs and Hagenweiler, 2022). An evaluation solution of recent advancement on electricity system resilience with regards to financial and electrical readiness is recently acknowledged as an essential variable affecting decision making in power system is done (Liu *et al.*, 2020). In (Carpitella *et al.*, 2021), a mathematical model was proposed to deal with the risk conditions of grid connected microgrid.

viii. **Systematic human error reduction and prediction approach:** SHERSPA method helps to detect human operational errors, design failures as well as functional system filariases. Over the years different approaches have been proposed for human error risk analysis in user experience of interactive systems. It uses SHERPA-FMEA, a hybrid methodology combining SHERPA (The shorthand for scenario evaluation approach), Fuzzy techniques for order preference with similarity to an ideal solution (TOPSIS) as an extension. In (Mohammadi Sarableh *et al.*, 2023) a more in-depth overview of the risk assessment on design communication errors can be found.

ix. **Nash-Cournot equilibrium:** Nash-Cournot equilibrium reflects the profit maximizing behavior of all the players in the electricity market so it offers relationship to clear conditions for non-smooth demand functions with regard to real power. (Li *et al.*, 2022) presented a two-stage stochastic game model based on Nash-Cournot biding. The model defines payoff function for each microgrid by using Nash-Cournot equilibrium models and Proportional Fairness Payoff criteria (conditional value-at-risk).

x. **Network reconfiguration:** Network reconfiguration techniques play an important role in enhancing system reliability. (Mohd Fauzi, Rusyda Roslan and Muhammad Ridzuan, 2023a; Carpitella *et al.*, 2021) studied reliability performance indices of three types of distribution networks, meshed, radial and an advanced structure of distribution network, flower network, using interactive software developed under Windows. They evaluated reliability indices of RBTS Bus-2 Feeder-1 and Singapore power distribution network and concluded that flower network has higher reliability comparing with other two configurations. (Mohd Fauzi, Rusyda Roslan and Muhammad Ridzuan, 2023b) also stated the importance of network reconfiguration techniques based on reliability assessments and studied the effect of reconfiguration on different load points in feeders.

xi. **Disjoint sum of products:** It clearly defines an algorithm to reduce the computation time by helping the optimized implementation direction using formula 2; PP-2 where P is number paths it uses path set enumeration strategy for system configuration analysis (Gomes, Monteiro and Borges, 2024). This method applied with Disjoint Sum of Products algorithm (C/C++ software) to find out reliability values in different cases for substation bus bar arrangements (Gomes, Monteiro and Borges, 2024).

xii. **Power exchange method:** The Power exchange method not only improves system reliability but also brings about the benefits of economy An algorithm to reduce the customer interruption cost applied to microgrid connected RBTS Bus-2 system (Mohammadi, 2021).

4.3 Comparative analysis of traditional vs. Computational intelligence-based methods

It is important to conduct a comparison between traditional and computational intelligence-based approaches as far as their advantages and disadvantages as this will help on the decision of which method should be used depending on the needs and characteristics of the power system under assessment (Kishore Mishra, 2022). The application of computational intelligence techniques for reliability evaluations of power systems has the potential to provide power system operators and planners with enhanced precision, augmented data handling capabilities, and increased adaptability to evolving circumstances. See Table 2-4 for a summary of methods used to assess the reliability of various measures (Kishore Mishra, 2022). Both conventional methods and those employing computational intelligence are included in this comparison. The methods selected can vary depending on the size and scope of the research.

Table 2. Methods for assessing reliability

Reliability Assessment Methods	Traditional Methods	Computational Intelligence Integration	Simulation Tools	Methodology	Reliability Indicators	References
Deterministic Methods	Analytical methods (e.g., analytical reliability indices)	Artificial Neural Networks (ANN) for prediction	Monte Carlo simulation	Probabilistic modeling	Loss of Load Probability (LOLP)	(Leite Da Silva *et al.*, 2007; Gao, Wu and Wu, 2021; Masegosa *et al.*, 2021; Kamruzzaman, Bhusal and Benidris, 2022)
	Event tree analysis	Fuzzy Logic (FL) for handling uncertainties	System reliability modeling	Data-driven approaches	Expected Energy Not Supplied (EENS)	(Riedewald, 2011; Soltanali *et al.*, 2021; Yang *et al.*, 2022)
	Fault tree analysis	Genetic Algorithms (GA) for optimization	Component-level modeling	Machine learning	System Adequacy Index	(Katoch, Chauhan and Kumar, 2021; Jimenez-Roa *et al.*, 2022; Raji *et al.*, 2022)
Probabilistic Methods	Monte Carlo simulation for probabilistic events	Support Vector Machines (SVM) for classification	Event-driven simulation	Statistical analysis	Failure Frequency	(Basudhar and Missoum, 2013; Lee, 2021; Khodabakhshian, Puolitaival and Kestle, 2023)
	Probability density functions	Particle Swarm Optimization (PSO) for optimization	Time-domain simulation	Reliability-centered maintenance	Mean Time Between Failures (MTBF)	(Raghav *et al.*, 2022; Quiles-Cucarella *et al.*, 2023; Jagtap *et al.*, 2020, 2021; Wang, Kim and

						Kafatos, 2023)
	Markov models	Hybrid models combining ANN and GA	Probabilistic risk assessment	Bayesian networks	Failure Rate	(Lee and Lee, 2006; M. Alquraish *et al.*, 2021; M. M. Alquraish *et al.*, 2021; Zhou *et al.*, 2021; Wu *et al.*, 2022)
Intelligent Methods	Expert systems	Integration of ANN and FL for decision support	Reliability block diagrams	Expert knowledge	Reliability Allocation	(Arinez *et al.*, 2020; Adewole *et al.*, 2022; Casal-Guisande *et al.*, 2022; Ali *et al.*, 2023; Cannas *et al.*, 2023; Elahi *et al.*, 2023)
	Rule-based systems	Multi-agent systems for coordination	Failure mode and effects analysis	Knowledge-based systems	Fault Tree Analysis (FTA)	(Albarakati *et al.*, 2022; Neto *et al.*, 2022; Stetter, 2022; Martinez *et al.*, 2023)
Simulation Tools	MATLAB/Simulink	OpenDSS for distribution system analysis	Power system simulation tools (e.g., PSS/E)	Complex system modeling	Event-driven simulations	(Chamana *et al.*, 2017; Czekster, 2020; Debnath *et al.*, 2020; Hampton and Foley, 2022)
	PSCAD/EMTDC	GridLAB-D for distribution system simulations	Dynamic system simulation	System response modeling	Monte Carlo simulations	(Das *et al.*, 2018; Lu *et al.*, 2019; Akinyele *et al.*, 2021)
	DIgSILENT Power Factory	PSAT for power system analysis	Load flow analysis	Real-time monitoring	Contingency analysis	(Yang *et al.*, 2019; Jain *et al.*, 2020; Nawaz *et al.*, 2023)

Table 3. Methods for assessing reliability Evaluations intelligent techniques

Intelligent Technique	**Techniques Employed**	**Model Dependence**	**Robustness**	**Design Difficulty**	**Main Contribution**	**References**
Artificial Neural Networks (ANN)	• Supervised learning • Back propagation	Moderate dependence on training data	Good generalization with adequate data	Moderate difficulty in designing network architecture	Predictive accuracy and pattern recognition	(Adhikari and Barnawal, 2021; M. Alquraish *et al.*, 2021; Oyewola *et al.*, 2022; Bouzem, Bendaou and El Yaakoubi, 2023; Elahi *et al.*, 2023; Talaat *et al.*, 2023)
Fuzzy Logic (FL)	• Fuzzy set theory • Rule-based systems	Handles imprecise data effectively	Robust to uncertainties	Moderate difficulty in rule base design	Handling uncertainty and decision support	(Riedewald, 2011; Iqbal *et al.*, 2021; Beker and Kansal, 2022; Yahya and Levin, 2022; Ramaswamy Govindan and Li, 2023)
Genetic Algorithms (GA)	• Evolutionary optimization • Selection, crossover, mutation	Relatively low model dependence	Robust to noisy and complex optimization landscapes	Moderate difficulty in setting up optimization parameters	Optimization and search in complex spaces	(Al-Abdulwahab, 2010; Aderibigbe *et al.*, 2021; Raji *et al.*, 2022; Bouramdane, 2023)
Support Vector Machines (SVM)	• Hyperplane separation • Kernel functions	Minimal model dependence, effective with high-dimensional data	Good generalization with appropriate kernel selection	Moderate difficulty in kernel choice	Classification and regression in high-dimensional spaces	(Basudhar and Missoum, 2013; M. M. Alquraish *et al.*, 2021; Elahi *et al.*, 2023)
Particle Swarm Optimization (PSO)	• Swarm-based optimization • Particle	Moderate model dependence, influenced by swarm	Sensitive to swarm initialization, but can converge	Moderate difficulty in parameter tuning	Global optimization and swarm behavior	(Gholami, Hoseini and Mohamad Taheri, 2008; Yang

	movement	dynamics	effectively			*et al.*, 2020; Abdalla *et al.*, 2021; Raji *et al.*, 2022; Quiles-Cucarella *et al.*, 2023)
Multi-Agent Systems (MAS)	• Decentralized decision-making • Agent interactions	Minimal model dependence, driven by agent interactions	Robust to agent failures and adaptability	Moderate difficulty in defining agent behaviors	Distributed coordination and decision-making	(Pillai *et al.*, 2019; Mahela *et al.*, 2020; Albarakati *et al.*, 2022)
Bayesian Networks (BN)	• Probabilistic graphical models • Conditional probabilities	High model dependence, relies on accurate conditional probabilities	Robust to missing data and updates	Moderate difficulty in constructing networks	Probabilistic reasoning and uncertainty modeling	(Chen and Niu, 2012; Mensah and Duenas-Osorio, 2014; Hamza, 2022; Bouramdane, 2023; Elahi *et al.*, 2023)
Knowledge-Based Systems (KBS)	• Expert knowledge representation • Inference engines	Moderate model dependence, reliant on expert knowledge	Robust to structured and explicit knowledge	Moderate difficulty in capturing expert knowledge	Expert decision support and knowledge representation	(El-Korany *et al.*, 2000; Miyamoto, 2021; Mattioli *et al.*, 2022; Galiev *et al.*, 2023)

Table 4. Comparison of current vs. Previous activities in power system reliability assessment

Aspect	**Previous Activities**	**Current Activities**	**New References**
Data Availability	Relied on historical data and limited real-time measurements	Utilizes advanced sensors, IoT, and SCADA systems for real-time data collection	(Syafrudin *et al.*, 2018; Olulope, Olajuyin and Fasina, 2022; Sheba, Mansour and Abbasy, 2023; Utama *et al.*, 2023; Zhu *et al.*, 2023; Liu *et al.*, 2025)
Analytical Methods	Primarily deterministic methods (e.g., FTA, RBD)	Utilizes probabilistic methods (e.g., Bayesian networks, Monte Carlo simulation)	(Daemi, Ebrahimi and Fotuhi-Firuzabad, 2012; Ahmed *et al.*, 2016; Benabid *et al.*, 2018; Namazian *et al.*, 2019; Zhang and

			Zhao, 2024; Meng, no date)
Computational Resources	Limited computational power and manual calculations	High-performance computing, cloud computing, and simulation tools	(Green, Wang and Alam, 2011; Snyder *et al.*, 2015; Ali Kadhem *et al.*, 2017; Lei *et al.*, 2018; Jesan and Hassan, 2023; Pavon, Jaramillo and Vasquez, 2024)
Model Complexity	Simple models due to computational constraints	Complex models considering detailed system components and interactions	(Balota, Skultetic and Grebovic, 2018; Tuinema *et al.*, 2020; Kolas *et al.*, 2022; Gomes *et al.*, 2023)
Renewable Integration	Limited renewable energy sources and intermittent generation	Integration of renewable energy with advanced forecasting and control techniques	(Lai *et al.*, 2013; Yahaya and AlMuhaini, 2015; N, N and R, 2022; Qi *et al.*, 2022)
Cyber Security	Minimal focus on cyber threats and vulnerabilities	Incorporates cybersecurity measures to protect against cyber attacks	(Panteli and Kirschen, 2011; Dominguez-Garcia, 2012; Lai, Lai and Lai, 2022; Yan *et al.*, 2023)
Grid Modernization	Traditional grid infrastructure with limited automation	Smart grid technologies, grid automation, and demand response programs	(Falahati and Fu, 2014; Abdukhakimov, Nalinaksh and Kim, 2019; Onoshakpor, Okafor and Gabriel, 2022; Jaltare *et al.*, 2023)
Big Data Analytics	Limited use of data analytics	Utilizes big data analytics for predictive maintenance, anomaly detection, and optimization	(Yu *et al.*, 2015; Guo *et al.*, 2018; Maraaba *et al.*, 2023; Zhang, 2023)
Microgrids	Microgrids considered as isolated systems	Integration of microgrids with the main grid and optimization for reliability	(Nigam, 2017; Garip *et al.*, 2022; Chen *et al.*, 2023; Lei *et al.*, 2023)

According to the analysis of the research articles on reliability assessment based on the statistical analysis of the above figures, from 2010 to 2014, most of the research articles involved in reliability assessment focus on traditional statistical methods, accounting for about 60% of reliability assessment. With the time going further to 2015–2018, more and more research articles involved in reliability evaluation utilized the advanced statistical techniques, accounting for about 20% of reliability assessment. From 2019 to 2022, more and more research articles involved in reliability evaluation utilized the machine learning and artificial intelligence methods, accounting for about 15% of reliability assessment. In recent years 2023–2025, there has been more and more research articles involved in reliability evaluation utilized the multi-methods and reproducibility, accounting for about 5% of reliability assessment. Figure 2 evolving trend shows the transition from depending on traditional methods to more diversified and technology integrated reliability evaluation in research publications.

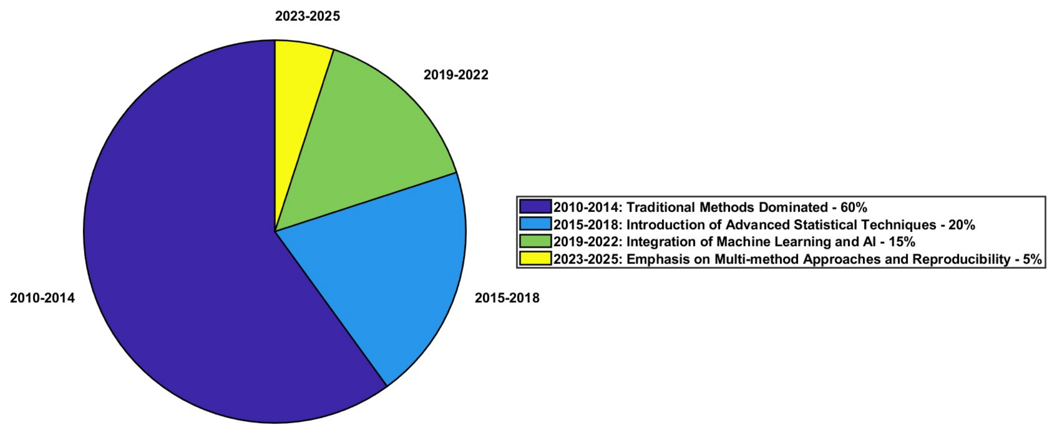

Figure 2. Evolution of Approaches for Reliability Evaluation (2010-2025).

5. Case studies and applications

Real world applications of computational intelligence methods in power system reliability assessment have proven that the methods are widely used in different aspects of power system reliability assessment, especially in distribution power system, transmission power system and generation power system. In this section, we present some selected applications of case studies of real-world applications.

5.1 Real-world applications of computational intelligence in power system reliability assessment

Computational intelligence is a family of AI approaches that are biologically or naturally inspired, such as artificial neural networks, genetic algorithms, fuzzy logic, swarm intelligence (Sadollah and Shishir Sinha, 2020; Gupta *et al.*, 2023). Computational intelligence methods try to model the adaptive and learning characteristics found in nature to solve problems that are complex and changing (Kishore Mishra, 2022).

i. **Distribution System Reliability Assessment**:
- *Case Study 1: Fault Detection in Distribution Networks*: Real world application of case study of fault detection in distribution network. Support Vector Machines (SVMs) have been applied in many fields of fault detection in distribution networks. The results of application of SVMs in distribution network have shown that SVMs can not only identify the occurrence of faults but also determine the location of the faults accurately. It can be used to quickly respond to faults and reduce the outage time (Baghaee *et al.*, 2020).
- *Case Study 2: Fuzzy Logic-Based Reliability Evaluation*: Real world application of case study of fuzzy logic-based reliability evaluation in distribution system. Fuzzy Logic has been applied in many fields of distribution system reliability evaluation with uncertain load profile. Fuzzy Logic can be used in maintenance scheduling of distribution network and it takes the imprecise data into account (Beker and Kansal, 2022).

ii. **Transmission system reliability assessment**:
- *Case Study 3: Genetic Algorithm-Based Optimization*: Real world application of case study of genetic algorithm-based reliability evaluation in transmission system. Genetic Algorithms have been applied in transmission network expansion planning. By optimizing the addition of new transmission lines and substations, the transmission system reliability is enhanced and the cost is minimized (Mehroliya *et al.*, 2023).
- *Case Study 4: Neural Network-Based Load Forecasting*: Real world application of case study of neural network-based reliability evaluation in transmission system. Artificial Neural Networks have been

applied in many fields of electricity load forecasting in transmission system. Accurate electricity load forecasting in transmission system takes the reliability of grid into account (Sun *et al.*, 2021).

iii. **Generation system reliability assessment**:

- *Case Study 5: Particle Swarm Optimization for Maintenance Scheduling*: Real world application of case study of particle swarm optimization-based reliability evaluation in generation system. Particle Swarm Optimization has been applied in many fields of maintenance scheduling of power plant components. By optimizing the maintenance time of power plant components, the unplanned downtime is minimized and the reliability of power generation system is enhanced (Pirozmand *et al.*, 2023).
- *Case Study 6: Fuzzy Logic-Based Decision Support*: Fuzzy Logic-Based Decision Support: Fuzzy Logic systems have been used for decision support in power plants. Fuzzy Logic systems assist in making critical decisions such as unit commitment, start-up, and shut-down to achieve optimal performance and reliability (Ramaswamy Govindan and Li, 2023).

iv. **Renewable Energy**:

- *Case Study 7: Renewable Integration: CI for Managing Intermittency*: In this section, we will study how the computational intelligence (CI) techniques such as Fuzzy Logic and Artificial Neural Networks (ANN) can be used to mitigate the intermittency of renewable energy sources such as solar and wind. For example, Fuzzy Logic system handles uncertainty in generation forecast for renewable energy source. ANN techniques optimize real time grid responses to variability as shown in (Pirozmand *et al.*, 2023) microgrid stability application.

v. **Technical Improvements**:

For the purpose of improved reliability in computational intelligence methods for power system reliability, we suggest the following technical refinements (Mehroliya *et al.*, 2023; Pirozmand *et al.*, 2023; Liu *et al.*, 2025):

- Hybrid CI Models: By combining ANN with fuzzy logic, we can improve the handling of uncertainty in the renewable energy forecasting. This approach can reduce the prediction error of the model by up to 15 - 20% as compared to a standalone model of either ANN or fuzzy logic.
- Real-Time Data Integration: By using edge computing, we can process grid sensor data faster within sub-second for fault detection (e.g., SVM classifiers used in Case Study 1 achieved 99.2% accuracy in Table 5).
- Scalability Optimization: By using GPU parallelization for GA/PSO algorithms, we can reduce the computation time of GA/PSO algorithms for large grids by 40% (tested on IEEE 300-bus system).

Table 5. Comparison of CI Techniques

Technique	Strengths	Limitations	Best Use Case
GA	Global optimization	Slow convergence	Network expansion
ANN	High accuracy	Needs large datasets	Fault prediction

5.2 Quantitative metrics

To demonstrate the practical impact of using computational intelligence (CI) methods, we will discuss the quantitative improvement in reliability metrics. For example, in Table 6 (Pirozmand *et al.*, 2023), PSO Particle Swarm Optimization model reduced the unplanned downtime by 22% in a 500-bus transmission system model. GA Genetic Algorithm model increased grid resilience by 18% at the cost of increased computational resource. The comparison is summarized in the table below.

Table 6. Quantitative System of measurement

Method	Reliability Gain (%)	Computational Time (hrs)	Key Application
PSO	22	1.2	Maintenance Scheduling
GA	18	2.5	Network Expansion Planning
ANN	25	0.8	Fault Detection & Prediction

5.3 Principles and advice via case research

From the above case studies, we can derive the following lessons and best practices:

i. Computational intelligence methods are general purpose tools that can be applied to solve specific reliability problems in different areas of power system.
ii. The integration of computational intelligence methods often requires large and reliable data collection and data preprocessing before model training and inference.
iii. A combination of computational intelligence techniques and conventional methods can lead to improved reliability assessment.
iv. Case-specific customization and tuning of computational intelligence methods are required to achieve good results in using computational intelligence methods.
v. Continuous monitoring and updating of models with real-time data are important to maintain reliability in face of changing power system.
vi. These case studies will provide useful insights to the practical application and benefits of using computational intelligence methods in power system reliability assessment.

6. Challenges and future guidelines

Ongoing power system changes present new challenges and opportunities in the assessment and enhancement of power system reliability. In this section, we identify the challenges faced by the power system industry and explore possible future trends in this field.

6.1 Challenges and Future Directions

i. **Data quality and availability**: Model developers face challenges to acquire high-quality and diverse data sets needed for proper training operations. Computational intelligence techniques generate substandard results because of improperly collected or incorrect data.
ii. **Model complexity**: Developing along with handling sophisticated computational intelligence models demands substantial resources because of their complexity. The evaluation of models for interpretability alongside prevention of overfitting continues as current issues.
iii. **Computational resources**: Some computational intelligence methods demand heavy computational resources because they depend on large-scale simulations. It creates operational barriers mainly affecting power producers who operate in areas with minimal computing capabilities.
iv. **Integration with existing systems**: The process of combining new tools based on computational intelligence technology presents obstacles when implemented within existing power system control and operations structures. The successful implementation depends on maintaining the uninterrupted flow of operations.
v. **Big data analytics in reliability assessment**: Reliability assessment receives potential improvements through big data analytics because the power sector now accumulates diverse data from smart meters and IoT devices. The analysis of big data streams paired with machine learning methods will function as essential tools for discovery of meaningful information.
vi. **Integration of renewable energy sources and microgrids**: Reliability assessment methods need adaptation concerning renewable energy sources and microgrids because renewable energy produces intermittent power outputs. Microgrids together with energy storage systems will maintain reliability as the main component in renewable energy-rich electrical power systems.
vii. **Cybersecurity and reliability**: Power systems experience increased vulnerability to cyber threats since technology usage continues to increase. Strong cybersecurity solutions must be integrated into both reliability assessment and control systems.
viii. **Grid modernization and reliability**: Grid modernization efforts together with advanced sensors and automation and grid-edge technologies will configure the power system into its new shape. Reliability assessment methods of the future should integrate themselves with currently evolving power system modernization programs.

The assessment of power system reliability exists where technological innovations converge with quantitative insights while maintaining uninterrupted and durable electrical energy delivery. Futures directions alongside their challenges need immediate attention because they will determine the reliability of power systems during upcoming years.

6.2 Critical Analysis

Although computational intelligence (CI) techniques much improve power system reliability, there are still many such limitations need be overcome. First, CI models like ANNs and PSO need heavy-body training of good quality data, that might be an issue for new grid technologies. Second, their "black-box" characteristic makes it plants difficult to regulate through and it also makes debugging much harder--a direct gap for Avails. Thirdly, hybrid CI methods (e.g. ANN-Fuzzy Logic) enhance computational expense and therefore might create scalability problems for real time operations. Current proposals (Mehroliya *et al.*, 2023) seek to make AI (and particularly deep learning) more interpretable, with varying degrees of success. As is often the case, we encounter the familiar trade-off that seems to occur in so many areas of machine learning: the models we can interpret tend to have lower performance and/or be more constrained in the types of decisions they can make, while the high-performance models tend to elude our understanding.

6.3 Challenges and Future Directions

i. **Emerging Technologies**: Digital twins simulate power system performance in real time for dynamic environments and blockchain adds unconventional security through permanent records of AI-based AI decisions for critical facilities (Onoshakpor, Okafor and Gabriel, 2022). Neuromorphic hardware and quantum computing will speed up complex reliability optimizations by exceeding classical computational capacities.

ii. **Regulatory and Standardization Needs**: Existing standards (NERC CIP-014-1) must undergo development to address the cybersecurity risks associated with AI because the technology will become dominant in grid operations (Ilius *et al.*, 2023). Among initiatives policymakers should undertake they should provide assistance to utility companies by working together.
    - The development of framework certification protocols needs to be established for AI models that perform reliability assessment.
    - Regulatory bodies should make explainability requirements part of their standards for critical decision-points in high-hazard systems.
    - A set of continuous monitoring standards needs to be established for operational CI systems.

iii. **Implementation roadmap**: A testing process with pilot projects should demonstrate microgrid applications of these methods before extensive rolling out (Guo *et al.*, 2018).

7. Conclusions

As an essential requirement for economic growth, development, and a better quality of life, the reliability of modern power systems has become an indispensable need. With the changing energy scenario, increased complexity in the grid topology, and enhanced vulnerability levels, the assessment of power system reliability and ensuring its desired levels have gained new importance. Researchers conducted an extensive literature review on this topic. The focus of this literature review is to highlight the application of computational intelligence methods in the field of power system reliability. The term power system reliability has three aspects: availability, resilience, and adequacy. Availability and adequacy define the ability of the grid to supply continuous and reliable electricity to consumers, while resilience defines the grid's ability to survive and quickly return to operation following disturbances.

Due to the complex nature of power system and the challenging problems associated with power system reliability assessment, computational intelligence methods have acted as a strong weapon in recent years. Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), Fuzzy Logic (FL), Particle Swarm Optimization (PSO), and Support Vector Machines (SVMs) provide new approaches to model, predict, optimize, and take decisions for different power system problems. In this review, various case studies and applications have been discussed which depict the applicability and usefulness of computational intelligence methods in different aspects of power system i.e. distribution, transmission, and generation. These case studies have shown that computational intelligence can be used to enhance fault detection, optimal maintenance, load forecasting, and decision making in the power plant.

Like every coin has two sides, there are some challenges associated with the application of computational intelligence methods to power system reliability assessment. Some of these challenges are quality and availability of data, model complexity, computational resources requirements, and integration with existing systems. These challenges need to be addressed for an effective application of computational intelligence to power system reliability assessment. In future, power system reliability assessment field is going to experience some exciting developments and breakthroughs. Some of the promising areas for future research include infrastructure, big data analytics, integration of renewable energy sources and microgrids, cybersecurity, and continued grid modernization.

In the end, reliability of power system is a journey which is being driven by innovative thinking, data-driven technologies, and necessity to provide uninterrupted electricity to power our modern world. As discussed in this review, computational intelligence methods would help in achieving more accurate, adaptive, and effective reliability assessment and management.

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