

Article

A Framework to Assess the Resilience of Energy Systems Based on Quantitative Indicators

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Abstract: The “Clean Energy for all Europeans” package highlights the need to create a resilient critical energy infrastructure in the European Union. Resilience is an emerging term to describe the energy system’s ability to withstand shocks caused by natural hazards, technical accidents, or intentional threats. In this paper, a framework to assess the resilience of energy systems using quantitative indicators is presented. Two main groups of resilience indicators are proposed that depend on what is being measured within the energy system: capacity (attribute-based) indicators or performance in the presence of disruption (performance-based) indicators. This study concentrates on the first resilience phase, when the energy system has to absorb the impact of the shock. The approach considers various disruptions (both internal and external) as triggering events. There is a particular focus on future shocks affecting the prospective energy system, which will have changed with respect to the current one. The future foresight capabilities and potential of the selected resilience indicators are demonstrated using calculations for the Lithuanian energy system. The results revealed that the most important factors that impact energy system resilience are a rich electricity production mix and the diversification of both supply and production in the prospective energy system.

Keywords: resilience; quantitative indicators; energy system; energy security; modeling



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1. Introduction

The “Clean Energy for all Europeans” package [1] fosters critical resilient energy infrastructure as a backbone of the Energy Union. Directive 2008/114/EC on critical infrastructures and Regulation 347/2013 on guidelines for trans-European energy infrastructure highlight the need to create a well-connected European Union (EU) energy infrastructure to ensure resilient and affordable energy supply to its customers. This is in line with the European Green Deal [2] objectives as one of the key principles for the clean energy transition is to ensure a secure and affordable EU energy supply.

The term resilience is used in various research disciplines. However, the term applied directly to energy systems or energy more generally is not widespread. The most common definition is provided by the International Energy Agency (IEA), which defines energy system resilience as “the capacity of the energy system or its components to cope with a hazardous event or trend, responding in ways that maintain their essential function, identity and structure while also maintaining the capacity for adaptation, learning and transformation” [3]. Some other definitions are consistent with the IEA and state that resilience refers to the capacity or the ability of the energy system to tolerate and withstand different types of disruptions [4–8]. As presented in those studies, resilience is an emerging term for describing an energy system’s ability to withstand shocks caused by natural hazards, technical accidents, or

intentional threats (i.e., physical or cyber-attacks). Although some definitions of energy system resilience exist, there is none that is agreed-on and accepted [9,10]. Also, in many studies, the concepts of energy security and energy resilience are intertwined, and special focus is given to energy security, with energy resilience analyzed as one of the dimensions of energy security [9,11–15]. In this paper, the differences between the definitions of energy security and energy system resilience are not considered critical, and the two terms are used interchangeably.

The literature on methods of assessing energy system resilience mostly cover two approaches: model-based and indicator-based approach. The most commonly applied modeling approaches to energy system resilience are based on stochastic and simulation models [16–20], optimization models [21–31], and agent-based models [32–35]. Although indicator-based approaches for the assessment of energy system resilience are still limited, some studies on resilience indicators exist [36–46].

However, regarding the assessment of energy system resilience using indicators, it may not always be proper to use a single or aggregated energy resilience indicator to measure the performance of the energy system. Instead, a framework of different indicators may be employed to assess the behavior of the energy system under different resilience phases in the presence of disruption.

This paper aims to present a framework of indicators for evaluating the resilience of energy systems, with a focus on their future potential situations. The use of indicators is a method that can be applied for analyzing resilience concerning the capabilities of energy systems and their potential degradation and recovery.

The proposed framework concentrates on the first resilience phase, when an energy system has to absorb the impact of the shock. The approach considers various disruptions (both internal and external) as triggering events, and there is particular focus on future shocks affecting the prospective energy system, which will have changed with respect to the current system. Thus, the future foresight capabilities of some resilience indicators are analyzed in this study by demonstrational calculations. For that, the energy system modeling tool for energy planning is employed.

The structure of the remaining part of the paper is as follows: Section 2 presents the proposed methodological approach; Section 3 describes the energy system model, key modeling assumptions, data, and scenarios used for methodology demonstration; the modeling results are discussed in Section 4; and main insights of the study are summarized in the conclusion, Section 5.

2. Energy System Resilience Indicators

In this section, a set of indicators that can be used to define energy system resilience is identified. The focus is the first resilience phase, when indicators estimate how an energy system absorbs the impact of the disruption.

The proposed indicator framework is developed considering:

- The authors' expert opinions and many years of academic and practical experience in the energy sector, including energy security, critical energy infrastructures, reliability, risk analysis, and related topics. The authors' experience spans both the national and international levels.
- Literature review of other authors on energy system resilience

The most important concern regarding energy system resilience is to measure the capacity of the energy system to absorb or limit the impact of disruption and to measure the performance of the energy system in the presence of disruption. This resilience measurement approach is consistent with the resilience metrics proposed in [41,42].

Resilience indicators, which measure a system's ability or capacity to absorb disruptions, are consistent with attribute-based metrics. Attribute-based indicators generally demonstrate characteristics of the energy system and its current resilience in comparison with other systems. These indicators measure what makes the energy system more or

less resilient. Resilience is measured based on the attributes of the energy system or its components, e.g., the number of generators on site.

Additional indicators of this group that demonstrate not the physical system's capacity but the organizational capabilities can also be employed to measure resilience. These typically include mitigation and emergency management, emergency plans, strategies, staff training, knowledge, organizations, people, control center maintenance, and other resources to perform required emergency response functions. However, these indicators are mostly utility-specific or nation-specific based on various requirements and standards and are mostly evaluated using a qualitative approach. Since this study focuses on quantitative resilience indicators, the above-mentioned measures are out of the scope of the study and are not discussed in more detail in this paper.

Resilience indicators, which measure a system's behavior/performance in the presence of disruptions, are consistent with performance-based metrics. These indicators allow for measuring changes in the resilience of energy systems. Performance-based indicators measure how resilient the energy system is in the case of disruption. These indicators do not directly reflect system characteristics but instead demonstrate how well the energy system performs in the presence of disruption. For example, energy demanded but not supplied can be an indicator of how well the energy system performs after the disruption. This contrasts with attribute-based metrics (e.g., energy reserves available). To evaluate performance-based indicators, energy system models are typically employed.

The proposed resilience indicator framework includes a tentative list of both types of resilience indicators, and it is provided below.

2.1. Ability/Capacity Indicators

***I*₁. Number of entry points**

This indicator measures the total number of all fuel supply entry points used for electricity production. Fuels such as natural gas, oil, and coal can enter an energy system in general through maritime ports, liquefied natural gas terminals, pipelines, and railways. In cases of interruption at any points, the supply could be increased in any unaffected others. This helps to insulate inland supply from supply disruption. The more entry points an energy system has, the less vulnerable it is to fuel supply disruptions. The indicator is measured by a count (*N*) of different entry points for the different fuels used for electricity production. The indicator demonstrates the ability of the energy system to tolerate both domestic and imported fuel supply disruptions.

However, if the goal is to compare the resilience of different energy systems or countries, this indicator must be normalized. For example, if a small country has few entry points and a large country has many, it does not necessarily mean that a small country will be less resilient. The number of entry points must be tied to a specific characteristic of the energy system, for example, maximum electricity demand. Then it should be normalized for a particular unit (volume), for example, per 1000 MW. This indicator would demonstrate the average number of entry points per unit of maximum electricity demand:

$$I_1 = N/D_{\max} \cdot U \quad (1)$$

where *N* is the number of entry points of fuels used for electricity production, *D*_{max} is the maximum electricity demand, and *U* is a selected unit of maximum electricity demand (e.g., per 1000 MW).

For example, if country A has 5 entry points for all fuels used for electricity production and the maximum electricity demand is 2000 MW, the indicator would be estimated as 2.5 entry points, on average, per 1000 MW of maximum electricity demand. In the same way, if country B has 8 entry points for all fuels used for electricity production and the maximum electricity demand is 4000 MW, the indicator would be estimated as 2 entry points, on average, per 1000 MW of maximum electricity demand. These calculations would result in 20% lower resilience in country B in comparison with country A.

A higher value of this indicator demonstrates higher energy system resilience to fuel supply disruptions. The same approach can be applied to similar indicators that measure the energy system's ability by counting different systems' elements.

I_2 . Number of electricity import sources

This indicator relates to the number of interconnectors providing electricity to an energy system. The more interconnectors the energy system has, the higher its resilience to external supply disruptions. The indicator is measured by a count (N) of different sources of electricity import. The indicator demonstrates the capacity of the energy system to absorb the impact of external supply (electricity import) disruptions. However, the origin of the import source is not taken into account in the resilience estimation.

For comparison of different energy systems, as in the case of I_1 , this indicator needs to be normalized in the same way:

$$I_2 = N/D_{\max} \cdot U \quad (2)$$

where N is the number of electricity import sources.

I_3 . Number of energy generators

This indicator measures the number (N_i) of energy generators that produce energy aggregated by type i , for example, the number of thermal (coal, oil, natural gas) power plants, the number of wind turbines or parks, or the capacity of solar installations. The number of generators also determines the amount of generation capacity that is connected for power generation in the presence of disruption. The more generators an energy system has, the more resilient it is to disruptions, e.g., unscheduled generator outages. In the presence of disruptions, a separate case of this indicator might include the number of energy generators located within the area that could be impacted by a disruption.

For comparison reasons, as in the cases of I_1 and I_2 , this indicator must be tied with a specific characteristic of the energy system:

$$I_3 = N_i/D_{\max} \cdot U \quad (3)$$

where N_i is the number of generators of type i .

I_4 . Capacity of transmission pipelines

In the case of natural gas, the higher the capacity of the transmission pipelines of an energy system, the larger the amount of natural gas that can be transmitted. Consequently, the pipeline may be also used for short-term storage, which might cover the gas supply for electricity production. The high capacity of system's pipeline increases the reaction options in case of supply disruptions, which results in higher energy system resilience. Transmission capacity from different sources is calculated as the sum of all the capacities of the transmission pipelines entering an energy system. This indicator is measured in any unit of volume per unit of time, for example, m^3/day or kWh/day .

However, to compare different energy systems or countries with each other, the indicator must be normalized to the consumption of energy per a certain period. It can be evaluated as a ratio of total capacity to consumption (as a percentage):

$$I_4 = TC/C \times 100\% \quad (4)$$

where TC is the total capacity of transmission pipelines and C is energy consumption.

I_5 . Capacity of transmission lines

The ability of the energy system to increase resilience is also dependent on the strength of the interconnections and electricity lines. This strength depends on both the number of transmission lines and the capacity of those lines. Greater capacity of transmission lines indicates higher capacity to reduce the impacts of both external and internal disruptions. This indicator can be measured in any energy capacity unit, for example, MW or GW .

As in the case of I_4 , for comparison of different energy systems, the indicator needs to be normalized in the same way using Equation (4).

I_6 . Length of the transmission pipelines

For natural gas, the longer the transmission pipelines in an energy system, the larger the quantity of natural gas stored in them. This feature of the energy system is known as linepack, which describes the total volume of natural gas contained within the system. This provides alternatives in case of supply disruptions. This indicator is measured in any unit of length (L), such as kilometers (km).

As in the previous cases, the indicator needs to be normalized for comparison purposes. The length of the transmission pipelines can be tied with, for example, the maximum electricity demand. This indicator demonstrates the average length per unit of maximum electricity demand:

$$I_6 = L/D_{\max} \cdot U \quad (5)$$

where L is the total length of the transmission pipelines.

I_7 . Length of the transmission lines

The length of the transmission lines in an energy system can be understood as the path length of these lines between different nodes (e.g., production and consumption). If long path lengths exist, the disruption has to passthrough a larger number of nodes and can be resolved before the entire energy system fails. Hence, a longer path (more nodes between different parts of the system) results in a slowing down of supply disruptions [43]. This factor increases energy system resilience. This indicator may be measured in any unit of length (L) (e.g., km) or in a number of nodes between, e.g., production and consumption sites. The indicator is relevant for both internal and external electricity supply disruptions. For comparison of different energy systems, as in the case of I_6 , this indicator needs to be normalized in the same way.

On the other hand, long paths in both cases (indicators I_6 and I_7) are associated with inherently more complex energy systems. The energy source is farther from its point of use, and more potential points of failure exist. In the case of disruption, it is more difficult to replace the disrupted part on an emergency basis. Additionally, a short path length allows an energy system to be more easily steered.

I_8 . Number of connections in the energy system

This indicator represents the degree centrality of a node in the system where nodes represent intervention points. As stated in [43], the degree centrality of a node can be calculated by summing the connections that a node has to other components in the system. Central nodes (nodes with high centrality) allow for a quick stabilization of the energy system's performance in the case of external or internal disruptions. This ability ensures higher energy system resilience. The energy system's interconnections also increase resilience by providing alternative energy supply routes. This indicator reflects energy system structure with respect to production sites. The indicator may be measured as a count (N) of different connections to other producers or /and consumers in an energy system.

As in the cases above, to compare different energy systems, this indicator is normalized per unit of maximum electricity demand.

I_9 . Configuration of the energy system

The energy system's configuration may also increase energy system resilience. As stated in [47], configurations allow the energy system to be modified in case of failure of one or more nodes and arcs by opening and closing switches. Switches may be controlled manually, automatically, or remotely using supervisory control and data acquisition systems. In the case of disruption, energy system operators are able to divert power through other parts of the system. This indicator is measured as a percentage of node connections that are operated manually, automatically, and remotely:

$$I_9 = N/N_{\text{Total}} \times 100\% \quad (6)$$

where N is the number of node connections that are operated manually, automatically, and remotely and N_{Total} is the number of all node connections in the energy system.

A higher indicator indicates higher energy system resilience.

Higher resilience should also be achieved when different system elements are not concentrated in one place but are in different locations within the system. For example, if most of the energy generators are located in one region of the energy system (e.g., on or near the coastline), it would reduce energy system resilience.

***I*₁₀. Modularity of the energy system**

This indicator measures the autonomy of different parts of the energy system that function independently. As stated in [43], higher modularity allows for the autonomous functioning of the different parts of an energy system (e.g., islanding). Energy system resilience increases if the overall modularity or/and the clustering of a system increases. External and internal disruptions spread less quickly in modularized systems and can be “blocked” at the entrance node to the module. This indicator is measured as a number (N) of independent distribution networks within the energy system.

To compare different energy systems, this indicator must be tied with a specific characteristic of the system. In this case, the proper characteristic is the total installed capacity. The indicator then would demonstrate the average number of independent distribution networks per unit of total installed capacity:

$$I_{10} = N/TIC \cdot U \quad (7)$$

where N is the number of independent distribution networks in the energy system and TIC is the total installed capacity.

***I*₁₁. Percentage of distributed energy technologies**

Energy systems that are based on distributed energy have lower vulnerability in the case of power disruptions (e.g., loss of power at critical loads). This indicator measures the ability to maintain energy supply during disruptions. Distributed energy technologies might be used to supply energy and create redundancy in the energy system.

The indicator is expressed as a percentage in the following manner:

$$I_{11} = N_{CF}/N_{Total} \times 100\% \quad (8)$$

where N_{CF} is the number of distributed energy technologies and N_{Total} is the number of all energy technologies in the energy system.

The higher this indicator, the higher the energy system resilience. However, for most energy systems today, distributed generation is not yet resolved, and this indicator may be more suitable for assessing the resilience of future energy systems.

***I*₁₂. Number of spare parts**

This indicator measures the number (N_i) of spare parts of type i an electric utility has on hand in the presence of disruption. It demonstrates the capabilities of the companies operating the systems through the maintenance of spare equipment (e.g., transformers, switches, cables) for rapid repair to absorb the impacts of disruption. A higher indicator demonstrates higher energy system resilience. However, the availability of spares usually depends on cost. For instance, electric power utilities often maintain small stocks of relatively inexpensive equipment for maintenance and emergencies. Some of the spare parts are difficult to maintain because of their high cost and specificity [47]. Thus, just having a larger number of spare parts necessarily increases resilience meaningfully. This number has to be tied with projected needs for these spare parts in the case of disruption. In this case, not only the number of spare parts has to be taken into account, but also the total number of parts that might be damaged and potentially need to be replaced in the case of disruption:

$$I_{12} = N_i/N_{Total} \times 100\% \quad (9)$$

where N_i is the number of spare parts of type i and N_{Total} is the total number of parts that might be damaged in the case of disruption.

***I*₁₃. Diversity indicators**

Diversity allows for the use alternative energy technology instead of the technology that has been disrupted. Many diversity indicators exist in the scientific literature, for ex-

ample, in [48]. In this paper, diversity indicators are divided into three groups according to which type of energy chain in the energy system is measured: (1) energy supply, (2) energy production, and (3) energy installation.

(1) Diversity of primary energy sources or fuels

This indicator demonstrates the diversity of the supply of primary energy sources (PES) or fuels used in energy production. It should be evaluated for particular PES or fuels such as coal, oil, natural gas, and biomass. Imported and domestic fuels can be aggregated into a single group. Diversification in the supply of PES or fuels should make an energy system more resilient in case the supply of a particular PES or fuel is missing. This indicator measures energy system resilience against various PES or fuel supply disruptions.

(2) Diversity in the energy production mix

The indicator demonstrates the level of dependency of one energy production technology in total energy production. Energy import technology also should be included as a separate technology in satisfying energy demand. High diversity in the energy generation mix ensures higher resilience in the case of one or other energy production technology is lost. This indicator relates to both internal and external disruptions.

(3) Diversity in installed energy capacity

This indicator demonstrates the diversification of installed capacity from different fuel sources that may be used to produce energy. The indicator measures the potential energy production. The more options an energy system has, the higher its resilience.

In this paper, the three groups of the above-described diversity indicators are measured in three different ways.

(a) Number of energy supply, production and installed energy technologies

Energy technologies are divided according to different energy diversity indicators discussed above:

(1) PES or fuels; (2) energy production; (3) installed capacity.

In this case, the indicator is evaluated by counting different energy technologies and is measured only by category count:

$$I_{13a} = N_i \quad (10)$$

where i represents three different energy technologies ($i = 1, 2, 3$), N_1 is the number of PES or fuels in energy supply, N_2 is the number of energy production technologies in energy production, and N_3 is the number of energy technologies in installed capacity.

The number of different energy technologies existing in the energy system shows the variety in energy supply, production, and installed capacity. The impact of this indicator is twofold: if the energy system shows low variety, it is more stable; however, in the case of disruption, such an energy system might not react properly due to lower capacity.

(b) Share of energy supply, production and installed energy technologies

This indicator demonstrates what share is covered by one energy technology, for example, in energy supply, the energy production mix or installed capacity. The high use of one technology increases the dependency in the energy supply, which exposes the energy system to potential disruptions in supply.

In this case, the indicator is calculated as follows:

$$I_{13b} = S_i^k / \sum_{i=1}^n S_i^k \times 100\% \quad (11)$$

where S_i^1 is the amount of supply of PES or fuel i , S_i^2 is the amount of energy produced from the energy production technology i , S_i^3 is installed capacity of energy technology i , and n is the total number of energy technologies.

This indicator measures diversity in the energy system from the dominance/distribution of one energy technology point of view. In general, a high share of one energy technology indicates low energy system resilience. This case refers to the balance of different energy technologies. A high balance is reached when energy technologies in the energy system are distributed evenly and potentially implies a higher degree of flexibility, which again reflects higher resilience. A low balance leads to lower resilience and is reached when energy supply or production is concentrated on one or a just a few energy technologies.

(c) Diversity indicators (SWI and HHI)

Balance across different energy technologies within the energy system is measured by the Shannon-Wiener index (SWI) or the Herfindahl-Hirschman index (HHI), which are widely used in the scientific literature [49–51]. Both indicators are expressed in numeric values based on the shares of energy technologies in the energy system. These indicators measure the balance and diversity in energy supply, energy production, and installed capacity. SWI and HHI indicate whether one energy technology is dominant or not in the energy system.

SWI is calculated as follows:

$$SWI = - \sum_{i=1}^n p_i^k \ln(p_i^k) \quad (12)$$

where p_i^1 is the share of PES or fuel i in the total supply, p_i^2 is the share of energy production technology i in the total energy production, and p_i^3 is the share of energy technology i in the total installed capacity.

If only one energy technology option is available, SWI is equal to zero. By contrast, if energy technology shares are even, SWI reaches a theoretical maximum that depends on the number of energy technologies in the energy system. In order to have limits for SWI, it can be normalized in the following way:

$$SWI_{norm} = - \left(\sum_{i=1}^n p_i^k \ln(p_i^k) \right) / \ln n \quad (13)$$

The normalized SWI is between 0 and 1. In both cases, the higher the SWI, the higher the diversity, which indicates higher energy system resilience.

HHI demonstrates the concentration of the individual shares of the energy technologies in the energy system. It is calculated as follows:

$$HHI = \sum_{i=1}^n (p_i^k)^2 \quad (14)$$

where p_i^k is expressed as a percentage.

The lower the HHI, the greater the diversity, again indicating higher energy system resilience. The minimum value is reached when all the shares are equal.

I₁₄. Largest single source of energy supply/production

This indicator is measured as a share of the largest energy supply or production of one technology in the total energy supply or production. The supply term includes not only energy production but also energy import in order to satisfy the energy demand. This indicator is expressed as a percentage of supply/production in the following manner:

$$I_{14} = SL/ST \times 100\% \quad (15)$$

where SL is the amount of the largest energy supply/production of one technology, ST is the amount of the total energy supply/production in the energy system.

If the share of one energy technology is dominant in the energy supply or production, the energy system is vulnerable to energy supply disruptions. A higher indicator demonstrates higher vulnerability and less energy system resilience.

I₁₅. Import dependency

One way to define this indicator is the share of energy import in the total energy demand. The indicator is evaluated as one minus the ratio between energy production and energy demand (as a percentage):

$$I_{15a} = (1 - P/D) \times 100\%, \quad (16)$$

where P is the amount of the produced energy and D is the energy demand.

A higher indicator indicates higher dependency on energy imports and thus less energy system resilience.

Another way to evaluate this indicator is the ratio between energy demand and energy production:

$$I_{15b} = D/P \quad (17)$$

If the indicator is lower than 1 (production > consumption), the energy system has energy export capabilities. This represents a more resilient energy system. However, if the indicator is higher than 1 (consumption > production), the energy system is dependent on energy imports, and high import dependency makes the energy system more vulnerable to external supply disruptions, that is, less resilient.

I₁₆. Share of renewable energy sources in energy production

This indicator defines the use of energy from nonfossil energy carriers in energy production. The availability of renewable energy sources (RES) depends on the analyzed energy system and can include hydropower, wind, solar, biomass, geothermal, and other sources, e.g., tides and waves.

This indicator is evaluated as the RES share in the energy production as a percentage, and calculation is based on the ratio of energy production from RES to the total energy production:

$$I_{16} = P_{RES}/P \times 100\% \quad (18)$$

where P_{RES} is the amount of energy production from RES.

A diversified energy mix is one way to increase energy system resilience. The use of renewable energy may offset the vulnerability coming from high import levels of fossil fuels. Small hydro systems may reduce the need for extensive transmission and distribution lines, which may generate new vulnerabilities. Wind, solar, and local biofuel technologies allow for energy generation from the local resources. Thus, the more RES is used as a share of the total energy production, the less vulnerable the energy system is to supply disruptions, which indicates higher resilience. However, if the penetration of RES is too deep and no proper balancing and storage options are available, energy system resilience might be lower as well due to the risk of blackout.

I₁₇. Energy reserves

One way to evaluate this indicator is to calculate the reserves to production ratio as a percentage:

$$I_{17} = ST/P \times 100\% \quad (19)$$

where ST is the capacity of storage/reserves.

Another way to measure the indicator is in the length of time (e.g., days, years). The indicator then gives the period for which the available reserves can be used for energy production. In both cases, a higher indicator reflects higher energy system resilience. The impact of disruption on reserves is heavily dependent on the amount of energy stored at the time of the disruption.

I₁₈. Spare capacity

This indicator measures the difference between the amount of energy produced in a unit of time (e.g., hours) and the amount of energy that could be produced at full capacity:

$$I_{18} = \sum_{i=1}^n ((IC_i \cdot t) \cdot CF_i - P_i) \quad (20)$$

where IC_i is installed capacity of energy technology i , t is time in hours ($t = 8760$ h on a yearly basis), CF_i is the capacity of the energy technology i , P_i is the amount of energy of produced by the energy technology i , and n is the number of energy technologies in the energy system.

This indicator demonstrates the ability of the energy system to produce more energy than is now being produced (if necessary). A higher indicator demonstrates higher energy system resilience to supply disruptions.

I_{19} . Ratio of total installed capacity to energy demand

This indicator is measured as the ratio between the available generation capacity and the energy demand. If the electricity system is analyzed, generation capacity might include not only electricity generators but connection lines (interconnectors) as well.

Calculation of the indicator is based on a ratio of the total installed capacity to the total energy demand:

$$I_{19} = TIC/D \times 100\% \quad (21)$$

This indicator addresses the energy system's excess generation capacity. High installed capacity demonstrates the energy system's capability of absorbing the impact of internal disruptions and satisfying the demand. A higher indicator reflects higher energy system resilience.

I_{20} . Energy cost stability

The prices of traditional fossil fuels are more volatile than the prices of RES. As the energy system (especially the electricity system) might be particularly vulnerable to these price fluctuations due to various factors, the stability of energy cost should be taken into consideration.

This indicator measures the stability of energy technology costs of electricity generation against energy or fuel price fluctuations. The calculation of the indicator is based on the fraction of energy or fuel cost to the energy technology costs of electricity generation (expressed as a percentage):

$$I_{20} = EC/TC \times 100\% \quad (22)$$

where EC is the energy or fuel cost and TC is the energy technology cost of electricity generation.

This indicator is specifically relevant in the case of cost shocks in the energy system. Greater fluctuation in the indicator reflects lower energy system resilience.

I_{21} . Energy demand

Reduced energy demand allows for reducing dependence on imports and decreasing expenditures on energy. However, the increase in energy demand due to extreme cold or hot weather might lead the energy system to disruptions. Less volatile energy demand leads to higher energy system resilience. Moreover, the higher the growth of energy demand, the less has been achieved in reducing vulnerability to supply disruptions.

2.2. Performance-Based Indicators

Indicators discussed in Section 2.1. mostly measure the energy system's capacity to absorb or limit the impacts of disruption. Some of these indicators (e.g., import dependency, RES share, diversity) show the changes in the energy system during the disruption. Thus, some indicators can measure the performance of the energy system in the presence of disruption and demonstrate the level of energy system resilience. Some quantitative indicators to measure the performance of the energy system in the case of a sudden shock are proposed further (the numbering of indicators is continuing).

I_{22} . Unserved energy

Unserved energy or energy not supplied can be described as an estimate of the energy that would otherwise have been used by customers but for disruption. The level of unserved energy can be evaluated either in a quantitative amount (e.g., PJ or GWh) or in percentage (%).

Based on [6,52], the first indicates how much energy was not provided during the studied time period as an absolute number. The second case is directly related to the first and is normalized using the energy demand in the studied time frame or on a yearly basis and expressed as a percentage:

$$I_{22a} = UE/D \times 100\% \quad (23)$$

where UE is the amount of unserved energy.

This indicator as a percentage can also be calculated in another way using the energy supply and energy demand variables:

$$I_{22b} = (1 - S/D) \times 100\% \quad (24)$$

where S is the amount of the supplied energy.

This performance-based indicator describes the impacts of energy supply disruptions on the performance of the energy system. A higher indicator indicates lower energy system resilience.

I_{23} . Time of unserved energy

Time of unserved energy can be measured in any unit of time per a certain timeframe (e.g., hours per year) or in the percentage of the time energy that is unserved per a certain timeframe. For example, the second measure on yearly basis can be calculated as follows:

$$I_{23} = TUE/8760 \times 100\% \quad (25)$$

where TUE is the number of hours in which energy demand is not met in a year.

This indicator is relevant in the case of supply disruptions. A higher indicator demonstrates lower energy system resilience.

I_{24} . Cost change

This indicator is used to evaluate the impacts of both supply and cost disruptions. This performance-based indicator defines changes (in most cases increases) in the energy system's total costs compared with the costs of the reference case (no disruptions). The total discounted cost of the energy system is the result of the objective function of most of the energy system optimization models.

As suggested in [52], energy cost change is based on the total discounted cost in the case of a disruption scenario and cost in the case of the reference scenario. The percentage of energy cost change is calculated in the following manner:

$$I_{24} = ((SC - BC)/BC) \times 100\% \quad (26)$$

where BC is the total cost of the scenario without disruptions and SC is the total cost of the scenario with disruptions.

This indicator reflects the percentage that a certain disruption changed (increased or decreased) the total discounted costs of the energy system. If the value is positive, the costs increased, and if the value is negative, the costs decreased. If the value is zero, the costs were not changed. A higher positive indicator indicates lower energy system resilience to cost and supply disruptions.

The above discussed performance-based indicators measure energy system resilience to various disruptions and demonstrate the system's performance in the presence of these disruptions.

The proposed indicator framework in Section 2 can also be applied to prospective energy systems including estimating the resilience against future disruptions. For estimating most resilience indicators, the energy system model, which models energy system development in the future, is needed. However, not all discussed resilience indicators can be evaluated from the results of energy system models. The evaluation of future foresight capabilities of such indicators should be performed from either statistical data (forecasts) or other detailed data from, for example, energy network models.

In the next sections, the performance of selected resilience indicators in the future perspective is demonstrated by conducting a modeling exercise using the energy system of Lithuania.

3. Energy System Model

In this section, the energy system model and key modeling assumptions are described. The modeling exercise is conducted in order to demonstrate the performance of the energy resilience indicators for different scenarios that represent future narratives of the energy system. It is mostly based on a detailed technical and economic analysis of future energy system performance for Lithuania. The model structure, used tools, key modeling assumptions, and scenarios are briefly described further.

3.1. Energy System Modeling Tool

The main step in running the demonstration example and estimating the resilience indicators is the modeling of the energy system. The study uses a long-term energy system modeling approach, which allows for the evaluation of resilience indicators for the future. In this study, the model of the Lithuanian energy system is constructed using the Open Source Energy Modeling System (OSeMOSYS). It is a tool developed by the KTH Royal Institute of Technology in collaboration with a range of other institutions. The objective function of OSeMOSYS is to minimize the total discounted costs of an energy system to meet the given demand for energy services, which can be met through a range of technologies. A more detailed description and implementation of the OSeMOSYS tool can be found in [53,54].

In order to develop the model of the Lithuanian energy system and to evaluate the performance of resilience indicators, it is necessary to make initial assumptions that could have significant impacts on the model itself and the results of the modeled scenarios.

3.2. Model Structure and Key Modeling Assumptions

In this demonstration example, the model structure is based on the MESCA (Model for Energy Security Coefficient Assessment), which was developed during the implementation of the European Commission project REEEM [55] and is described in more detail in [56]. The mathematical model for the energy system focuses on the electricity system. However, the district heating system in Lithuania is related to the electricity system with combined heat and power plants.

The energy system in the model is represented by fuel supply, electricity, and heat generation and supply systems. It is also characterized by existing and candidate technologies such as power plants, heat boilers, transmission and distribution networks, local and imported fuel, and electricity imports. Each technology is characterized by technical and economic parameters, e.g., efficiency, lifetime, installed capacity, and costs.

The analysis period is from 2015 to 2050 in 1-year time steps. Each year in the model is divided into 15 time slices that represent 5 seasons and 1 typical day per season: night, day, and peak. This approach is applied from the OSeMBE (Open Source energy Model Base for the European Union) [57], which is one of the main applications of the OSeMOSYS tool. This division into time slices at the same time reflects average electricity load and wind variable generation. A discount factor of 5% was used. The model also includes already implemented and foreseen major energy system infrastructure projects, e.g., power and gas interconnections with neighboring countries.

3.3. Data

The main data for the technical and economic parameters of technologies were taken from the TIMES PanEU model, which was the key model developed within the REEEM project [58] and the MESCA model [56]. Additional data, such as the year division into time slices, electricity consumption patterns, availability, and capacity of RES were derived from the OSeMBE model [57], which is the model implemented in the OSeMOSYS tool and

developed as an open-source engagement model. Electricity demand projections are taken from the electricity transmission system operator of Lithuania, LITGRID [59]. The main MESCA data that we used in the modeling exercise are stored in the database of the Open Energy Platform [60].

3.4. Scenarios

Scenarios in the performed exercise were constructed according to the assumptions of base and high RES pathways developed in the REEEM project and reported in the First Integrated Impact Report [61]. Both scenarios are based on the transition of the energy system to a low-carbon energy future.

The main factors defining energy system scenarios are emissions of greenhouse gases (GHG) and the use of RES. It was assumed that GHG emissions in the emission trading sector (ETS) should be reduced by 21% in 2020, by 43% in 2030, and by 83% in 2050 compared to the 2005 emission levels. However, the GHG emission targets for non-ETS are set as +15% in 2020, −9% in 2030, and −60% in 2050. These targets demonstrate that emission increase at the beginning of the study period is allowed.

Another factor used for scenarios assumptions is the national RES targets. The existing targets of renewable share in gross final consumption for Lithuania in the base case are 23% in 2020, 36% in 2030, 56% in 2030, and 75% in 2050. Assumptions for the GHG emission and renewable energy targets are based on the EU 2020 Climate and Energy Package [62], the 2030 Climate and Energy Framework [63], and the EU Roadmap 2050 [64] and are in line with the Paris Agreement [65].

In general, the base and high RES scenarios did not demonstrate significantly different results, and therefore, additional assumptions for both scenarios were introduced and adopted in this study. Two scenarios are considered: Scenario 1 (SC1), which corresponds to the base pathway and represents current energy system trends, and Scenario 2 (SC2), which corresponds to the high RES pathway that assumes higher renewable energy generation targets.

Since the focus of the study is on the electricity system, RES share targets are applied for final electricity consumption and are modified for the analyzed scenarios. We added an assumption regarding the constraint for electricity import. It is assumed that electricity imports over time will be replaced by local electricity generation, which should reach a certain share. The assumed targets for the use of RES and the share of local electricity generation in the country are presented in Table 1.

Table 1. Shares of RES in the final electricity consumption and local electricity generation.

Scenario	Type of Share	2020	2030	2040	2050
SC1 (Base)	Share of RES	23%	36%	56%	75%
	Share of generation	20%	50%	65%	80%
SC2 (High RES)	Share of RES	30%	45%	72.5%	100%
	Share of generation	35%	70%	85%	100%

Assumptions for SC2 correspond to the outlined objectives in the National Energy Independence Strategy of the Republic of Lithuania [66].

Hypothetical disruptions in the energy system

The main goal of most resilience indicators is to evaluate energy system performance in the case of disruptions or shocks and investigate the impacts. Disruptions in the energy system might occur for different reasons, for example, failures or unplanned outages of technical equipment, weather-related events, volatility in global energy prices, or attacks (both physical and cyber) on energy infrastructure. All these events usually affect the energy system in two ways: interruption of energy supply sources and energy price shocks. In this paper, the focus is on these types of disruptions that might have an impact on the energy system.

In order to demonstrate the performance of resilience indicators for the future, constructed scenarios (SC1 and SC2) must be also modeled in the case of certain disruptions (shocks). Therefore, additional disruption scenarios have been developed for this purpose.

In contrast to reliability, resilience usually is associated with long-duration power disruptions caused by high-impact and low-probability events. Here, some disruptions to the electricity system are hypothesized as separate scenarios, and the long-term impacts to the energy system with the selected resilience indicators are investigated. In order to compare the results of the analyzed scenarios, it is assumed that these disruptions occur in the same time frame, from 2025 to 2035, under each of the two analyzed scenarios. The analyzed disruption scenarios are the following:

- D1. The loss of energy import sources;
- D2. The loss of natural gas supply;
- D3. The loss of biomass supply;
- D4. The loss of wind PPs (both onshore and offshore) in electricity production.

Such extreme hypothetical disruption scenarios were selected for purposes of demonstrating the long-term performance of the resilience indicators for the future.

4. Modeling Results

The modeling exercise was performed using the energy system model described in Section 3. First, the energy system model was run in the case of two scenarios (SC1 and SC2) without any disruptions in the system. This was to demonstrate how the energy system might develop under certain assumptions and constraints in the future. It should be emphasized that this is not a forecast but a hypothetical development of the energy system under different assumptions within different scenarios. Then, each of the scenarios is run under different disruption scenarios as introduced in Section 3.4. Selected resilience indicators are evaluated for these scenarios and the results provided.

4.1. Installed Capacity and Electricity Production

Among the main results are the electricity production mix and the installed capacities in each analyzed scenario. These results may highly affect the performance of the energy system in the case of various disruptions, and the performance will be measured with resilience indicators. The results of the installed capacities of power plants and their interconnectors as well as the electricity production in Lithuania in the analyzed scenarios are presented in Figure 1.

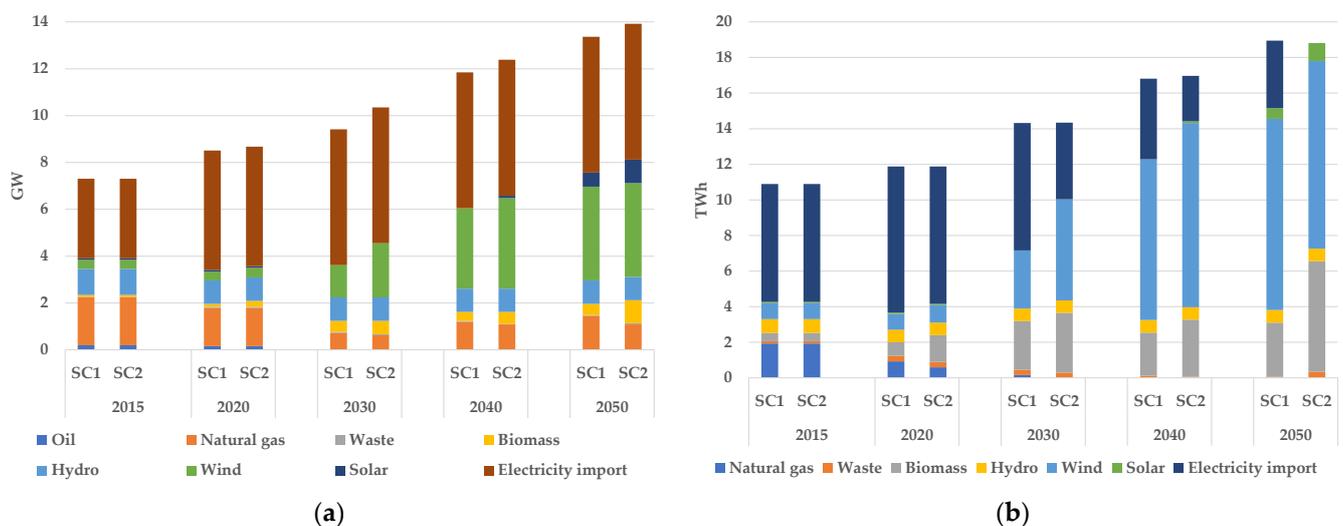


Figure 1. (a) Installed capacities of electricity production sources; (b) electricity production by different energy technologies.

The largest shares of installed capacity of power plants at the beginning of the study period come from natural gas (52%), hydro (28%), and wind (10%) in both scenarios. Over time, the installed capacities of fossil fuel-fired plants decrease, and capacities of RES increase significantly. At the end of the analysis period, the largest share has wind (approx. 50% in both scenarios) with the contributions of biomass, hydro, solar, and natural gas. However, these shares have slightly different results among scenarios; for example, solar and biomass have higher shares in SC2, and natural gas has higher share in SC1. Furthermore, the total installed capacity in 2050 is higher by 4% in SC2 in comparison with SC1.

Electricity imports at the beginning of the study period are a dominant source of electricity supply. The share of imported electricity covers 60–70% of the total electricity requirement in Lithuania in both scenarios until 2020. Due to assumptions in both scenarios, electricity imports decrease significantly over time, mostly replaced by wind energy, biomass technologies, and some solar at the end of the study period.

A faster decline in electricity imports and a faster increase in RES is observed in SC2, in which assumed targets were more ambitious regarding RES than in SC1. Electricity production from wind and biomass is growing in time to compensate for electricity import reductions. Thus, the share of wind energy in electricity production in 2030 reaches 23% in SC1 and 40% in SC2; in 2050 the share excels at approx. 57% in both scenarios.

The penetration of RES technologies over time changes the diversity in the energy system and the type of the largest share in the electricity mix. In SC1, electricity imports decrease to 54% by 2030 and wind attains 57% by 2050. In SC2, wind energy attains 40% by 2030 and 56% by 2050, having the largest share. The modeling of the energy system is also performed in the case of various disruptions (both supply and cost shocks), which were introduced and discussed in more detail in Section 3.4.

4.2. Resilience Indicators under Hypothetical Disruptions in the Energy System

Several disruptions to the Lithuanian energy system that might have an impact on electricity supply were hypothesized under analyzed scenarios. In order to demonstrate the performance of the energy system under these disruptions, several resilience indicators were selected and evaluated: (a) unserved energy (I_{22}); (b) cost change (I_{24}); (c) import dependency (I_{15}); (d) share of RES (I_{16}); and (e) the diversity indicators (I_{13}) (SWI and HHI). However, the results present the estimates only of these indicators, which demonstrate some changes in the energy system due to disruptions.

4.2.1. The Loss of Electricity Import Sources (D1)

In this disruption scenario, the loss of all five electricity import sources (differentiated by import country) in the Lithuanian energy system was considered. First, the unserved energy indicator was observed (Figure 2), which indicates the percentage of electricity import needed for the energy system to “survive” (to avoid unserved energy).

This indicator is demonstrated only during the time period of disruption. Higher impact of the disruption and lower energy system resilience are seen in SC1, which is more dependent on electricity imports in comparison with SC2. In SC1, 23% of electricity imports is needed for the energy system to avoid unserved energy in 2025, whereas the value in SC2 is 8% at the same time. However, the indicators in both scenarios decrease with the decreasing dependency on electricity import. The energy system can survive without electricity imports from 2029 in SC2 and from 2034 in SC1.

In 2025, the share of electricity imports in the electricity supply still covers the largest proportion in both scenarios without disruptions, 62.5% in SC1 and 47.5% in SC2. This is estimated by the import dependency indicator, presented in Figure 3. Obviously, the values of this indicator should not be taken into account during disruption scenarios (SC1_D1 and SC2_D1) when all electricity import sources are lost and indicators are equal to 0.

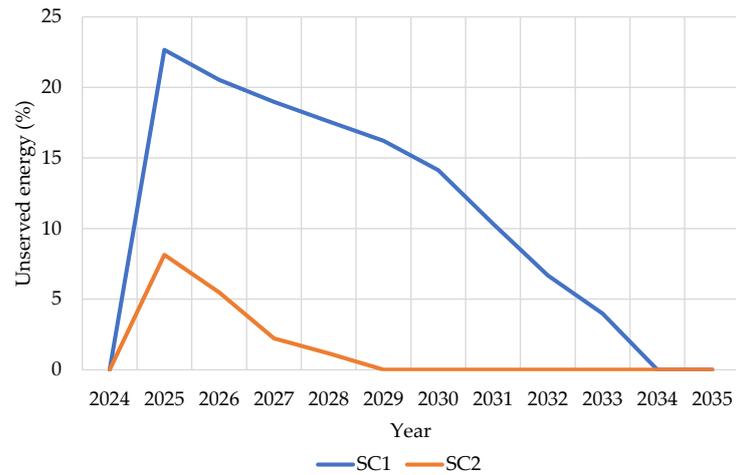


Figure 2. Unserved energy (%) in the case of the loss of all electricity import sources.

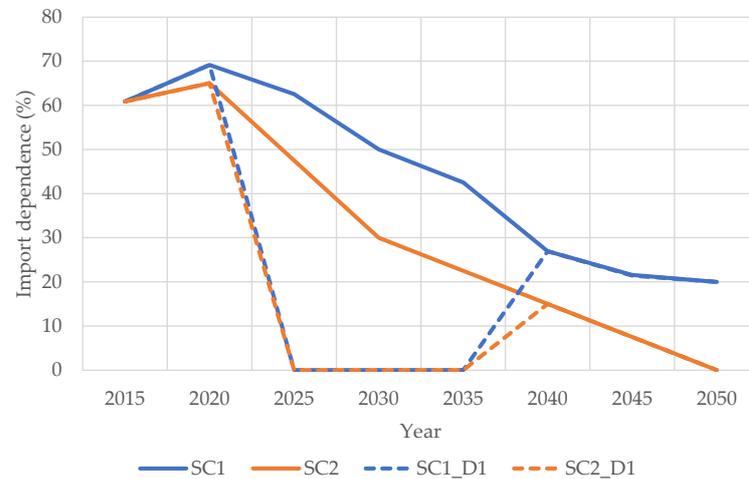


Figure 3. Import dependence (%) in the case of the loss of all electricity import sources.

Change in energy system total costs was also evaluated during the disruption time frame (Figure 4). Over time, the indicators increase since relatively cheaper electricity imports are replaced due to unavailability with technologies that produce electricity at higher costs.

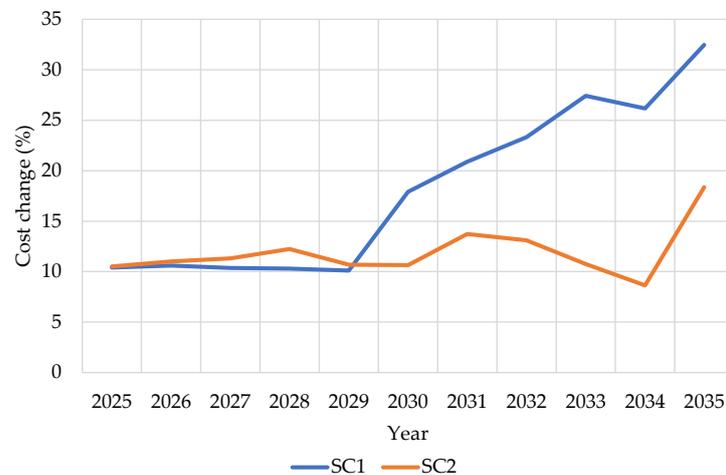


Figure 4. Cost change (%) in the case of the loss of all electricity import sources.

SC1 demonstrates less resilience to cost changes than SC2 when all electricity import sources are lost. In 2035, SC1 demonstrates an increase of ~33%, and in SC2, the increase is ~18% at the same time.

The results for the estimated indicators demonstrate that over time, the analyzed energy system tends to be more resilient to disruptions related to the loss of electricity imports. In both analyzed scenarios, a decrease in dependency on electricity imports is observed, and SC2 performs better since it assumes higher RES targets and is less dependent on electricity imports in comparison with SC1.

4.2.2. The Loss of Natural Gas Supply (D2)

In this disruption scenario, the complete loss of natural gas supply for energy production is considered. In SC1 and SC2, electricity from natural gas is produced until 2030 (due to constraints on RES targets), and the share has a decreasing trend; therefore, this disruption does not significantly change the electricity mix. The shares of natural gas in electricity production in 2025 are approx. 2.1% in SC1 and 2.6% in SC2. The lost portion of natural gas for electricity production is simply replaced by electricity imports in the case of disruption from 2025. Unserved energy during the disruption period is not observed, and the change in total costs of the energy system reached a maximum value of 0.5% and is not analyzed in more detail.

The estimates of these two indicators demonstrate high energy system resilience in both scenarios in the case of the loss of natural gas supply. However, this observation is applied only to the electricity system. The heating system is more impacted by this disruption, but details are not analyzed since it is out of the scope of this study.

Figure 5 shows the import dependency indicator, which in the case of the loss of natural gas supply demonstrates that the energy system relies more on electricity imports during the disruption period. However, the difference is not significant since over time, the energy system in both scenarios is decreasingly dependent on electricity production from natural gas.

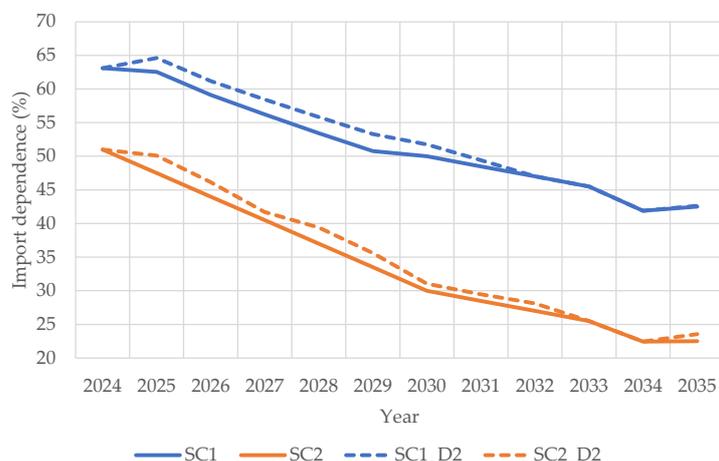


Figure 5. Import dependence (%) in the case of the loss of natural gas supply.

Import dependence is decreasing due to constraints in both scenarios on electricity production in the country. In addition, these constraints are neglected in the case of a shock to let the energy system absorb the impact first, but this is not necessary to fulfill the requirement due to certain targets set in both scenarios.

The diversity indicators (SWI and HHI) in Figure 6 show a better balance across different energy production technologies in electricity production in scenarios without disruption.

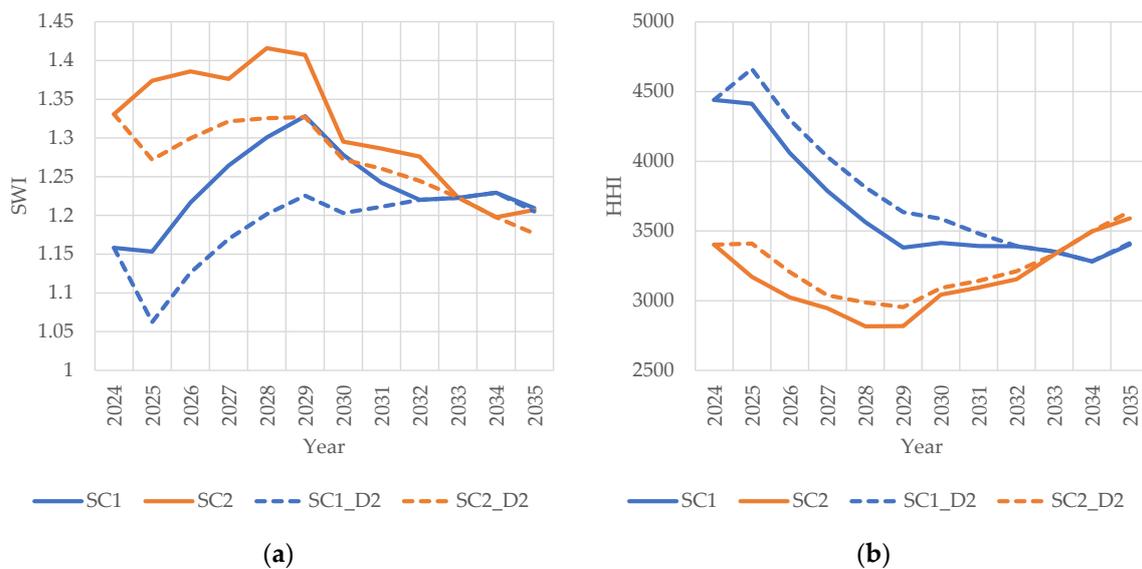


Figure 6. Diversity indicators in the case of the loss of natural gas supply: (a) SWI; (b) HHI.

During the shock phase, less diversification is observed due to the loss of one energy production technology in electricity production. SC2 performs better (SWI higher, HHI lower) in terms of diversity at the beginning of the analyzed period in comparison with SC1. Over time, the share of electricity imports is decreasing, which results in better performance of the diversification indicators; however, the share of wind PP is increasing and comprises a large portion at the end of the period, which results in a lower balance of electricity production in SC2 than in SC1.

In general, the results for the resilience indicators in both scenarios demonstrate the high resiliency of the electricity system to the loss of natural gas supply during 2025–2035.

4.2.3. The Loss of Biomass Supply (D3)

In this disruption scenario, the complete loss of biomass supply for energy production is analyzed. SC1 and SC2 in the period of disruption are more dependent on biomass supply than on natural gas supply. The maximum share of biomass in electricity production during the analyzed period is approx. 21% in SC1 (reached in 2026) and 25% in SC2 (reached in 2027). Later, these shares in both scenarios decrease because wind energy rapidly penetrates the energy system and takes the role of the largest share from electricity imports.

The lost portion of biomass for electricity production at the beginning of the disruption period (2025–2029) is mostly replaced by natural gas. By 2030, electricity imports overtake the lost portion of biomass in the electricity supply with a higher share in SC1. Unserved electricity during the disruption period is not observed in this case. The change in total costs of the energy system during the disruption time frame is presented in Figure 7.

The largest increase in costs is observed at the beginning of the period when the share of biomass in electricity production reaches its peak. Biomass technologies due to unavailability to produce electricity are replaced with technologies that produce electricity at higher cost. However, over time, the indicators decrease, and the cost increase is lower when the electricity system is less dependent on biomass supply. SC2 demonstrates less resilience to cost changes than SC1 when biomass supply is lost. In 2035, cost increases by 12% in SC1 and by 13% in SC2, with averages of almost 20% and 21% for SC1 and SC2, respectively (Figure 7).

These results do not contradict the scenario assumptions in which SC2 has higher RES targets. The performance of the RES share in the electricity production and import dependency during the disruption phase is presented in Figure 8.

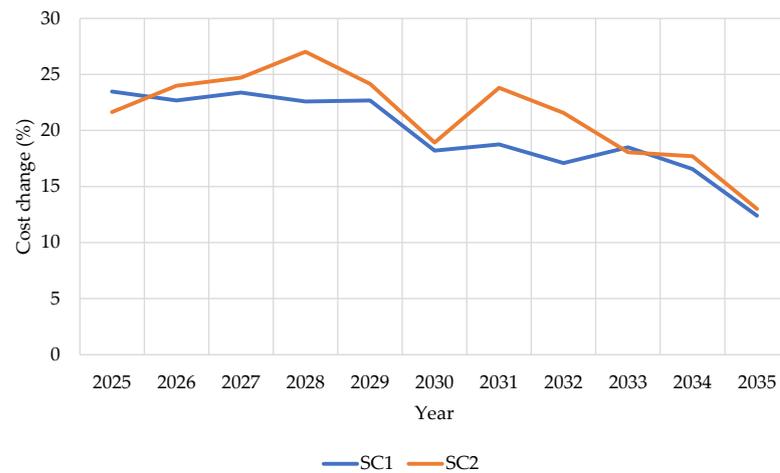


Figure 7. Cost change (%) in the case of the loss of biomass supply.



Figure 8. Resilience indicators in the case of the loss of biomass supply: (a) RES share; (b) import dependence.

In 2025, when the sudden loss of biomass supply occurs, the share of RES in the electricity production drops by 20 percentage points (from 35% to 15%) in SC1 and by 19 percentage points (from 47% to 28%) in SC2 (Figure 8a). This difference until the end of the disruption remains at a similar level. The loss of biomass supply leads to noncompliance with RES obligations that were implemented as constraints in energy systems without disruption. The energy system is not able to maintain the same level of RES due to the disruption.

Electricity import dependence has two sudden upturns in 2025 and 2030 (Figure 8b). The reason for the first is that the lost portion of biomass for electricity production is mostly replaced by natural gas and some by electricity imports. In 2030, electricity from natural gas is no longer produced, and its full share is replaced by electricity imports, which largely results in increased dependency on imports.

The results of these indicators are also reflected in the diversification indicators. The high share of electricity imports results in the low performance of the SWI and HHI indicators during the disruption period (Figure 9). For example, dependency on electricity imports in SC1 reaches even 70%, which reflects a poor balance in the electricity supply.

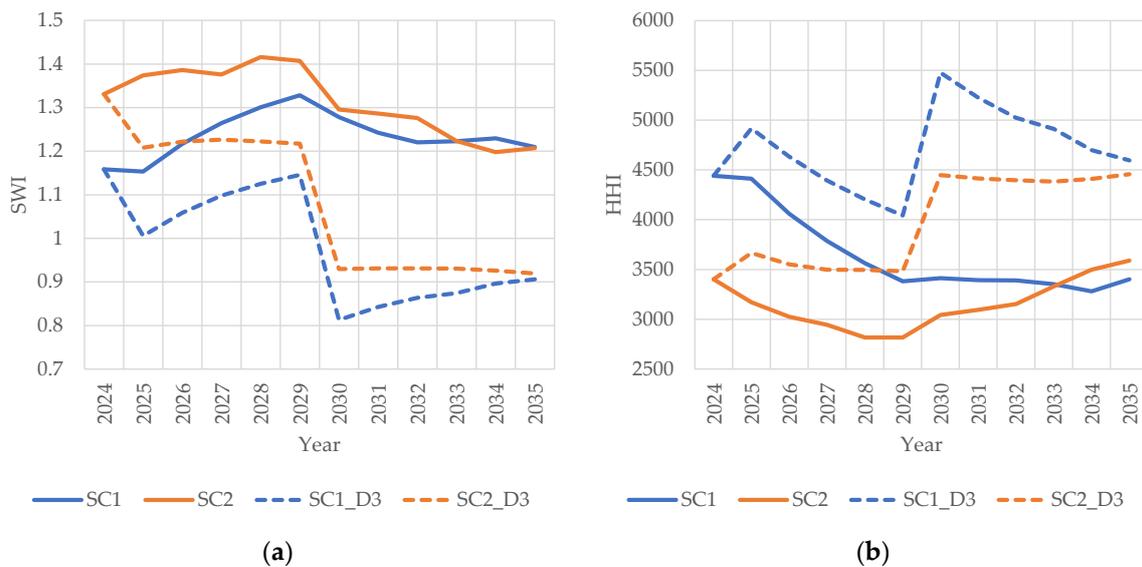


Figure 9. Diversity indicators in the case of the loss of biomass supply: (a) SWI; (b) HHI.

The results for the estimated indicators demonstrate that SC1 is more resilient to the loss of biomass supply in comparison with SC2. However, the resilience in both scenarios over time increases with the decreasing share of biomass in electricity production. It has been also shown that the RES share targets and targets for the share of electricity generation in the country that were assumed in the scenarios were not fulfilled; instead, the energy system had to cover electricity production with other technologies such as natural gas and electricity imports.

4.2.4. The Loss of Wind Generators (D4)

The complete loss of wind PPs (both onshore and offshore) is considered in this disruption scenario. SC2 during the disruption period is much more dependent on electricity production of wind technologies in comparison with SC1. The share of wind energy in electricity production during this period increases from 7% to 37% in SC1 and from 19% to 52% in SC2. After the disruption period, this share increases further since wind energy shows excellent penetration into the energy system to fulfill the RES targets we set as scenario assumptions.

The lost share of wind energy for electricity production is mostly replaced by electricity imports. Unserved electricity during the disruption period is not observed. The change in total costs of the energy system was estimated during the disruption time frame and is presented in Figure 10.

This indicator results in an opposite effect in comparison with the loss of biomass supply. The largest increase in costs is observed at the end of the period, when the share of wind energy in electricity production is much higher. The cost change indicator in SC2 demonstrates less resilience to the loss of wind PPs in comparison with SC1. The highest values are observed in 2034 in both scenarios, 21% in SC1 and 31% in SC2 (Figure 10).

RES share, import dependence, and the diversity indicators reveal changes in the energy system under this disruption as well. In 2025, when electricity production from wind PPs is lost, the share of RES is diminished by 6 percentage points (from 35% to 29%) in SC1 and by 17 percentage points (from 47% to 30%) in SC2 (Figure 11a). RES share during the disruption does not exceed 29% in SC1 and 33% in SC2. The sudden shock has a higher impact on the energy system in SC2 since the differences in RES share in the cases with and without disruption are significantly higher in comparison with SC1.

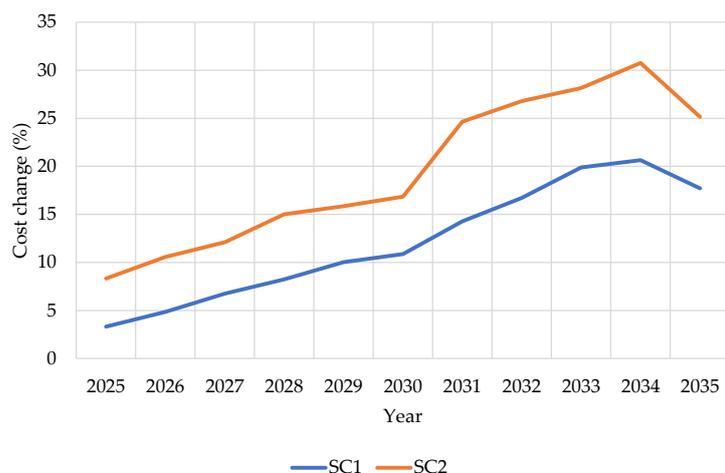


Figure 10. Cost change (%) in the case of the loss of wind generators.

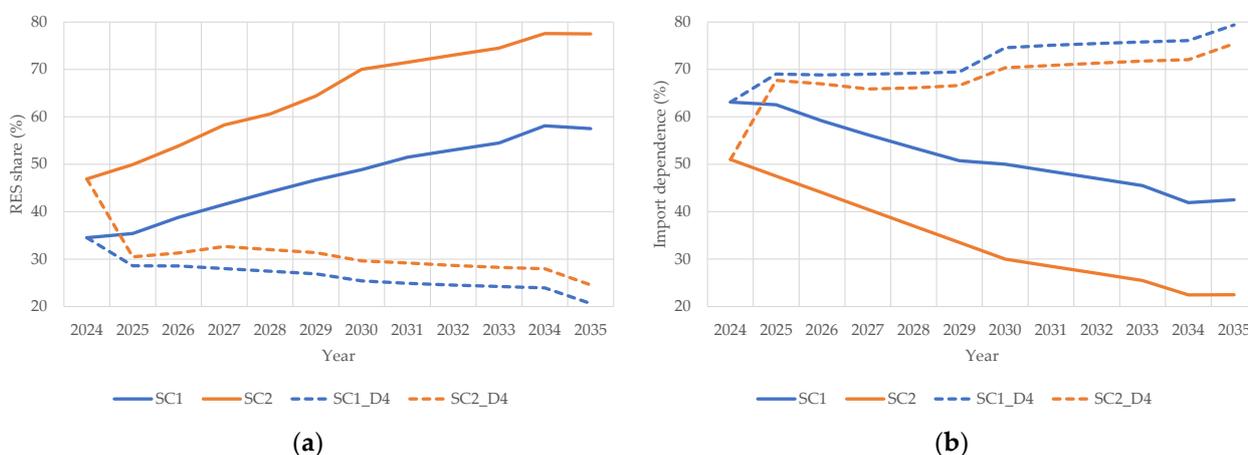


Figure 11. Resilience indicators in the case of the loss of wind generators: (a) RES share; (b) import dependence.

The indicator of the import dependency confirms that in the case of disruption, most wind energy is being replaced by electricity imports (Figure 11b). During the disruption period, the share of electricity imports is increasing and observes maximum values of 79% in SC1 and 75% in SC2, which are much higher than of those scenarios without disruption.

The diversity indicators in Figure 12 demonstrate significant changes in the balance across different electricity production technologies in the case of disruption.

The loss of wind energy in electricity production also shows less diversification. A significant increase in import dependency results in a low balance across technologies. Both these effects reduce the good performance of the diversity indicators during the disruption phase. In 2030, the electricity from natural gas is no longer produced and thus has an impact on the diversification of the energy system.

The results for the estimated indicators demonstrate that SC1 has higher resilience to the loss of the wind PPs in electricity production in comparison with SC2. In addition, the performance of both scenarios in terms of energy system resilience to the analyzed disruption over time decreases slightly. The main reason for that is that the energy system over time has to fulfill the RES requirements and production targets, which makes the electricity production highly dependent on wind energy.

This modeling exercise was performed for demonstrational purposes. The selection of different hypothetical disruptions, other analysis periods, or some other assumptions might result in different estimates of resilience indicators and impacts on the energy system.

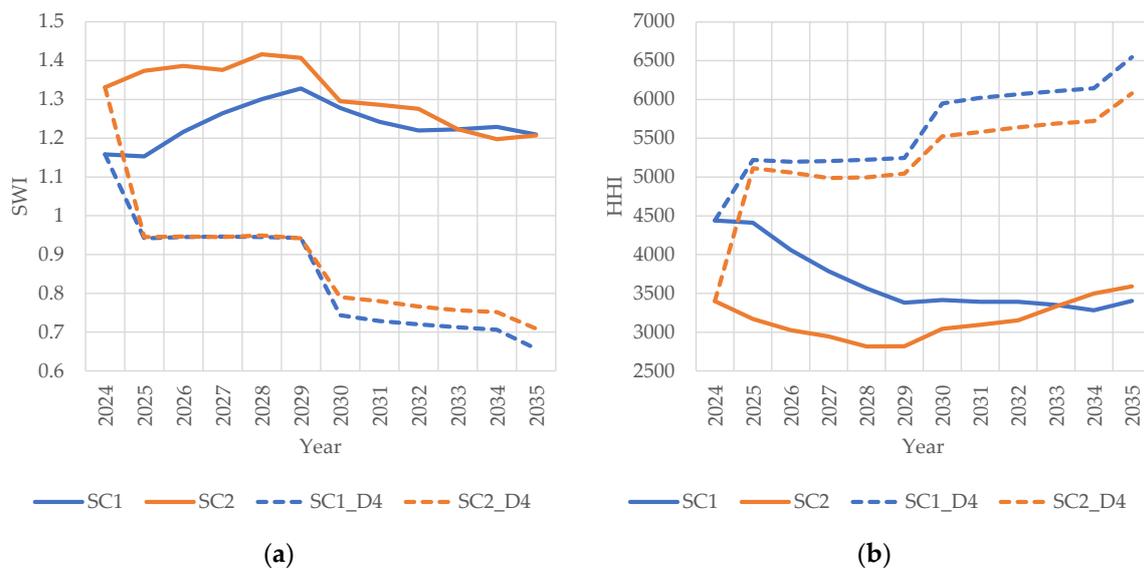


Figure 12. Diversity indicators in the case of the loss of wind generators: (a) SWI; (b) HHI.

5. Conclusions

In this paper, a framework of quantitative indicators used to assess the resilience of energy systems was proposed. The empirical application of the theoretically derived indicators allowed for demonstrating the performance of the resilience indicators under different shocks in the prospective energy system.

Resilience indicators can be divided into two types depending on what is being measured within the energy system: capacity (attributes-based) or performance in the presence of disruption (performance-based).

Resilience indicators, which measure the capacity of the energy system to absorb the impact of disruptions, are consistent with the attributes of the energy system and its components. These indicators measure what makes the energy system resilient. Typically, these include but are not limited to the number of supply and import sources, generators, spare parts, and transmission lines and pipelines; the capacities and lengths of those lines; centrality and modularity in the energy system; the availability of distributed energy and microgrids; diversity (shares, SWI, HHI); the largest single source; energy import dependence; the RES share, spare capacity, and energy reserves; cost stability; and level of energy demand. Some of these indicators (e.g., import dependence, RES share, diversity) also might be employed to measure the changes in an energy system during the disruption.

Resilience indicators, which measure the performance of the energy system in the presence of disruptions, allow for measuring changes in an energy system's resilience. These indicators demonstrate how resilient the energy system is in the case of disruption. They are not directly based on system characteristics but instead measure how well the energy system performs in the presence of disruption. The main resilience indicators of this type are energy not supplied, time of unserved energy, and cost change. Performance-based indicators can be used to measure the resilience of energy systems in different types of disruptions that cause the loss of energy system elements. The type of disruption depends on which elements or components (e.g., lines, generators, fuel supply) in the energy system are lost.

The demonstrational calculations revealed that one of the most important factors that impact energy system resilience is the electricity production mix in the prospective energy system. Diversification plays a considerable role in absorbing the impacts of the disruption. Diversity is also one of the key features for the ability to restabilize an energy system. In the case of disruptions, it allows an easier shift from one technology to another, typically with the lowest costs, if available at the disruption moment. Lower dependence

on energy imports and a higher share of RES in electricity production results in higher energy system resilience.

The proposed indicator framework allows for assessing energy system resilience at the present moment and for the future. Estimates of the resilience indicators measure an energy system's resilience to separate disruptions or combinations of disruptions at different times in the future. The proposed resilience indicators that capture certain aspects of resilience of energy systems can be used in the planning and design of energy systems. This will also allow for comparing different development scenarios of the energy system that may reflect different system development strategies.

The framework for assessing the resilience of the energy system presented in this paper is based on a quantitative assessment approach. However, energy system resilience as a topic requires a holistic evaluation approach. In order to obtain a complete picture, possible future research might include a qualitative assessment approach to the proposed framework.

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References

1. European Commission (Directorate-General for Energy). *Clean Energy for All Europeans*; European Commission (Directorate-General for Energy): Brussels, Belgium, 2019; ISBN 9789279998430.
2. European Commission. Energy and the Green Deal. Available online: https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal/energy-and-green-deal_en (accessed on 17 May 2022).
3. International Energy Agency (IEA). *Making the Energy Sector More Resilient to Climate Change*; International Energy Agency: Paris, France, 2015; p. 16.
4. Chaudry, M.; Ekins, P.; Ramachandran, K.; Shakoor, A.; Skea, J.; Strbac, G.; Wang, X.; Whitaker, J. *Building a Resilient UK Energy System: Working Paper*; The UK Energy Research Centre: London, UK, 2009.
5. Jewell, J. *The IEA Model of Short-Term Energy Security (MOSES)—Primary Energy Sources and Secondary Fuels*; International Energy Agency: Paris, France, 2011.
6. Espinoza, S.; Panteli, M.; Mancarella, P.; Rudnick, H. Multi-phase assessment and adaptation of power systems resilience to natural hazards. *Electr. Power Syst. Res.* **2016**, *136*, 352–361. [[CrossRef](#)]
7. Ciapessoni, E.; Cirio, D.; Pitto, A.; Panteli, M.; Van Harte, M.; Mak, C. Defining Power System Resilience. *Electra* **2019**, *306*, 32–34.
8. Molyneaux, L.; Brown, C.; Wagner, L.; Foster, J. Measuring resilience in energy systems: Insights from a range of disciplines. *Renew. Sustain. Energy Rev.* **2016**, *59*, 1068–1079. [[CrossRef](#)]
9. Gholami, A.; Shekari, T.; Amirioun, M.H.; Aminifar, F.; Amini, M.H.; Sargolzaei, A. Toward a consensus on the definition and taxonomy of power system resilience. *IEEE Access* **2018**, *6*, 32035–32053. [[CrossRef](#)]
10. Arghandeh, R.; Von Meier, A.; Mehrmanesh, L.; Mili, L. On the definition of cyber-physical resilience in power systems. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1060–1069. [[CrossRef](#)]
11. Azzuni, A.; Breyer, C. Definitions and dimensions of energy security: A literature review. *Wiley Interdiscip. Rev. Energy Environ.* **2018**, *7*, e268. [[CrossRef](#)]
12. Jewell, J.; Cherp, A.; Riahi, K. Energy security under de-carbonization scenarios: An assessment framework and evaluation under different technology and policy choices. *Energy Policy* **2014**, *65*, 743–760. [[CrossRef](#)]
13. Sovacool, B.K. Evaluating energy security in the Asia pacific: Towards a more comprehensive approach. *Energy Policy* **2011**, *39*, 7472–7479. [[CrossRef](#)]
14. Cherp, A.; Jewell, J. The concept of energy security: Beyond the four as. *Energy Policy* **2014**, *75*, 415–421. [[CrossRef](#)]

15. Gracceva, F.; Zeniewski, P. A systemic approach to assessing energy security in a low-carbon EU energy system. *Appl. Energy* **2014**, *123*, 335–348. [[CrossRef](#)]
16. Hosseini, S.; Barker, K. A Bayesian network model for resilience-based supplier selection. *Int. J. Prod. Econ.* **2016**, *180*, 68–87. [[CrossRef](#)]
17. Shen, L.; Cassottana, B.; Tang, L.C. Statistical trend tests for resilience of power systems. *Reliab. Eng. Syst. Saf.* **2018**, *177*, 138–147. [[CrossRef](#)]
18. Panteli, M.; Mancarella, P. Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events. *IEEE Syst. J.* **2017**, *11*, 1733–1742. [[CrossRef](#)]
19. Fang, Y.P.; Sansavini, G. Optimum post-disruption restoration under uncertainty for enhancing critical infrastructure resilience. *Reliab. Eng. Syst. Saf.* **2019**, *185*, 1–11. [[CrossRef](#)]
20. Senkel, A.; Bode, C.; Schmitz, G. Quantification of the resilience of integrated energy systems using dynamic simulation. *Reliab. Eng. Syst. Saf.* **2021**, *209*, 107447. [[CrossRef](#)]
21. Ahmadi, S.; Khorasani, A.H.F.; Vakili, A.; Saboohi, Y.; Tsatsaronis, G. Developing an innovating optimization framework for enhancing the long-term energy system resilience against climate change disruptive events. *Energy Strateg. Rev.* **2022**, *40*, 100820. [[CrossRef](#)]
22. Chen, B.; Chen, C.; Wang, J.; Butler-Purry, K.L. Sequential Service Restoration for Unbalanced Distribution Systems and Microgrids. *IEEE Trans. Smart Grid* **2018**, *9*, 6793–6805. [[CrossRef](#)]
23. Yuan, W.; Wang, J.; Qiu, F.; Chen, C.; Kang, C.; Zeng, B. Robust Optimization-Based Resilient Distribution Network Planning Against Natural Disasters. *IEEE Trans. Smart Grid* **2016**, *7*, 2817–2826. [[CrossRef](#)]
24. Nezamoddini, N.; Mousavian, S.; Erol-Kantarci, M. A risk optimization model for enhanced power grid resilience against physical attacks. *Electr. Power Syst. Res.* **2017**, *143*, 329–338. [[CrossRef](#)]
25. Fotouhi, H.; Moryadee, S.; Miller-Hooks, E. Quantifying the resilience of an urban traffic-electric power coupled system. *Reliab. Eng. Syst. Saf.* **2017**, *163*, 79–94. [[CrossRef](#)]
26. Almoghathawi, Y.; Barker, K.; Albert, L.A. Resilience-driven restoration model for interdependent infrastructure networks. *Reliab. Eng. Syst. Saf.* **2019**, *185*, 12–23. [[CrossRef](#)]
27. Uemichi, A.; Yagi, M.; Oikawa, R.; Yamasaki, Y.; Kaneko, S. Multi-objective optimization to determine installation capacity of distributed power generation equipment considering energy-resilience against disasters. *Energy Procedia* **2019**, *158*, 6538–6543. [[CrossRef](#)]
28. Javadi, E.A.; Joorabian, M.; Barati, H. A sustainable framework for resilience enhancement of integrated energy systems in the presence of energy storage systems and fast-acting flexible loads. *J. Energy Storage* **2022**, *49*, 104099. [[CrossRef](#)]
29. Li, X.; Du, X.; Jiang, T.; Zhang, R.; Chen, H. Coordinating multi-energy to improve urban integrated energy system resilience against extreme weather events. *Appl. Energy* **2022**, *309*, 118455. [[CrossRef](#)]
30. Sun, Q.; Wu, Z.; Ma, Z.; Gu, W.; Zhang, X.P.; Lu, Y.; Liu, P. Resilience enhancement strategy for multi-energy systems considering multi-stage recovery process and multi-energy coordination. *Energy* **2022**, *241*, 122834. [[CrossRef](#)]
31. Hoettecke, L.; Thiem, S.; Schäfer, J.; Niessen, S. Resilience optimization of multi-modal energy supply systems: Case study in German metal industry. *Comput. Chem. Eng.* **2022**, *162*, 107824. [[CrossRef](#)]
32. Thompson, J.R.; Frezza, D.; Necioglu, B.; Cohen, M.L.; Hoffman, K.; Rosfjord, K. Interdependent Critical Infrastructure Model (ICIM): An agent-based model of power and water infrastructure. *Int. J. Crit. Infrastruct. Prot.* **2019**, *24*, 144–165. [[CrossRef](#)]
33. Dehghanpour, K.; Colson, C.; Nehrir, H. A survey on smart agent-based microgrids for resilient/self-healing grids. *Energies* **2017**, *10*, 620. [[CrossRef](#)]
34. Ren, F.; Zhang, M.; Soetanto, D.; Su, X. Conceptual design of a multi-agent system for interconnected power systems restoration. *IEEE Trans. Power Syst.* **2012**, *27*, 732–740. [[CrossRef](#)]
35. Nan, C.; Sansavini, G. A quantitative method for assessing resilience of interdependent infrastructures. *Reliab. Eng. Syst. Saf.* **2017**, *157*, 35–53. [[CrossRef](#)]
36. Panteli, M.; Mancarella, P.; Trakas, D.N.; Kyriakides, E.; Hatziargyriou, N.D. Metrics and Quantification of Operational and Infrastructure Resilience in Power Systems. *IEEE Trans. Power Syst.* **2017**, *32*, 4732–4742. [[CrossRef](#)]
37. Jufri, F.H.; Widiputra, V.; Jung, J. State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies. *Appl. Energy* **2019**, *239*, 1049–1065. [[CrossRef](#)]
38. Roege, P.E.; Collier, Z.A.; Mancillas, J.; McDonagh, J.A.; Linkov, I. Metrics for energy resilience. *Energy Policy* **2014**, *72*, 249–256. [[CrossRef](#)]
39. Mujjuni, F.; Betts, T.; To, L.S.; Blanchard, R.E. Resilience a means to development: A resilience assessment framework and a catalogue of indicators. *Renew. Sustain. Energy Rev.* **2021**, *152*, 111684. [[CrossRef](#)]
40. Raoufi, H.; Vahidinasab, V.; Mehran, K. Power systems resilience metrics: A comprehensive review of challenges and outlook. *Sustainability* **2020**, *12*, 9698. [[CrossRef](#)]
41. Watson, J.-P.; Guttromson, R.; Silva-Monroy, C.; Jeffers, R.; Jones, K.; Ellison, J.; Rath, C.; Gearhart, J.; Jones, D.; Corbet, T.; et al. *Conceptual Framework for Developing Resilience Metrics for the Electricity, Oil, and Gas Sectors in the United States*; Office of Electricity: Washington, DC, USA, 2015.
42. Vugrin, E.; Castillo, A.; Silva-Monroy, C. *Resilience Metrics for the Electric Power System: A Performance-Based Approach*; Sandia National Laboratories: Albuquerque, NM, USA, 2017.

43. Binder, C.R.; Mühlemeier, S.; Wyss, R. An indicator-based approach for analyzing the resilience of transitions for energy regions. Part I: Theoretical and conceptual considerations. *Energies* **2017**, *10*, 36. [CrossRef]
44. Gasser, P.; Cinelli, M.; Labijak, A.; Spada, M.; Burgherr, P.; Kadziński, M.; Stojadinović, B. Quantifying electricity supply resilience of countries with robust efficiency analysis. *Energies* **2020**, *13*, 1535. [CrossRef]
45. Zhang, Y.; Liu, W.; Shi, Q.; Huang, Y.; Huang, S. Resilience assessment of multi-decision complex energy interconnection system. *Int. J. Electr. Power Energy Syst.* **2022**, *137*, 107809. [CrossRef]
46. Zhao, Q.; Du, Y.; Zhang, T.; Zhang, W. Resilience index system and comprehensive assessment method for distribution network considering multi-energy coordination. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107211. [CrossRef]
47. Karagiannis, M.G.; Chondrogiannis, S.; Krausmann, E.; Turksezer, Z. Power grid recovery after natural hazard impact. *Jt. Res. Cent. Eur. Union* **2017**. [CrossRef]
48. Kruyt, B.; van Vuuren, D.P.; de Vries, H.J.M.; Groenenberg, H. Indicators for energy security. *Energy Policy* **2009**, *37*, 2166–2181. [CrossRef]
49. Stirling, A. Diversity and ignorance in electricity supply investment. Addressing the solution rather than the problem. *Energy Policy* **1994**, *22*, 195–216. [CrossRef]
50. Fedor, P.J.; Spellerberg, I.F. Shannon–Wiener Index. In *Reference Module in Earth Systems and Environmental Sciences*; Elsevier: Amsterdam, The Netherlands, 2013.
51. Grubb, M.; Butler, L.; Twomey, P. Diversity and security in UK electricity generation: The influence of low-carbon objectives. *Energy Policy* **2006**, *34*, 4050–4062. [CrossRef]
52. Martišauskas, L.; Augutis, J.; Krikštolaitis, R. Methodology for energy security assessment considering energy system resilience to disruptions. *Energy Strateg. Rev.* **2018**, *22*, 106–118. [CrossRef]
53. Howells, M.; Rogner, H.; Strachan, N.; Heaps, C.; Huntington, H.; Kypreos, S.; Hughes, A.; Silveira, S.; DeCarolis, J.; Bazillian, M.; et al. OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development. *Energy Policy* **2011**, *39*, 5850–5870. [CrossRef]
54. OSeMOSYS—Home. Available online: <http://www.osemosys.org/> (accessed on 18 February 2022).
55. REEEM Home | REEEM. Available online: <https://www.reeem.org/> (accessed on 24 February 2022).
56. REEEM-D6.2_Regional Energy Security Case Study of the Baltic Region and Finland | Zenodo. Available online: https://zenodo.org/record/3368544#_yhc2mZaxWUK (accessed on 24 February 2022).
57. Henke, H.T.J.; Gardumi, F.; Howells, M. The open source electricity Model Base for Europe—An engagement framework for open and transparent European energy modelling. *Energy* **2022**, *239*, 121973. [CrossRef]
58. Times | REEEM. Available online: <https://www.reeem.org/times/> (accessed on 25 February 2022).
59. Lithuanian Electricity Transmission System Operator LITGRID report. In *Development Plan of the Electric Power System and Transmission Grid 2021-2030*; LITGRID: Vilnius, Lithuania, 2021; p. 54. Available online: <https://www.litgrid.eu/index.php/grid-development/-/electricity-transmission-grid-ten-year-development-plan/3851> (accessed on 25 February 2022).
60. Open Energy Platform. Available online: <https://openenergy-platform.org/dataedit/view/scenario?query=misca> (accessed on 25 February 2022).
61. REEEM-D1.2a_First Integrated Impact Report | Zenodo. Available online: https://zenodo.org/record/3366029#_YhiWiJaxWUK (accessed on 25 February 2022).
62. 2020 Climate & Energy Package. Available online: https://ec.europa.eu/clima/eu-action/climate-strategies-targets/2020-climate-energy-package_en (accessed on 25 February 2022).
63. 2030 Climate & ENERGY framework. Available online: https://ec.europa.eu/clima/eu-action/climate-strategies-targets/2030-climate-energy-framework_en (accessed on 25 February 2022).
64. Roadmap 2050. Available online: <https://www.roadmap2050.eu/> (accessed on 25 February 2022).
65. The Paris Agreement | UNFCCC. Available online: <https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement> (accessed on 25 February 2022).
66. Ministry of Energy of the Republic of Lithuania. *National Energy Independence Strategy of the Republic of Lithuania*; Ministry of Energy of the Republic of Lithuania: Vilnius, Lithuania, 2018.