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Characterising the security of power system topologies through a combined assessment of reliability, robustness, and resilience

Jesus Beyza [a], Jose M. Yusta [b,*]

[a] National Centre for Energy Control, Blvd. Adolfo López Mateos 2157, Los Alpes, Álvaro Obregón, 01010, Mexico City, CDMX, Mexico
[b] University of Zaragoza, Department of Electrical Engineering, C/ María de Luna 3, 50018, Zaragoza, Spain

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ABSTRACT

Electricity has a prominent role in modern economies; therefore, ensuring the availability of electricity supply should be a top priority for policymakers. The joint assessment of reliability, robustness, and resilience can be a useful criterion to characterise different topologies and improve the security of supply. This paper proposes a novel integrated analysis of these three attributes to quantify the security of power grid topologies. Hence, eight case studies with different topologies created using the IEEE 24-bus reliability test system were analysed. Reliability was evaluated by applying the sequential Monte Carlo approach, robustness was evaluated by simulating cascading failures, and resilience was evaluated by analysing recovery curves. The different indicators associated with each of the three evaluations were then calculated. The results obtained were discussed both graphically and quantitatively in a novel three-dimensional representation, where the importance of joint analysis was also highlighted. The proposed method can serve as an additional tool for planners to identify possible investments or improvements in power system topologies.

1. Introduction

Electrical power systems should be reliable, robust, and resilient. In the current decarbonisation process in modern societies, they have become increasingly important for the continuous operation of daily activities. Thus, threats and disruptions to electricity security are increasing and evolving at the same rate as in the power grid [1]. Therefore, more studies are required to analyse the associated attributes, ensure that systems are increasingly secure on a daily basis, and track the changing patterns of systems under different threats that affect the sector.

The distinction between the concepts of reliability, robustness, and resilience in a power system is clearly defined in the scientific literature [2]. According to Georges Zissis's message in the IEEE Industry Applications Magazine [3], "reliability is the probability that a system will perform in a satisfactory manner for a given period when it is used under specified operating conditions". This attribute evaluates the network performance in the event of a loss of one or two assets. In contrast, "robustness is the ability of a system to avoid malfunctioning when a fraction of its elements fail, or the ability of a system to perform the intended task under unexpected disturbances" [4,5]. More aggressive than reliability, this attribute considers the elimination of multiple assets and quantifies the network performance in the event of cascading failures. Finally, "resilience is a system's ability to withstand, adapt, and absorb from a major disruption within acceptable degradation parameters and recover within a satisfactory timeframe". This concept generally analyses HILP events, such as extreme natural disasters [6–8]. These three joint attributes are currently known as the "R3 concept" [3]. Fig. 1 outlines as an example of the R3 concept.

Currently, there is a strong desire to improve the performance and quality of electrical networks.

This desire results from the development and transformation of more sustainable, resilient, and carbon-free societies. The R3 concept is a field of research that requires the proposal of new integrated methodological frameworks to study the different interrelated attributes that encompass reliability, robustness, and resilience. The scientific literature describes methods to study some of these attributes [10]; for example, previous studies used energy hub-based methods, models order reduction, metaheuristic searching genetic algorithms, multicriteria decision analysis, advanced intelligent strategies, and linear programming [11–16].

However, one of the largest challenges in studying R3 concept is cascading failures. These events are complicated to study because they can result from countless reasons or causes; thus, studying them is

* Corresponding author.
E-mail addresses: jesus.beyza@cenace.gob.mx (J. Beyza), jmyusta@unizar.es (J.M. Yusta).

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Nomenclature

Abbreviations

DC	Direct current
DFS	Depth-first search algorithm
HILP	High-impact low-probability
E	Energy not supplied for reliability assessment [MWh]
EDNS	Expected demand not supplied [MW]
EENS	Expected energy not supplied [MWh/yr]
EFLC	Expected frequency of load curtailment [outages/yr]
ENS	Energy not supplied for resilience assessment [MWh]
LOLE	Loss of load expectancy [h/yr]
LOLP	Loss of load probability [%]
N	Number of disruptions
RD	Recovered demand [p.u]
SD	Satisfied demand [p.u]

Indices

n, m	Nodes or buses
d	Loads
g	Generators
i	Islands
j	Number of closed power lines
k	Lines
p	Disruption
q	Year
r	Recovery stage
s	Steps

Variables

Δ_n	Voltage angle at node n [radians]
P_k, P_g, P_n	Power flow through line k, power of the generator g, and power demand at node n [MW]
μ_k	Binary variable indicating the open or closed state of the power line (open, $\mu_k = 0$, closed, $\mu_k = 1$)
D_i	Demand on each island i [MW]
SD_s	Satisfied demand in step s [p.u]
RD_r	Recovered demand in stage r [p.u]
$MTTF$	Meantime to failure [h]
$MTTR$	Meantime to repair [h]
TTR	Time to repair [h]
TTF	Time to failure [h]
r	Random number uniformly distributed between [0,1]
ADLC	Average duration of load curtailment [h/outage]
Dd	Duration of disruption [h]

Parameters

P_k^{max}, P_k^{min}	Maximum and minimum capacity of the power line k [MW]
P_g^{max}, P_g^{min}	Maximum and minimum capacity of the generator g [MW]
Δ_n^{max}, Δ_m^{min}	Maximum and minimum voltage angle at node n [radians]
N_y	Number of simulated years
B_k	Susceptance of the power line k [p.u]
N_c	Maximum number of power lines to be closed
α_k	Overload tolerance parameter of the power line k
λ	Failure rate of the assets
μ	Repair rate of the assets

Sets

D	System loads
E	Isolated elements
G	Generators
I	Islands
K	Power lines
L	Closed power lines
M	Nodes or buses

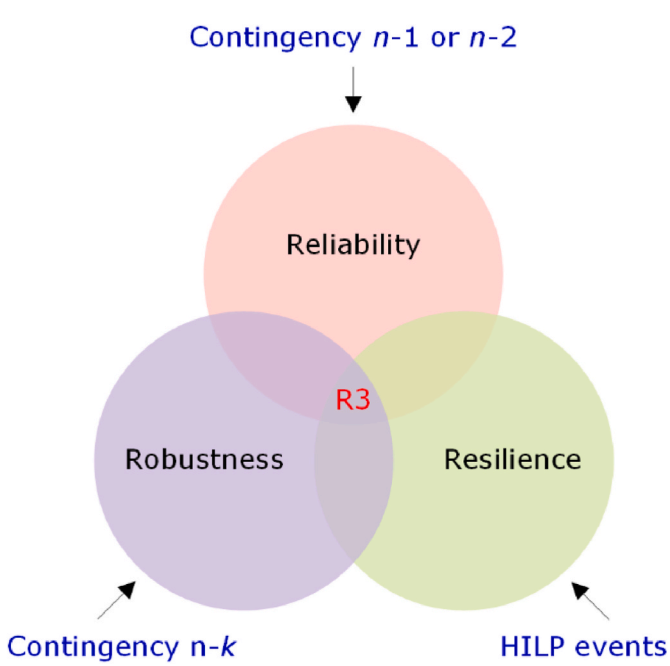

Fig. 1. Schematic representation of the R3 concept [9].

unfeasible. Hence, the complex network theory (or graph theory) may be suitable for modelling the dynamic behaviour, analysing the propagation of disturbances, and quantifying the structural robustness of a system [17–20]. Furthermore, note that this technique has the potential to identify both critical assets and the events that can trigger cascading failures [21–26].

Some studies more focused on extreme disturbances have indicated that both reliability and robustness studies should consider the impact of weather conditions because they can severely impact the system and sectors linked to it. Under this premise, some studies proposed metrics, protection strategies, and theoretical frameworks to analyse this problem in detail [27–29].

Resilience is an entirely new area of research that encompasses procedures and techniques to solve problems associated with protecting and restoring the services provided by a power system. Some academics have evaluated the resilience of networks considering the strengths and weaknesses of both the topology and power transfer capacities of transmission lines under different disturbances, such as natural disasters, earthquakes, and floods [30–32]. Owing to the increase in disruptions, it is important to evaluate the resilience of a network after a high-impact disturbance [33,34], which is related to the concept of resilience. Therefore, some researchers have proposed procedures to plan the iterative recovery of a system after a disruptive event [35–37].

Another factor considered in some combined robustness and resilience studies is the fundamental change in the structure and generation mix of power systems. For example, some articles have reviewed cutting-edge practices, whereas others have offered integrated analyses of decision-making [38,39]. The main aim is to analyse the different reconfiguration options and select the optimal solution for its implementation. Additionally, other studies have provided definitions, metrics, guidelines, practical challenges, and technical problems related to the attributes of resilience [40–43].

In summary, the following deficiencies can be identified in the existing literature related to the reliability, robustness, and resilience of power systems:

1. No related articles has proposed an integrated study of the three concepts on the topology of power systems. Most existing publications correspond to the study of these concepts individually, and very few others correspond to the analysis of only two of the concepts [2,7,11,27,44]. All the studies examined different problems from the one proposed in this paper.
2. The concepts of reliability, robustness, and resilience are used to evaluate power systems from different perspectives; therefore, the conclusions of the studies already published can be expanded and improved by considering a joint and integrated vision.
3. The characteristics and relationships between the concepts must be explored; for example, identifying how a certain improvement in one indicator does not necessarily imply improvements in the other indicators. Published studies did not address this problem.

Reliability, robustness, and resilience are discussed in several aspects and from different perspectives in the scientific literature; however, few studies considered these three concepts in an integrated manner. The latter motivated the specific objective of this study, which was to develop a theoretical and data-based methodological framework to explore the characteristics and relationships between all concepts in an electrical power system. Combined studies of reliability, robustness, and resilience could better reflect the performance of a network. Including the three attributes in a joint analysis can be an incentive for future research in this area. However, it is important to note that this document does not discuss how to improve the study of these attributes but rather emphasises the critical role of these concepts in an electrical network. A reliable power system may not be robust or resilient to other threats or disturbances; therefore, the task of ensuring electricity security should be a priority for decision-makers.

The main contributions of this article can be summarised as follows:

1. An integrated reliability, robustness, and resilience assessment is performed to quantify the security of the power system topologies.
2. A novel three-dimensional representation is proposed to represent the integrated results and provide an additional strategy to the traditional procedures. Here, we seek to provide a visual representation of the relationship between these concepts.
3. Different case studies with different topologies are analysed to demonstrate the performance of the proposed approach and to obtain integrated results.

Based on the above and the provisions and guidelines in the scientific literature, the reliability assessment was performed by applying the sequential Monte Carlo technique and measuring the indices of EENS, EDNS, EFLC, LOLE, LOLP, and ADLC. The robustness evaluation was completed by simulating cascading failures and quantifying the SD index at each stage of system disintegration. This iterative procedure eliminates an asset, quantifies the power flows in the network, removes the system's overloaded links, and identifies and balances the resulting subsystems to determine whether a cascading event continues or ends. A resilience study was performed using a mixed-integer optimisation problem, where the integer variables represent the operational state of the power lines, and the real variables represent the scheduled dispatch of the generators. This procedure uses the system's state of disintegration at the end of the cascading failure as input data and determines the power lines that must be closed iteratively and the redispatch of generation plants for the optimal recovery of network connectivity. The RD index was measured at each recovery stage, whereas the ENS index was measured at the end of the recovery process.

The three previous procedures use a standard model of DC power flows because they yield rapid solutions. While other methods can be used depending on the required accuracy sought in the results, the only objective here was to establish an integrated framework for future development; therefore, this model is adequate. The proposal made here is novel and original in the field of power system security. The reliability, robustness, and resilience procedures were programmed using MATLAB R2021a platform. The different results obtained were discussed both graphically and numerically in a sequential study framework. Subsequently, a joint analysis of the three concepts was presented. The proposed approach can significantly positively impact the performance and quality of a power network, improve consumer satisfaction, and inform planners in the decision-making process for better investment in network topologies. Numerical tests to investigate the similarities and differences between the concepts were conducted in eight case studies based on the IEEE 24-bus reliability test system (RTS) [45].

The remainder of this article is organised as follows: Section 2 describes the reliability, robustness, and resilience procedures used to evaluate of a power system in an orderly and systematic manner. Section 3 presents case studies based on a well-known IEEE 24-bus RTS. Section 4 discusses the simulation results obtained by applying the procedures described above. Finally, Section 5 summarises the main conclusions of this study.

2. Reliability, robustness, and resilience methodologies

In this section, the procedures used to evaluate the reliability, robustness, and resilience of an electrical power system are described. In general terms, the reliability is evaluated by applying the sequential Monte Carlo technique, the robustness is evaluated by simulating cascading failures, and the resilience is evaluated by developing a mixed-integer optimisation problem. These three procedures follow the foundations of scientific literature.

2.1. Reliability procedure

Reliability is divided into two areas that are well established in the scientific literature: adequacy and security. On the one hand, adequacy evaluates whether the generation capacity adjusts to the demand and constraints of the system. On the other hand, security studies focus on the performance of a power system against the outage of one or two components. This study focused on the security of power systems. This type of evaluation can be performed from an analytical or simulation perspective. The first one requires initial assumptions to simplify the problem and produce an analytical; hence, the resulting analysis may lose its relevance. The second one simulates the random behaviour of the system through multiple experiments and considers all possible contingencies in the network. The Monte Carlo technique is a simulation approach [46,47]; therefore, it was used in this research work. In the Monte Carlo technique, two main techniques, non-sequential and time-sequential, are used. The former considers each time step or system state independently, whereas the latter realistically simulates both the actual chronological process and the random behaviour of the system [48,49]. This study used the sequential Monte Carlo technique for reliability assessment because it is flexible, accurate, and enables the calculation of different indicators. For a more detailed description, please refer to Refs. [46,47]. The implementation of the sequential Monte Carlo technique for the reliability analysis is presented in Algorithm 1.

Algorithm 1. Reliability

Input: technical data of the power system and N.

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Output: statistical indicators EENS, EDNS, EFLC, LOLE, LOLP and ADLC.
Step 1. Start: establish the operational state of the assets, that is, normal or failure.
Step 2. Modelling of outages: these events are modelled using the MTTF and MTTR indices. These indicators are inversely related to λ and μ of the assets,

$$MTTF = \frac{1}{\lambda}; \tag{1}$$

$$MTTR = \frac{1}{\mu}; \tag{2}$$

Step 3. Time between states: quantify the time that the assets spend in normal and failure state, that is, TTR and TTF,

$$TTR = -\ln(r) \times MTTR; \tag{3}$$

$$TTF = \frac{-\ln(r)}{\lambda} \times 8760; \tag{4}$$

This step is repeated for a specific time, frequently one year.
Step 4. Overlapping time: calculate the overlapping times of failures of the elements (when several components are simultaneously out of service) for a temporal resolution of 1 h in a time horizon of 1 year, that is, 8760-time steps of 1 h each.
Step 5. Power flows: conduct a DC power flow study considering the operational state of the components throughout the year.
Step 6. Reliability indicators: evaluate the security of the power system through reliability indices (5)–(10), using the results from Step 5.

$$EENS = \frac{\sum_{p=1}^{N_y} \sum_{q=1}^{N_q} E_{p,q}}{N_y}; \tag{5}$$

$$EDNS = \frac{EENS}{8760}; \tag{6}$$

$$EFLC = \frac{\sum_{p=1}^{N_y} N_p}{N_y}; \tag{7}$$

$$LOLE = \frac{\sum_{p=1}^{N_y} \sum_{q=1}^{q} Dd_{p,q}}{N_y}; \tag{8}$$

$$LOLP = \frac{LOLE}{8760}; \tag{9}$$

$$ADLC = \frac{LOLE}{EFLC}; \tag{10}$$

Step 7. Iterations: repeat the previous steps until a covariance of less than 6% is obtained for the EENS index [50].

Generally, this procedure assumes that each asset of an electrical system can have two states: operational and failure. It is assumed that the residence time of the component is exponentially distributed and that the state transition is determined by both its current state and the transition rates. The transition rates between the two states are the failure and repair rates of the components. The random samples of the state of each component are statistically dependent, that is, they are related to the previous sample. Subsequently, when the overlapping times are determined, it executes the DC power flows and calculates the reliability indicators of the studied electrical system. According to previous studies [50,51], this procedure is repeated several times until the covariance of the EENS indicator is less than 6%.

2.2. Robustness procedure

The robustness of power systems, including cascading phenomena, is an active field of research. Most of the contributions in the literature evaluate the robustness of the power grid with respect to the modelling and analysis of cascading failures, in particular for cascading effects due to line overloads under faults or targeted attacks [11,17–19,21,52]. Blackouts are disastrous events generally caused by cascading failures, which includes a series of iterative events that can include voltage problems and the disconnection of power lines and loads. These events are complicated to model because they encompass hundreds of highly dynamic events. However, it is important to analyse and model them because they affect hundreds of thousands of people and cause enormous economic losses [17]. In this study, the robustness was measured in operational areas both before and after cascading failure [53]. The SD index was used to measure the functionality of an electrical power system during such disturbances. This index varies between 1 and 0 and is measured according to the assets isolated during the disintegration of the network. As the SD index decreases, the impact on disconnected loads increases. Algorithm 2 describes the ordered and systematic steps used to model cascading failures in an electrical power system.

Algorithm 2. Robustness

Input: technical data of the power system and α.
Output: degradation of the electrical power system. SD in s, I, E, and μ_k, i.e. open or closed.
Step 1. Start: $SD_{base} = D_{load}$, I = { · } and E = { · }. At the beginning, all the power lines are operational.
Step 2. DC power flows: calculate P in each k within the network and determine P_k^{max} of the lines using (11).

$$P_k^{max} = \alpha_k \times P_k; \tag{11}$$

Step 3. Initiating event: randomly remove an asset from the system. The latter represents the event that triggers the cascading failure.
Step 4. Increase or decrease flows: determine the increases or decreases in each power line; initialise s = 1 as the first disintegration stage.
Step 5. Triggering of switches: evaluate the condition $|P_k^s| < P_k^{max}$ in all power lines of the system. Remove all overloaded links, i.e. $|P_k^s| > P_k^{max}$, and go to Step 6; otherwise, go to Step 10.
Step 6. Transversal graph algorithm: use DFS to determine I and E formed after the activation of the switches.
Step 7. Energy balance:
a) for each island I_i with generators g $\in I_i$ evaluate
- if $\sum_{g \in I_i} P_g < \sum_{d \in I_i} P_d$, then do $D_{I_i}^s = \sum_{g \in I_i} P_g$ in stage s.
- if $\sum_{g \in I_i} P_g > \sum_{d \in I_i} P_d$, then do $D_{I_i}^s = \sum_{d \in I_i} P_d$ in stage s.

b) for each subnet I_i without generators g $\in I_i$; do $D_i^s = 0$, respectively.
Step 8. Satisfied *demand*: calculate (12),

$$SD_s = \frac{\sum_{i \in I} D_{I_i}^s}{SD_{base}} \text{ in } s; \tag{12}$$

Step 9. Iterations: iterate s = s + 1 and go to Step 4.
Step 10. End: if $|P_k^s| < P_k^{max}$ $\forall k$, the algorithm ends.

The procedure begins by collecting the technical data of the electrical network and calculating the power flows to determine the maximum transfer capacity of the lines. Next, it randomly removes an asset, determines the changes in the flows, and removes all overloaded power lines resulting from the redistributed network flows. Note that the cascading failure initiation event is random, such as involuntary human errors or technical failures in the equipment and hardware. The constant tripping of protection mechanisms in the power lines resulting from the propagation of the cascading failure can result in the formation of different islands in the system. Therefore, this procedure incorporates a transversal graph algorithm to identify subsets formed during the disintegration stages. The DFS algorithm was used here to simplify the resolution of this problem [54]. This technique is widely recognised as an effective tool for solving various graphs problems. The algorithm starts at the root node and scans each branch before backtracking. Fig. 2 shows the tree structure of the cascading failure process used in Algorithm 2. Islands without generators are considered dead and are marked in red, while islands with generations are marked in green. The intermediate islands where cascading failure continues are marked in blue.

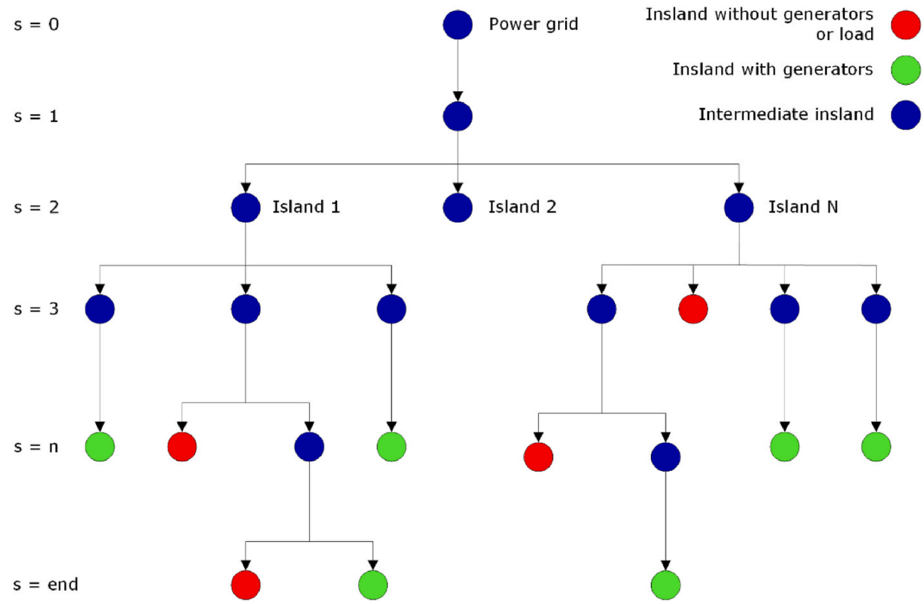

Fig. 2. Tree structure of the cascading failure process.

The tree structure shows how an island can undergo changes during the process and disintegrate into more islands, where some remain operational and others are deeply affected. Cascading failure continues on all intermediate islands in blue. The constant redistribution of flows can cause further overloads on other links; thus, each intermediate island can result in an additional group of islands where the cascading event also continues simultaneously. Thus, each time one or more power lines are disconnected during the disintegration stage, the DFS algorithm identifies and orders each island for a correct simulation. Similarly, these islands must comply with the balance between demand and generation; thus, load shedding is used to satisfy the energy balance. Isolated elements or subnets without generation are considered unsatisfied loads during the disintegration process. The iterative procedure continues until no overloaded elements remain or all assets are isolated.

2.3. Resilience procedure

After a major disturbance, the degradation of an electrical system is a function of robustness; thus, resilience depends on both the robustness and rapid recovery of the disconnected load. Therefore, a mixed-integer optimisation problem is proposed to recover both the loads and connectivity of the system after cascading failure. The optimisation output is the quantified optimal resilience characteristic and state of the transmission lines. For demonstration, the RD index is used to represent the resilience of the system. The optimisation objective is to maximise this resilience metric after the cascading failure is modelled using Algorithm 2. This optimisation problem is subject to several constraints. Algorithm 3 describes the iterative procedure for determining the power lines that must be closed in each recovery stage of the power system.

Algorithm 3 uses the final disintegration of a power system as input data to initialise both the recovered demand and initial operational state of the power lines. Similarly, it considers the maximum number of lines that can be reconnected and the redispatch of generators in each recovery stage. It then constructs an optimisation problem based on the standard DC power flow equations and establishes the minimum and maximum thresholds for the different equations. The maximum threshold of the power lines is calculated using Algorithm 2. When the set of equations is constructed, the objective function for the corresponding recovery stage is maximised. The output consists of the recovered demand and power lines, which must be closed during the restoration stage. Finally, these results are saved, and new closed power lines are set in their corresponding equations. If all power lines are closed, the algorithm ends; otherwise, the algorithm repeats the procedure until all remaining lines are closed.

Algorithm 3. Resilience

Input: outputs of Algorithm 2, i.e., SD in the last *s*, *I*, E, and μ_k. Similarly, N_c in each r.
Output: recovery of the electrical power system. RD and μ_k in each r.
Step 1. Start: initialise $RD_r = SD_{S_{final}}$ and $\mu_k = 1$ for closed lines and $\mu_k = 0$ for open lines at r = 1. The initial satisfied demand and the states of the lines correspond to the final disintegration state obtained with Algorithm 2.
Step 2. Optimisation problem based on the standard model of DC power *flows:* consider (13) to (21)

$$max\ (RD_r - RD_{r-1}) \tag{13}$$

subject to:

$$P_g^{min} \leq P_g^r \leq P_g^{max}\ \forall g \in G \tag{14}$$

$$P_k^{min} \cdot \mu_k^r \leq P_k^r \leq P_k^{max} \cdot \mu_k^r\ \forall k \in K \tag{15}$$

$$\Delta_n^{min} \leq \Delta_n^r \leq \Delta_n^{max}\ \forall n \tag{16}$$

$$-\sum_{k \in K} P_k^r - \sum_{g \in G} P_g^r - \sum_{d \in D} P_d^r = 0\ \forall n \tag{17}$$

$$B_k\left(\Delta_n^r - \Delta_m^r\right) - P_k^r \geq 0\ \forall k \tag{18}$$

$$-B_k\left(\Delta_n^r - \Delta_m^r\right) - P_k^r \leq 0\ \forall k \tag{19}$$

$$\sum_{k \in K} \mu_k^r \leq N_c \tag{20}$$

$$RD_r = \sum P_n^r\ \forall n \tag{21}$$

The maximum thresholds of (15) are initially determined in Algorithm 2.
Step 3. Solve the optimisation problem: maximise (13), subject to constraints (14)–(21) in each r.
Step 4. Solution: save the results of RD_r and μ_k^r; set the variables μ_k^r restored as constants $\mu_k^r = 1$ for all subsequent iterations.

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(*continued*)

Step 5. Evaluation: if $\forall k \in (K - k^{'})$: $\mu_k^s = 1$ go to Step 7; otherwise, go to Step 6.
Step 6. Iterations: iterate r = r +1 and go to Step 3.
Step 7. End: if $\forall k \in (K - k^{'})$: $\mu_k^s = 1$; the algorithm ends.
Step 8. Energy not supplied: calculate the ENS index for the resilience curve, i.e. the area above the curve.

3. Case studies

This section describes the IEEE 24-bus RTS through which eight case studies with different topologies were constructed [45]. That is, the original system was used, and lines were added to obtain different networks for comparison. First, the case studies are presented, and then the guidelines followed for the reliability, robustness, and resilience simulations are described.

3.1. Test system

Fig. 3 shows the IEEE 24-bus RTS. This network is composed of 24 buses, 33 generators and 38 power lines, and transformers. The maximum demand is 2850 MW. The parameters of the lines, load characteristics, and input data for the stochastic failure model for the buses, transformers, and lines are described in Ref. [45]. This test network has been well documented in the scientific literature.

Eight different case studies based on the previous system were used to assess reliability, robustness, and resilience. The case studies included adding and combining three different power lines to the original system (14–15, 14–24, and 6–9). The objective was to obtain different topologies of the same system and to perform comparative evaluations between them. The lines added to the original system satisfied type n-1 and n-2 contingencies according to the provisions provided in Ref. [55]. Considering the representation of the test system shown in Fig. 3, the eight case studies were as follows:

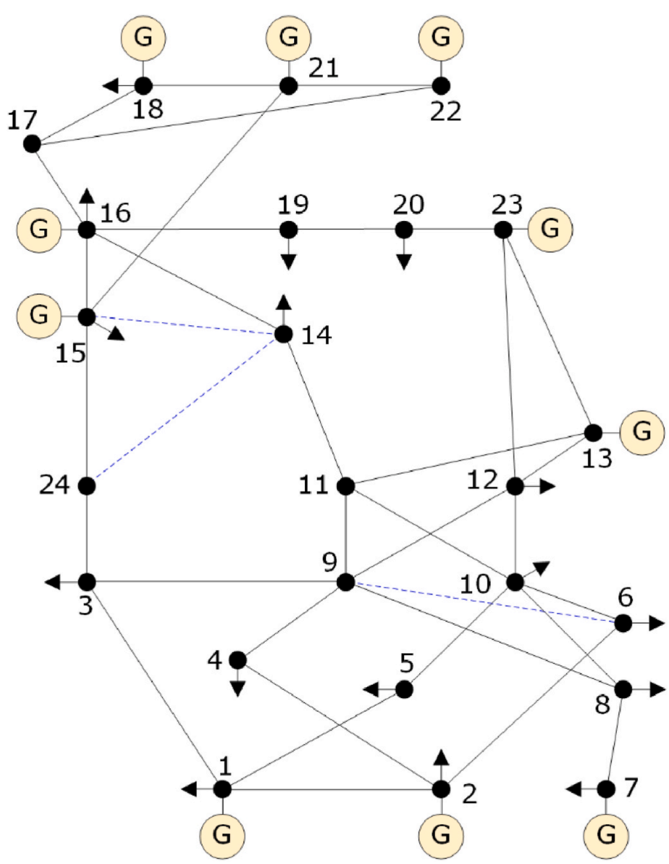

Fig. 3. Topology of the IEEE 24-bus RTS. The lines in blue represent the additional power lines.

- **Case 1:** the original system.
- **Case 2:** addition of line 14–15 to the original system.
- **Case 3:** addition of line 14–24 to the original system.
- **Case 4:** addition of line 6–9 to the original system.
- **Case 5:** addition of lines 14–15 and 14–24 to the original system.
- **Case 6:** addition of lines 14–15 and 6–9 to the original system.
- **Case 7:** addition of lines 14–24 and 6–9 to the original system.
- **Case 8:** addition of lines 14–15, 14–24, and 6–9 to the original system.

3.2. Simulation guidelines in the analysis of reliability, robustness, and resilience

Different guidelines were followed when applying Algorithms 1, 2, and 3 to the eight case studies described above to perform a comprehensive and accurate analysis of the different indicators studied. As reliability evaluation is a classic analysis in power systems, this study followed the already published studies in this field of research. That is, 1500 one-year iterations were executed in each network, obtaining covariance values lower than 6% in all cases [44].

Robustness evaluation is a complex procedure that involves different parameters and characteristics of the studied system. For example, an electrical system can have different levels of robustness depending on where the initial failure occurs, level of congestion of the lines, operational assets, load level, etc. Therefore, some researchers prefer to characterise robustness from a topological and structural perspective; thus, it is invariant to other factors that occur in the network [56]. This type of analysis is also advantageous because it offers another perspective on the system. To conduct a complete evaluation of robustness, in this study, we eliminated the lines adjacent to the buses (except for buses 6, 9, 14, 15, and 24 because new lines were added) to begin the network disintegration process.

Furthermore, because the system had a constant load, we also considered different levels of overload in the links for the same scenario to obtain different states of disintegration for the initiating event. Therefore, 114 scenarios were executed with $\alpha = 1$, 1.1, 1.2, 1.3, 1.4, and 1.5 in each case study, that is, a total of 912 simulations for the eight cases. Finally, the robustness of each case was measured by averaging the set of results obtained, which provided an overview of system performance.

In contrast, the resilience evaluation was performed from the averaged states of disintegration of the eight cases after applying the robustness procedure. We assumed that the maximum number of lines that could change state in each recovery stage was three. The number of lines that can operate to recover a collapsed electrical system depends on the physical characteristics of the network and the procedures applied by each control centre. In this study, only three power lines were used for simulation. Finally, the ENS index was calculated for each case, assuming that each interval of redispatch and reconfiguration required approximately 15 min on average, because it was necessary to plan, execute, and verify the manoeuvres. Although other times could be used, the time between the manoeuvres and redispatch used in this study corresponded to a value close to reality.

4. Simulation results

This section discusses the simulation results obtained after the reliability, robustness, and resilience were evaluated in the eight case studies described above. The three procedures were programmed in MATLAB R2021a and executed on a personal computer with a 3.40 GHz Intel® Core™ i7 CPU and 16 GB of RAM. The run times for the reliability, robustness and resilience studies were 294.99 h, 167.91 s, and

31.81 s, respectively.

Table 1 shows the different reliability indicators calculated for the eight cases after applying Algorithm 1, and Fig. 4 presents the convergence results of the EENS indicator. Case 6 was the best case, in which an improvement of 2.19% was obtained compared with Case 1. Note that Case 5 also had a very similar percentage improvement to Case 6, although owing to decimal point values, this case was positioned after Case 6. In Case 8, the improvement was 1.86% over that of the original system, indicating an improvement in the system performance. However, Cases 2 and 7 had EENS values very close to each other, although Case 7 was more connected than the others. This was because line 14–15 reduced the congestion of two lines adjacent to bus 14. This line also coincided with Case 6. The same occurred when line 6–9 was added in Case 6, which was the most reliable case. However, the focus was on line 14–15 because it decongested the links adjacent to the generator connected to bus 15. The remaining indicators exhibited similar behaviours to the analysis performed previously. The results showed that the reliability was improved by adding lines to the original system; however, certain lines located on buses with poor connectivity exhibited better results. From highest to lowest, the reliability was in the order of Cases 6, 5, 8, 2, 7, 4, 3, and 1.

Fig. 5 shows the dispersion of the last value of the robustness indicator SD after applying Algorithm 2 and the mean values obtained in the eight cases. The mean values of the SD index for Cases 1–8 were 0.34, 0.38, 0.34, 0.35, 0.40, 0.39, 0.35, and 0.40 p.u, respectively. The plotted results show that the cases had different satisfied demand values at the end of the network collapse, indicating that the redistributed flows after the initial disturbance differed in each case. However, when averaging the set of results for each case, the robustness of Case 8 improved by 9.43% compared with that of Case 1. That is, the most connected case was the most robust to cascading failures. This was reasonable as the power lines were less congested. The results also showed that all the cases in which one or two lines were added improved the robustness of the original system. Cases 3 and 4 had improvements of 0.52% and 1.17%, respectively, when considering less-connected cases compared with Case 1. However, Case 2 improved by 5.71% compared with the original system and was even better than Case 7 with two lines. Note that Case 2 corresponded to the addition of line 14–15, which was also identified as an asset that improved the reliability of the system. The robustness of the cases was ordered, from highest to lowest, as Cases 8, 5, 6, 2, 7, 4, 3, and 1. These findings suggest that complex meshed topologies are more robust against the propagation of cascading failures than less meshed topologies, provided that there are vital assets that increase the energy transfer or reduce link congestion.

The curves in Fig. 6 illustrate the general concept and demonstrate the advantages of the restoration strategy proposed in Algorithm 3. The cases started began with different values of satisfied demand and different states of disintegration for greater realism. Numerically, Cases 1 and 5 began from topologies in which 27 and 32 power lines were lost, respectively. The results indicated that each system recovered its disrupted loads; however, some of them were superior because they required fewer manoeuvres to restore the load more promptly. The ENS indices for Cases 1–8 were 3277.82, 2108.23, 3701.65, 2233.49, 2564.52, 2371.71, 2110.90, and 1359.00 MWh, respectively. Considering this indicator, Case 8 was the most resilient because it improved by

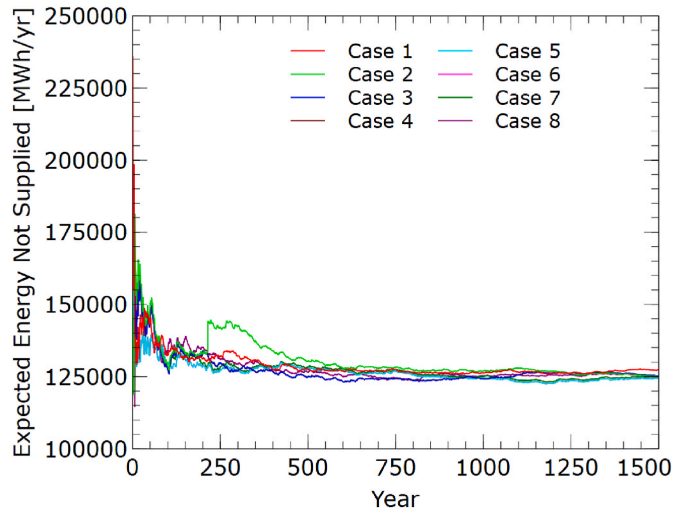

Fig. 4. Convergence of the EENS indicator for the eight cases.

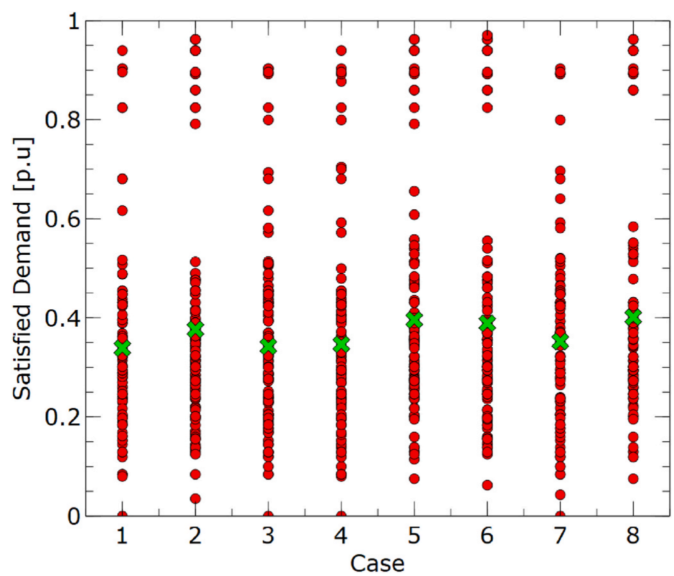

Fig. 5. Dispersion of the robustness results for the eight cases.

58.53% compared with Case 1, whereas Case 3 was the least resilient because it worsened by 12.93% compared with Case. 1. Cases 2 and 7 improved by 35.68% and 35.60%, respectively, compared with the original system, which placed them in the second and third positions, respectively. The cases can be ordered from highest to lowest resilience as Cases 8, 2, 7, 4, 6, 5, 1, and 3. Note that the order of the cases is not directly related to the meshing of the network as it is to the robustness, although Case 8 with the addition of three links was the most resilient, and Case 3 with the addition of a single link was the least resilient. As far as this study is concerned, the cases had between 32 and 33

Table 1
Reliability results.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
EENS	127,285.95	124,988.11	125,259.72	125,258.70	124,504.17	124,504.00	125,029.97	124,921.43
EDNS	14.53	14.27	14.30	14.30	14.21	14.21	14.27	14.26
EFLC	19.07	18.93	19.06	19.05	18.93	18.93	18.83	18.97
LOLE	731.41	721.78	726.59	726.60	720.12	720.13	720.79	723.20
LOLP	8.35	8.24	8.29	8.29	8.22	8.22	8.23	8.26
ADLC	38.35	38.14	38.13	38.13	38.03	38.03	38.28	38.12

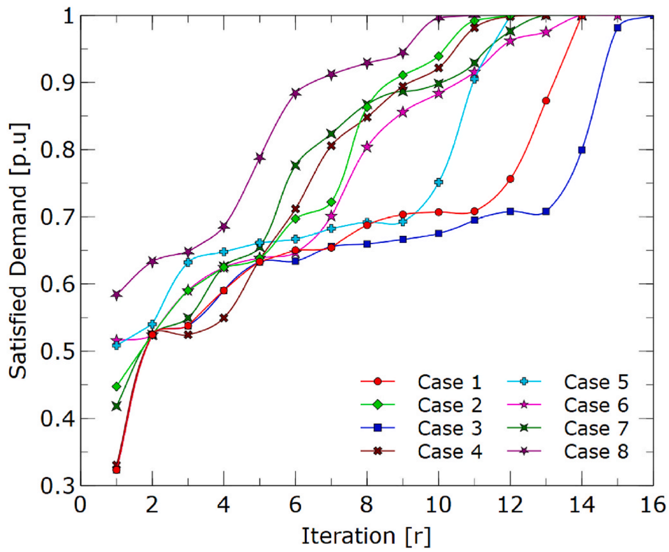

Fig. 6. Optimal recovery curves for the eight cases.

disconnected lines, but their combinations were completely different in each case; thus, the subsequent reconnection strongly influenced both the recovery and ENS index. This appeared to indicate that resilience can be influenced by several factors, such as the topological state of disintegration, load distribution, energy transfer limits, and loss of critical assets. Therefore, it is reasonable that the order of the cases obtained here was different, which again confirmed the requirement for joint and integrated studies to characterise the behaviour of power system topologies. The resilience evaluation demonstrated that the network topology influenced the recovery of the system. For example, Cases 1 and 3 had different recovery curves, although they began from similar values of satisfied demand. In other words, the topology has a fundamental role in the design of resilient systems.

Examining the results more comprehensively, Table 2 shows the improvement percentages of the EENS, SD, and ENS indices for reliability, robustness, and resilience evaluations. These values are expressed as percentages of the increases or decreases compared with the original system (Case 1). Fig. 7 shows a three-dimensional representation of these results. On the one hand, the results indicated that most of the topologies improved on reliability, robustness, and resilience, except for Case 3, which exhibited the worst performance in terms of resilience. Similarly, the topology of Case 8 was the most robust and resilient of all the systems but slightly less reliable than the topologies of Cases 5 and 6 because it had 0.33% more ENS. The topologies of Cases 2, 5, and 6 were intermediate among the three attributes. On the other hand, although the topologies of Cases 4 and 7 exhibited good performance in terms of reliability and resilience, they had a slightly poor performance in terms of robustness because their improvement percentages were minimal compared with the more robust topologies. However, the performance of these two topologies was superior to that

Table 2
Percentages of increase in the EENS, SD and ENS indicators in the reliability, robustness, and resilience evaluations compared with Case 1.

	Reliability [Δ EENS (%)]	Robustness [Δ SD (%)]	Resilience [Δ ENS (%)]
Case 1	0.00	0.00	0.00
Case 2	1.81	5.71	35.68
Case 3	1.59	0.52	−12.93
Case 4	1.59	1.17	31.86
Case 5	2.19	8.61	21.76
Case 6	2.19	7.58	27.64
Case 7	1.77	2.02	35.60
Case 8	1.86	9.43	58.52

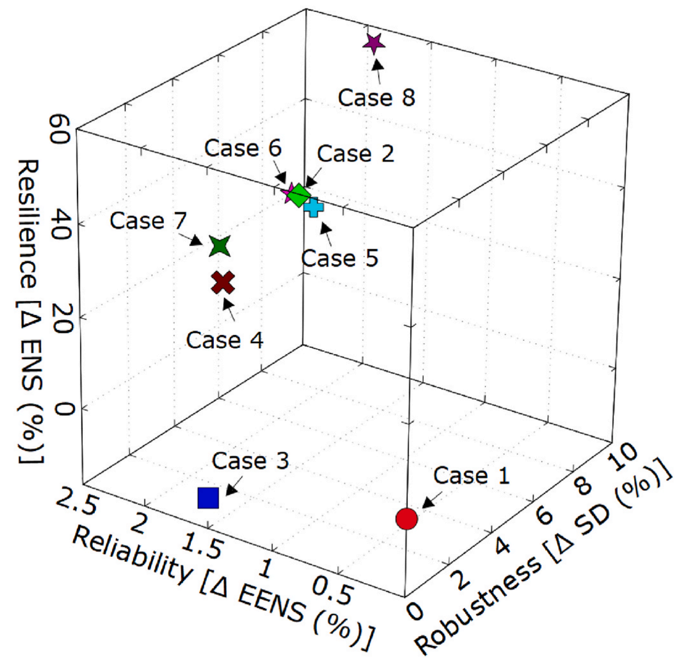

Fig. 7. Results obtained integrated into an R3 concept.

of Case 3.

The results integrated into the R3 concept also demonstrated that the addition of lines mostly had a positive impact on the operating conditions of the original system because they enabled an increase in the power transfer capacity between different zones and reduced congestion in the power lines. They also aided in the adaptation to the different disturbances simulated in the network and facilitated optimal resource management during the recovery process. Generally, and corresponding with other related publications, reliability is improved by adding more power lines and meshing the network; however, the network can become less robust because it is more exposed to cascading failures. Similarly, a less robust system implies greater disintegration because of a cascading event, which directly influences resilience. However, it is important to note that some lines were more beneficial than others; thus, the R3 concept can offer a better compromise solution for the design of electrical power systems.

Finally, the results obtained in the R3 framework can be used to make investment decisions or improvements in the power grid topology from an integrated perspective of the three concepts. For example, a decision-maker can determine a compromise solution for a power system by weighing reliability, robustness, and resilience in an integrated manner, as considering the concepts separately can result in contradictory views on the problem and, to some extent, impact the security of supply. Note that these conclusions do not invalidate other transmission network planning strategies under other criteria for improving system capacity to ensure optimal technical and economic performance. This is because the conclusions reached in this manuscript do not replace the conclusions obtained with the methods of analysis widely used and recognised in the industry, mainly focused on traditional adequacy and security criteria. Instead, the R3 framework can be an additional strategy for the traditional tools already used in power systems.

Additionally, renewable energy sources are an integral part of the current process of decarbonisation of power systems and, as such, recent articles consider these assets in their studies. Here, the results could be different depending on how the simulation is performed, what guidelines are considered, or even what percentage of renewable resources are available in each case study. For example, in terms of reliability, the case study with renewables would be expected to be less reliable than the case study with fossil generation, mainly due to the stochastic nature of renewable resources. In terms of robustness, the case studies with and without renewables could have similar behaviour because cascading events can happen irrespective of the type of generation, as they are influenced by the operation of the protection devices. However, it would be important to note that synchronous generators can remain connected during and after a fault; in contrast, challenges arise in maintaining adequate frequency response as the share of inverter-based renewables increases. In terms of resilience, the case study with renewables could recover the load of the system faster than the case study with fossil generation because the first one could have distributed generation to restore inoperative areas (if sufficient wind or solar resources were available). Nevertheless, renewable energy sources do not represent any obstacle in the proposal presented here, as it is possible to consider them [57,58].

Other areas for improvement in this research include the following:

1. The robustness study could be improved with a more complex methodology to capture both the frequency dynamics and the triggering mechanisms of the protection devices in a cascading event.
2. The integration of indicators could be further extended by considering multi-criteria techniques for a better ranking of network topologies.

5. Conclusions

This paper proposes a methodological framework based on data to analyse the reliability, robustness, and resilience of a power system from an integrated perspective. A sequential Monte Carlo technique was applied to evaluate the reliability, a cascading failure procedure was used to quantify the robustness, and a recovery procedure based on a mixed-integer optimisation problem was used to calculate a resilience metric. For this analysis, eight case studies were used based on the well-known IEEE 24-bus RTS, in which different indicators of reliability, robustness, and resilience were calculated. The results obtained were presented both graphically and numerically and were comprehensively discussed in a three-dimensional representation that considered the ranking of each case in each concept. This representation demonstrated the advantage of representing the three concepts in an integrated manner rather than separately. The findings showed that most meshed topology of an electrical system cannot always be guaranteed as the best from the perspective of each criterion, but generally, it offers the best optimal results for the security of supply. For example, the reliability study indicated that Case 6, with only two lines, was more reliable than Case 8 with three lines by 0.33% in relation to the ENS index. Although this is a small value, the unavailability of energy has strong economic repercussions in modern economies. In contrast, Case 8 was more robust and resilient than Case 6 by 2.50% and 42.70%, respectively, which could indicate that a meshed topology has advantages because it enables higher demand to be satisfied in the event of disturbances or failures and the power supply to be restored earlier. The results also showed that a power line can have a favourable impact on the security of supply, as demonstrated by Cases 1 and 2, where Case 2 had improvements of 1.81% in reliability, 10.53% in robustness, and 35.68% in resilience. The findings presented here clearly and accurately demonstrated the requirement for more integrated studies to obtain a much broader view of the operational behaviour of power systems. A planner can perform this procedure and run it to identify possible investments or improvements in the power system topology. A power system planner can use these results to identify possible investments or improvements in power system topology. This paper is a starting point for future developments. Future work will incorporate other methods of analysis and consider other strategies for integrating indicators.

Credit author statement

Jesus Beyza: Conceptualization; Investigation; Methodology; Writing - original draft. **Jose M. Yusta**: Conceptualization; Funding acquisition; Project administration; Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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