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# Economic Modeling of Energy Security of Distributed Power Systems in the Post-Crisis Period: Scenario Analysis and Assessment of Tail Risks

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## Abstract

This study investigates the transformation of energy security in distributed energy systems under growing uncertainty, geopolitical shocks, and fuel market volatility. A risk-based multi-objective optimization framework is proposed that integrates economic performance (LCOE, CAPEX, and OPEX), system reliability, and systemic risk measured by Conditional Value-at-Risk (CVaR). The empirical analysis is based on European electricity market data for 2010–2025 and combines historical analysis with stochastic scenario generation and Monte Carlo simulation to evaluate the impacts of exogenous shocks. The results reveal a structural shift in the European electricity market after 2021, characterized by increased sensitivity to fuel price fluctuations and a transition to a more volatile operating regime. Although a higher share of renewable energy improves economic and environmental performance, it does not ensure system resilience without complementary flexibility measures, including energy storage and demand-side management. The proposed framework demonstrates that integrating these measures substantially reduces systemic risk under crisis conditions. The analysis also identifies a persistent post-crisis risk pattern, reflected in elevated CVaR values after market stabilization, which is consistent with the hypothesis of risk hysteresis. Rather than proving hysteresis, the results indicate sustained risk persistence following major external shocks. The proposed framework extends existing approaches to energy security assessment by integrating economic efficiency, reliability, and risk within a unified optimization model. Its modular structure enables adaptation to different electricity markets through recalibration of local parameters, providing a practical decision-support tool for strategic planning under uncertainty.

**Keywords:** energy security; distributed energy systems; fuel price volatility; Conditional Value-at-Risk (CVaR); multi-objective optimization; scenario analysis; structural break

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## 1. Introduction

Modern energy systems operate in conditions of growing turbulence caused by a combination of geopolitical conflicts, structural transformation of energy markets, and accelerated transition to a low-carbon economy. Especially since 2021, global and European energy markets have shown a sharp increase in volatility, accompanied by supply volatility, fuel price fluctuations, and increased systemic risks [1,2]. Under these conditions, energy security ceases to be exclusively a matter of security of supply and is transformed into a complex multidimensional category encompassing economic efficiency, risk resilience, and adaptability of energy systems [3,4].

Traditional approaches to energy security analysis are based on the principles of minimizing costs and ensuring continuity of supply. However, such approaches are insufficient to describe the behavior of modern distributed power systems, which are characterized by a high share of renewable energy sources, decentralization of generation, and a significant dependence on external shocks. The integration of renewable energy, despite its positive impact on decarbonization, increases generation variability and complicates system balance management [5,6].

Despite the significant development of research in the field of energy security and optimization of energy systems, a number of conceptual and methodological gaps remain in the modern scientific literature. First, most existing models focus on optimizing individual criteria, such as cost-effectiveness, reliability, or environmental performance, while integrating these characteristics into a single risk-based optimization model remains underdeveloped [7,8]. Secondly, the long-term effects of crisis phenomena on the functioning of distributed energy systems have not been sufficiently studied, especially taking into account the structural changes that have occurred in the European energy market since 2021 [9,10]. Third, existing approaches predominantly assess medium risks, while the estimation of extreme losses and tail risks in the optimization process is used in a limited way [11,12]. In addition, methodological approaches to the management of operating resources of energy supply companies, proposed by Chukhrai, Sorochak, and Bokhonko [13], are mainly considered at the level of individual enterprises and are not yet sufficiently integrated with multi-criteria models of optimization of energy systems at the macro level. Taking into account these gaps, this study aims to form an integrated methodological framework that combines economic criteria, systemic risk assessment, and reliability indicators in a single multi-criteria optimization procedure. Based on the identified research gaps, the following working hypotheses are formulated in the work:

**H1.** *The elasticity of transmission of fuel price shocks into electricity prices in the post-crisis period (2021–2025) is significantly higher than in the pre-crisis period (2010–2020).*

**H2.** *The integration of energy storage systems and demand management mechanisms provides a significant reduction in systemic risk, as measured by the Conditional Value-at-Risk (CVaR) indicator, compared to configurations that do not use these tools.*

**H3.** *After the end of crisis shocks, there is a steady persistence of an increased level of systemic risk, which is compatible with the hypothesis of risk persistence and needs to be taken into account during strategic planning for the development of energy systems.*

The aim of the study is to develop, mathematically substantiate, and empirically test a multi-criteria risk-based model for optimizing the energy security of distributed energy systems, which integrates indicators of economic efficiency, systemic risk, and reliability to support management decision-making in conditions of high uncertainty.

The main contributions of this research are as follows:

A multi-criteria risk-based optimization model has been developed, which integrates LCOE, CAPEX, OPEX, CvaR, and reliability characteristics into a single optimization function.

A methodological approach combining scenario analysis, stochastic Monte Carlo modeling, and multi-criteria optimization for estimating the impact of exogenous crisis shocks on the functioning of distributed energy systems has been proposed.

An empirical assessment of structural changes in the European electricity market based on data for 2010–2025 is carried out and the change in the risk characteristics of the system in the pre-crisis, crisis, and post-crisis periods is analyzed.

It is substantiated that the use of integrated flexibility tools, in particular energy storage systems and demand management mechanisms, contributes to reducing systemic risk and increasing the resilience of distributed energy systems.

The scientific novelty lies in the creation of an integrated risk-based methodology for optimizing energy security, which, in contrast to existing approaches, combines economic efficiency, technical reliability, and assessment of extreme risks using CVaR within a single mathematical model. The methodology is complemented by scenario modeling of crisis events and stochastic analysis, which provides an assessment of the resilience of energy systems in conditions of high uncertainty. In addition, the study expands current approaches to the analysis of post-crisis dynamics of systemic risk by assessing the sustained persistence of elevated CVaR values after the end of crisis impacts as an empirical manifestation of risk inertia compatible with the hypothesis of risk hysteresis. The practical value of this study lies in the proposed model's potential for use by public administration, transmission, and distribution system operators, energy companies, and investors to substantiate strategies for the development of distributed generation, evaluate investment decisions, form programs to increase the flexibility of energy systems, and minimize systemic risks in the context of crisis phenomena and high market uncertainty.

## 2. Literature Review and Theoretical Foundations

The modern literature on energy economics considers energy systems as stochastic multidimensional environments in which uncertainty, geopolitical instability, and price volatility jointly shape system performance indicators and investment decisions. Energy security is no longer interpreted as a purely deterministic engineering constraint—instead, it is understood as a dynamic problem of economic equilibrium under conditions of uncertainty, where cost efficiency, reliability, and system stability interact nonlinearly [4,5].

Conceptually, the analytical apparatus of this study is based on four thematic blocks within the literature: (1) methodology of multi-criteria optimization of power systems; (2) the risk-based approach and CVaR as a measure of tail risks; (3) transmission of fuel shocks and structural changes in the market; (4) the role of system flexibility and renewables in the post-crisis period.

Multi-criteria optimization of power systems: Previous classic works [7,8] have formed a paradigm of multi-energy systems (MES), in which optimization models move from a single-criteria approach to cost minimization to an integrated analysis of economic, technical, and environmental parameters. Ueckerdt et al. [14] introduced the concept of system costs of renewable energy integration, which takes into account not only direct capital costs but also the cost of balancing the system. In recent studies [15,16], the MES paradigm has evolved toward accounting for antifragility—the ability of a system not only to withstand shocks, but also to adapt to them. At the level of individual energy supply companies, methodological tools for optimizing resource allocation to reduce operational losses have been developed in [13], forming an important micro-level context for macro-level models of multi-criteria optimization.

Risk-based assessment and CvaR: The methodological basis of CVaR optimization was laid down in the fundamental work of Rockafellar and Uryasev [17]. Further development of the method for energy applications was later presented in multiple papers [11,12], while another [18] demonstrated that CVaR metrics better reflect the tail risks of European energy markets. A methodologically related approach to risk assessment is developing within the framework of financial security of enterprises: earlier work [19] systematized the tools for assessing financial security, emphasizing the need for an integrated analysis of tail risks and structural indicators of resilience—a conceptual logic that finds a direct parallel in the proposed integration of CVaR with the indicator of economic resilience.

Transmission of fuel shocks: Empirical studies [1,9,10] confirm the strengthening of spillovers between fossil fuel markets and electricity markets after the 2022 energy crisis. One study [2] records the transition of the European market to a state of sustained high volatility, while another [20] shows that consumer price expectations become an additional channel for the transmission of shocks. Still others [21,22] demonstrate the asymmetric effects of geopolitical risks on the fossil and renewable energy markets.

System flexibility and the role of renewables: Wang and Tian [5] show that the integration of renewables reduces average costs, but increases the dispersion of generation. Tugcu and Menegaki [6] investigate the "renewable energy-security" relationship in panel data and capture a positive but nonlinear effect; Neumann and Brown [16] analyze pricing in renewable-dominated systems. Three previous studies [23–25] form a methodological framework for assessing flexibility through demand response and energy storage mechanisms. A separate aspect that has so far not been sufficiently integrated into flexibility models concerns the organizational and communication component of the functioning of energy companies: Malynovska et al. [26] demonstrate, using the example of the energy sector, that the efficiency of communication units directly affects the quality of implementation of adaptive solutions in crisis conditions. In addition, since the management of modern distributed power systems (smart grids) relies heavily on digitalization, ensuring their operational flexibility requires the transformation of traditional approaches and the implementation of adaptive business models, the effectiveness of which during crises is best studied using the example of the highly dynamic IT sector [27].

Despite significant methodological advances, there are several gaps: (1) the integration of CVaR assessment with structural fracture analysis in a single model remains fragmented; (2) the effect of risk inertia (path dependency) is rarely formalized as a separate empirically verifiable category. This article addresses these gaps within a single multi-criteria model.

In order to clearly define the methodological differences of the proposed approach, Table 1 shows a comparison of its main characteristics with the most common multi-purpose models of optimization of energy systems. The comparison covers key optimization criteria, risk assessment methods used, uncertainty modeling approaches, validation procedures, and the ability to account for crisis scenarios. This allows us to demonstrate that the proposed model does not replace existing approaches, but expands their capabilities by integrating economic efficiency, technical reliability, stochastic modeling, and systemic risk assessment in a single multi-criteria optimization environment.

**Table 1.** Comparison of the proposed optimization framework with existing multi-objective optimization models.

| Comparison Criterion | Traditional Multi-Purpose Models | Proposed Model |
|---|---|---|
| Main goal of optimization | Minimizing the cost or $CO_2$ emissions | Minimizing cost and risk and maximizing sustainability at the same time |
| Economic indicators | Mostly CAPEX or total costs | Integrated LCOE, CAPEX, OPEX, fuel costs, power losses, and deficit costs |
| Risk assessment | Predominantly absent or used variance or VaR | CVaR for assessing extreme risks |
| Considering uncertainty | Deterministic or scenario models | Monte Carlo simulation (10,000 scenarios) |
| Power system reliability | Partially taken into account | Integrated as one of the optimization criteria |
| Risk of power shortage | Generally, not modeled separately | Explicitly evaluated through an indicator (Rdef) |
| Crisis scenarios | Usually not taken into account or considered in a limited way | Price shocks, fuel supply disruptions, and sudden changes in demand are taken into account |
| Type of energy system | Centralized power systems or separate technologies | Distributed power system (PV, wind, BESS, gas microturbine, microgrid) |
| Optimization function | One- or two-criterion | Multi-criteria integrated function with weighting factors |
| Practical orientation | Planning the development of energy under stable conditions | Supporting decision-making in the face of crises, high uncertainty, and market volatility |

## 3. Methodology

The presentation of our methodology is built according to the following logic: first, the conceptual architecture of the proposed framework and the assumptions underlying it are presented, then the mathematical formulation of the multi-criteria optimization problem, after which the empirical base, calibration procedure, and scenario design are characterized, and the section ends with a description of validation and sensitivity analysis.

### *3.1. Conceptual Framework and Model Architecture*

The proposed multi-criteria optimization model (Figure 1) is designed to support decision-making with respect to the development of distributed energy systems under conditions of high uncertainty and crisis impacts and is based on the principles of stochastic optimization and uncertainty accounting [11,12], whereby energy security is defined as a function of the costs, risks, and systemic adaptability of distributed energy systems.

### *3.2. Model Assumptions and Practical Applicability*

To ensure mathematical correctness and computational efficiency, a number of assumptions were made during the construction of the model.

First, the study is based on the assumption that the energy system under analysis is a typical distributed system that includes photovoltaic (PV) installations, wind farms, battery energy storage systems (BESS), gas microturbines, and local microgrids.

Secondly, the model uses aggregated annual statistical data for the period 2010–2025, so short-term operational processes, hourly operating modes of equipment, seasonal load fluctuations and features of power system balancing are not considered.

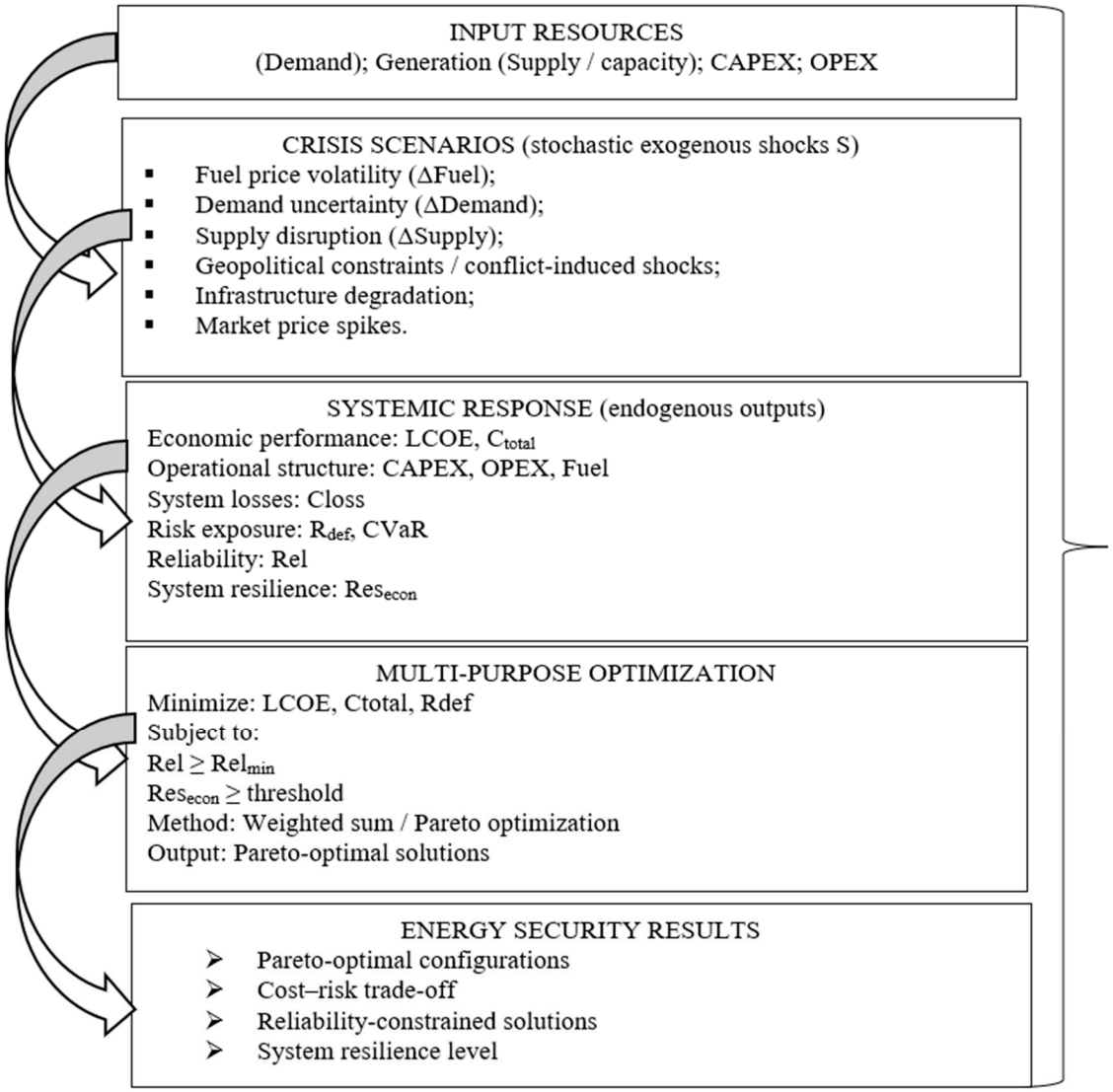



**Figure 1.** Structural–logical model of technical and economic optimization of energy safety of distributed power systems in the face of crisis impacts. Note: Developed by the authors based on optimization of stochastic energy systems and CVaR-based risk modeling approaches.

Thirdly, uncertainty is described using Monte Carlo scenario modeling, which takes into account possible changes in fuel prices, fluctuations in demand, and disruptions in the supply of energy resources. It is assumed that the formed scenarios provide a sufficiently representative reflection of the potential crisis conditions encountered in the functioning of energy systems.

Fourth, risk assessment is carried out using the CVaR indicator, which characterizes expected losses in the most adverse scenarios and is a more informative indicator compared to using only average or expected cost values [3,4].

Fifthly, the weighting factors of the target optimization function are considered normalized and can vary depending on the strategic priorities of state policy or management decisions. To confirm the stability of the results obtained, an analysis of the sensitivity of the model to changes in these coefficients was carried out.

A feature of the proposed approach is the integration of the fuel variable, which acts as a key endogenous driver of instability, which is consistent with current research on the volatility of energy markets [10,18]. The crisis environment is modeled as a set of external and internal shocks that disrupt the balance of electricity supply and demand and increase the volatility of economic parameters [1,2,9]. In the period after 2021, the following main types of shocks were identified: geopolitical restrictions on the supply of energy resources; price volatility of fuel markets; infrastructure damage; technical degradation of generating assets; structural uncertainty of demand. The formalization of crisis impacts is carried out through the Shock Matrix, which describes the change in key economic variables (CAPEX, OPEX, fuel, LCOE, scarcity risk, and reliability) under the influence of Si scenarios. The empirical analysis is based on the panel structure of time series for the period 2010–2025, where the unit of observation is a calendar year with aggregated technical and economic indicators of the power system. Scenario segmentation was used to account for structural fractures: 2010–2020—stable mode; 2021—transitional crisis breakdown; 2022–2025—highly volatile crisis regime.

In the proposed study, scenario modeling is based on normal and lognormal distributions of random variables, which provide sufficient statistical stability to model typical crisis scenarios and correspond to approaches common in energy market studies. At the same time, such assumptions may not accurately reflect the extreme events with "thick tails" characteristic of periods of deep energy crisis. Therefore, the proposed model may underestimate the probability of the implementation of the most unfavorable scenarios. A promising area of further research is the integration of heavy-tailed distributions (in particular, Student's t and generalized Pareto distribution), which will allow for more accurate consideration of the asymmetry of distributions and complex relationships between key risk factors.

### *3.3. Mathematical Formulation of the Model*

To ensure comparability, index rationing (2010 = 100) is used, which eliminates the impact of inflationary and currency fluctuations. The total costs of the energy system are defined as the sum of capital expenditures ($CAPEX$), operating costs ($OPEX$), costs related to electricity losses in the grid ($C_{loss}$), and energy deficit costs ($C_{deficit}$). The economic structure of the energy system is described in terms of aggregate costs:

$$C_{total} = CAPEX + OPEX + C_{loss} + C_{deficit}, \quad (1)$$

where $C_{total}$ is total system cost, reflecting total costs during the analysis period; $CAPEX$ denotes capital expenditures related to investments in the construction, modernization and expansion of energy infrastructure (generation, grids, energy storage, etc.); $OPEX$ denotes operating costs, which include operation, maintenance, personnel, fuel and other operating costs of the system; $C_{loss}$ denotes costs associated with electricity losses in the network (transmission and distribution losses), including technical and partially commercial losses; and $C_{deficit}$ denotes energy deficit costs (cost of energy deficit/unmet demand cost), reflecting economic losses due to unmet demand or restrictions in the supply of electricity.

The levelized cost of electricity (LCOE) is defined as the ratio of the total costs, including capital expenditures (CAPEX), operating costs (OPEX), and fuel costs (Fuel), to the total amount of electricity produced during the analysis period. The LCOE estimation approach takes into account the systemic costs of integrating renewable energies [14]. The LCOE level is defined as:

$$LCOE = \frac{\sum (CAPEX + OPEX + Fuel)}{\sum Energy}, \quad (2)$$

where LCOE is the cost of electricity production, which reflects the average cost of 1 unit of electricity produced for the entire life cycle of an energy facility; *Fuel* is the cost of fuel needed for electricity generation (relevant for thermal, gas, and hybrid generation systems), which reflects energy costs and is a key source of economic instability in crisis conditions; and *Energy* is the total amount of electricity produced during the calculation period or during the life cycle of the facility.

Risk of energy deficiency $R_{def}$ is defined as the probability of excess of demand for electricity over available supply, which is formally expressed as:

$$R_{def} = P(Demand > Supply), \tag{3}$$

where $R_{def}$ is the probability of an energy deficit, which characterizes the risk of not meeting the demand for electricity in the system, and $P(Demand > Supply)$ is the likelihood that the demand for electricity exceeds the available supply (generation and/or import), resulting in a shortage of power in the power system.

The Electricity Supply Reliability Index is defined as the proportion of electricity demand met and is calculated as a unit minus the ratio of the volume of energy deficit to total demand. Reliability of the system:

$$Rel = 1 - \frac{Energy_{deficit}}{Energy_{demand}}, \tag{4}$$

where $R_{el}$ denotes electricity supply reliability index, which characterizes the ability of the energy system to meet the demand for electricity; $Energy_{deficit}$ is the volume of unmet demand for electricity (energy shortage) arising from generation restrictions, network restrictions, or extreme modes of system operation; and $Energy_{demand}$ is the total electricity demand for the period under review.

Systemic risk is further assessed through the CVaR indicator, which is used to assess tail risks, a standard approach in risk-aware optimization [17].

Economic sustainability of the system $Res_{econ}$ is defined as inversely proportional to the volatility of the total costs of the energy system and is calculated as the inverse of their standard deviation. The economic sustainability of the power system is defined as the inverse function of the variation of aggregate costs:

$$Res_{econ} = \frac{1}{\sigma\left(C^{total}\right)}, \tag{5}$$

where $Res_{econ}$ represents the economic resilience of the energy system, which reflects the ability of the system to maintain cost stability over time under conditions of uncertainty and shocks; $\sigma\left(C^{total}\right)$ is the standard deviation of the total costs of the energy system $C^{total}$, used as a measure of their variability (volatility) during the analysis period; and $C^{total}$ denotes the aggregate energy system costs, including CAPEX, OPEX, energy losses, and deficit costs.

The proposed model is based on 3 blocks of indicators (Table 2):

- Economy: LCOE, *Ctotal*;
- Risk: CVaR (systemic financial/cost risk), $R_{def}$ (risk of deficiency);
- Reliability/stability: Rel або $Res_{econ}$

The general optimization task is formulated as multi-criteria:

$$min\ Z = w_1\ LCOE + w_2\ C_{total} + w_3\ R_{def} + w_3\ CVaR + w_4\ R_{def} - w_5\ Res_{econ}, \tag{6}$$

where $R_{def}$ is risk of power shortages, and $Res_{econ}$ is the integral indicator of economic stability of the system. Each criterion corresponds to a separate weight coefficient; variable $R_{def}$ is included in the target function once, and the reliability index Rel, specified as a constraint and not as a component of the target function, is under conditions:

$$Rel \geq Rel_{min}, \quad Res_{econ} \geq Res_{threshold},$$

where $Z$ is the target function (objective function), that is, a generalized indicator that we optimize; $CVaR$ is the risk of losses in crisis scenarios (necessarily separately); $R_{def}$ is the operational risk of shortage; $Res_{econ}/R_{el}$ is the opposite effect (therefore with the sign "–"); $LCOE$, $C_{total}$ represent different levels of costs (not duplicated, because LCOE = normalized cost, and Ctotal = system costs); and $w_1$, $w_2$, $w_3$ are weighting factors reflecting priorities among cost-effectiveness, cost, and risk.

**Table 2.** Integrated components of the CVaR-oriented model.

| Group | Showman | Description | Role in the Model |
|---|---|---|---|
| Economic costs | LCOE | Present cost of electricity | Cost minimization |
| Economic costs | $C^{total}$ | Total costs (CAPEX, OPEX, losses, deficit) | Overall economic efficiency |
| Risk | CVaR | Expected losses in the tail of the distribution | Minimization of crisis losses |
| Risk | $R_{def}$ | Probability of energy deficiency | Balance of supply and demand |
| Sustainability | $Res_{econ}$ | Inverse cost volatility | Improve system stability |

Note: Developed by the authors on the basis of a synthesis of the literature on CVaR-oriented optimization of energy systems and distributed generation [7,8,17]. The classification of indicators and their description and integration into the proposed optimization framework constitute the original contribution of this research.

Although LCOE and $C^{total}$ are related to economic costs, they characterize different levels of economic valuation. LCOE is a specific measure of the cost of producing a unit of electricity over the life cycle of a technology and is used to compare alternative generation technologies, while $C^{total}$ characterizes the total system costs of the operation of the energy system, including capital investments, operating costs, fuel costs, and costs related to energy shortages.

In the baseline scenario of the study, they are normalized in such a way that

$$\sum_{i=1}^{5} w_i = 1, \quad w_i \geq 0, \tag{7}$$

where $w_1 \ldots w_5$ are weighting factors reflecting the relative importance of the present cost of electricity, aggregate system costs, systemic risk, deficit risk, and economic sustainability, respectively. Their normalization provides a balanced contribution of each criterion to the integral optimization function.

The weights were determined using the Analytic Hierarchy Process (AHP) based on expert paired comparisons of the criteria. The resulting local priorities were normalized and used as weights of the target function.

To check the stability of the results obtained, a sensitivity analysis was performed by varying the weight factors within ±20%, which showed the invariance of the main conclusions regarding the optimal configuration of the system.

This indicator reflects the ability of the system to maintain cost stability in various scenarios of crisis impacts.

Crisis influences are integrated through the scenario vector $S$, which modifies the basic parameters of the system:

$$X^* = X + \Delta S; \tag{8}$$

$$X \in \{CAPEX,\ OPEX,\ Fuel,\ LCOE\}. \tag{9}$$

This approach provides a transition from a static cost-minimization model to an adaptive scenario-oriented assessment of distributed energy systems.

This classification is the basis for further scenario analysis.

In the baseline scenario, the power system demonstrates a balanced configuration with a moderate share of renewable sources and controlled dependence on fuel generation.

The role of multi-component power systems and flexibility is emphasized in research on multi-energy systems [7,8]. The problem is solved through multi-criteria optimization (weighted sum approach), scenario analysis of crisis states, stress testing of the system, and comparison of Pareto-optimal configurations. The proposed methodology provides integration of economic, technical and risk parameters; formalization of Fuel as an endogenous driver of instability; scenario modeling of crisis conditions; transition from cost-minimization to risk-aware optimization; and a basis for assessing energy security in conditions of high volatility. It interprets energy security as an integral characteristic formed as a result of the interaction of the costs, risks, and reliability of the power system. The target function reflects the trade-off between minimizing economic costs (LCOE, $C^{total}$) and reducing the systemic risk of deficit ($R_{def}$), provided that a minimum level of reliability ($Rel$) and economic sustainability ($Res_{econ}$) is ensured. The fuel variable plays a key role in the model as a channel for the transmission of external shocks to the system, since it determines the variable component of costs and is characterized by the greatest volatility in the conditions of crisis impacts. The increase in Fuel values directly affects the increase in LCOE and total costs, and also indirectly increases the risk of shortages due to generation instability. The CVaR indicator is used to assess systemic risk in conditions of uncertainty and reflects potential losses in extreme (crisis) scenarios. This allows the progression from average risk assessments to tail risk analysis, which is critical for energy systems during periods of high volatility. The scenario approach ensures the adaptability of the model, allowing behavior assessment of the system under different types of crisis shocks (fuel, demand, infrastructure). The integration of the Shock Matrix formalizes the influence of external factors on the key parameters of the model and allows us to switch to stress-testing of the power system.

Thus, previous research [7,8] forms the basis for the transition to a multidimensional assessment of energy systems that takes into account cost-effectiveness, reliability, and sustainable development. Developing these approaches, the proposed model expands them by integrating risk-based indicators and adaptability of the system in conditions of uncertainty. The proposed model reflects the transition from the traditional paradigm of cost minimization to a multidimensional risk-based optimization of energy security, which integrates economic efficiency, risks, and adaptability of the energy system in conditions of uncertainty. The proposed model is empirically implemented on the basis of long-term data of the European electricity market for the period 2010–2025. The dataset contains aggregate indicators of energy prices, cost structures, and system performance, allowing for analysis of both pre-crisis and crisis periods.

### *3.4. Empirical Base, Data Sources, and Calibration*

The methodology of the study is formed on the basis of a combination of statistical analysis, scenario modeling, and CVaR-oriented multi-criteria optimization of energy systems. The empirical basis comprises long-term data of the European electricity market

for 2010–2025, obtained from the databases of the International Energy Agency (IEA) and Eurostat, covering electricity prices, generation structures, fuel volatility, and the level of penetration of renewable energy sources.

The use of annual time aggregation provides an opportunity to analyze long-term structural changes in energy security and compare economic and technical indicators within a single timeline. At the same time, this approach may not fully reflect short-term price volatility, seasonal effects, and rapid changes in the modes of operation of energy systems, which are important for assessing operational risks. Therefore, the proposed model is intended primarily for strategic analysis and support for long-term management decisions. It is advisable to focus further research on the use of monthly, daily, or hourly data, in particular from the ENTSO-E Transparency Platform, which will increase the accuracy of short-term risk assessment and improve the calculation of the CVaR indicator.

To ensure the reproducibility of the results and increase the methodological validity of the scenario analysis, the evaluation of the functioning of distributed energy systems was carried out using stochastic modeling within the framework of a CVaR-oriented optimization approach. The simulation was based on a combination of scenario analysis and the Monte Carlo method, which made it possible to take into account the uncertainty of key parameters of the energy market and assess the behavior of the system in the face of crisis shocks. The stochastic simulation included 10,000 iterations for each scenario (baseline scenario, fuel price shock, demand surge, supply disruption). Within each iteration, random trajectories of changes in the main input parameters of the system were generated: fuel prices, electricity demand level, availability of generating capacity, share of renewable energy sources (RES penetration), and level of use of energy storage systems (BESS utilization). The variation parameters were formed on the basis of the historical series of the International Energy Agency (IEA) and Eurostat for the period 2010–2025 [28]. For the pre-crisis period (2010–2020), a moderate-volatility regime was used, while for the crisis and post-crisis periods (2021–2025), the variance parameters were adapted to the conditions of increased fuel-driven volatility. In the model, fuel price shocks were set as a stochastic process with an average deviation of +60% relative to the baseline, which corresponds to empirically recorded crisis changes in the European energy market in 2021–2023. The demand surge scenario was modeled due to a 20% increase in peak load relative to baseline demand, while the supply disruption scenario assumed a 25% reduction in available generation with a simultaneous increase in the load on reserve capacities. Normal and lognormal distributions were used to model uncertainty depending on the nature of the variable: a lognormal distribution was used for prices and costs, while a normal distribution with parameters calibrated by historical volatility was used for demand and capacity availability. The risk assessment was carried out on the basis of the Conditional Value-at-Risk (CVaR) indicator with a confidence level of 95%, which corresponds to modern approaches to tail-risk analysis in energy systems. The CVaR value was defined as the mathematical expectation of losses in the worst 5% of implementations of the total cost distribution of the system (Table 3).

**Table 3.** Stochastic simulation parameters and calibration assumptions.

| Parameter | Base Value | Shock Parameters | Distribution | Source/Calibration |
|---|---|---|---|---|
| Fuel price | 1.0 | +60% | Lognormal | Historical volatility (IEA) |
| Electricity demand | 1.0 | +20% peak load | Normal | Dynamics of demand in Eurostat |
| Generation availability | 1.0 | −25% | Normal | Assumptions of crisis mode |

**Table 3.** *Cont.*

| Parameter | Base Value | Shock Parameters | Distribution | Source/Calibration |
|---|---|---|---|---|
| RES Penetration | 42% | Endogenous | Beta | Model optimization |
| Storage use | 0.52 | Up to 0.78 | Beta | BESS Operational Dynamics |
| Confidence level (CVaR) | 95% | - | - | Optimization settings risks |
| Number of iterations of Monte Carlo | 10,000 | - | - | Convergence criterion (author's calculations) |

Note: Developed by the authors on the basis of stochastic Monte Carlo modeling, CVaR risk optimization procedures, and empirical calibration using International Energy Agency data and Eurostat databases [28].

### *3.5. Scenario Design and Crisis Impact Matrix (Shock Matrix)*

All scenarios are implemented through the Shock Matrix, which provides a single procedure for parameterizing crisis events and their integration into the stochastic optimization model.

$$S = [S_{ij}] \quad (10)$$

In the matrix, $i$ is the type of crisis impact, $j$ is the energy system indicator, and $S_{ij}$ is the magnitude of the change in the corresponding parameter in percentage or relative units.

The matrix is a structured set of scenarios in which each type of crisis impact is described by corresponding changes in the key input parameters of the model, including fuel prices, electricity demand, availability of generating capacity, and the share of renewable energy sources.

The quantitative parameters of the scenarios were determined by analyzing historical data of the European electricity market for 2010–2025 using information from the International Energy Agency (2025) and Eurostat, as well as the results of scientific research [10]. The calibration of the scenarios was carried out in such a way as to reflect the characteristic scale of changes observed during the energy crisis of 2021–2023 (Table 4).

**Table 4.** Shock Matrix used for stochastic scenario generation and calibration.

| Shock Scenario | Variable Affected | Shock Magnitude | Distribution | Calibration Basis | Data Source |
|---|---|---|---|---|---|
| Baseline scenario | All variables | 0% | Historical empirical distribution | Average market conditions (2017–2019) | Eurostat; [28] |
| Fuel price shock | Natural gas price | +60% | Lognormal | Average increase during the 2021–2022 energy crisis | [28] |
| | Coal price | +28% | Lognormal | Historical market observations | [28] |
| | Electricity wholesale price | Endogenous | Derived | Model response | Authors' calculations |
| Demand surge | Electricity demand | +20% | Normal | Peak winter demand | Eurostat |

**Table 4.** *Cont.*

| Shock Scenario | Variable Affected | Shock Magnitude | Distribution | Calibration Basis | Data Source |
|---|---|---|---|---|---|
| Supply disruption | Available generation capacity | −25% | Normal | Forced outages and fuel shortages | Eurostat; [28] |
| Renewable intermittency | RES generation | ±20% | Beta | Historical wind and solar variability | [28] |
| BESS | Storage capacity | +30% | Deterministic | Moderate storage deployment scenario | [24] |
| Demand response (DR) | Peak demand | −10% | Deterministic | Demand flexibility programs | [25] |
| Combined resilience scenario | BESS + DR | BESS (+30%), DR (−10%) | Integrated simulation | Joint flexibility scenario | Authors' calculations |

The magnitudes of exogenous shocks were calibrated based on historical observations of the European electricity market in the period 2010–2025. Fuel price shocks were derived from the observed increase in natural gas and coal prices during the 2021–2022 energy crisis, while supply and demand shocks were calibrated against Eurostat electricity balance statistics. The variability of renewable generation was estimated based on historical fluctuations in wind and solar capacity. Flexibility scenarios involving BESS and demand response (DR) were parameterized from values frequently reported in the literature and validated using sensitivity analysis. To assess the reliability of the proposed system, all shock scales were further altered within ±20% during sensitivity testing, while the qualitative rating of the optimization results remained unchanged.

For each scenario, stochastic modeling was performed using the Monte Carlo method, within which the values of the input parameters around the specified scenario values were varied. This made it possible to assess the distribution of possible outcomes, calculate the CVaR indicator, and determine the stability of the optimal solution amidst changes in the external environment.

The values of the crisis impacts were calibrated based on the historical dynamics of the European electricity market for 2010–2025. The calibration was carried out by comparing scenario parameters with actual changes in fuel prices, demand levels, availability of generating capacities, and indicators of energy system functioning, using statistics from [24,25,28].

This made it possible to assess not only the average level of risk, but also potential extreme losses in conditions of high market instability. The final results given in Tables 3–10 reflect the average values after the convergence of the stochastic distribution and stabilization of the risk function within the optimization algorithm. The proposed approach provided the possibility of an integrated assessment of economic efficiency, system reliability, and crisis resilience of distributed energy systems, taking into account nonlinear relationships among fuel dependence, RES share, use of energy storage, and market volatility parameters (Table 5).

**Table 5.** Comparison of risk assessment indicators used in energy systems.

| Indicator | Dignity | Flaws | Reason for Use (or Non-Use) in Research |
|---|---|---|---|
| Value-at-Risk (VaR) | Easy to calculate, widely used | Does not take into account the amount of losses outside the threshold value; is not a coherent measure of risk | Used as a baseline but not as a primary criterion |
| CVaR | Takes into account the average losses in the "tail" of the distribution; coherent measure of risk; suitable for optimization | Requires more calculations | The main risk indicator in the proposed model |
| Sustainability indices (Resilience Index) | Characterize the system's ability to recover | Do not directly assess economic losses | Used as an additional criterion |
| Reliability indicators (LOLP, LOLE, etc.) | Reflect technical reliability | Do not account for the economic consequences of risk | Used to assess the technical component |
| Standard deviation (Variance) | Ease of interpretation | Accounts for positive and negative deviations equally | Insufficient to assess crisis risks |

Note: Systematized by authors based on [11,12,17].

**Table 6.** Dynamics of technical and economic indicators of distributed energy systems in 2010–2025.

| Year | LCOE, USD/MWyear | CAPEX, USD/kW | OPEX, USD/MWyear | Share of the Fuel Component in Total Costs, % | Energy Production Index, % |
|---|---|---|---|---|---|
| 2010 | 215 | 4200 | 38 | 52 | 100 |
| 2011 | 208 | 4050 | 37 | 50 | 103 |
| 2012 | 198 | 3890 | 36 | 48 | 106 |
| 2013 | 189 | 3700 | 35 | 46 | 109 |
| 2014 | 183 | 3520 | 34 | 45 | 112 |
| 2015 | 171 | 3310 | 33 | 42 | 116 |
| 2016 | 160 | 3090 | 31 | 39 | 121 |
| 2017 | 149 | 2860 | 30 | 36 | 126 |
| 2018 | 137 | 2610 | 28 | 33 | 132 |
| 2019 | 126 | 2380 | 27 | 30 | 138 |
| 2020 | 118 | 2190 | 26 | 27 | 145 |
| 2021 | 112 | 2050 | 25 | 25 | 151 |
| 2022 | 128 | 2140 | 29 | 31 | 147 |
| 2023 | 119 | 2010 | 27 | 26 | 154 |
| 2024 | 108 | 1890 | 24 | 22 | 162 |
| 2025 | 97 | 1760 | 22 | 18 | 171 |

**Table 7.** Long-run electricity price evolution (EU household index, 2010 = 100).

| Period | Price Index | Mode Characteristics |
|---|---|---|
| 2010 | 100 | Basic level |
| 2015 | 112 | Adjustable stability |
| 2019 | 118 | Gradual growth |
| 2020 | 120 | COVID-19 shock |
| 2022 | 165 | Energy crisis |
| 2023 | 172 | Post-crisis inertia |
| 2024 | 168 | Partial correction |
| 2025 | 170 | New volatility state |

Note: Based on data [28].

**Table 8.** Baseline system performance.

| Showman | Meaning |
|---|---|
| Total cost (index) | 100 |
| LCOE ($/kWh) | 0.072 |
| RES penetration | 42% |
| Reliability | 0.96 |
| CVaR | 0.08 |
| Fuel dependency | 0.38 |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

**Table 9.** Fuel price shock.

| Showman | Meaning | Δ |
|---|---|---|
| Total cost | 134 | +34% |
| LCOE | 0.098 | +36% |
| Reliability | 0.89 | −7% |
| CVaR | 0.21 | +162% |
| RES penetration | 47% | +5% |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

**Table 10.** Demand surge scenario.

| Showman | Meaning |
|---|---|
| Total cost | 118 |
| Reliability | 0.91 |
| CVaR | 0.15 |
| Storage utilization | 0.78 |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

To ensure resilience, the model is tested in several exogenous shock scenarios, including fuel price volatility, demand spikes, and supply disruptions. These scenarios reflect the real shocks observed in European energy markets, especially after 2021.

### 3.6. Model Validation and Robustness Analysis

Model validation is carried out using three complementary approaches. First, the modeled dynamics of electricity prices and aggregate energy system costs (including CAPEX, OPEX, fuel costs, and energy scarcity costs) are compared with observed market trends, confirming the model's ability to reproduce structural fractures and increasing volatility in the post-2021 period. Secondly, sensitivity analysis is carried out to assess the stability of results for key parameters, in particular fuel costs and fluctuations in electricity demand. Thirdly, CVaR-based risk assessments are calculated for different scenarios, demonstrating persistent tail risk behavior under stress modes of power system functioning.

The results show that the model adequately reflects the nonlinear interactions among costs, risks, and flexibility of the system, confirming its applicability for analyzing energy security in crisis conditions.

The proposed methodological framework provides a comprehensive assessment of the relationship among economic efficiency, system reliability, and risks of distributed energy systems. On its basis, scenario modeling for various crisis conditions has been performed, and the results obtained make it possible to assess the influence of individual factors on the value of the target function and the CVaR systemic risk indicator. The following section presents the results of the empirical analysis and their interpretation.

This study is of a scenario-optimization nature, so hypothesis testing is carried out through comparison of scenarios, sensitivity analysis, verification of the robustness of the model, and empirical comparison with historical dynamics.

## 4. Results

This section presents the results of applying the proposed model to the data of the European electricity market for 2010–2025. The analysis is aimed at testing the formulated hypotheses, assessing the impact of crisis scenarios on key parameters of energy security, and determining the effectiveness of the risk-based optimization system. In the study, distributed power systems are considered as a set of localized energy solutions, including solar photovoltaic (PV) systems, local wind turbines, BESS, gas microturbines, and hybrid microgrids integrated at the level of local consumers and territorial energy nodes. Analysis of the dynamics of their technical and economic indicators during 2010–2025 allows us to assess the transformation of the cost structure, the level of dependence on the fuel component, and changes in the economic efficiency of distributed energy systems in the face of crisis challenges. Particular attention is paid to the LCOE, CAPEX, and OPEX indicators and the share of fuel costs, which form the basis for further assessment of energy sustainability and risk tolerance of distributed generation (Table 6).

The results show a steady decline in the normalized cost of electricity (LCOE) and capital expenditures of distributed power systems (CAPEX) during the analyzed period, which confirms the growth of the competitiveness of distributed generation technologies. At the same time, the reduction in the share of the fuel component in the cost structure demonstrates an increase in energy sustainability and a decrease in dependence on traditional energy resources. The temporary deterioration of indicators in 2022 is explained by crisis phenomena in energy markets and the impact of external shocks, but further stabilization confirms the adaptive potential of distributed energy systems in the face of energy instability.

Based on the identified trends in changes in the technical and economic indicators of hybrid distributed energy systems, represented by solar, wind, and storage energy components, it is advisable to further assess the level of their resilience to crisis impacts and uncertainties of the energy market. In this regard, the next stage of the study is the validation of the CVaR model, which allows us to assess the risk scenarios of the functioning

of distributed energy systems and determine the effectiveness of their adaptation in the face of energy shocks and crisis changes. The validation results are based on a CVaR-oriented optimization model and empirical analysis of the functioning of the distributed power system under uncertainty. The focus is on testing the model's ability to replicate structural changes in the electricity market, assessing scenario shocks, analyzing risks, and verifying the system's resilience to exogenous impacts. Validation of the proposed model is carried out within a single risk-based optimization framework that integrates economic efficiency, systemic risks, and indicators of energy system resilience. Empirical research [1,28] demonstrates a pronounced nonlinear dynamic of electricity prices in the EU, including structural fracture after 2021. In the period 2010–2019, the market was characterized by relative stability with gradual growth, while after 2020 there is a transition to a new regime of high volatility (Table 7).

The results confirm the transition from a relatively stable market regime to a fuel-sensitive high-volatility regime after 2021, and the formation of a new post-crisis equilibrium regime, which is characterized by an increased level of prices and continued instability. Based on long-term data, four stages of the evolution of the energy market have been identified:

(1) Stability regime (2010–2015)—low volatility, dominance of regulated mechanisms;
(2) Transition regime (2016–2020)—an increase in the share of RES and a gradual increase in fluctuations;
(3) Crisis regime (2021–2023)—a sharp increase in price shocks and fuel-driven volatility;
(4) Post-crisis inertia (2024–2025)—partial price correction while maintaining an increased level of systemic risk.

The baseline scenario is characterized by relatively balanced parameters of the system's functioning (Table 8).

The results of the baseline scenario reflect the reference (control) state of the power system before the impact of crisis shocks and form a baseline trajectory for further scenario analysis. Under these conditions, the energy system is characterized by a relatively balanced structure of costs and risks: the level of present value of energy (LCOE) is \$0.072/kWh, and the share of renewable energy sources (RES penetration) is 42%, which indicate a moderate level of decarbonization while maintaining the stability of the system. The reliability level (reliability = 0.96) indicates the high ability of the system to meet demand, while the CVaR at 0.08 reflects a relatively low level of tail risks given the underlying conditions. At the same time, the fuel dependence index (fuel dependency = 0.38) remains a critical structural parameter that determines the sensitivity of the system to external price and geopolitical shocks. It is this variable that forms the main channel for the transmission of crisis influences into the model and acts as a key trigger for further instability in the context of volatility in energy markets. A 60% increase in fuel prices leads to a significant increase in costs and risks. Thus, the baseline scenario serves not only as a starting point, but also as an analytical standard for assessing the degree of deviation of the system under the influence of exogenous shocks. In this context, the next stage of the study is the modeling of the fuel price shock, which is one of the most critical factors in the instability of modern energy systems and allows us to identify the limits of their resilience and adaptability. The baseline scenario acts as an abstract configuration of the power system before the impact of crisis shocks and is used as a basis for further stress-testing. The fuel price shock scenario demonstrates a significant deterioration in sustainability indicators and an increase in systemic risk (Table 9).

The growth of CVaR indicates the system's high sensitivity to fuel volatility. Price volatility and shock transmission between energy markets have increased significantly [10]. The 20% increase in demand during peak periods results in a moderate load on the system.

After analyzing the scenario of a fuel price shock, which revealed a high sensitivity of the power system to fuel cost volatility and a significant increase in risks, it is advisable to focus on assessing an alternative type of crisis impact. In particular, the demand surge scenario is considered, which allows us to study the behavior of the system in conditions of capacity overload and structural generation deficit (Table 10).

The system partially compensates for demand through the use of energy storage. A 25% reduction in generation is the most critical shock. The analysis of the demand growth scenario demonstrates that even under the conditions of partial adaptation of the system due to the use of energy storage, increased sensitivity to peak loads and limited generation flexibility remain. In this context, the next stage of the study is focused on the supply disruption scenario, which allows us to assess the resilience of the power system in the face of a direct reduction in available generating capacities (Table 11).

**Table 11.** Supply disruption scenario.

| Showman | Meaning |
|---|---|
| Total cost | 127 |
| Reliability | 0.84 |
| CVaR | 0.26 |
| Backup usage | 0.91 |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

The results show the critical role of reserve capacities in stabilizing the system. The elasticity of the transmission of fuel shocks into the price system increases significantly during the crisis period. The analysis of the supply disruption scenario showed that the limitation of generating capacities and the increase in dependence on backup sources significantly increase the systemic risk and reduce the level of reliability of the power system. In this context, the study next moves on to assessing the fuel price transmission elasticity as a key indicator of the market's structural sensitivity to external crisis influences (Table 12).

**Table 12.** Fuel price transmission elasticity.

| Period | Elasticity |
|---|---|
| 2010–2016 | 0.21 |
| 2017–2020 | 0.34 |
| 2021–2025 | 0.62 |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

This confirms the structural transition to a fuel-sensitive regime. Risk dynamics demonstrate steady growth during the crisis. The analysis of the elasticity of the transmission of fuel shocks into pricing demonstrates an increase in the structural sensitivity of the energy market to fluctuations in fuel costs during the crisis period. In this context, the next stage of the study is aimed at assessing the dynamics of CVaR (2010–2025), which allows us to identify changes in tail risks and the long-term evolution of systemic riskiness.

It should be noted that the elasticity estimation periods (2010–2016, 2017–2020, 2021–2025) are aggregated differently than the CVaR dynamic modes in Figure 2, since a reliable estimation of elasticity requires longer subsamples.

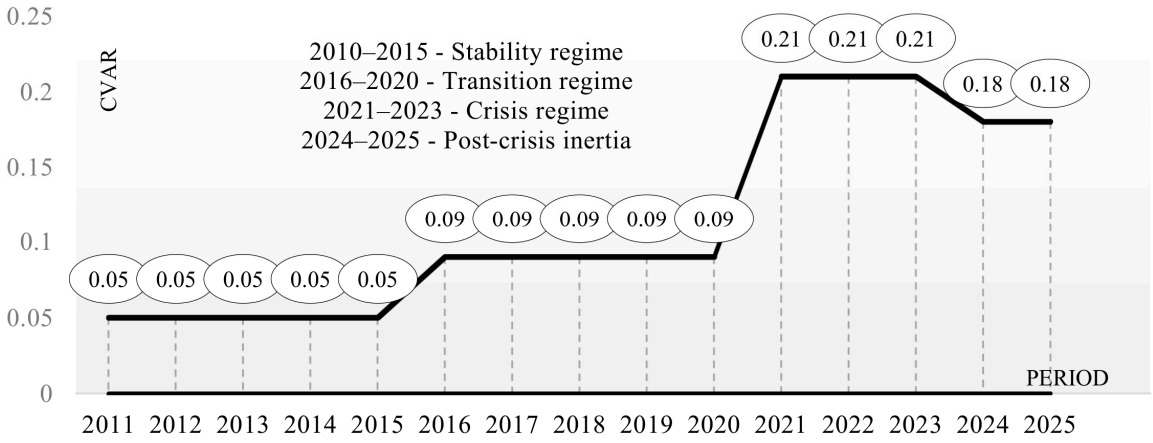



**Figure 2.** Dynamics of the indicator Conditional Value-at-Risk (CVaR), obtained based on the results of stochastic scenario modeling of the systemic market risk of distributed energy systems in Europe in 2010–2025 (highlighted regimes (stability, transition, crisis, and post-crisis inertia) reflect the change in the level of systemic risk under the influence of geopolitical shocks, fuel price volatility, and structural changes in the energy market). Note: Formed by the authors on the basis of CVaR-oriented stochastic modeling using data from the International Energy Agency and Eurostat.

Given that the results of stochastic modeling confirmed the dominant role of fuel volatility in the formation of systemic risks, the next stage of the study is to assess the sensitivity of the energy system to changes in fuel prices. This approach makes it possible to determine the nonlinear nature of the relationship among the scale of fuel shock, the level of systemic risk (CVaR), the reliability of operation, and the dynamics of the total costs of the power system (Table 13).

**Table 13.** System risk sensitivity to fuel price volatility.

| Fuel Price Increase | CVaR | Reliability | Total Cost Index |
|---|---|---|---|
| +20% | 0.11 | 0.94 | 108 |
| +40% | 0.16 | 0.91 | 121 |
| +60% | 0.21 | 0.89 | 134 |
| +80% | 0.29 | 0.84 | 149 |

Note: Formed by the authors based on the results of stochastic modeling, Monte Carlo simulation, and CVaR-oriented optimization using datafrom [28].

The results of sensitivity analysis demonstrate a pronounced nonlinear nature of the impact of fuel volatility on the functioning of distributed energy systems. With the rise in fuel prices, there is a proportional increase in the total costs of the system and a simultaneous deterioration in reliability indicators. With an 80% increase in fuel prices, the CVaR value rises to 0.29, while the reliability level decreases to 0.84, which indicates a significant increase in tail risks and structural instability of the power system. The results obtained confirm that fuel dependence acts as a key channel for the transmission of crisis shocks in distributed energy systems and forms long-term risk inertia in conditions of high market volatility.

In this context, it is advisable to further assess the long-term dynamics of systemic risk through the analysis of the CVaR indicator in 2010–2025, which allows us to identify structural changes in the risk profile of the energy market and assess the transformation of the modes of operation of energy systems in the pre-crisis, crisis, and post-crisis periods (Figure 2). It reflects the time dynamics of the Conditional Value-at-Risk (CVaR) indicator, which is used in the study as an integral indicator of the systemic market risk of distributed

energy systems. CVaR values are obtained as a result of stochastic scenario modeling calibrated according to historical data of the European electricity market for 2010–2025. The identified regimes characterize the successive stages of market development: stable (2010–2015), transitional (2016–2020), crisis (2021–2023), and post-crisis (2024–2025). The sharp increase in CVaR after 2021 reflects increased systemic market risk influenced by geopolitical events, the energy crisis, and high volatility of fuel markets. The persistence of elevated CVaR values in 2024–2025 is interpreted as a manifestation of persistent post-crisis risk inertia.

The dynamics of CVaR demonstrate the presence of a structural fracture after 2021 and the transition of the energy system to a highly volatile crisis mode of operation. During 2010–2015, the CVaR value remained stable at 0.05, indicating a relatively low level of tail-risk and moderate systemic volatility. In 2016–2020, there was a gradual increase in CVaR to 0.09, reflecting a transitional phase of energy market transformation and increased RES integration.

After 2021, there has been a sharp increase in CVaR to 0.21, which confirms a significant increase in crisis instability, fuel-driven volatility, and structural sensitivity of the power system to external shocks. Although 2024–2025 saw a partial decrease in CVaR to 0.18, the level of risk remains significantly higher compared to the pre-crisis period. This indicates the formation of the post-crisis risk inertia effect and the transition to a new mode of operation of energy systems with an increased level of uncertainty.

Integrated analysis demonstrates nonlinear relationships among RES penetration rate, fuel dependence, system flexibility, and systemic risk measures.

A moderate level of penetration of renewable energy sources contributes to increased economic efficiency and reduced fuel dependence. At the same time, an excessive increase in the share of RES without proper integration of energy storage systems leads to increased operational instability due to generation-intermittent ties and imbalances between supply and demand.

The results of the study show that the combination of the development of RES, BESS, and flexible backup capacities allows distributed energy systems to approach Pareto-optimal configurations, which are characterized by lower costs, higher reliability, and less systemic risk.

The generalization of the results confirms that fuel volatility remains a key driver of system instability in modern power systems. At the same time, the importance of flexibility-oriented infrastructure, including BESS and demand-response mechanisms, for ensuring energy security in the face of crisis impacts is growing.

*Model validation and testing of research hypotheses*. The proposed model was tested using an integrated approach that combines empirical, scenario, and parametric validation. Since the study is aimed at developing a multi-criteria optimization model, and not a model for forecasting time series, its adequacy was evaluated not through classical indicators of forecast error (RMSE or MAE), but through the ability to reproduce known patterns of development of the European energy market and provide sustainable optimization solutions in various crisis scenarios. The empirical validation consisted of comparing the simulation results with the actual structural changes in the European electricity market in 2010–2025. Particular attention was paid to verifying the reproduction of price volatility growth, the increased impact of fuel factors after 2021, and the increase in systemic risk assessed using CVaR. Additionally, a sensitivity analysis was performed, within which the weighting factors of the target function and the parameters of crisis scenarios were varied. The results showed that the overall structure of optimal solutions remained stable over a wide range of parameter changes, which confirms the robustness of the proposed model. It

should be noted that the proposed validation procedure corresponds to the nature of the study, which is focused on optimization rather than forecasting.

Therefore, the main criterion for the quality of the model is its ability to provide stable and economically sound solutions in various crisis scenarios. Further validation may involve the backtesting of CVaR and other statistical methods for testing risk models based on longer time series or data from individual energy companies.

To test the formulated research hypotheses, the results of scenario modeling were systematized for each hypothesis (Tables 14 and 15). The assessment was carried out by comparing the baseline and alternative scenarios, analyzing changes in key energy security indicators, and checking the stability of the results in the face of variation in the model parameters.

**Table 14.** Results of testing research hypotheses.

| Hypothesis | Verification Criterion | Result | Conclusion |
|---|---|---|---|
| H1 | Elasticity of fuel shock transmission | 0.21 → 0.62 | Confirmed |
| H2 | CVaR change after BESS + demand response integration | 0.31 → 0.20 (–35.5%) | Confirmed |
| H3 | CVaR after the market stabilizes | CVaR = 0.18 against 0.05 in pre-crisis | Partially confirmed (consistent with the hypothesis) |

Note: Calculated by the authors. Sources of values: H1—Table 12; H2—Table 15; H3—Figure 2 and Table 8.

**Table 15.** Empirical testing of hypothesis H2: the impact of flexibility tools on systemic risk.

| Script | CVaR | ΔCVaR |
|---|---|---|
| Crisis scenario without flexibility tools (Fuel + 60%, Capacity − 25%) | 0.31 | — |
| The same scenario with the integration of energy storage systems (BESS + 30%) and demand management (DR − 10%) | 0.20 | −35.5% |

Note: Calculated by the authors based on the results of stochastic Monte Carlo modeling (10,000 iterations).

To assess the robustness of the results, a sensitivity analysis was additionally performed, within which the parameters of crisis scenarios and the weighting coefficients of the target function were varied. In all the studied configurations, the direction of changes in the main indicators remained unchanged, which confirms the stability of the conclusions obtained. One of the results of the study is the identification of a stable persistence of an increased level of systemic risk after the end of crisis events, which is interpreted as a manifestation of risk hysteresis. Within the framework of this study, risk hysteresis is understood as a situation in which the CVaR indicator does not return to the pre-crisis level even after partial normalization of external economic conditions. This effect may be due to the inertia of energy market adaptation, changes in the structure of generation, long-term effects of price shocks, transformation of supply chains, and changes in regulatory policy. To assess the persistence of this phenomenon, a scenario analysis was performed using Monte Carlo simulation and sensitivity analysis, the results of which showed that the increased level of CVaR is maintained over a wide range of variations in the initial parameters. At the same time, it should be noted that the results obtained do not prove the existence of hysteresis in a strict econometric sense, since the study did not include specialized tests for structural fractures or long-term dependence of time series. Therefore, it is advisable to interpret the detected effect as systemic risk stability, compatible with the hypothesis of hysteresis, and not as its final confirmation.

## 5. Discussion

The role of renewables is ambiguous: they increase efficiency, but require system flexibility (storage, demand response) [24,25]. Our results confirm that energy systems are moving into a mode of increased instability, where geopolitical risks and fuel dependence play a key role [21,22]. Modern energy systems operate in a mode of structural transformation, which is characterized by a transition from stable market conditions to high volatility and an increase in systemic risk. Detected regime shift after 2021 is consistent with research findings that indicate a stronger link among energy markets, geopolitical shocks, and price volatility [1,9]. Empirical results show a clear change in the functioning of the European energy market: from stable (2010–2016) to crisis (2021–2025). Similar structural fractures have also been recorded in Energy Economics studies, which emphasize that energy markets have entered a state of "persistent high-volatility equilibrium" after 2021 [2]. The increase in CVaR to 0.21 during the crisis period confirms an increase in systemic risk, which is in line with the findings on increased tail-risk in European energy systems [1]. The results on elasticity (rising to 0.62 in 2021–2025) suggest an increased transmission of fuel shocks into electricity prices. This is consistent with empirical studies showing that gas and oil markets have become key drivers of electricity volatility in Europe [9,10]. Thus, the system has moved into a fuel-sensitive regime, where fuel markets determine not only costs, but also the risk structure of the energy system. The results show that increasing the share of RES increases economic efficiency, but does not guarantee stability without flexible mechanisms (storage, demand response). This is consistent with the findings of Wang and Tian [5], which demonstrate that renewable energy reduces average costs but increases generation dispersion. A similar trade-off between decarbonization and stability has also been confirmed in other papers [22,25], emphasizing the need to integrate energy storage systems to compensate for the volatility of RES. Empirical results clearly indicate that system flexibility is a key stabilizing factor: the use of energy storage (0.78) and reserve capacities (0.91) significantly reduces reliability losses under stress scenarios. This is consistent with research that highlights that grid flexibility is a critical factor in reducing the risk of shortages and CVaR [16,23]. Thus, energy security in modern conditions is determined not only by the structure of generation, but also by the ability of the system to adapt. One of the key results of this research has been to identify the effect of risk inertia (hysteresis): even after partial stabilization (2024–2025), the level of CVaR does not return to pre-crisis values. This is consistent with the concept of path dependency in energy systems, according to which crisis shocks have a long-term impact on market structure [28].

The results obtained have several key policy implications: the transition from cost minimization to risk-aware optimization is necessary for modern energy systems; investments in storage and grid flexibility are more effective than just increasing RES penetration; reducing dependence on fuel markets is critical to reducing systemic risk; and energy policy should account for structural instability after 2021 as the new normal.

These findings are consistent with the recommendations of the International Energy Agency on the transformation of energy systems towards resilience-based energy governance.

The proposed multi-criteria optimization model is developed as a universal methodological framework to support decision-making in the field of development of distributed energy systems under conditions of high uncertainty and crisis impacts. Although the empirical calibration of the model is based on the data of the European electricity market for 2010–2025, its mathematical structure does not depend on the characteristics of a particular country or market organization model. The versatility of the model is ensured by the use of general economic and technical indicators—in particular, LCOE, CAPEX, OPEX, reliability indicators, and CvaR—which are widely used in the international practice of assessing the efficiency and risks of energy systems. The multi-criteria optimization function re-

tains its structure independently of the regulatory environment, while adaptations require only model parameters, uncertainty scenarios, and system constraints. In particular, it is necessary to take into account the specifics of the structure of generation, fuel balance, cost of investments, operating costs, tariff regulation, market pricing mechanisms, and the level of penetration of renewable energy sources, as well as indicators of reliability and sustainability of the energy system. For fossil-fuel-dominated countries, the focus should be on modeling the risks of fuel dependence and price volatility. On the other hand, for energy systems with a high share of renewable energy sources, it is advisable to expand scenario modeling by including weather factors, variability in electricity generation, development of energy storage systems, and demand management mechanisms. At the same time, the results presented in this study should be interpreted with the understanding that they were obtained on the basis of the statistical characteristics of the European market.

Despite the fact that the proposed model is focused primarily on the strategic optimization of energy security at the level of energy systems and the electricity market, its results are of direct practical importance for energy supply companies. In particular, CVaR systemic risk assessment, crisis scenario analysis, and multi-criteria optimization results can be used to inform management decisions on the allocation of financial resources, reserve capacity planning, development of energy storage systems, optimization of fuel procurement, and operational risk management. In this context, the proposed macro-level approach complements the methodological recommendations on the allocation of resources of energy supply companies proposed by [13], providing them with strategic guidelines formed on the basis of the analysis of market risks and long-term trends in the development of energy systems.

Thus, the integration of macro-level models for assessing energy security with micro-level mechanisms of resource management creates a holistic basis for decision-making both at the level of state energy policy and at the level of individual energy supply enterprises. At the same time, the observed increase in systemic risk cannot be explained solely by fluctuations in fuel prices. Regulatory policy changes, structural transformation of generation, accelerated adoption of renewables, and geopolitical factors could have had an additional impact. Thus, the results obtained reflect the complex effect of the interaction of several factors, and not only the effect of individual market shocks. The results of the empirical analysis confirm the H1 hypothesis regarding a significant increase in the elasticity of the transmission of fuel shocks to electricity prices in the post-crisis period. Quantitative estimates are given in Tables 12 and 14. The results obtained are consistent. The results of the study show that increasing the share of renewable energy sources does not in itself ensure an increase in energy security. Achieving climate goals requires the simultaneous development of energy storage systems, demand management mechanisms, and reserve capacities. This creates a trade-off between minimizing short-term costs and ensuring the long-term sustainability of power systems. Therefore, energy policy should take into account not only economic efficiency, but also risk-based decision-making criteria. The H2 hypothesis has also received empirical confirmation. Comparison of the baseline scenario with the alternative scenario, which involves the integration of energy storage systems and demand management mechanisms, showed a decrease in CVaR by about 35%. The result obtained shows that the combination of energy storage with flexible demand management mechanisms not only increases the reliability of the power system, but also significantly reduces the risk of extreme adverse scenarios. This finding is consistent with previous scientific research [12,17,24,25], which highlights the important role of energy storage technologies and demand-side management tools in increasing the resilience of distributed energy systems. The results of the analysis are consistent with the H3 hypothesis on the sustainable persistence of an increased level of systemic risk (risk persistence). Despite the

partial stabilization of the European energy market after the end of the most acute phase of the energy crisis, the level of systemic risk assessed using CVaR remains significantly higher than pre-crisis values. This indicates the long-term impact of crisis shocks on the functioning of distributed energy systems and the formation of a new equilibrium with an increased level of risk, which depends not only on the current market conditions, but also on the accumulated consequences of previous crises. The results also complement the findings of scientists [3,4,21] on the need to consider the long-term resilience and adaptability of energy systems when developing models for their optimization. The generalized results of hypothesis testing are given in Tables 14 and 15. The proposed model can be used by government agencies, system operators, and energy companies to assess strategic risks and select optimal configurations for the development of distributed energy systems under conditions of high uncertainty.

*Limitations of the study and directions for further research*. Despite the results obtained, the proposed model has a series of limitations that must be taken into account when interpreting the results. First, scenario modeling is based on the use of normal, lognormal, and beta distributions, which adequately describe most market processes but may not accurately reproduce extreme "fat-tailed" events typical for crisis periods. In future studies, it is advisable to consider the application of copular models, Student's distribution, or the generalized Pareto distribution for more accurate modeling of the relationships between risk factors and the assessment of tail risks. Secondly, the empirical analysis is based mainly on the annual data of the European electricity market for 2010–2025. This level of temporal aggregation is sufficient to investigate long-term structural changes, but may not fully reflect intradural or seasonal volatility, which is important for assessing short-term operational risks. It is advisable to base further research on monthly, daily, or hourly data, which will increase the accuracy of risk dynamics modeling. Thirdly, the proposed model does not take into account the direct impact on greenhouse gas emissions of European pricing mechanisms, primarily the European Union Emissions Trading System (EU ETS) and the Carbon Border Adjustment Mechanism (CBAM). Given the growing role of these tools in the formation of the cost of electricity production and investment decisions, their integration into the multi-criteria optimization model is a promising direction for further research. In addition, the proposed model was tested on the data of the European electricity market, which limits the possibility of direct transfer of the results obtained to other regions with a different generation structure, regulatory environment, or level of penetration of renewable energy sources. Further research may be aimed at adapting the model to the energy markets of North America, Asia–Pacific, and developing countries. In general, the further development of this study is related to the expansion of the model by integrating carbon pricing mechanisms, the application of more flexible statistical approaches to uncertainty modeling, the use of data with high temporal resolution, and the inclusion of additional criteria for assessing the resilience of energy systems. This approach will increase the universality of the proposed methodology and its practical value for supporting strategic decisions in the field of energy security.

## 6. Conclusions

This study is aimed at assessing the transformation of energy security of distributed power systems in the context of crisis impacts using a scenario-oriented multi-criteria model that integrates economic, risk, and structural parameters of the system's functioning. The results confirm that modern energy systems have switched to a new mode of operation, which is characterized by increased price volatility, increased sensitivity to fuel shocks, and increased systemic risk. Empirical data for 2010–2025 demonstrate a clear structural fracture after 2021, which indicates the formation of a post-crisis energy environment with

signs of long-term instability. It has been established that fuel volatility is a key factor that determines the dynamics of costs, the level of risk of shortages, and the overall stability of the power system. The results confirm the transition to a fuel-sensitive regime, which is consistent with current research on energy transformations [6,25]. The results of scenario modeling show that renewable energy increases the economic efficiency of the system but does not provide a sufficient level of stability without the development of flexibility mechanisms, in particular energy storage and demand management systems. It is these elements that act as key stabilizers in the face of crisis shocks. In addition, the presence of the effect of risk inertia has been established, wherein the level of systemic risk (CVaR) does not return to pre-crisis values even after partial stabilization of the market. The growth of CVaR during a crisis period indicates an increase in tail risks [4,5], pointing to the long-term nature of the impact of crisis events on the structure of energy systems. Overall, the results confirm the need to move from the traditional cost minimization strategy to a risk-aware energy system optimization approach that simultaneously takes into account the cost-effectiveness, risk, and adaptability of the system.

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**Data Availability Statement:** The data used in this study are publicly available. The empirical dataset (2010–2025) on electricity prices, generation structures, fuel-price volatility, and the level of renewable energy source (RES) penetration in the European electricity market was compiled from open-access databases of the International Energy Agency (IEA) and Eurostat. IEA data are available at https://www.iea.org/data-and-statistics (accessed on 10 August 2026), and Eurostat energy statistics are available at https://ec.europa.eu/eurostat/web/energy/data (accessed on 10 August 2026). The scenario-modeling and CVaR-optimization results generated during this study are available from the corresponding author upon reasonable request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| BESS | Battery Energy Storage System |
| CAPEX | Capital Expenditures |
| CBAM | Carbon Border Adjustment Mechanism |
| CVaR | Conditional Value-at-Risk |
| ETS | Emissions Trading System |
| EU | European Union |
| IEA | International Energy Agency |
| LCOE | Levelized Cost of Electricity |
| MES | Multi-Energy Systems |
| OPEX | Operating Expenditures |
| PV | Photovoltaic |
| RES | Renewable Energy Sources |

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