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# MODELING THE RESILIENCE OF POWER SYSTEMS TO CRITICAL EXTERNAL IMPACTS*

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## Abstract

*Energy systems form the core of modern societal functioning, and their reliability directly influences public safety as well as the stability of national and regional economies. In the context of increasing hybrid threats, assessing the vulnerability of power networks and their capacity to maintain operational resilience has become critically important.*

*The purpose of this research is to develop a minimal mathematical model that enables the analysis of power system behavior under critical disturbances and supports the prediction of systemic failures and their consequences. The proposed approach integrates two complementary levels. The deterministic level describes the dynamic response of the power grid and the cascade effects associated with line overloads and frequency deviations from nominal values. This is achieved through the use of swing equations for synchronous machines and the computation of power-flow redistribution under crisis conditions. The stochastic level introduces uncertainty stemming from random equipment failures and rare but severe external shocks, modeled via a Poisson process combined with heavy-tailed distributions.*

*To evaluate system resilience, multiple computer simulations are performed, yielding key indicators such as Expected Unserved Energy (EUE), average recovery time (TTR), and the probability of system collapse. The model is sufficiently realistic, incorporating correlated component failures and limited repair resources.*

*The practical relevance of the study lies in its applicability to risk assessment, scenario analysis, verification of emergency automation systems, and prioritization of infrastructure restoration. Thus, the model serves as a versatile analytical tool for engineers and energy policy experts seeking to enhance energy security and system resilience.*

**Keywords:** power system, swing equations, stochastic processes, external shocks, equipment failures.

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## Introduction

Energy security is a fundamental component of human security, as the uninterrupted operation of electric power systems (EPS) directly influences economic stability, quality of life, and the protection of the population during crisis situations[1]. In the twenty-first century, the reliability of energy infrastructure has become increasingly critical due to the growing number of risk factors, ranging from natural disasters and technological accidents to cyber threats and geopolitical crises[2]. Modern EPS are becoming progressively more interconnected and digitalized, which enhances their efficiency but simultaneously increases their vulnerability to significant external disturbances capable of triggering systemic failures and cascading outages[3]. Classical methods of power system stability assessment are primarily based on deterministic models that accurately describe frequency dynamics and power-flow redistribution, but they do not capture the stochastic nature of external shocks and the unpredictability inherent in emergency developments[4]. Probabilistic and statistical approaches, on the other hand, enable the assessment of equipment failure risks but often substantially oversimplify the physical processes underlying system dynamics[5]. As a result, a methodological gap emerges between engineering-based and stochastic approaches, limiting the precision of forecasts and reducing the practical applicability of the models under uncertainty[6].

In the recent years, increased attention has been directed toward the combined use of physical and probabilistic techniques within the broader framework of resilience, the capacity of EPS to withstand critical impacts and recover from them[7]. This integration leads to the development of hybrid models in which continuous system dynamics coexist with a discrete flow of random events such as external shocks, protection actions, equipment failures, and recovery processes[8]. The present study aims to develop a stochastic–deterministic model that enables a quantitative assessment of EPS behavior under the influence of rare, high-impact disruptive events. The proposed model conceptualizes the power system as a dynamic stochastic network whose elements and interactions evolve over time under the influence of both physical laws and random factors[9]. This approach makes it possible to compute not only traditional power engineering indicators but also probabilistic resilience metrics such as the probability of system collapse ($P_{collapse}$), Expected Unserved Energy (EUE), Time to Recovery (TTR), and an integrated Resilience Index (RI)[10].

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This research contributes to the advancement of analytical tools for risk assessment and the enhancement of energy security, offering both engineering–economic and socio-political relevance in the context of contemporary international challenges[1].

## Theoretical Background

The development of comprehensive resilience models for power systems, models that account for both the physical dynamics of electrical networks and the probabilistic nature of external disturbances, has become increasingly important. Accordingly, the proposed stochastic–deterministic framework is based on combining two complementary levels of representation: a physical level and an event-based level. The first captures the continuous dynamics of the power system, while the second model's random external shocks, protection actions, and recovery processes. The physical level is grounded in classical representations of synchronous generator dynamics, described by the swing equations. These equations reflect the balance between mechanical and electrical power inputs and link rotor frequency deviations to the system's inertia. This approach makes it possible to conceptualize the power system as an ensemble of interconnected oscillators whose collective dynamics determine system stability. Deviations of system frequency from its nominal value serve as an indicator of the balance between electricity generation and consumption, while the time required for power-flow redistribution across network nodes reflects the system's ability to adapt to disturbances.

However, deterministic descriptions alone are insufficient for analyzing real-world crisis scenarios, where random events disrupt normal system operation. To address this limitation, the model incorporates a stochastic component that captures external shocks of various origins: natural disasters, cyberattacks, physical damage to lines and equipment due to accidents, military actions, or climate-related factors. These events are modeled using random processes, specifically, Poisson processes for frequent events and heavy-tailed distributions for rare but high-impact events. This dual representation reflects the destructive potential of disturbances: mild for frequent events and severe for rare events capable of causing systemic failures or cascading outages.

Protective mechanisms play a critical role in shaping the system's response. One of the most widely used methods for preventing collapse is Under-Frequency Load Shedding (UFLS). This protection mechanism is triggered when frequency drops below predefined thresholds and sequentially disconnects portions of the load to halt further frequency decline and prevent generator desynchronization. The model incorporates a multi-stage UFLS scheme with distinct activation delays, enabling realistic reproduction of power system behavior under critical conditions. An essential element of the model is the stochastic representation of recovery processes. Each component of the power system can transition between operational and failed states with certain probabilities. These transitions form a Markov chain, whose parameters are determined by average repair durations and recovery priorities. Thus, the system is treated as a dynamic structure evolving under the influence of random events and repair procedures, whose durations are modeled as random variables.

To quantify resilience, several key metrics are introduced. The probability of system collapse, $P_{collapse}$ represents the share of simulated scenarios in which a large-scale disruption of power supply occurs. The EUE expresses the average amount of energy not delivered to consumers. The TTR measures the speed at which the system returns to normal operation.

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Additionally, the RI is employed, defined as the area under the service-level curve over time. It characterizes the overall capability of the system to withstand external impacts and recover from them.

In summary, the proposed theoretical framework integrates physical, stochastic, and operational aspects of power system behavior. It allows the analysis of various disturbance types, the evaluation of the effectiveness of protection and recovery strategies, and the formulation of quantitative resilience metrics suitable for both scientific research and practical tasks related to energy security.

## Research Methodology

The research methodology employed in this study is based on the development of a hybrid stochastic–deterministic model designed to analyze the resilience of EPS under large-scale external disturbances. The core idea of the approach lies in combining physical equations governing frequency dynamics and power-flow redistribution with probabilistic models describing random shocks, equipment failures, and recovery processes. This integrated framework enables the assessment of EPS behavior under uncertainty and facilitates the derivation of quantitative resilience indicators[1].

### General Structure of the Model

The EPS is conceptualized as an electrical network composed of nodes (generators and loads) and links (transmission lines) representing system elements. Each node is characterized by inertia, damping, and primary frequency response parameters, while transmission lines are constrained by thermal and stability limits[2].

The continuous part of the model describes the time evolution of system frequency and power-flow distribution as functions of power imbalance. These processes are computed using simplified dynamical equations numerically integrated with small time steps.

Superimposed on this physical layer is a discrete event-driven layer that simulates external shocks, equipment failures, protection actions, and recovery processes. Each event alters the state of the EPS, resulting in the disconnection of system elements, reduction of load, or, conversely, the restoration of equipment. By combining continuous dynamics with discrete stochastic transitions, the model produces a comprehensive representation of EPS evolution under random disturbances[3].

### Stochastic Component

External disturbances are modeled using a random process, specifically, a Poisson process with parameter $\lambda$, which determines the expected number of shocks per unit time. To capture the behavior of large-scale, high-impact disturbances, heavy-tailed distributions (such as Pareto or log-normal) are applied. Each shock is characterized by its destructive magnitude, the number of affected system components, and the time of occurrence[4]. Recovery processes are modeled using random variables with exponential distributions. By selecting appropriate parameter values, the model accounts for varying repair durations of lines and generators. As a result, the EPS is represented as a collection of elements existing in

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[1] Federico Milano, *Power System Modelling and Scripting,* Springer, London, 2010, pp. 1–10

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one of three states—operational, disconnected, or under repair—with stochastic transitions occurring between them[1].

### Power System Response and Protection Mechanisms

In the proposed model, each external event induces a change in the topology of the electrical network and triggers a redistribution of power flows. When a power imbalance persists for a specified duration, the affected system element, either a transmission line or a generator, is disconnected by the automatic protection system[2].

In addition, the model incorporates a multi-stage UFLS scheme activated when system frequency falls below predefined thresholds. When the frequency reaches a critical level, a portion of the load is shed, thereby preventing further degradation of system stability and avoiding the onset of a systemic collapse[3].

### Simulation Procedure

System resilience is assessed using a Monte Carlo simulation framework. For each scenario, the occurrence times of external shocks, as well as the sequence of equipment failures and recoveries, are generated randomly. Between these stochastic events, the model performs numerical integration of the dynamic equations while accounting for system responses and protection actions[4]. At the end of each simulation run, all key parameters, including system frequency, power flows, shed load, and the operational states of system components—are recorded. This procedure is repeated many times (up to several hundred runs), enabling statistically reliable estimates of the probability of system failures and recovery-related performance metrics[5].

### Model Parameters and Input Data

The computational experiments employ the following model parameters: peak system load of 12,000 MW; available power reserve (PR) ranging from 5% to 25%; shock arrival rate $\lambda$ varying from 0 to 0.05 events per hour; Pareto distribution parameter $\alpha = 2$; generator recovery times ranging from 4 to 24 hours; and transmission line recovery times ranging from 2 to 12 hours[6]. The modeled EPS is assumed to exhibit an inertia level on the order of 10–100 arbitrary units. The UFLS mechanism is represented by a three-stage scheme: disconnection of 5% of peak load at a frequency drop to 49.0 Hz; an additional 10% at 48.5 Hz; and a further 20% at 48.0 Hz. In the simplest case, as illustrated in Figure 1, the simulation is performed using a single UFLS threshold, disconnecting 5% of the load at 49.0 Hz, followed by a continuous frequency decline down to 48.0 Hz without any additional load shedding.

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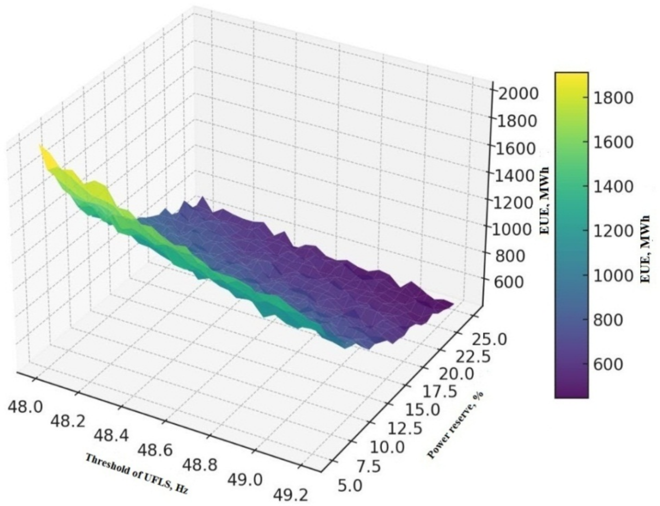

**Figure 1.** Dependence of the expected undelivered energy (EUE) on the volume of activated power reserve (PR) and the threshold of UFLS[1]

### Resilience Metrics, Validation, and Reproducibility

Based on the simulation results, the following model indicators are computed: EUE, TTR, $P_{collapse}$, and RI. These probabilistic metrics enable comparative evaluation of different disturbance scenarios and assessment of the effectiveness of various resilience-enhancing measures[2]. Model validation is carried out using baseline scenarios-stable system operation without shocks, single-element outages, and typical UFLS activation patterns. Numerical accuracy is ensured through adaptive integration methods and checks based on the energy conservation principle[3]. All stages of the simulation process are fully formalized, ensuring reproducibility of results and facilitating the application of the model in practical research on energy security.

### Numerical Modeling Tools

To implement the proposed model in practice, a modular computational architecture was employed, ensuring flexibility, scalability, and reproducibility of results. The model was tested using several computational environments - Python, MATLAB, and Julia - each offering distinct advantages for specific components of the simulation framework. Python served as the primary platform for implementing the stochastic–deterministic scheme. Using the NumPy and SciPy libraries, numerical integration of differential equations describing frequency dynamics and power-flow redistribution was performed. The panda power package was used for calculating electrical power flows under varying line and generator states. For executing multiple Monte Carlo simulations, the joblib library enabled efficient parallelization across multiple processor cores, thereby ensuring statistical reliability of the results within reasonable computation time.

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MATLAB was used to verify the continuous dynamics of the power system and the relay protection algorithms. The SimEvents toolbox allowed the implementation of the discrete event-driven component of the model, including the generation of random shocks, protection actions, and restoration schedules. MATLAB's strengths in visualizing time-domain processes and conducting parameter sensitivity analyses made it suitable for validating the physical layer of the model and ensuring consistency between its stochastic and dynamic components. Julia was employed to optimize the computational performance of the experiments. The DifferentialEquations.jl and PowerModels.jl packages provide high-speed numerical solvers for systems of equations. Combining Python-like syntax with C-level execution performance, Julia represents a promising platform for further developing the model-particularly in the direction of parallel simulations and cloud-based computations. The architecture of the implemented model consists of several modular components, including:

- a shock-generation module, which determines the timing and frequency of random external impacts;
- a dynamic integration module, responsible for numerically solving the equations governing system frequency and power flow;
- a protection module, implementing UFLS algorithms;
- a recovery module, modeling probabilistic repair processes;
- analytical modules calculating the resilience metrics (EUE, $P_{collapse}$, TTR, RI).

Data exchange among modules is handled through unified data structures, enabling easy modification of model parameters, the integration of additional computational components, or replacement of existing ones. Owing to this architecture, the developed computational environment can be used not only for academic research but also for applied purposes, such as risk assessment, operator training, or analysis of post-fault restoration strategies.

## Discussion of the Results

The simulation results demonstrate that integrating deterministic and stochastic approaches enables a more comprehensive representation of power system behavior under diverse external disturbances. The analysis of the resulting probabilistic resilience metrics provides insights into the relationship between the structural properties of the EPS, the configuration of its protection mechanisms, and the likelihood of systemic collapse. Several of the obtained results - expressed as functional dependencies of key resilience metrics on the model parameters - are presented in Figures 1-3.

The EUE metric characterizes the expected amount of energy not delivered to consumers as a result of power imbalance. In general, lower EUE values indicate that the power system is more effective at withstanding shocks and restoring its normal operating state more rapidly. Special attention is given to the influence of parameters related to power reserves and the UFLS scheme on the behavior of the modeled EPS. As shown in Figure 1, EUE decreases as the available spinning reserve (PR) increases. It should also be noted that higher reserve capacity leads to smaller frequency deviations and a reduced probability of system collapse. Appropriately selected activation thresholds of the UFLS stages ensure early and proportionate load shedding, thereby preventing the development of cascading outages. However, excessively aggressive UFLS settings may result in unnecessary load disconnections and an increase in EUE, highlighting the need for an optimal balance between UFLS response speed and service continuity. The TTR metric represents the average time required for the EPS to recover to at least 90% of its initial service level. Its value is directly influenced by the rate of repair processes, availability of reserve capacity, and the coordination of operator actions. As illustrated in Figure 2, TTR decreases - similar to EUE - with increasing PR, and rises as the shock arrival rate grows.

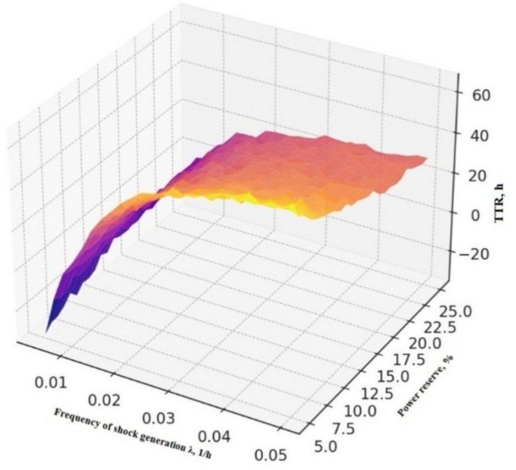

**Figure 2.** Dependence of the mean time to recovery (TTR) on the frequency of shock generation (λ) and the volume of power reserves (PR)[1]

The probability $P_{collapse}$ is defined as the fraction of scenarios in which large-scale consumer outages occur. A decrease in this metric indicates improved overall resilience of the EPS. The effect of shock frequency on $P_{collapse}$ is presented in Figure 3.

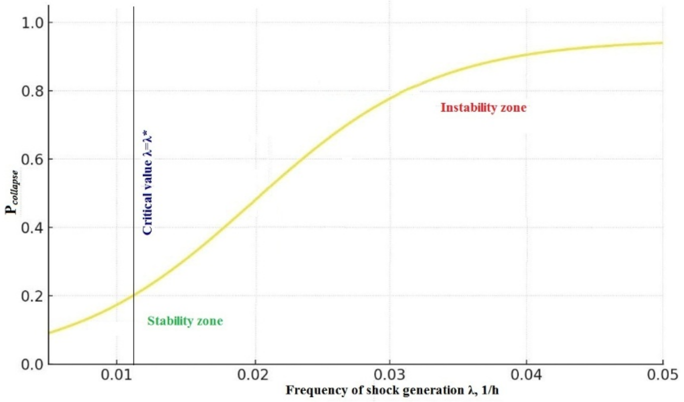

**Figure 3.** The dependence of the probability of system collapse ($P_{collapse}$) on the frequency of shock generation (λ). The λ parameter has a critical value of λ*=0.01125[2]

The RI captures the integral dynamics of the service level over time, indicating how rapidly the EPS restores its functionality after a disturbance or failure. This index is particularly useful for selecting and comparing alternative protection and recovery strategies.

Analysis of scenarios with varying shock arrival rates λ demonstrates that the modeled system exhibits a nonlinear relationship between resilience metrics and the frequency of external disturbances (see Figures 2 and 3). At low values of λ, the EPS remains stable because the recovery time is short; however, when λ exceeds a critical threshold λ = λ*, a pronounced increase in the probability of system collapse is observed (Figure 3),

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[1] Authors' own simulation results

[2] Authors' own simulation results

accompanied by a corresponding increase in recovery time (Figure 2). This behavior indicates the presence of a limiting regime beyond which the EPS transitions into a collapse state, resulting in large-scale disruption of electricity supply. The significance of the obtained results lies in the ability to derive quantitative assessments of the consequences of various emergency scenarios, predict reserve and resource requirements, determine restoration priorities, and optimize protection parameters. Thus, the proposed model can serve as a decision-support tool for operators and regulators, as well as for strategic planning and risk analysis in the broader context of energy security.

## Conclusions

The conducted study enabled the development and validation of a stochastic–deterministic model designed to analyze the resilience of EPS under large-scale external disturbances. Unlike traditional approaches that rely solely on deterministic descriptions, the proposed model integrates the physical dynamics of the electrical network with stochastic processes representing random factors affecting the EPS. This integration provides a more realistic representation of system behavior during crisis conditions.

The developed methodology allows for the quantitative assessment of the probability of system collapse, the integral resilience index, the average recovery time, and the expected amount of unserved energy under various disturbance scenarios. Through multiple Monte Carlo simulations, statistically robust results are obtained, while the introduced metrics (EUE, TTR, RI, and $P_{collapse}$) enable comparative evaluation of different operating regimes and protection configurations.

The minimal nature of the model is achieved through the use of an approximate frequency-dynamics description based on the swing equations, without incorporating the detailed internal processes of generators. This simplification enables high-speed Monte Carlo simulations while accounting for the stochastic nature of numerous events within the EPS, including external shocks, protection actions, equipment failures, and recovery processes.

The practical applicability of the model follows from its ability to support planning and evaluation of diverse measures aimed at enhancing energy security using well-defined resilience metrics. The model can be employed by system operators, regulators, and expert organizations to justify decisions related to reserve and resource management, tuning of emergency automation, and the development of infrastructure restoration plans.

Future development of the model may include incorporating additional external and internal factors into scenario analyses, extending the recovery module to account for variable restoration priorities, and introducing a feedback module based on real-time grid monitoring data. Such enhancements will support the creation of a universal platform for assessing the resilience of critical energy infrastructure under growing hybrid risks.

In summary, the proposed model constitutes a resilience analysis tool for power systems that effectively combines engineering and probabilistic approaches and contributes to the advancement of the scientific foundations of energy security.

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