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Logistics of electricity supply in crisis situations

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Abstract
The aim of the article is to develop a quantitative model to estimate the risk of power outages in the context of increasing meteorological variability. The paper assumes that modern power systems, as critical infrastructure, require a transition from a reactive to a proactive risk management approach. A two-stage analytical model has been proposed, enabling separate estimation of the probability of a power outage and its consequences, namely the failure duration and the scale of impact on consumers. The model was based on logistic regression, duration models, and a set of variables describing weather conditions, infrastructure characteristics, reliability history, spatial conditions, and the operator's operational capabilities. Historical data for the West Pomeranian Voivodeship, including SAIDI, SAIFI and MAIFI indicators, were used for calibration. The usefulness of the model was verified through simulation analysis of three crisis scenarios: winter, summer, and multi-event. The results indicate that the model enables spatiotemporal risk forecasting up to 72 hours in advance, supporting operational planning and network resilience assessment. The proposed solution may be a tool for supporting decisions in crisis management and in planning investments to increase energy security.

Keywords
energy security, crisis management, energy logistics, risk of power outages, grid resilience.

Introduction

The functioning of modern, highly developed societies and a globalised economy is inextricably linked to ensuring continuous and stable access to electricity, which is the foundation of national security. The National Power System (NPS) is one of the most complex technical and logistical systems, in which power supply must be continuously and precisely balanced with demand in real time. Even short-term disruptions in energy supplies, especially across large areas, lead to immediate paralysis of key sectors of the economy and critical infrastructure, including healthcare, water supply, transport, and ICT systems. In extreme cases, the cascading nature of a failure can lead to a complete destabilisation of the power system, referred to in the literature as a blackout (Gryz et al., 2022).

In recent decades, there has been a clear increase in the frequency and intensity of extreme weather events, which is a consequence of progressive climate change. Phenomena such as strong windstorms, lightning storms or intense snowfall combined with icing pose a significant threat to transmission and distribution infrastructure, especially those of an overhead nature (IPCC, 2023). The West Pomeranian Voivodeship is particularly susceptible to this type of impact, which, due to its coastal location and high forest cover, regularly exposes power lines to damage from strong winds and falling trees.

The economic and social dimensions of climate change exposure are not uniformly distributed across EU member states: countries with higher industrial energy intensity and lower shares of low-carbon generation face disproportionately large transition costs alongside elevated physical risk to supply infrastructure (Stankevičienė & Borisova, 2022). A TOPSIS-based ranking of EU countries by climate vulnerability – drawing on sectoral data for industry, energy, waste, and agriculture – illustrates how the spatial heterogeneity of meteorological risk is compounded by heterogeneity in economic exposure, a finding that underscores the relevance of region-specific calibration such as that performed for West Pomerania in the present study.

In the face of increasing environmental risks, the traditional, reactive approach to disaster management in power distribution systems is proving to be insufficient. Responding only after damage occurs leads to significant operational losses and extended energy restoration times. As a consequence, the importance of proactive approaches, based on advanced analytical tools and predictive models, which enable early identification of threats and optimisation of prevention and intervention activities (Zhang et al., 2010), is growing.

The analysis of the logistics of electricity supply requires a detailed understanding of the technical infrastructure, which serves as the physical basis for the implementation of transmission processes. The National Power System is not a homogeneous structure, but a hierarchical system, composed of heterogeneous subsystems, the efficiency of which determines the reliability of the entire system. From the perspective of security engineering and crisis management, it is crucial to understand the structure, principles of operation and technical limitations of individual elements of this system. The power infrastructure can be divided into four main segments: generation system (generation), high-voltage transmission network (LV), distribution network (HV, MV, LV) and control and supervision infrastructure (OT/IT systems) (Dołęga, 2013).

To fully understand the logistics of electricity supply in extreme conditions, it is necessary to precisely and multidimensionally define the concept of a crisis situation and the mechanisms of disruption propagation, as described in the literature as the domino or ripple effect. This analysis should go beyond the common understanding of the crisis and be based on well-established theoretical and legal foundations. The term "crisis" derives from the Greek (krisis) and means a turning point or decision-making moment. In security and management sciences, a crisis is defined as a state of violent imbalance in the system, requiring immediate decisions under conditions of uncertainty, limited information availability, and time pressure. Therefore, a crisis situation poses a threat to the achievement of an organisation's or a state's key goals, resulting from the impact of factors with high destructive potential that exceed the system's adaptability (Dolgui et al., 2018).

In response to the presented challenges, the aim of this article is to conduct a multidimensional analysis of the functioning of electricity supply logistics in the conditions of intensifying crisis situations and to develop an innovative, quantitative model for estimating the risk of power outages. The proposed approach aims to support decision-making in energy companies by enabling more efficient planning of operational activities and increasing the power system's resilience to environmental disturbances.

The relationship between corporate sustainability commitments and operational performance has attracted growing conceptual attention. An utilitarian analysis of sustainability adoption in business demonstrates that energy efficiency initiatives can substantially enhance profitability by reducing energy costs while simultaneously mitigating environmental impacts – with social responsibility initiatives further amplifying competitive advantage through brand value and stakeholder engagement (Mumcu, 2024). This enterprise-level perspective complements the grid-level analysis developed here: widespread corporate adoption of energy management programmes reduces aggregate peak load on distribution networks, thereby attenuating the severity of congestion-related failure events captured in the model's consequence stage.

Literature review

Contemporary scientific achievements in safety engineering, systems theory, and supply chain management clearly indicate that the state's critical infrastructure functions as a highly complex, nonlinear social engineering system with a well-developed network structure. In a systemic perspective, the stability of this type of system is not static but a dynamic, emergent process determined by the continuous influence of endogenous and exogenous factors (Helbing, 2013). The literature emphasises that traditional, deterministic models of reliability analysis are proving insufficient in the face of increasing complexity and the susceptibility of systems to low-probability but high-impact disturbances (Aven, 2011).

The key theoretical issue is the conceptualisation of the concept of a crisis situation, which in terms of management sciences is defined as a state of rapid destabilisation of the systemic balance, leading to the loss of the ability to perform basic operational functions in conditions of limited information, high decision-making pressure and increased uncertainty (Comfort, 2007). The analysis of this concept in the literature indicates the need for a multidimensional approach that takes into account both organisational and legal aspects. In the Polish normative system, the definition of a crisis situation has been formalised in the Crisis Management Act (2007), which emphasises the element of structural inadequacy of resources relative to the scale of the threat. Logistically, this implies the need to exceed standard operating procedures and to implement extraordinary mechanisms for allocating resources (Machowski, 2007).

In the context of the power sector, the literature defines the security of energy supply as the ability of a system to continuously and synchronously balance supply and demand under dynamic technical constraints. The state of crisis is equated with the loss of regulatory capacity due to market mechanisms, which forces the implementation of non-market instruments, such as administrative restrictions on power consumption or consumer-controlled shutdowns. Research indicates that such events should be analysed from a procedural rather than an incidental perspective, as reflected in phased models of the crisis (Wang et al., 2022).

Systematic measurement of energy security progress requires a multi-indicator framework that captures supply reliability, infrastructure integrity, import dependence, and interconnection capacity simultaneously. Multi-criteria decision analysis of Baltic States demonstrates that countries investing in grid interconnections and supplier diversification achieve consistently better scores across all supply security sub-indicators, including those directly associated with the likelihood of consumer-level supply interruptions (Streimikiene, 2020). The SAIDI, SAIFI, and MAIFI indicators employed in the present study are best interpreted within a multidimensional framework, in which each reliability statistic reflects not only infrastructure condition but also the broader supply security architecture within which the distribution network operates.

Cross-border energy regulation in the EU adds complexity to national-level supply risk assessments. Analysis of the German Gas Storage Levy (Gasspeicherumlage) shows that unilateral crisis-response measures – even when domestically effective – can generate compliance conflicts with EU internal market principles and create investment uncertainty that delays infrastructure upgrades (Hudak et al., 2025). The governance dimension identified in that study is directly relevant to the risk model proposed here: distribution network operators whose investment programmes span multiple administrative jurisdictions face an enlarged regulatory risk surface that compounds the meteorological and technical risks quantified in the present model.

Particular importance in the literature is given to the classical Fink phase model, which distinguishes four stages of crisis development: the prodromal, acute, chronic and extinction phases (Fink, 1986). This model, adapted to the analysis of power systems, enables the identification of early symptoms of destabilisation and the structuring of management activities based on the stage of disruption development. Operationally, this allows for a shift from a reactive to a proactive risk management model (Xu et al., 2021)

An important research stream is the analysis of the mechanisms of disruption propagation in complex logistics networks, conceptualised in the Anglo-Saxon literature as the ripple effect (Moreno-Baca et al., 2025). This phenomenon describes the cascading propagation of locally initiated disturbances that, as a result of feedback loops and structural dependencies, lead to a systemic escalation of effects. Unlike the bullish whip effect, which refers to the amplification of demand signals, the ripple effect refers to material and structural supply-side disturbances, whose characteristics fall into the category of low-frequency–high-impact events (Ivanov, 2020).

Recovery strategies function as dynamic capabilities when they are embedded in organisational routines prior to a disruption rather than improvised in its aftermath; empirical evidence shows that proactive and reactive recovery approaches exert differential mediation effects – information sharing, cross-functional coordination, and pre-negotiated redundancy operate with different efficacy depending on whether the disruption is sudden or prolonged (Darko & Ayamga, 2025). The distinction maps directly onto the three crisis scenarios modelled in this paper: the winter and summer events represent acute, localised failures for which rapid-response protocols are decisive, whereas the multi-event scenario requires the sustained, adaptive capability associated with long-duration recovery.

The logistics of energy supply in disrupted conditions shares core structural features with humanitarian and post-conflict supply chains. Evidence from warehouse-centred supply chains operating under damaged infrastructure demonstrates that energy-autonomous facilities and offline-capable management systems maintain operational continuity precisely when grid connectivity is compromised (Nosar, 2025). Lateral transhipment policies and prepositioned resource depots translate directly to electricity distribution: repair crews, mobile substations, and spare transformer units must be pre-staged to reduce both the probability of prolonged outages and their geographic spread, in a manner analogous to the readiness and prepositioning logic formalised in four-R resilience frameworks.

Supply chain agility – encompassing responsiveness, flexibility, visibility, resilience, and adaptability – determines how quickly a logistics network can reconfigure following an unexpected disruption (Mogaka & Njururi, 2024). Within energy distribution, this framework maps directly onto operational recovery: the speed with which crews are dispatched, spare components sourced, and switching configurations adjusted following a grid failure is a function of precisely those agility dimensions, which explains why operator capability variables feature prominently in the second stage of the proposed risk model alongside weather and infrastructure covariates.

In the case of power systems, the literature indicates a particular intensity and dynamics of the analysed phenomenon, resulting from the physical properties of electricity flow. The inability to store it and the need for immediate balancing cause local disturbances that lead to the redistribution of flows according to Kirchhoff's laws, generating overloads on subsequent network elements. As a result, cascading shutdowns occur, which, in extreme cases, result in a system blackout. This mechanism provides a model example of the materialisation of the ripple effect in infrastructure systems (Mishra et al., 2021).

The Energiewende experience in Germany illustrates how regulatory deficits in grid expansion translate into heightened supply instability risk: industry discourse consistently identifies delayed construction of high-voltage transmission lines and lack of coordination between federal and state levels as primary sources of mounting grid instability, ahead of pricing policy or generation mix concerns (Borshchevska, 2016). Regulatory approval procedures, which in some cases lasted 10 or 15 years, created a persistent infrastructure gap. Investment prioritisation informed by quantitative risk scores of the kind produced by the present model provides exactly the evidence base that such regulatory frameworks require.

In parallel, the influence of network topology on its susceptibility to interference is a parallel area of research. The literature on network theory indicates that centralised structures, characterised by the presence of critical nodes (hubs), are highly sensitive to damage to these nodes (Albert et al., 2000). Distributed systems are an alternative in which redundancy and functional decomposition increase system resilience. In this context, the concepts of microgrids and distributed energy, which enable the operation of autonomous "energy islands" during system disruptions, are of particular importance (Lasseter, 2011).

The literature also emphasises the interdisciplinary nature of the effects of crisis situations, pointing to the occurrence of cascading cross-sectoral failures. Disruptions in the electricity sector are triggering knock-on effects across other critical infrastructure sectors, leading to a multidimensional destabilisation of the socio-economic system. The analysis of these relationships is an important element of contemporary research on system security (Tong et al., 2025).

In response to the increasing complexity and unpredictability of threats, the literature points to the need to change the paradigm of security management, from a fail-safe approach to a safe-to-fail concept. This means designing systems capable of controlled functional degradation while reducing the scale of disruption consequences. Redundancy, diversification of sources, and the ability to quickly reconfigure the system are crucial, and these attributes are attributed here (Lin et al., 2024).

Grid-level storage technologies are increasingly recognised not only as enablers of low-carbon transition but as structural components of supply security. The deployment of photo-redox flow batteries – evaluated in both coal-intensive and high-solar contexts – improves grid stability by buffering demand spikes and smoothing the intermittency of renewables (Boutouil et al., 2025). From the perspective of the risk model proposed here, local storage nodes effectively reduce both the probability of propagating a local imbalance into a wider outage and the expected duration of any disruption that does occur, justifying their inclusion as operator capacity parameters in the logistic regression stage.

Contemporary research also highlights the growing role of artificial intelligence-based analytical tools and decision support systems. These technologies enable the modelling of complex disruption scenarios and the optimisation of decision-making processes under conditions of high uncertainty and time pressure, which represents an important direction for the development of energy logistics research (Chen et al., 2023).

The institutional capacity of governments to absorb and deploy artificial intelligence tools has been shown to exert a measurable influence on the pace at which renewable electricity capacity is brought online, with higher AI-readiness scores associated with both larger installed renewable bases and more stable grid output profiles (Lyeonov et al., 2025). This relationship is directly relevant to proactive outage risk management: jurisdictions that invest in decision-support and automation infrastructure are better positioned to operationalise predictive models of the type proposed in this paper, as the necessary data pipelines, forecasting platforms, and automated dispatch systems require institutional AI capability as a prerequisite.

Short-term power system forecasting has gained renewed importance as renewable intermittency and cyber threats increase the risk of supply disruptions. Research on ecological microgrids demonstrates that ultra-short-term generation and load forecasts – produced by black-box, grey-box, and white-box models – directly support storage scheduling and demand response, thereby reducing the probability of critical overload events, which are classified as high-consequence failure scenarios in the present model (Wojciechowski et al., 2025). The finding that off-grid islanding capability requires real-time, data-driven forecast-and-control loops reinforces the case for embedding operational forecasting variables – grid-segment autonomy level and storage dispatch latency – as explanatory covariates in spatiotemporal risk functions.

The application of lean supply chain principles in crisis settings confirms that waste elimination, cost optimisation, and robust internal controls are decisive for improving operational efficiency: empirical analysis of humanitarian aid organisations shows that supply chain efficiency accounts for over 43% of variance in organisational performance, with explanatory power rising to 66.5% when organisational characteristics are included (Nyile, 2025). These findings reinforce the operational logic of proactive risk management for distribution system operators, where pre-planned crew allocation and material staging are the direct analogues of humanitarian prepositioning.

Material and Methods

Modern operational logistics, operating in conditions of high meteorological variability, requires a departure from a qualitative approach in favour of quantitative methods, characterised by measurability, repeatability, and the possibility of formal verification. In practice, this means that managers and network dispatchers need to be equipped with analytical tools to forecast the locations of potential disruptions, estimate their likelihood of occurrence, and determine the resources needed to remove them.

The main objective of the analytical model designed in this study is to quantitatively assess the risk of electricity supply interruptions. This assessment is carried out within a defined time horizon that can be adapted to the distribution company's operational needs. Depending on the analysis's objective, this horizon can include both the next 24 hours, suitable for operational management, and the seven-day period, suitable for medium-term planning. The estimation is carried out for a separate analytical area marked with the index. In practice, this area may correspond to a single power line, a transformer station or a separate administrative unit, for instance, a municipality Hi.

The model is not limited to determining the probability of an accident, but also provides an estimate of its expected socio-economic impact. The effect of an outage is defined by two basic measures: the forecasted outage duration, expressed in minutes, and the number of end consumers without power. Such an approach is consistent with the classical understanding of risk in the theory of reliability of engineering systems, in which risk is a function of the probability of an event and its consequences.

The correct functioning of the estimation model requires the adoption of several boundary assumptions. First, it is assumed that the total risk of an energy outage is a function of four interdependent groups of factors: external conditions, infrastructure vulnerability, consumer exposure, and the energy company's operational capacity. External conditions refer primarily to the impact of meteorological phenomena on infrastructure. Infrastructure vulnerability includes its physical susceptibility to mechanical and electrical damage. Audience exposure means the scale and importance of the audience connected to a given network element. Operational capabilities, on the other hand, refer to the ability to intervene quickly and restore power efficiently.

Secondly, the model adopts a discrete-time structure, in which emergency events are described in strictly defined intervals, for instance, hourly or daily. This solution allows the model to be used both in retrospective mode, used to analyse historical events and identify weak points in the system, and in predictive mode, used to forecast future risk based on numerical weather forecasts.

Third, according to reliability theory, the risk in the model is assessed using two distinct components: the probability of an interruption and the effect of the interruption. The separation of these components is of significant analytical importance because high-probability events can generate relatively small effects, while rare events can lead to catastrophic consequences.

Fourth, it is assumed that historical data on failure rates and network technical parameters are representative of typical operating conditions. At the same time, it should be emphasised that extreme events, which fall outside standard statistical distributions, require additional support through a separate scenario analysis.

On the basis of the research assumptions defined above, a group of so-called explanatory variables (constituting the target result) has been distinguished, which are defined by the following mathematical notations:

- ${Y_{i,t}}^{(H)} \in \{0,1\}$ – it is a basic binary variable (taking only zero or one values), determining whether there will be any power outage in a given area and at all in the analysed time window, counted from the moment t to the moment $t + H$.

- $D_{i,t}$– a continuous variable expressing the forecasted duration of the outage, measured strictly in minutes, with the absolute condition that an emergency event (a binary variable with a value of one) actually occurred on the examined network fragment.
- $A_{i,t}$ – a variable characterising the physical scale of the impact of the accident. Depending on the analytical perspective adopted, it can be measured as the total number of disconnected energy consumption points or as the volume of so-called energy not supplied to the system (this term is used in the international literature as Energy Not Supplied).

To precisely estimate the values of the above-mentioned result variables, the model's mathematical mechanism uses a wide range of input explanatory variables (parameters powering the algorithm). For the purposes of correct identification, they are divided into five extensive, main analytical categories.

The first group consists of weather and environmental factors that describe the exposure of infrastructure to external threats. These include, above all, forecasted maximum wind gusts, precipitation type and intensity, the probability of pipe icing, extreme temperatures, lightning, and heat waves. To simplify the model's structure, these variables can be aggregated into a synthetic indicator of the intensity of the phenomena, referred to as the severity index.

The second category consists of infrastructure features, reflecting the physical vulnerability of network assets to damage. This group includes the share of overhead lines relative to cable lines, the length of network sections, the age of devices, the type and cross-section of cables, and the number of separation points and connectors. Variables describing the availability of backup power, the level of system redundancy and the occurrence of bottlenecks in the network topology are also important.

The third group is the reliability history, based on empirical failure rates reported by the relevant institutions. These variables are used to calibrate the underlying risk level. For the West Pomeranian Voivodeship, data for 2024 were used, coming from the reports of the distribution system operator ENEA Operator Sp. z o.o., approved by the Energy Regulatory Office. Based on data covering 2,827,774 recipients, the following input parameters were identified: the SAIDI index for unplanned interruptions, including catastrophic interruptions, was 99.89 min/customer/year; the SAIFI index was 1.86 events/recipient/year; and the MAIFI index was 4.65. In addition, the Mean Time Between Failures (MTBF) and the failure rate per unit length of the line are also taken into account. Table 1 presents the basic indicators of the duration and frequency of power outages for 2024.

Tab 1. Electricity Outage Rates in 2024

Indicator	Total value	Unit
Number of recipients	2 827 774	pcs.
SAIDI for planned breaks	26,34	min.
SAIDI for unplanned breaks	98,52	min.
SAIDI for unplanned interruptions, including catastrophic interruptions	99,89	min.
SAIFI for planned breaks	0,14	–
SAIFI for unplanned interruptions	1,86	–
SAIFI for unplanned interruptions, including catastrophic interruptions	1,86	–
MAIFI	4,65	–

Source: elaboration based on data from ENEA Operator Sp. z o.o.

The fourth category is the technical and spatial environment. It includes factors related to topography and land use, such as the density of trees in the vicinity of power lines, the terrain's complexity, the availability of access roads for repair crews, and the density of buildings. These parameters affect both the probability of damage and the ability to take quick intervention measures.

The fifth group consists of the company's operational capabilities, reflecting its organisational resilience and effectiveness of response. This category includes the number of available energy emergency brigades, the average travel time to the site of failure, the availability of materials and spare parts, and the current load on the dispatching system due to other emergency events. These variables primarily affect the forecasted duration of breaks.

The transition from variable identification to the construction of an estimation model requires determining the appropriate spatial and temporal resolutions of the data. All identified factors, from meteorological parameters to infrastructure characteristics to historical failure rates, must be standardised and integrated into one coherent input matrix. Spatially, the analysed area can be divided into elementary operating units, e.g., sections of medium-voltage lines bounded by dissection points or cells of a regular geometric grid. For each unit and for each time period, the model is assigned the values of all explanatory variables.

In the case of the West Pomeranian Voivodeship, geographical conditions are of particular importance. The region's coastal location increases exposure to strong wind events, especially in autumn and winter. At the same time, the high level of afforestation is conducive to mechanical damage to overhead lines due to the fall of trees and branches. In such conditions, empirical reliability indicators, in particular SAIDI and SAIFI, serve as a reference point for determining the so-called baseline risk, understood as the typical level of infrastructure failure under standard operating conditions.

The model's mechanism assumes that deviations in weather parameters from reference levels strengthen the underlying risk. For example, an increase in the forecasted wind speed above a certain design threshold can lead to a dynamic increase in the probability of damage. At the same time, variables describing operational capabilities, such as shortening the travel time of repair crews due to their optimal deployment, act as mitigating factors, limiting the expected duration of failure.

The result of the preparatory stage is the construction of a multidimensional vector of features for each point of the network. These vectors, denoted as for the set of variables used to estimate probability and for the set of variables describing the effect of the event, provide the numerical basis for further modelling. On this basis, it is possible to use logistic regression models and duration models, leading to the determination of a synthetic risk indicator of power outages $X_{i,t}Z_{i,t}$.

Results and discussion

The architecture of the proposed model is based on a two-step analytical approach that separates two distinct phenomena in the power system: the probability of an energy supply interruption and its effects. In the first stage of the model, the probability of an emergency event is estimated, while in the second stage, its consequences are determined, understood as the expected duration of the break and the scale of its impact on end users. Only the combined consideration of both components allows for the construction of a synthetic risk indicator.

- *Estimation of the probability of an interruption*

The primary statistical tool used to model failure probability is logistic regression. The choice of this method results from its interpretability, relatively simple calibration, and the possibility of quantitatively assessing the impact of individual explanatory variables on the model's output. The probability of an interruption occurring in a given time window describes the relationship:

$$p_{i,t} = Pr\left(Y_{i,t}^{(H)} = 1 \mid X_{i,t}\right) \tag{1}$$

In order to relate this probability to a set of explanatory variables, including, m.in, meteorological parameters, infrastructure features and spatial conditions, the logit function is used:

$$logit\ (p_{i,t}) = \beta_0 + \beta^T X_{i,t} \tag{2}$$

In the above equation, the parameter acts as a free term and corresponds to the baseline failure level of the infrastructure under reference conditions, i.e. in the absence of extraordinary external loads. This parameter can be estimated based on historical data. In the analysed case, data from the ENEA Operator for 2024 were used. Assuming that the value of the SAIFI indicator for unplanned interruptions taking into account catastrophic events amounted to 1.86 events per recipient per year, the base probability of failure occurrence in the daily time horizon can be approximated as follows:

$$p_{basic} = \frac{1{,}86}{365} \approx 0{,}0051 \tag{3}$$

Then this value is converted to logit:

$$\beta_0 = ln\ \left(\frac{p_{basic}}{1-p_{basic}}\right) \tag{4}$$

After substitution:

$$\beta_0 = ln\ \left(\frac{0{,}0051}{0{,}9949}\right) \approx ln\ (0{,}005126) \approx -5{,}27 \tag{5}$$

The obtained value is the starting point for further estimation. A parameter vector describes the impact of external variables on changes in risk level. For example, assuming that an increase in wind speed by 1 km/h causes an increase in the value of the logit function by 0.05, for a phenomenon with an intensity of 100 km/h, the value of the component will be:

$$0{,}05 \times 100 = 5{,}00 \tag{6}$$

Then:

$$logit(p_{\text{new}}) = -5{,}27 + 5{,}00 = -0{,}27 \tag{7}$$

By applying the reverse logistic function, the following is obtained:

$$p_{\text{new}} = \frac{1}{1+e^{-(-0{,}27)}} = \frac{1}{1+e^{0{,}27}} \approx 0{,}433 \tag{8}$$

This means that in the analysed scenario, the probability of an outage increases from the baseline level of 0.5% to about 43.3%.

However, it should be noted that when the relationships between input variables and the risk of failure are strongly nonlinear, logistic regression may be insufficient. This is especially true in threshold situations where damage to infrastructure increases sharply after exceeding a certain value of environmental parameters. In such cases, it may be reasonable to use more advanced machine learning methods, such as gradient boosting or random forest.

From the point of view of statistical practice, it is also necessary to take into account the fact that power outages belong to the category of rare events. This results in a significant imbalance in the dataset, requiring the use of appropriate sampling techniques, weighting observations, and selecting model quality assessment metrics. In such applications, measures that are robust to class imbalance, such as the area under the precision–recall curve (PR-AUC), are of particular importance. In addition, to ensure the correct interpretation of the obtained probabilities in alarm systems and to support decision-making, it is advisable to calibrate them using isotonic regression or Platt scaling.

- *Estimation of the impact of the failure: duration and scale of impact*

After detecting an interruption in the energy supply, the model moves to the stage of estimating its effects. One of the basic parameters is the duration of the failure. This variable takes only positive values, and its empirical distribution is usually asymmetric and right-skewed. Consequently, to model the duration of breaks, it is reasonable to use the logarithmic-normal distribution, described by the equation:

$$ln\,(D_{i,t}) = \gamma_0 + \gamma^T Z_{i,t} + \varepsilon \tag{9}$$

In this equation, the parameter denotes the base logarithmic duration of the failure under normal conditions. To estimate it, the SAIDI for unplanned interruptions, taking catastrophic events into account, can be used. For the analysed area, this value is 99.89 minutes, so:

$$\gamma_0 = ln\,(99{,}89) \approx 4{,}60 \tag{10}$$

This parameter is then corrected by a vector of variables, including m.in, the type of damaged network element, the availability of standby switches, the travel time of technical crews, and the number of simultaneous failures in the region. Assuming, for example, that the co-occurrence of a storm and a blockage of access roads increases the value of the logarithmic repair time by 0.70, the following is obtained:

$$ln\,(D_{\text{new}}) = 4{,}60 + 0{,}70 = 5{,}30 \tag{11}$$

After reverse transformation:

$$D_{\text{new}} = e^{5{,}30} \approx 200{,}34 \tag{12}$$

The result indicates that the expected failure duration increases from about 100 to more than 200 minutes.

In more complex operational situations, especially in multi-event crises, the time to complete the repair may be unknown at the time of analysis. In this case, there is a problem of censoring data, characteristic of time-to-event analyses. In such conditions, it is reasonable to use survival analysis methods, including the Cox proportional hazards model or accelerated failure time (AFT) models, which allow modelling of the power restoration process.

The second component of the failure effect is the scale of the impact. It can be modelled deterministically based on the network topology by identifying the number of power consumption points behind the damaged infrastructure element, or estimated using regression models that describe the number of consumers affected by the outage or the volume of undelivered energy.

- *Aggregation of the synthetic risk indicator*

A comprehensive assessment of a crisis situation in the power system requires aggregating the estimated probability of an outage with the expected duration of the outage and the severity of the consequences, given the importance of a given power supply facility. The final risk indicator can be written in the form of:

$$R_{i,t} = p_{i,t} \cdot \mathbb{E}[D_{i,t} \mid break] \cdot W_i \tag{13}$$

where denotes the weight of the consequence assigned to the area or network element under analysis. This parameter reflects the importance of a given node from the perspective of energy supply continuity and assigns the highest values to critical infrastructure, such as hospitals, water supply systems, or rescue units. W_i

In engineering practice, the results of the model should be reported at multiple levels, i.e., as the probability of failure, a forecast of its duration in the form of selected quantiles, and an aggregated risk indicator. This way of presenting results increases their operational usefulness and allows for more precise support for dispatching decisions.

- *Infrastructure resilience assessment*

The presented analytical apparatus can be used to assess the quantitative resilience of the power infrastructure, understood as the system's ability to reduce the frequency of failures, mitigate their effects, and quickly return to a state of functional equilibrium. In this perspective, the resilience of the system depends both on preventive measures that reduce the likelihood of damage, and on organisational and technical solutions that shorten the time of power restoration.

The effect of the planned modernisation can be estimated by comparing the level of risk before and after the implementation of a given solution:

$$\Delta R = R_{before} - R_{\mathrm{after}} \tag{14}$$

This indicator allows for an economic and technical assessment of the effectiveness of alternative investment options. As a result, the distribution company can assess whether it is more cost-effective to install an overhead line in a given area or to use cheaper but potentially more effective solutions, such as installing additional remotely controlled switches or increasing the operational capacity of technical services.

To demonstrate the practical usefulness and flexibility of the developed statistical apparatus, a simulation of its operation was conducted for three typical crisis scenarios considered highly probable in the conditions of operation of Polish power grids. The presented variants enable assessing the impact of differentiated inputs on estimation model results and demonstrate how the resulting forecasts can support the optimisation of logistics processes in a distribution company.

Scenario 1. Strong wind and wet snow – a crisis in winter conditions

The first scenario assumes the influence of a deep atmospheric low in winter, accompanied by strong gusts of wind, intense snowfall, and temperature oscillations. Such meteorological conditions generate an increased risk of icing of cables and mechanical damage to the overhead infrastructure $0°C$.

Numerical forecasts of wind gusts, precipitation intensity and air temperature have been introduced into the model. These data were supplemented with infrastructural variables, including the degree of tree cover in technological belts and the share of overhead lines in the network structure in the analysed area. In the first stage, the logistic regression model determines the spatial distribution of the probability of an interruption in the energy supply, i.e. the parameter, for a forecast horizon of 24 to 72 hours. Then, the duration model, based on the logarithmic-normal distribution, estimates the expected repair time, including the median and high quantile of the variable distribution, assuming that deteriorated road conditions and icing increase the time to repair failures. In the last step, the results obtained are aggregated into a synthetic risk indicator, which makes it possible to identify priority areas from the point of view of operational activities $p_{i,t}DR_{i,t}$.

As a result, the model generates a ranking of network sections by risk level and forecasts demand for logistics resources, including the number of energy emergency brigades, which should be prepositioned in areas at risk before the onset of a meteorological phenomenon.

Scenario 2. Violent storms and lightning – crisis in summer conditions

The second scenario refers to summer-typical, local, and fast-developing storm systems. These phenomena are characterised by high spatial dynamics and a high frequency of lightning, which can cause both transient disturbances and permanent damage to elements of the power infrastructure.

The basis for entering the model is data from storm detection systems, including the intensity of convective phenomena and the density of lightning. It is complemented by infrastructure variables describing the condition of lightning protection installations and historical summer failure rate data. Due to the nature of the analysed threat, in which short-term interruptions and transient short circuits dominate, the classical binary model has been replaced by the frequency model. For this purpose, the Poisson distribution or negative binomial distribution was used to estimate the variable denoting the expected number of emergency events in a given time window. At the same time, the potential impact of these disruptions on the functioning of critical customers, in particular hospitals and water infrastructure, was estimated $N_{i,t}^{(H)}$.

The simulation results include the projected number of emergency events in the region and the identification of areas with insufficient surge protection performance. This information can serve as a basis for operational activities involving temporary power switching, load redistribution, or the implementation of protection mechanisms in microgrids.

Scenario 3. Multi-event crisis – accumulated storm fronts

The third scenario is the most complex variant analysed in the study and concerns a situation in which a large storm system affects a significant part of the voivodeship simultaneously. This type of event leads to the cumulative occurrence of multiple parallel failures, significantly limiting the operator's operational capacity.

In addition to the standard variables describing the intensity of the meteorological phenomenon, the multi-event parameter was introduced into the model, understood as the expected number of simultaneous damages in the region. This variable directly affects the model's operational component, reflecting the decreasing availability of repair crews and the increase in response times. As a result, the probability of failure increases simultaneously across many locations, while the duration model must account for repair queuing, which involves postponing the handling of lower-priority events. At this stage, it is also possible to compare different variants of the logistic response, such as temporary support from neighbouring voivodeships, emergency grid switches or the use of generators for critical infrastructure facilities $p_{i,t}$.

The analysis results in a quantitative assessment of which of the considered organisational and technical activities lead to the greatest reduction in the risk indicator at the regional level. The model also allows you to assess the impact of these actions on reducing extreme power recovery times, described by high quantiles of the repair time distribution $R_{i,t}$.

Conclusions

The simulation analysis of three crisis scenarios confirmed that the developed two-stage risk estimation model can be an effective tool for supporting crisis management decisions in the power sector. The approach used makes it possible to simultaneously take into account both the probability of an interruption in the supply of electricity and the expected effects of this event, expressed by the duration of the failure and the scale of its impact on end users.

The results indicate that integrating logistic regression and duration models with historical data and current meteorological forecasts enables effective risk forecasting within the spatio-temporal system. Of particular importance is the ability to designate areas of increased risk 24 to 72 hours in advance, which provides the basis for implementing preemptive measures. In practice, this means it is possible to deploy technical crews earlier, secure means of transport and repair materials, and launch backup power sources for critical infrastructure facilities.

The study also showed that the proposed model significantly increases the rationality of logistics processes in a distribution company. It replaces the reactive approach, based on eliminating the effects of failures after they occur, with a proactive approach in which operational activities are planned based on forecasted risk levels. Such a change in the management paradigm is conducive not only to shortening response time but also to improving the efficiency of technical and human resources.

Based on the scenarios, it was also concluded that the model can serve as a tool for assessing the resilience of the power infrastructure. Comparing the risk level before and after the implementation of specific modernisation measures enables a quantitative assessment of the investment's effectiveness. As a consequence, it becomes possible to compare alternative network development variants more objectively, such as cabling overhead lines, installing remotely controlled sectioning connectors, or increasing the operational capacity of technical services.

The results of the research also indicate that the model's greatest value lies in its application flexibility. It can be used for risk analysis in winter conditions, associated with strong winds and wet snowfall, as well as in summer storm situations, and in complex multi-event crises involving large areas of the network. This means that the proposed solution is universal and can be adapted to different types of threats and different levels of distribution system organisation.

In light of the results, it should be concluded that the combination of meteorological data, infrastructure parameters, reliability indicators, and logistics information provides a solid basis for the construction of modern decision-support systems in the power industry. In the context of increasing climate variability and the frequency of extreme events, the implementation of such models is becoming an important element in maintaining the continuity of energy supply, protecting critical infrastructure, and strengthening energy security.

At the same time, it should be emphasised that further development of the model should include validation on real operational data, extension to more advanced machine learning techniques, and the inclusion of additional variables describing recipients' behaviour and organisational constraints on operators. This will allow for further increases in forecast accuracy and the practical usability of the model in real operating conditions.

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