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An MCDM Approach for the Integrated Assessment of Vulnerability and Reliability of Power Systems

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Abstract: Fault analysis of modern power systems cannot be only addressed on classical reliability techniques but also considering the impact of cascading failures. This paper proposes an original integrated approach for the risk management of a power system subject to random contingencies by using vulnerability and reliability quantitative measures. Five different systems based on the IEEE-RTS have been studied from the vulnerability and reliability perspectives. According to the calculation carried out and the Multi-Criteria Decision Making (MCDM) method applied to better consider the integration of both concepts, the vulnerability and reliability perspectives are complementary viewpoints that can help to design a more robust critical infrastructure.

1 Introduction

In the last years, increasing efforts have been developed on the analysis and prevention of possible disruptions of electricity supply. Two complementary approaches can be taken into account to manage these risks in power systems, considering high-probability but low-impact events and low-probability but high-impact events [1–3].

The first kind of events is related to N-1 contingencies and it comes under the scope of the reliability. Reliability can be defined as the ability of the electric power system to meet the demand with continuity and an acceptable level of quality. Several approaches are possible to assess the reliability of the power systems, from analytical to Monte Carlo probabilistic models. Monte Carlo is a more flexible methodology in comparison with analytical approaches but it takes more computation time, especially when complex operating conditions and system states are considered [4].

The second kind of events is related to N-k contingencies and it refers to cascading failures in power systems. Vulnerability can be defined as the level of degradation of a system when deliberate attacks or random failures make the network elements successively out of operation. A single outage of a transmission line of the power grid can lead to an overload of other lines, making more likely the failure of other electric assets and finally resulting in a catastrophic failure of the whole system. Some of the biggest blackouts have occurred in recent years, causing serious economic damage and driving the need for vulnerability assessment of the electric power critical infrastructures [5]. In the scientific literature some works analyze the vulnerability of electrical infrastructures through the use of different techniques. For instance, some authors justified that the statistical measures of graph theory are adequate to carry out assessments of structural vulnerability on power systems [1]. Other researchers are using alternative measures, such as [6] that incorporated several topological and power flow based indices into a general framework able to evaluate system vulnerability and, consequently, provide information about the susceptible areas of the energy infrastructure.

The concepts of reliability and vulnerability are both related to the continuity of operations of critical infrastructures, and their study is required to prevent potentially destructive events [7]. However, researchers have not considered integrating both risk analysis perspectives into a unique decision framework. Few papers can be found in literature about joint consideration of reliability and vulnerability [8, 9]. Reliability analysis has been the main approach for risk management in electrical critical infrastructures and vulnerability analysis has received attention only in last years, but both concepts should be taken simultaneously into account to improve the planning of the expansion of power systems.

Previous research applied to power systems concluded that vulnerability analysis should be used as a complement to reliability analysis but it did not address how to use the results from vulnerability and reliability analyses for making decisions on critical infrastructures [8]. In contrast, our research provides a robust calculation of reliability and vulnerability indices and, at the same time, a combination of both approaches to improve the decision making process on the best network topology under an integrated risk assessment framework using MCDM. We propose a method to compare the performance of different networks under reliability and vulnerability criteria.

The rest of this paper is organized as follows: first, Section 2 introduces the methodology and the algorithms proposed to calculate vulnerability and reliability. A case study is presented in Section 3. Then, simulation results of the vulnerability and reliability analyses are shown and explained in Section 4. Finally, in Section 5, the comparison and discussion of results are done, and an MCDM method is applied to jointly analyze both concepts. The paper summary and conclusions will be provided in Section 6.

2 Methodologies

2.1 Structural vulnerability assessment

Vulnerability is an internal characteristic of critical infrastructures that measures the inability of the system to withstand the effects of failures [10]. Frequently, it is quantified based on the largest connected component, both before and after cascade events [11].

To determine the impact of cascading failure events, power grid performance is measured according to the electrical loads that remain connected after several interdiction events. Some measures have been applied to previous research works to estimate load shedding as a percentage of the total system demand [12–14]. In this

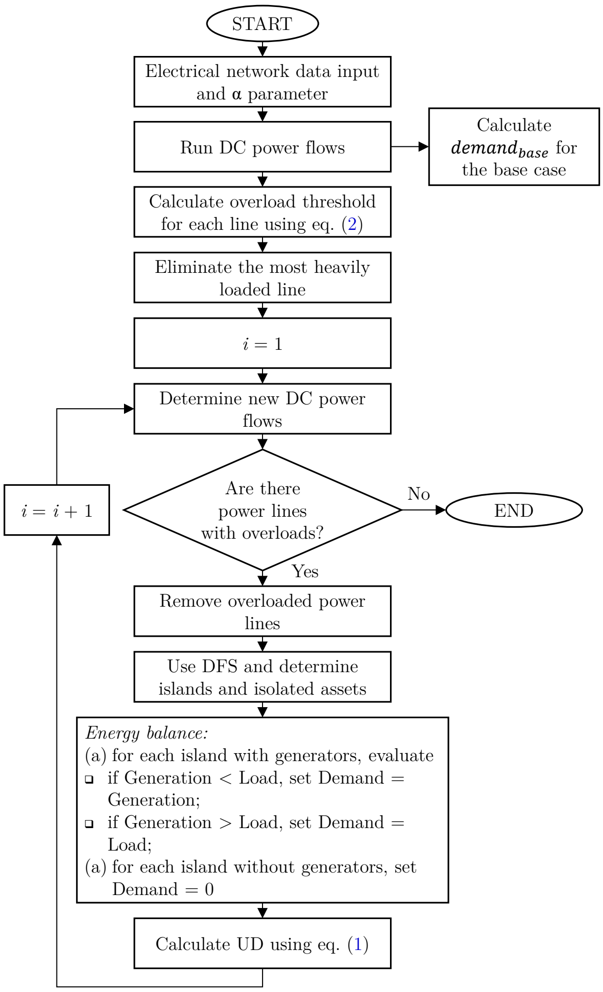

Fig. 1: Flowchart to calculate the structural vulnerability of power systems.

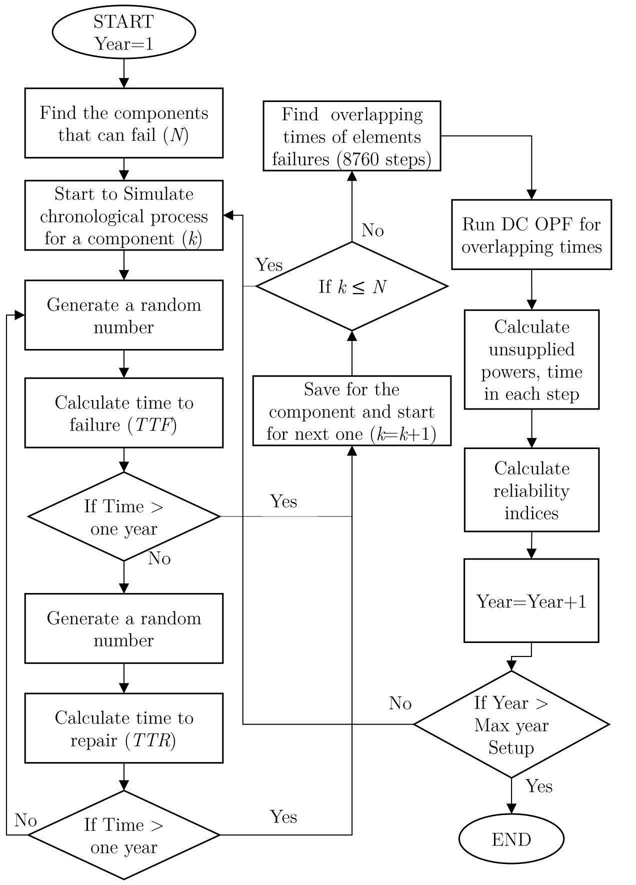

Fig. 2: Flowchart of reliability analysis of power systems.

article, we propose the unsatisfied demand (UD) index to measure the power system performance when it is subject to cascading failures caused by disconnection of overloaded power lines.

The UD metric allows determining the impact of cascading failures by quantifying the demand that can be satisfied in the electrical infrastructure after multiple line removals. The UD index is calculated as follows:

$$UD = 1 - \frac{\sum_i Demand_i}{Demand_{base}} \tag{1}$$

where:
$Demand_i$: demand met on island i.
$Demand_{base}$: total demand for base case.

The UD index varies between 0 and 1. Thus, as the UD index increases, the impact on satisfied demand in the power system also increases.

The flowchart of the algorithm presented in Fig. 1 allows determining the structural vulnerability of the power grids. The calculation is performed using (1) where the UD index is calculated during each disintegration stage of network.

Initially, the algorithm calculates DC power flows and determines power line overload limits using a user-defined parameter α, as shown in (2).

$$Overload_{threshold} = \alpha_j \times Flow_{base_j} \tag{2}$$

where:
α_j: tolerance parameter of line j
$Flow_{base_j}$: base power flow of line j

Cascading failures are initiated by removing the most heavily loaded line. The algorithm then calculates the new power flows and verifies that the power lines do not exceed the overload threshold determined in (2). If the latter is not achieved, the overloaded electrical lines are removed, and then the formation of islands or isolated elements caused by the previous event is determined. We used Deep First Search (DFS) algorithm to solve the problem mentioned above [15].

Due to the formation of multiple islands, the developed algorithm incorporates an energy balance routine to determine the maximum demand that can be satisfied in each subnet. In other words, islands with a generation higher than their demand will be able to satisfy the connected load, while islands with a generation lower than their demand will only be able to satisfy the load equivalent to the generation. Islands without generation or isolated buses are considered as unsatisfied load in the algorithm. Cascading events also continue on these islands. In this way, DC power flows are run in each subsystem and, in parallel, the UD index is calculated. The algorithm ends once all power lines have been removed or there are no more overloads in the system.

DC load-flow models provides a suitable capability for this kind of power system security analysis. In this regard, voltage magnitudes might not be a major concern and DC power flow studies provide sufficient accuracy [16].

The algorithm has been programmed in the MATLAB programming environment.

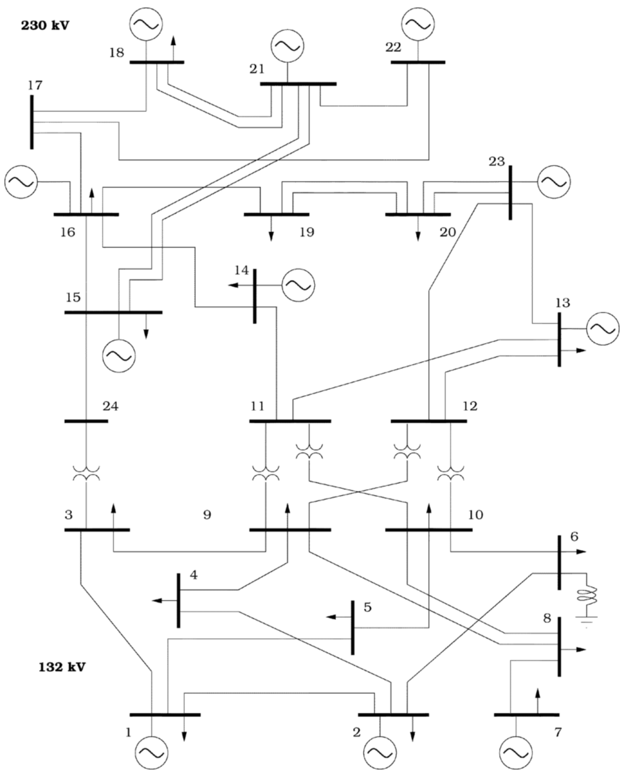

Fig. 3: Diagram of IEEE 24-bus Reliability Test System.

2.2 *Reliability assessment*

In Monte Carlo simulation, two main techniques are usually employed: time-sequential and non-sequential. In non-sequential techniques (system state sampling) each time step or system state are considered independently while sequential techniques can be used realistically to simulate the actual chronological process and random behavior of system [17, 18].

Time-sequential Monte Carlo technique is used here for the reliability assessment because is more flexible, accurate and provides calculation of different indices such as Expected Frequency of Load Curtailments (EFLC) but it needs more computation time [4, 17–19]. For an in-depth description, some useful references can be found in the literature [3, 20, 21].

Implemented time-sequential Monte Carlo technique for reliability assessment of a power system is presented in the flowchart of Fig. 2 using the following steps [4, 17, 18]:

Step 1. specify the initial state and number of components that can fail. It is assumed that all components are in a normal state and have only two states (normal and failure).

Step 2. calculate the residing time (the time the component spends in each state). In this case, uniform random numbers (r) are used, and Time To Failure (TTF) and Time To Repair (TTR) are sequentially calculated employing failure rates (λ) and Mean Time To Repair (MTTR) of components, using (3) and (4):

$$TTF = -\frac{\ln(r)}{\lambda} \times 8760 \tag{3}$$

$$TTR = -\ln(r) \times MTTR \tag{4}$$

This step should be repeated for each component for a specific time span, normally one year.

Step 3. after providing the artificial history of the system in above steps, overlapping times of elements failures are needed. The time steps considered are hours of one year (8760 steps).

Step 4. power flow calculation of new topology by considering the element failures. Optimal DC power flow (OPF) is employed to specify the effects of failed elements removal on supplied energy and normal operation of system. MATLAB is used for OPF calculations [22].

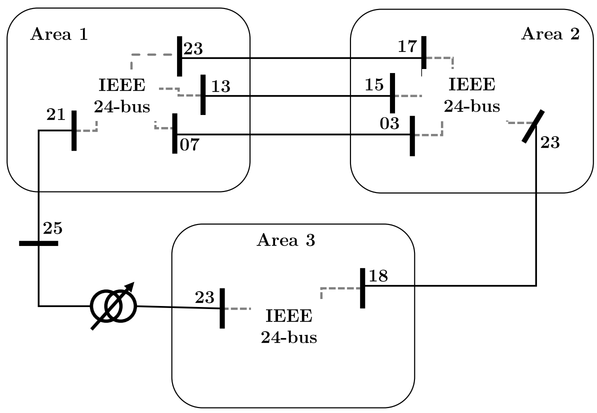

Fig. 4: Three areas diagram IEEE RTS-96.

Step 5. calculate the reliability indices using the results provided from previous step and following reliability indices [4, 8, 17, 18]:

- *Expected Energy Not Supplied (EENS) (MWh/year):*

$$EENS = \frac{\sum_{i=1}^{N_y}(\sum_{j=1}^{N_i} E_{j,i})}{N_y} \tag{5}$$

Where, $E_{j,i}$ is power system energy not supplied of j^{th} power interruption, in year *i*, N_y is total number of simulated years and N_i is total number of interruption in year *i*.

- *Expected Demand Not Supplied (EDNS) (MW):*

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

- *Expected Frequency of Load Curtailment (EFLC) or Loss of Load Frequency (LOLF) (outages/year):*

$$EFLC = \frac{\sum_{i=1}^{N_y} N_i}{N_y} \tag{7}$$

- *Expected Duration of Load Curtailment (EDLC) or Loss of Load Expectancy (LOLE) (hours/year):*

$$EDLC = \frac{\sum_{i=1}^{N_y}(\sum_{j=1}^{N_i} D_{j,i})}{N_y} \tag{8}$$

Where, $D_{j,i}$ is duration of j^{th} power interruption, in year *i*.

- *Probability of Load Curtailment (PLC) or Loss of Load Probability (LOLP) (%):*

$$PLC = \frac{EDLC}{8760} \tag{9}$$

- *Average Duration of Load Curtailments (ADLC) or Loss of Load Duration (LOLD) (hour/disturbance):*

$$ADLC = \frac{EDLC}{EFLC} \tag{10}$$

Step 6. The steps 2-5 are repeated and the indices are accumulated until the coefficient of variation EENS is less than tolerance error. According to previous works, a relative tolerance error of 6 % is established [4].

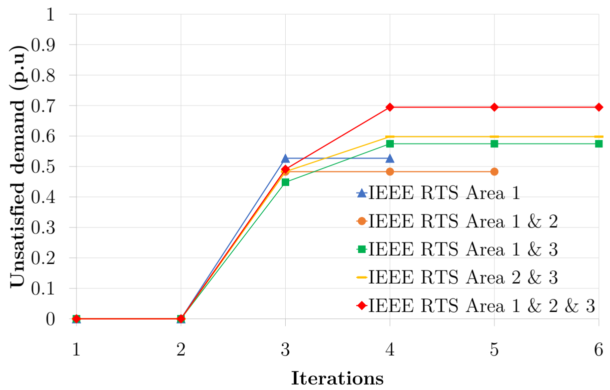

Fig. 5: Vulnerability curves.

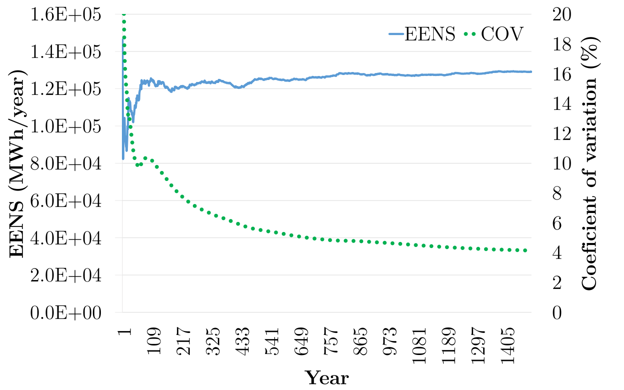

Fig. 6: EENS and coefficient of variation for area 1 and 1500-year time span.

3 Case studies

In this paper, the IEEE Reliability Test System (RTS-96) [23] is used as a test system. This network is a good test case for bulk power system reliability evaluation studies because of available required data (see Fig. 3). IEEE RTS-96 bus system has three areas that are mirrored copies of Fig. 3. These areas are interconnected with different components (Fig. 4). For example, Area 1 is connected with three lines to Area 2, Area 2 with 1 line to Area 3 and Area 3 is connected with an extra bus, a transformer and a line to Area 1 [24]. In this paper, five different combinations of the three areas are used for reliability evaluation in five case studies. In each area, 94 components can fail i.e., 24 buses, 32 generators and 38 branches and transformers. In addition to data which are available in [23], failure rate and MTTR of buses are considered 0.001(/year) and 24 hours, respectively [8]. It is assumed that the annualized peak power demand for each area is 2850 MW [23].

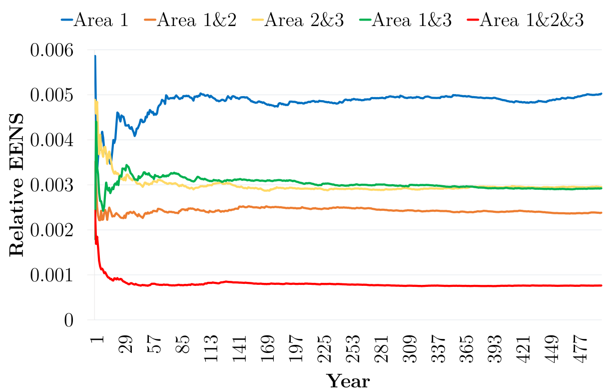

Fig. 7: Comparison of reliability index (Relative EENS) for different topologies.

4 Simulation results

4.1 Results of vulnerability analysis

Fig. 5 reports the degradation of the networks under study caused by the outage of transmission line 14-16. This power line is the most loaded in all systems. We obtain the plotted results after applying the algorithm shown in Fig. 1 by considering a parameter $\alpha = 1$ in all cases.

The curves represent the unsatisfied demand (UD) calculated during each disintegration step of the network. Initially, the UD index has a value equal to 0 when all the load in the power grid is satisfied. Then, the UD index progressively increases until a value equal to 1 when the whole system is disintegrated due to the removal of the overloaded lines. At this point, the system cannot meet the demand of the power grid.

Fig. 5 shows that Area 1 & 3, Area 2 & 3 and Area 1 & 2 & 3 reach their maximum point of disintegration in iteration six, while Area 1 & 2 in iteration five and Area 1 in iteration four. The above indicates that the propagation of cascading effects grows as the network increases in size.

Therefore, it can be observed that Area 1 & 2 & 3 is the most vulnerable network since 70 % of the demand is not satisfied, while Area 1 & 2 proves to be the most robust network since about 50 % of the load on the power network remains satisfied. In short, the most vulnerable systems can be determined graphically from least to most vulnerable as follows: Area 1 & 2, Area 1, Area 1 & 3, Area 2 & 3 and Area 1 & 2 & 3. In this manner, we have a measure of the behavior of the networks under study, which allows us to classify them according to their degree of vulnerability.

4.2 Results of reliability analysis

The time-sequential Monte Carlo Simulation approach has been applied to the same five different topologies from IEEE RTS-96. Fig. 6 shows the deviations of EENS and coefficient of variation (COV) for a 1500-years simulation. The simulation process can be stopped when the coefficient of variation (COV) for EENS or EDNS is less than 6 %, following recommendations from [4]. Convergence is slower than others [8] and it is also clear from comparing the coefficient of variation (COV) of different reliability indices in Table 1. As it can be concluded from Fig. 6, it is not necessary to run a 1500-years simulation to reach a coefficient of variation (COV) below 6 %. Thus, results plotted in Fig. 7 are obtained from calculations done for a 500-year simulation.

Fig. 7 shows that connecting similar networks that can meet their demands by self-generation increases the reliability index (Relative EENS). Moreover, how the three coupled networks are connected is also important. Here, Area 1 & 2 is more reliable because there are three interconnecting lines between the networks 1 and 2, providing redundancy to the system. Area 1 & 3, that has three interconnecting components, has similar behavior. However, Area 2 & 3, with only one interconnecting component, is less reliable. The reason can be the small failure rates of the bus (0.001/year) and the transformer (0.02). Therefore, these components can be ignored in one-year simulation span. So, we can assume that Areas 1 & 3 and 2 & 3 have interconnecting lines with failure rates of 0.52 and 0.53 /year, respectively.

Table 1 Annualized system indices for the IEEE-RTS (AREA 1)

Reliability index	Ref. [8]	Ref. [25]	This paper	COV (%)
EENS	127546	134590.60	130513.96	5.54
EDNS	14.56	15.36* (134590.6/8760)	14.90	5.54
EFLC	18.8	18.57	19.12	3.83
EDLC	732	740.22* (0.0845 × 8760)	744.69	3.43
PLC	8.3	8.45	8.50	3.43
ADLC	38.8	39.86* (740.22/18.57)	38.95	3.23

***These are calculated using available data in reference [25]**

Table 2 Annualized system indices and data for the IEEE-RTS

Reliability index	Area 1	Area 1 & 2	Area 1 & 3	Area 2 & 3	Area 1 & 2 & 3
Total Demand (MW)	2850	5700	5700	5700	8550
Number of Components	94	191	191	189	289
EENS (MWh/year)	130513.96	118913.10	145876.59	147422.55	56990.00
Relative EENS (EENS/Total Demand/8760 hours)	0.0052	0.0024	0.0029	0.0030	0.0008
EDNS (MW)	14.90	13.57	16.65	16.83	6.50
EFLC (outages/year)	19.12	26.33	26.86	26.69	18.08
EDLC (hours/year)	744.69	901.17	1017.94	1029.78	439
PLC (%)	8.50	10.29	11.62	11.76	5.01
ADLC (hour/disturbance)	38.95	34.22	37.90	38.58	24.30

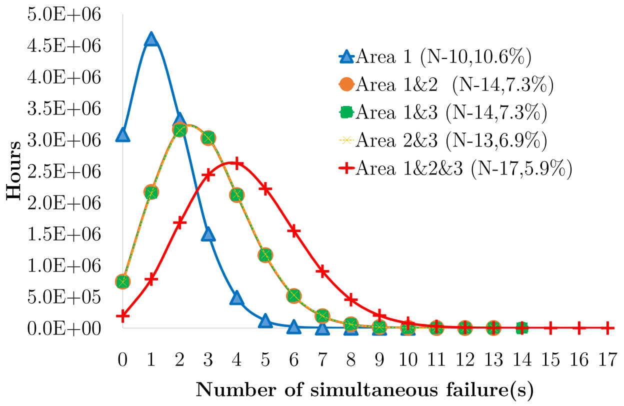

Fig. 8: Distribution of number (hours) of simultaneous failures in different topologies for a 1500-year time span (maximum number of possible simultaneous failure and maximum percentage of simultaneous component failures are presented in parenthesis).

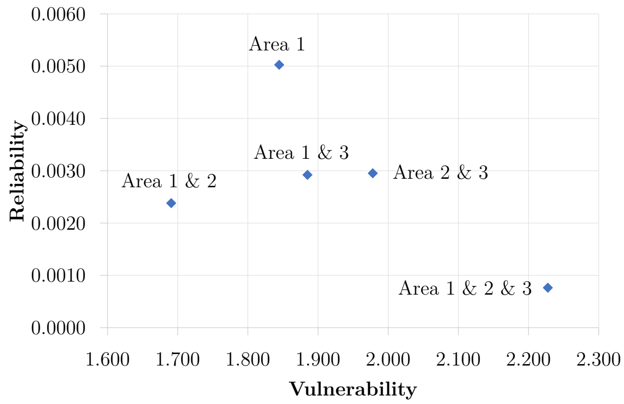

Fig. 9: Comparison of Relative EENS (reliability index) and vulnerability index for different systems.

5 Discussion

5.1 *Reliability and vulnerability concepts*

Reliability and vulnerability assessment study the ability of a system to perform its desired functions under given conditions for a period of time and the weakness level of a system to failures, disasters or attacks, respectively [8, 26]. Reliability assessment is dependent on probability of component failure but vulnerability assessment does not consider probability. Other difference relies on the different number of simultaneous failures that both techniques take into account.

Fig. 6 and Fig. 7 show that vulnerability assessment considers 0 to 100 % of components removal. On the other hand, in order to show the number of simultaneous failures in reliability assessment, 1500-year time span (1500 × 8760 hours) for all topologies is simulated. The results are presented in Fig. 8. It shows that the percentage of simultaneous failures decreases when the dimension of the network increases. In addition, it shows that reliability analysis only considers maximum 10.6 % of component outages. Vulnerability assessment can complement the reliability analysis considering the rest of N-*k* failures.

5.2 *Reliability and vulnerability comparison*

This section is intended to the joint comparison and discussion of the results of reliability and vulnerability assessment, integrating both risk analysis perspectives.

With respect to the structural vulnerability analysis, observing Fig. 5 it is possible to conclude that Area 1 & 2 & 3 is the least robust case since the unsatisfied demand is higher than in the remaining cases under study. In other words, large systems are highly vulnerable, when compared to those systems with small size but more compact.

With respect to the reliability analysis, it is possible observing Figs. 6 and 7 how the largest system (Area 1 & 2 & 3) is the less sensitive to power outages as a consequence of any element malfunctioning, i.e., the most reliable. In fact, the ranking of Relative EENS from Table 2 (Area 1 & 2 & 3, Area 1 & 2, Area 1 & 3, Area 2 & 3, Area 1) seems to be quite different to that obtained from the vulnerability results shown in Fig. 5 plotted from lowest to highest vulnerability (Area 1 & 2, Area 1, Area 1 & 3, Area 2 & 3, Area

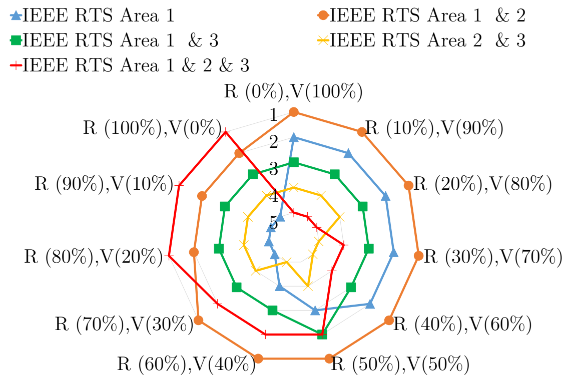

Fig. 10: Ranking of five IEEE RTS topologies based on the decision-makers' priorities on Reliability (R) and Vulnerability (V).

1 & 2 & 3). This reasoning suggests that a vulnerable power system may not be unreliable, or inversely, an unreliable energy power system is not necessarily vulnerable. The interconnection of energy sub-systems 1, 2 and 3 results in a global system with higher reliability, i.e., the lowest value of Relative EENS for Area 1 & 2 & 3 in Fig. 9. However, the amount and type of interconnection links between the sub-systems are crucial from the vulnerability perspective. The values of vulnerability in Fig. 9 have been obtained through the parameter AUC (area under curve) for each curve in Fig. 5. The values of reliability have been taken from the results of Relative EENS shown in Table 2.

The pairwise comparison in Fig. 9 lets us confirm the previous conclusions: the system named as Area 1 is the least reliable, but more robust, because of its compact size, and the system of Area 1 & 2 & 3 is the most reliable, but less robust, since reliability improves with interconnections, but vulnerability becomes worse due to faster propagation of cascading failures.

5.3 *Reliability and vulnerability integration*

In this section, the goal is to show how the decision-makers' priorities on reliability and vulnerability could be taken into account to select the best topology. Multi-Criteria Decision Making (MCDM) methods are usually applied to provide a ranking of alternatives using different measures and criteria. The Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS) is one of the MCDM method to find the best alternative that is the closest to the positive ideal solution and farthest to the negative ideal solution [27, 28]. In our case, we consider five different topologies of IEEE RTS as the alternatives and vulnerability and reliability indices as the measures.

Thanks to TOPSIS approach, the ranking of five IEEE RTS topologies based on the decision-makers' priorities are shown in Fig. 10 scoring each topology. Reliability (R) and Vulnerability (V) weights are considered for decision making. For example, from decision-makers' perspective "R(10 %), V(90 %)" means the weights of reliability and vulnerability are 10 and 90 percent, respectively, and the final scores of topologies are from 1 (the best) to 5 (the worst).

Fig. 10 shows that IEEE RTS Area 1 & 2 would be mostly the best topology. But when considering vulnerability weights between 0 and 20 % (reliability between 80 and 100 %) IEEE Area 1 & 2 & 3 becomes a better topology. These two solutions dominate the other three networks IEEE Areas 1, Areas 1 & 3, and 2 & 3 as it can be also checked in Fig. 9.

6 Conclusion

In this paper, a novel methodology has been developed for the joint consideration of vulnerability and reliability of power systems. Indices to measure system vulnerability as well as power and energy related definitions frequently used on reliability studies (EENS, EFLC, EDLC, among others) have been integrated into a wide discussion, aiming to quantitatively determine the pros and cons of the current energy transmission system designs. Five different topologies based on the IEEE RTS-96 test case have been studied from the vulnerability and reliability perspectives. According to the information available and calculation carried out, the behavior of the system from the vulnerability viewpoint could be different to that observed from the reliability perspective. For example, the largest system, Area 1 & 2 & 3, shows the highest reliability (relative EENS value, 0.0008) but the worst vulnerability (value of area under curve of unsatisfied demand, 2.2275). On the contrary, the smallest system, Area 1, has low reliability (0.0050) but good vulnerability measure (1.8446). Thanks to the use of a multicriteria approach, TOPSIS, rankings of the five IEEE RTS-96 topologies have been obtained, considering different Reliability (R) and Vulnerability (V) weights based on the decision-makers' priorities. The analysis also depends on how each topology is planned and interconnected. Reliability improves with interconnections between the systems, making a power system more reliable as more interconnected is but making it simultaneously more vulnerable as it is more exposed to propagation of cascading failures. Then, a compromise solution can be found for each power system, weighting reliability and vulnerability into an integrated decision framework.

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