

MODELING AND IMPROVING THE RELIABILITY OF SMART ELECTRICAL GRIDS

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Abstract

The transformation of conventional power systems into intelligent electric networks, or Smart Grids, has introduced significant improvements in efficiency, flexibility, and sustainability. However, this evolution also brings new reliability challenges due to complex cyber-physical interactions, integration of distributed energy resources, and increased exposure to cyber threats. This paper presents a comprehensive methodology for assessing and improving the reliability of smart grids through hybrid modeling, real-time analytics, and fault-tolerant system design. Key components with the highest impact on system reliability—such as communication modules and cyber interfaces—are identified and analyzed. A hybrid reliability model combining probabilistic techniques with machine learning methods is developed and illustrated through a case study involving redundant control systems. The results demonstrate that strategic redundancy and predictive diagnostics can significantly enhance the resilience of modern power infrastructures. The study concludes with recommendations for integrating reliability considerations into autonomous grid operation.

Keywords: Smart Grids; Reliability Modeling; Cyber-Physical Systems; Fault Tolerance; Redundancy; Machine Learning

I. Introduction

Modern trends in power engineering are marked by a large-scale transformation of traditional energy systems toward smart electrical grids (Smart Grids). These systems represent an integration of physical power infrastructure with digital control technologies, advanced communication networks, and distributed generation, including renewable energy sources. The primary goal of this transformation is to enhance the efficiency, flexibility, resilience, and environmental sustainability of power supply systems.

Despite their numerous advantages, smart grids introduce significant challenges in the area of reliability due to their architectural and operational complexity. Unlike conventional centralized systems, Smart Grids operate under high uncertainty driven by variable energy generation, fluctuating loads, and risks associated with cyber-physical interactions [1]. Furthermore, deep digitalization makes the system vulnerable to cyberattacks, communication failures, software malfunctions, and unpredictable cascading events.

Ensuring high reliability is therefore a key requirement in the design, operation, and modernization of intelligent power systems. Addressing this task requires a comprehensive approach that integrates reliability engineering, systems analysis, digital modeling, cybersecurity, and predictive analytics. In today's context, it is essential not only to monitor the current state of the system but also to predict its behavior, identify vulnerabilities at early stages, and respond to failures in an automated and adaptive manner.

This study aims to explore quantitative modeling approaches for assessing and improving the reliability of smart electrical grids, and to propose technical and algorithmic solutions that enhance system resilience [2]. Special attention is given to the analysis of structural and functional vulnerabilities, the development of reliability models, the use of digital twins, and the evaluation of fault-tolerant strategies within increasingly complex energy infrastructures.

II. Problem statement

The evolution of conventional power systems into smart grids has introduced both unprecedented capabilities and new layers of complexity. While digitalization, decentralized control, and integration of renewable energy sources have improved operational flexibility and sustainability, they have also made modern power systems increasingly susceptible to diverse and often interrelated failure mechanisms. Reliability assurance in this context requires not only classical redundancy and hardening strategies but also intelligent modeling and predictive risk assessment tailored to dynamic, cyber-physical environments.

Smart grids are characterized by their hybrid nature—where physical components such as transformers, relays, and power electronics operate in conjunction with digital assets, including smart meters, control algorithms, and communication infrastructure [3-5]. The reliability of such systems is influenced by multiple interconnected domains: physical failures (e.g., thermal stress in power electronics), software errors, communication delays, cyber-attacks, and operational uncertainties due to variable renewable generation.

A critical problem lies in the inability of traditional reliability models to adequately capture the multi-layered interactions and dynamic behavior of smart grids. These models are typically component-centric and static, failing to reflect the probabilistic nature of control decisions, data-driven operations, and event-based disruptions.

To quantify the reliability challenges, a multi-factorial risk assessment was performed. Figure 1 illustrates the risk index for major components of a smart grid system, calculated as the product of failure probability and impact severity.

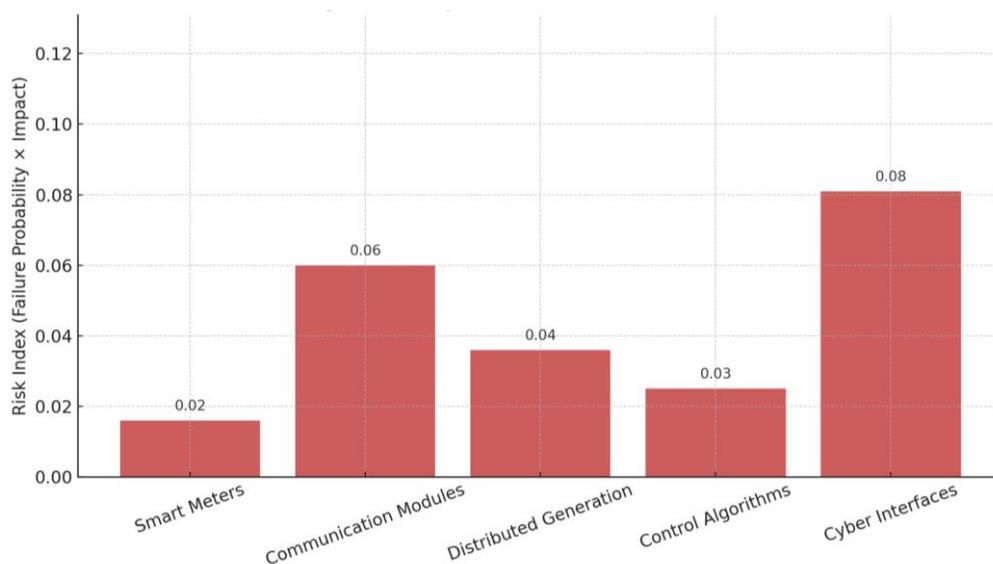


Figure 1. Component risk index in Smart Grids

The diagram highlights the disproportionate influence of communication modules and cyber interfaces on systemic risk. Although smart meters exhibit a lower individual risk index, their widespread deployment amplifies potential cascade effects. The data reveal the necessity of focusing reliability improvement strategies on software-intensive and cyber-integrated modules.

Furthermore, in contrast to legacy grids with deterministic operating modes, smart grids function under stochastic, often adversarial, conditions. Load demand fluctuates unpredictably, communication delays affect system stability, and distributed energy resources may introduce asynchronous operation [6].

Addressing this problem requires a shift from traditional static modeling toward integrated frameworks that combine:

- Probabilistic and hybrid modeling techniques,
- Real-time data analytics,
- Predictive diagnostics,
- Redundant and adaptive control architectures.

The following sections of this paper present a methodological approach for modeling the reliability of smart grids using a multi-domain framework. It incorporates cyber and physical variables and proposes strategies for enhancing system-level reliability through redundancy, self-healing capabilities, and data-driven anomaly detection.

To complement the visual risk index analysis, Table 1 presents quantitative reliability characteristics for typical smart grid components, including failure probability, estimated repair time, and resulting unavailability metrics.

Table 1. Reliability characteristics of key Smart Grid components

Component	Failure probability (P _f)	Mean Time To Repair (MTTR), h	Unavailability (U = P _f × MTTR)
Smart Meters	0.08	4	0.32
Communication Modules	0.15	6	0.90
Distributed Generation	0.12	5	0.60
Control Algorithms	0.10	3	0.30
Cyber Interfaces	0.18	7	1.26

This table shows that cyber interfaces and communication modules not only exhibit higher failure probabilities, but also longer repair durations, leading to significantly higher unavailability [7]. This quantitative assessment reinforces the earlier conclusion drawn from Figure 1, and highlights where reliability interventions should be prioritized.

The combination of Figure 1 and Table 1 underscores the need to address:

- Latent software vulnerabilities,
- Communication bottlenecks,
- Reactive instead of predictive maintenance, as principal causes of reliability degradation in smart grids.

Accordingly, the following section develops a multi-layered reliability model that accounts for these factors and proposes targeted solutions.

III. Problem solving

The reliability of intelligent electric networks is shaped by the interplay of physical infrastructure, digital communication, and autonomous control. As these systems evolve toward

higher degrees of automation and complexity, conventional static reliability assessment becomes insufficient. Instead, a dynamic, integrated modeling approach is required to capture the cyber-physical interactions that determine operational continuity.

To address this, we propose a hybrid reliability modeling framework that combines probabilistic structures—such as Markov chains and Bayesian networks—with real-time data analytics. This allows the simulation of fault propagation, dependencies between control elements, and response behaviors under uncertainty. Such modeling is essential not only for understanding failure mechanisms, but also for designing systems with embedded resilience.

A practical illustration can be drawn from a typical dual-channel control unit in a smart substation. Let us assume that the primary channel has a failure-free probability of $P_{\text{main}}=0.95$, while the backup module performs with $P_{\text{backup}}=0.90$. Since these operate in parallel (i.e., the system remains operational if at least one channel works), the combined system reliability is given by:

$$P_{\text{system}}=1-(1-P_{\text{main}})\cdot(1-P_{\text{backup}})=1-(0.05)(0.10)=0.995$$

Thus, the system achieves a 99.5% probability of uninterrupted operation, significantly outperforming either component alone. This result highlights how basic redundancy, when correctly applied, enhances the fault tolerance of critical smart grid subsystems.

In addition to structural enhancements, intelligent monitoring systems contribute to adaptive reliability management. The availability of real-time data streams—originating from PMUs, digital relays, and SCADA logs—enables the deployment of machine learning algorithms for dynamic reliability estimation [8-10]. For example, gradient boosting models such as XGBoost can predict the degradation of switching devices by analyzing thermal cycles and switching frequency, while LSTM neural networks can detect subtle anomalies in communication signals before they escalate into systemic faults.

Table 2.: *Machine learning applications in Smart Grid Reliability*

Application Area	ML Method	Diagnostic Output
Predictive maintenance	XGBoost	Remaining Useful Life (RUL)
SCADA anomaly detection	LSTM	Early fault time identification
Cybersecurity diagnostics	Random Forest	Intrusion risk classification

From a system design perspective, dual-channel DC power architectures offer a foundational layer of physical redundancy. These architectures, often comprising two isolated battery banks with independent chargers, support protection and automation systems even under fault conditions. As illustrated in Figure 2, such a setup allows the grid to maintain control functions despite individual subsystem failures.

Moreover, the integration of self-healing protocols, embedded in the digital control layer, ensures automatic fault isolation and service restoration [11, 12]. This not only minimizes outage durations but also enables distributed intelligence within the grid.

Altogether, the reliability of smart electric networks cannot be decoupled from their digital backbone. By combining fault-tolerant design, intelligent prediction, and cyber-resilient control, we establish a foundation for sustainable, autonomous, and highly reliable operation across all levels of the modern power system.

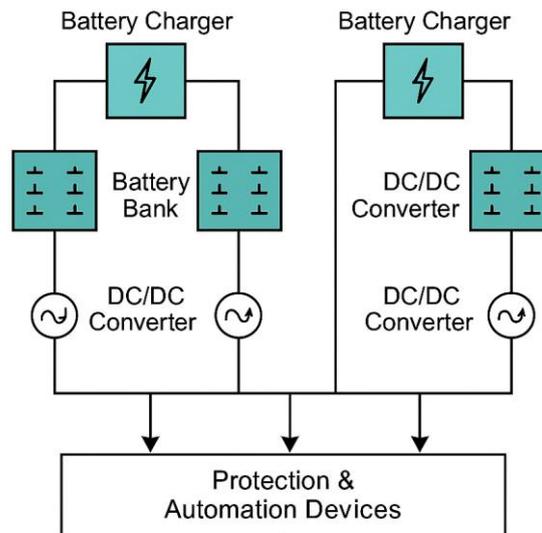


Figure 4.: Dual-Channel DC auxiliary power architecture

V. Conclusions

The ongoing digital transformation of electric power systems has significantly reshaped the concept and implementation of reliability. In intelligent electric networks, where cyber-physical integration is intrinsic, reliability can no longer be ensured through conventional redundancy or isolated component-level analysis. Instead, it must be addressed as a system-wide attribute that evolves dynamically with operational conditions, data flows, and control logic.

This paper has presented a structured methodology for modeling and enhancing the reliability of intelligent electric grids. The proposed approach combines probabilistic modeling, real-time data analytics, and architecture-level fault tolerance. Through illustrative case studies and quantitative examples, it was shown that even simple forms of structural redundancy—such as dual-channel configurations—can yield substantial reliability improvements when strategically applied. Furthermore, the integration of machine learning techniques allows for predictive diagnostics, enabling preemptive maintenance and anomaly mitigation.

The key findings can be summarized as follows:

- Reliability modeling in smart grids requires a transition from static evaluation to dynamic, data-driven frameworks that reflect cyber-physical dependencies;
- Hybrid architectures employing probabilistic models and AI-based prediction offer a scalable and adaptive foundation for reliability assessment;
- Practical implementation of fault-tolerant designs (e.g., redundant power supply channels) significantly enhances operational continuity;
- Machine learning methods, particularly XGBoost and LSTM, have proven effective in estimating remaining useful life and detecting latent anomalies in grid components and communication infrastructure.

Future work should aim to deepen the integration of reliability metrics into autonomous control systems, enabling self-adaptive grid behavior in real-time. Additionally, the development of standardized datasets and testbeds for reliability modeling would accelerate the validation and benchmarking of proposed methods.

In conclusion, ensuring the reliability of intelligent electric networks is not only a technical necessity but a strategic imperative for the future of sustainable and resilient energy systems.

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