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Planning resilient networks against natural hazards: Understanding the importance of correlated failures and the value of flexible transmission assets

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ABSTRACT

Natural hazards cause major power outages as a result of spatially-correlated failures of network components. However, these correlations between failures of individual elements are often ignored in probabilistic planning models for optimal network design. We use different types of planning models to demonstrate the impact of ignoring correlations between component failures and the value of flexible transmission assets when power systems are exposed to natural hazards. We consider a network that is hypothetically located in northern Chile, a region that is prone to earthquakes. Using a simulation model, we compute the probabilities of spatially-correlated outages of transmission and substations based on information about historical earthquakes in the area. We determine optimal network designs using a deterministic reliability criterion and probabilistic models that either consider or disregard correlations among component failures. Our results show that the probability of a simultaneous failure of two transmission elements exposed to an earthquake can be up to 15 times higher than the probability simultaneous failure of the same two elements when we only consider independent component failures. Disregarding correlations of component failures changes the optimal network design significantly and increases the expected levels of curtailed demand in scenarios with spatially-correlated failures. We also find that, in some cases, it becomes optimal to invest in HVDC instead of AC transmission lines because the former gives the system operator the flexibility to control power flows in meshed transmission networks. This feature is particularly valuable to systems exposed to natural hazards, where network topologies in post-contingency operating conditions might differ significantly from pre-contingency ones.

1. Introduction

Network security is paramount for the well-functioning of power systems and for delivering reliable energy supply to consumers. A power outage can have catastrophic effects in the economy due to lost output, delayed production, and damaged infrastructure [1]. In addition, power outages can lead to human deaths [2]. For these reasons, power systems are normally planned and operated following strict standards of security and reliability [3].

Today, extreme weather events, natural hazards such as earthquakes and tsunamis, and physical attacks are the most common causes of major failures of power grids [4,5]. These exogenous events can cause simultaneous failures of multiple components of a power grid, increasing the likelihood of outages that affect broad geographical regions.

According to a recent report by the Oak Ridge National Laboratory, more than 95% of electric disturbance events affecting at least 50,000 customers between 2000 and 2016 in the US were triggered by some climate-related event, including severe winter storms, hurricanes, tornadoes, heavy rain, heat waves, and lightning [6]. In Puerto Rico, Hurricane Maria in 2017 caused so much damage to the grid that some

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people lost power for more than ten months [7].

Power grids in earthquake-prone areas can also be vulnerable to correlated component failures. For example, on February 27, 2010, a major earthquake affected some of the most populated areas in Chile and caused simultaneous failures of generation, transmission, and distribution assets, resulting in the curtailment of an equivalent of 75% of the annual peak demand for power in the system [8]. In 2011, Japan experienced the fourth strongest earthquake ever recorded in history, followed by a tsunami. The event triggered the disconnection of nearly 23 GW of generation and caused multiple failures both in transmission and distribution systems [9].

As expected, these major outages due to natural disasters can be very costly for the economy. A study by the US President's Council of Economic Advisers and the US Department of Electricity Delivery and Energy Reliability reports that weather-related power outages between 2003 and 2012 have cost the US economy an average of $18 billion to $33 billion, but this number can increase up to $75 billion in a year with major weather events [10]. Consequently, investment and operation strategies that are effective at reducing the impact of natural disasters and physical attacks on the power grid can result in relatively large economic savings.

Historically, power networks have been designed and operated by using the so-called $N-k$ security criterion (e.g., $k=1$ or $k=2$), meaning that power systems must withstand the outage of one ($k=1$) or two ($k=2$) elements without shedding (significant volumes of) demand and without violating the operating limits established in security standards [3]. This security criterion, however, has been questioned for years because it does not properly acknowledge the probabilistic nature of power outages and the cost of curtailing demand [11]. For example, the $N-1$ criterion does not recognize that long power lines may be more prone to fail than short lines or transformers in substations that are closely monitored. In addition, the $N-k$ criterion does not necessarily prevent power outages that result from correlated component failures, which are more likely to occur than independent failures when a power grid is exposed to natural disasters or extreme weather events [12].

To cope with these limitations, there is a body of work that recommends replacing deterministic standards with probabilistic (or stochastic) approaches to ensure a secure design and operation of power networks [3,11–19]. Under a probabilistic approach, outage risks can be appropriately measured and balanced against the costs of designing and operating the grid in a manner that could reduce such risks [13].

In spite or their benefits, probabilistic models present a number of challenges in order to be successfully applied in practice. For example, probabilistic models are more complex and harder to solve and scale up than deterministic models with minimum security standards, such as an $N-k$ requirement. The number of possible contingent states of the network grows exponentially with the number of network elements, which increases the computational complexity of probabilistic models as number of elements in the system goes up. Reliability data is not always available, especially dependencies and correlations among network outages that are hardly ever observed; hence outage dependencies are usually ignored in order to make models tractable. Also, information and communication technologies (ICT), protection and control systems are usually assumed 100% reliable.

Part of the computational challenges that result from the use of probabilistic models can be addressed through model simplifications or decomposition algorithms. In terms of simplifications, the authors in [20] show different alternatives to simplify network models with security constraints. In terms of computational algorithms to solve optimization problems, one alternative is to rely on the concept of the so-called "umbrella" outages and constraints that seek to identify, prior to running the mathematical program, a subset of relevant network outages that result in the exact same solution as considering the entire set of outages [19,21]. Another alternative is the application of Benders decomposition, which has been successfully used in security analysis for network [19,22] and generation investment planning [23,24]. Other modern solution algorithms and heuristics, such as optimization via simulation, have also been utilized recently [25,53].

In terms of the reliability of corrective control actions, there are a few references associated with modeling malfunctions of ICT, protection and control systems. Reference [26] utilizes the concept of the so-called hidden outages to model failures corresponding to malfunctions that are hidden, unrevealed until these are exposed by abnormal system conditions, transforming an initially benign outage into a major incident. Interestingly, such failures can be hedged by making appropriate decisions through probabilistic optimization models [27,28].

Outage dependencies and correlations have been recently gaining increased attention in network analysis and design. In communication networks, for example, various works have recognized outage dependencies and correlations for reliable operation and design [29–33]. In power systems, outage dependencies and correlations are also gaining attention because system operators have become more aware of the risks associated with natural hazards [12]. The current literature usually models simultaneous outages like a series of outages that cascade very rapidly across the system. This is the case of models such as those explained in [34–36], in which several power flow simulations are undertaken after triggering an initial network outage that can overload other parts of the network and so cascade into a major event. A stochastic optimization model for network investment, however, requires encapsulation of the above mentioned series of outages into a scenario tree [37]. Such scenario tree should describe the final state of the system after outages occur. In this vein, a series of cascading outages can be represented by a single contingent state of the system where multiple elements failed simultaneously. As failures in a cascading event are clearly not independent, dependent probabilities must be used correlating the outage probabilities of multiple elements after a given triggering event happened.

In this context, this paper studies the effects of including simultaneous system failures with dependencies in probabilistic network planning models to design resilient power networks. We refer to resilient networks as we focus on hedging against the impacts of exogenous high impact and low probability events (i.e., natural hazards) on the power system. To do so, we use a two-stage stochastic transmission expansion planning model, where, in the first stage, network investments and pre-contingency dispatch decisions are made and, in a second stage, redispatch decisions and demand curtailments occur as recourse decisions. The two-stage scenario tree is built using a Monte Carlo simulation process that, first, simulates the occurrence of an earthquake event and, then, simulates the following potential network outages. We compare the results of this model against two other models: a deterministic $N-k$ planning model and a stochastic planning model that ignores dependencies. Finally, we use the model to quantify the value of a portfolio of hybrid AC and DC power lines, attempting to further understand the benefits of utilizing flexible HVDC technologies to mitigate risks against correlated simultaneous outages. To our knowledge, this is the first study of this kind.

We structure the rest of the paper as follows. In Section 2 we provide a qualitative description of the methodology used to simulate earthquakes and a general description of the deterministic and probabilistic models used for optimal network design. In Section 3 our case study, which consists of a 14-bus network located in Northern Chile, and our main results. Finally, in Section 4 we conclude.

2. Methodology

2.1. Overview

We propose a stochastic mathematical program to design power transmission networks with probabilistic outage scenarios. This program decides on new network infrastructure (i.e. lines and transformers) and its corresponding system operation, by minimizing the sum of the investment cost, operational or generation cost (pre-fault cost and post-fault expected cost), and the expected cost of the energy not supplied. We use this mathematical program to evaluate three different design criteria, varying the different outage scenarios and probabilities that are considered.[1]

In the first case, the program determines network investments that satisfy the N-1 security criterion, meaning that scenarios consider the failure of only one component, their probabilities are even and for each scenario all energy demand must be satisfied. The cost of corrective actions in the form of reserve utilization are also neglected. We refer to this variant of the mathematical program as the **N-1 robust model**. In the second case, scenarios consider single and multiple failures, but their probabilities are calculated assuming that components fail independently according to their failure rates, we refer to this variant as the **Stochastic model with independent probabilities**. In the third case, scenarios also consider single and multiple failures, but their probabilities capture correlations. We refer to this variant as the **Stochastic model with failures correlation**. Such correlation can be caused by a common mode, for example, a natural hazard (e.g. storms, earthquakes) that may couple outage probabilities within a given location. Notice that reliability data are fundamentally ignored by the first model, while unavailability of each network component is the same in the second and third models. The difference between these two models is the appropriate recognition of dependencies in reliability data in the last case.

The stochastic optimization mathematical program used in this study is based on [19], with modifications to incorporate both line and substation failures and HVDC power lines. In order to make a fair comparison of the solutions of the three above-mentioned variants or models, we carry out an out-of-sample analysis by comparing the performance of each network design solution against a new sample of outages, statistically independent from the ones previously used. Thus, we calculate new expected costs for each of the three solutions to properly compare their performance. Importantly, for generating random outage scenarios, we first generate random natural hazards, which have the ability to increase and couple the probabilities of outage scenarios. We use earthquakes as the selected natural hazard since the way how they impact on outage probabilities has been already well established [25,53].

2.2. Mathematical optimization program

We modified the stochastic optimization formulation in [19] to incorporate additional features. This corresponds to a two-stage stochastic problem, where in a first-stage (before uncertainty is revealed) the investment in transmission infrastructure and pre-fault power generation levels and reserves are decided. In the second stage, for each scenario, recourse actions can be applied after transmission infrastructure and generating units fail, by modifying the generation dispatches (using the scheduled generation reserve committed in the first stage). Also, if demand cannot be met at a given scenario, then this induces a lost-load cost. The program minimizes the first-stage cost (investment cost and pre-fault operational costs) plus the expected value of the second stage decisions (post-fault operational and lost-load cost) over the set of outage scenarios given to the problem.

The main modifications to the model presented in [19] are:

- Investment decisions in HVDC network infrastructure. Apart from conventional AC lines and transformers, the model can now invest in HVDC lines too at a higher cost than traditional AC lines. This is modeled by relaxing the Kirchhoff's voltage law (KVL) that couples busbar angles as indicated in [38].

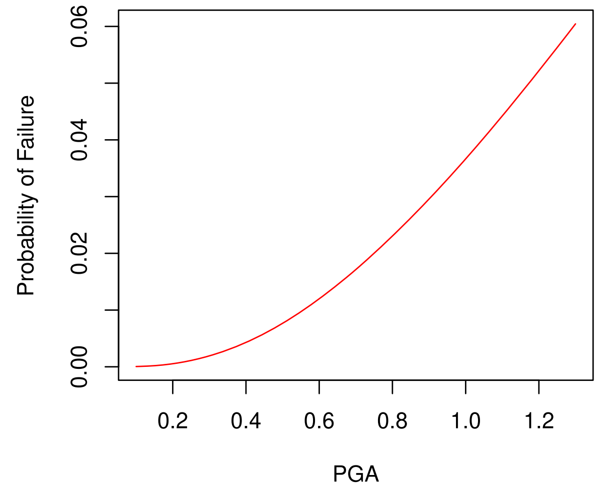


Fig. 1. Seismic fragility curve of transmission tower.

- Substation failures, modeled by derating the capacity of all network infrastructure directly connected to the targeted substation, including lines to generation and demand. Unlike power lines, whose failures are modeled in an binary on/off fashion, substations may present various damage states with different derated capacities.

These two features where added in order to analyze (i) the value of flexible network equipment in the provision of security of supply and (ii) the effect of substation failures, which are normally ignored in system reliability analysis as pointed out in [25,53]. The resulting model is presented in Appendix A. This optimization model captures the tradeoffs between incurring in additional investment costs (building new transmissions lines), and the consequent cost of system operation pre- and post-fault, considering lost-load costs and the potential support from flexible HVDC equipment in reducing pre- and post-fault operational costs via relaxing KVL.

We remark that this mathematical program strongly depends on the scenarios supplied. Providing representative scenarios considering geographically correlated failures, allows to optimize investment decisions in a more adequate fashion. On the contrary, providing scenarios neglecting correlations and assuming independent failure probabilities, may produce inappropriate investment propositions. In this context, we study the differences caused by outage correlations in network expansions, along with assessing the performance of these solutions in an out-of-sample analysis. We also compare these stochastic solutions against those determined by the **N-1 robust model**, which ignores failure probabilities and corresponds to the current state of affairs in network planning.

2.3. Scenario generation

We use a two-layer uncertainty process to generate correlated scenarios and we use earthquakes as the common mode that correlates failures. In the first layer, realization of a given earthquake occurs. In the second layer, a given network outage occurs as a consequence of the given earthquake. This two-layer uncertainty process is modeled as follows:

1. A random earthquake is generated via uniform random selection from a predefined list. The list contains data from historical earthquakes with their location, depth and magnitude.
2. Following the occurrence of the earthquake generated in the previous step, we calculate the peak ground acceleration (PGA) at the location of every network component, following the ground motion attenuation formula proposed by [39]. We use the PGA at every

[1] For the sake of clarity, in this paper the term *mathematical program* refers to the main stochastic optimization problem, from which each *variant* or *model* is derived.

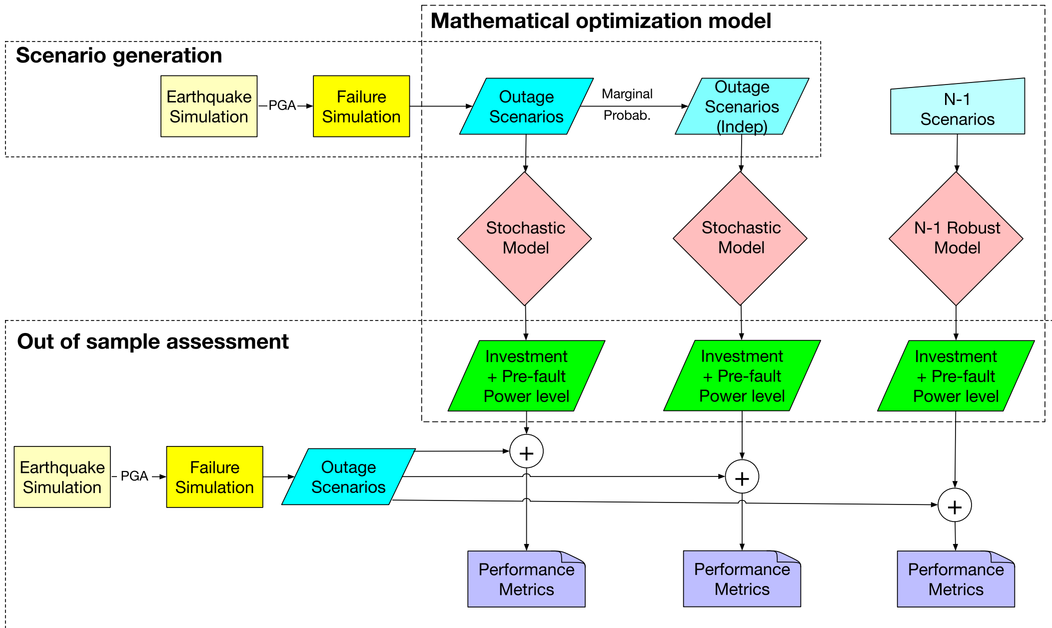


Fig. 2. Methodology to generate scenarios and compare the resulting decisions from the different models.

equipment's location to determine the failure probability of the component by using the appropriate fragility curve. As an example, fragility curves for a carrying transmission tower are presented in Fig. 1, as obtained by [40]. Fragility curves for other network components can be obtained from [41].

3. With the (conditional) failure probability of every network component, we generate an outage scenario by using a Monte Carlo simulation. An outage scenario consists of the combination of the states of all network components after the earthquake occurs.

While transmission lines present two possible states (on/off), substations and generators may present various derated states after an earthquake occurs as explained next.

- Transmission lines: First, we consider two damage states for transmission towers: no damage state and outaged state. In this vein, a power line is available only if no towers have been damaged. The fragility curve used to determine the failure probability of a tower is that in [40].
- Substations: Unlike transmission towers, we consider that substations can partially operate, so we define different damage states that affect substation's capacity. Hence, a substation can be available, partially available (with 3 damage levels: 95%, 60% or 30% of the original capacity) and fully damaged, following the set of fragility curves described in [41]. As explained earlier, this is modeled by derating the capacity of all network infrastructure directly connected to the targeted substation, including lines to generation and demand.
- Generators: Like substations, we consider that a generator can be fully available, partially available and fully damaged after an earthquake occurs. The failure probabilities, derated capacities and the fragility curves are the same ones used for substations.

After a comprehensive set of outage scenarios has been generated by using the above-mentioned Monte Carlo based method, we eliminate repeated scenarios and calculate their probabilities based on the observed frequency of them. The reduced set of scenarios and their probabilities are used to solve the **Stochastic model with failures correlation**, obtaining its optimal investments and dispatch decisions. To run the **Stochastic model with independent probabilities**, instead, we first calculate the marginal probability of failure of each network component as the number of simulations where the targeted component presents a specific damage state, divided by the total number of simulations. By using these marginal probabilities, we run a new Monte Carlo simulation to obtain a new set of outage scenarios assuming independence. As before, we eliminate repeated scenarios and calculate their probabilities based on the observed frequency of each scenario, and we use these data to solve the stochastic model. Finally, to run the **N-1 robust model**, there is no need for using Monte Carlo simulations as all outage scenarios considered in this model are included with equal probability.[2]

2.4. Out of sample assessment

To compare the performance of the solutions obtained by the three models, we undertake an out-of-sample assessment, in which we generate a very large number of new samples of damage states, which are used to evaluate the three solutions. To obtain a fair comparison, while the first-stage decisions of every solution (i.e. network investments and pre-fault network operations) are fixed, post-fault decisions are accommodated to minimize post-fault costs. That is, we solve the second-stage of our optimization problem to decide the recourse actions that minimize the total cost for each individual scenario. With these results, we compute the following metrics: annualized network investment costs, average generation costs and average lost-load costs of demand not supplied. We also compute various quantiles and empirical distributions of these costs.

A scheme of the methodology and the inputs/outputs of each model can be found on Fig. 2.

3. Case study and results

Instance We use the IEEE 14-busbar network presented in [42], considering 8 new candidate transmission lines as potential investments.

[2] Note that, in the robust model, the exact value of scenario probabilities does not matter as long as these are weighting factors higher than 0. This is so since the model presents extra constraints to prevent demand curtailments and costs of corrective actions are modified, equalizing them to zero.

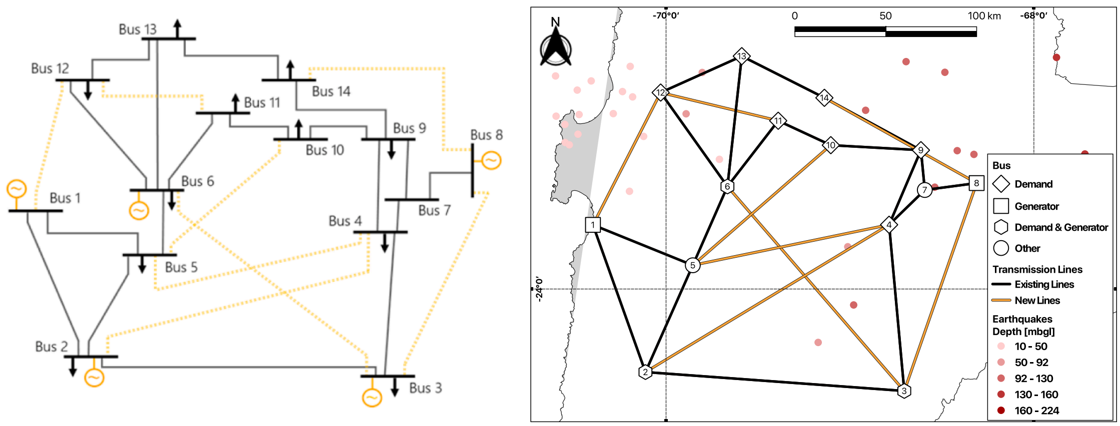


Fig. 3. IEEE 14-busbar network with 8 candidate transmission lines (in yellow) and its location in the north of Chile. Red dots on the map refers to the potential earthquakes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3 shows the original IEEE 14-busbar network, with the 8 new candidate transmission investment alternatives in yellow. Detailed data about demand, generation and transmission characteristics (including line capacities, reactances and costs) are presented in Appendix B. We also consider HVDC investment alternatives available for the same 8 new candidate transmission lines, but with an investment cost that is 50% higher than the AC alternative.

As described earlier, we assume that this network is located in an area affected by earthquakes. In particular, we assume that the IEEE 14-busbar networks is located in northern Chile, an area that is prone to this type of natural hazard [43]. Fig. 3 shows the location of the network in northern Chile and the coordinates of each bus are described in Appendix B.

Northern Chile is also an area where some of the largest copper mines in the world are located and where most of the demand for electricity comes from industrial processes. For this industry, the cost of interrupting the supply of power is much higher than, say, the cost of curtailing demand for residential customers. For this reason, we assume a high value of lost load, equal to 110,000 $/MWh, which reflects a preference for a highly-reliable power grid.[3]

We assume that thermal generators have a ramping limit of 20% of their nominal capacity. For all network components, we assume a repair time of 168 hours (one week), which represents the unavailability of damaged network infrastructure following a major earthquake.

In terms of the transmission infrastructure, we assume that high-voltage transmission towers are located along each transmission line every 300 m. Fragility curves of generation, transmission lines and substations are taken from [40] and [41]. For illustration purposes, we consider that the set of possible scenarios of earthquakes that could occur in the future is based on the list of earthquakes with significant magnitude (5.5Mw or more) that occurred in northern Chile between years 2000 and 2019. The position and magnitude of the considered earthquakes can be found in the U.S. Geological Survey catalog available online [48].

Table 1
Probability of multiple failures for the dependent simulated scenarios and its corresponding independent scenarios.

Num. of failed lines	Dependent scenarios	Independent scenarios
-	71.6776%	66.2774%
1	18.6936%	27.6609%
2	7.4592%	5.3621%
3	1.7964%	0.6427%
4	0.3260%	0.0535%
5	0.0440%	0.0033%
>5	0.0032%	0.0002%

Scenario Generation and Analysis

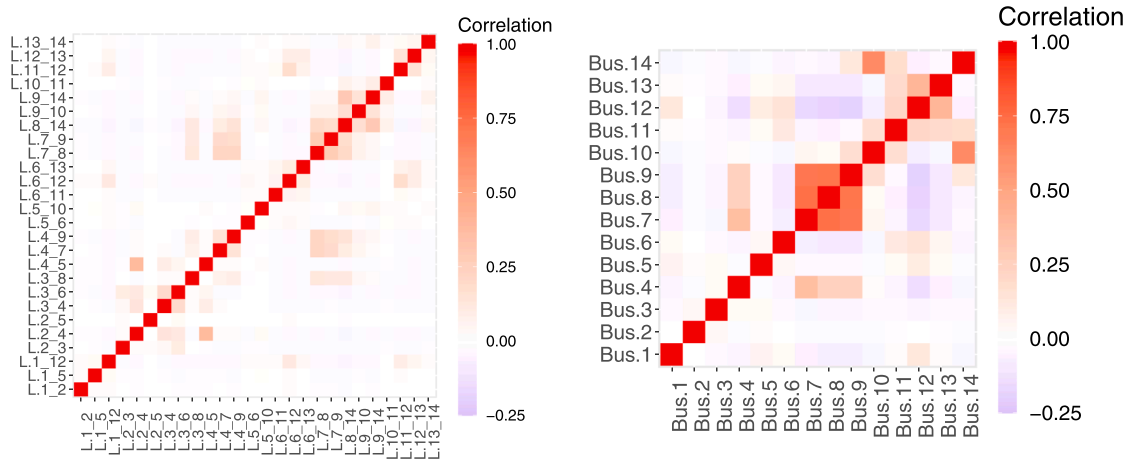
We simulate 250,000 realizations by randomly generating earthquakes and its subsequent network outages. After generating the above-mentioned dependent scenarios, marginal failure probabilities can be calculated for each system component. Detail results of these values can be observed in Table B.5 in the appendix.

With the marginal probabilities of component failures we simulate another set of 250,000 realizations by randomly generating independent network outages. In this vein, Table 1 compares the probability of observing exactly k failures in the set of dependent scenarios and in the set of independent scenarios. The table shows that the probability that all transmission lines remain available ($k = 0$) is smaller for the independent case as earthquakes generate a positive failure correlation between components (this is so because components tend to fail simultaneously). The failure of two or more components accounts for only 6% of the scenarios in the independent case. However, they represent 10% of the scenarios in the dependent case. When failures of more lines are considered, more significant differences arise. Notice that for $k \geq 3$, failures with k transmission lines are consistently underestimated in the independent model. These events are three times more probable in the dependent model for $k = 3$, seven times more likely for $k = 4$ and more than 10 times more probable for $k > 4$. These differences should not be neglected since these correspond to the scenarios with the highest losses and, therefore, they are likely to impact investment decisions.

An analysis of the correlation between components shows the same behavior at a more detailed level. In fact, it can be seen from Fig. 4 that correlations are significant.

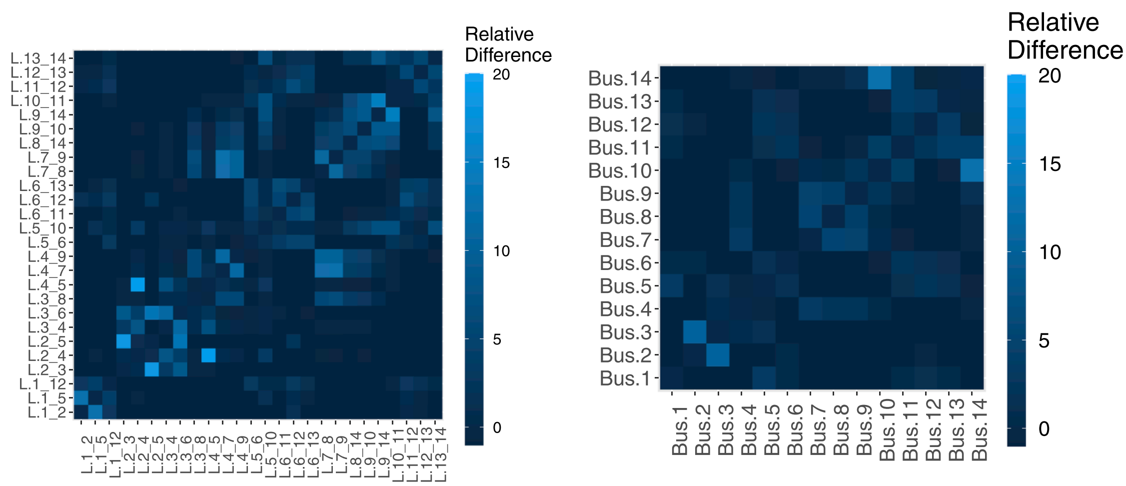
These substantial values of the correlations, together with small failure probabilities, cause that simultaneous failures of components occur considerably more often than expected under the independent assumption. In fact, the probability of simultaneous failure of a pair of transmission lines can attain a value up to 15 times the probability of the

[3] Note that while this value might seem excessively high, many power systems around the world are planned and operated using strict reliability standards. For instance, in the US, systems are planned using a resource-adequacy standard that aims for no more than 1 h of interrupted service in 10 years. According to a recent report for the National Association of Regulatory Utility Commissioners (NARUC), the implied value of lost load required to justify this resource-adequacy target is nearly 300,000 $/MWh [44], which is almost three times the value we used in this study. Finding what is the right reliability target, in line with the actual economic value that society places on avoiding demand curtailments, is an ongoing subject of research [45–47], but beyond the scope of this paper.



(a) Transmission lines (b) Busbars

Fig. 4. Correlation between failures in the generated scenarios.



(a) Transmission lines (b) Busbars

Fig. 5. Relative difference between the probability of simultaneous failure of two or more components under the dependent and independent assumption. In figure (b), we consider that busbars are in a failure state when the available capacity is less than 60%.

same simultaneous event under the independent assumption. See Fig. 5 for a comparison between the pair-wise simultaneous failure probabilities of transmission lines and busbars.

Resulting topologies We solved the three optimization models to evaluate the impact of the different criteria, namely the N-1 robust model (**RN-1**), the stochastic model with independent probabilities (**EI**) and the Stochastic model with failures correlation (**ED**). We also consider the latter model with the option of HVDC lines (**ED-HVDC**). The resulting infrastructure (including the new transmission lines) are displayed in Fig. 6.

The resulting networks differ considerably for the different models. From the 8 candidate transmission lines, the resulting network from **RN-1** presents 7 new lines, **EI** presents 6 new lines, and **ED** decides to build 4 new lines only. Also, **RN-1** is the only model selecting lines 3 −6 and 3 −8, which have the two highest investment costs among all candidate transmission lines. In line with previous research [19], these results demonstrate that deterministic investment decisions are significantly more costly than those determined by the stochastic counterparts as shown in Table 2. Indeed, **RN-1** must be able to supply all demands in case of an N-1 outage occurs, irrespective of how cost-effective is such criteria. In this case, this necessarily drives higher investment costs.

On the contrary, both stochastic models (**ED** and **EI**) do consider scenarios with demand curtailments when some components fail, alleviating the need for network investments. Among the stochastic solutions, **EI** underestimates the scenarios with multiple failures, so optimal decisions of the model mainly hedge against single failures. On the other hand, **ED** appropriately captures correlations. Interestingly, capturing correlations, in this case, drives less transmission investments. The associated risk levels of these investment propositions will be presented and discussed in the next section.

A completely different set of decisions is obtained when HVDC lines are considered as candidates. Hence, the optimal solution of **ED-HVDC** build 7 new transmission lines, where 5 of them adopt the HVDC technology. Compared with **ED**, these lines increment the investment costs from \$2.8M to \$7.3M (as shown in Table 2). Nevertheless, this is proved worth by the reduction in other cost components as explained in the next section. Importantly, as HVDC lines can bypass the KVL, they provide a more flexible alternative to operate the system while dealing with pre- and post-fault network congestions.

Out-of-sample assessment analysis We evaluate the reliability of the

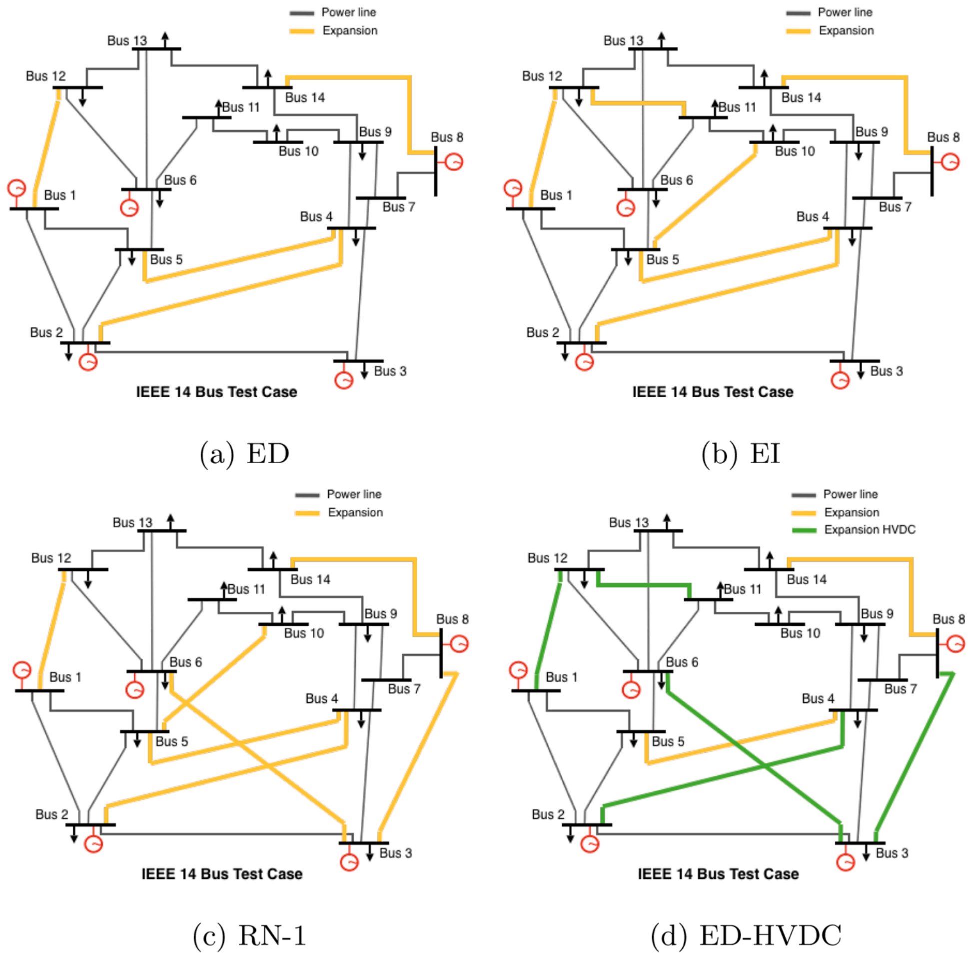


Fig. 6. Topology constructed for each criteria.

Table 2
Costs of each solution under an out-of-sample evaluation (mean value and [5% - 95%] quantiles).

	ED-HVDC	ED	EI	RN-1
Investment	7.3M	2.8M	3.7M	5.6M
Generation	118.3M [118.0M - 118.4M]	138.8M [138.6M - 139.0M]	144.4M [144.1M - 144.6M]	134.7M [134.4M - 134.9M]
Lost-Load	135.2M [0 - 618.2M]	138.9M [0 - 628.3M]	142.7M [0 - 694.8M]	155.5M [0 - 701.3M]
Total Cost	260.8M	280.5M	290.8M	295.8M

resulting network for each model under an out-of-sample evaluation of 250,000 simulations. We recall that given the initial pre-fault configuration (new transmission lines and power generation levels) of the network, we decide the optimal re-dispatch actions under all outage scenarios, obtaining an empirical distribution of the post-fault costs. In Table 2 we present the mean value and the $[5\% - 95\%]$ quantiles of the investment, generation and unsupplied energy costs for each solution. Results show that **ED** model produces the lowest expected total cost, compared with the other models that do not consider HVDC technology as an option. In fact, the resulting network from **EI** has a higher generation and unsupplied energy costs than **ED**, with a 3.6% of increase in the total cost. This is so since **EI** underestimates the occurrence of multiple failures. This is worsened by the **RN-1** model, where multiple failures are completely neglected. Although the expected generation cost is 3% lower than **ED**, the expected cost of the energy not supplied is 12% higher, resulting in an increased total expected cost. This demonstrates that risks associated with deterministic decisions in terms of unserved energy can be significant, despite their higher investment costs.

Observing the quantiles of the different cost components, we note that generation costs do not vary significantly across scenarios (less than 1% in the worst case). On the contrary, the costs of energy not supplied can be considerably different among the outage scenarios. To better understand this, we show in Fig. 7 the empirical cumulative distribution of the unserved demand costs for each solution. It can be seen that, under the presence of an earthquake, in approximately 40% of the cases the total demand can be supplied for all models. However, the figure also shows that the unsupplied energy costs can be as high as $1,000M in the worst cases. In the figure we can also observe that **RN-1** performs consistently worse than the other resulting networks. We also observe that **ED** produces a small but systematically significant reduction in the unsupplied energy costs compared with **EI**. All these comparisons have been validated by statistical tests (paired sampled *t*-test) over the simulations.

Finally, the solution with HVDC lines considerably improves the economic and reliability performance in operational timescales. In fact, both generation costs and unsupplied energy costs are reduced against all other solutions. This can be explained by the more flexible operation of the HVDC lines, which can better manage pre and post-fault congestion scenarios, maximizing the amount of demand supplied and taking advantage of the cheapest generation available.

4. Conclusions

Natural hazards pose major threats to the secure operation of power

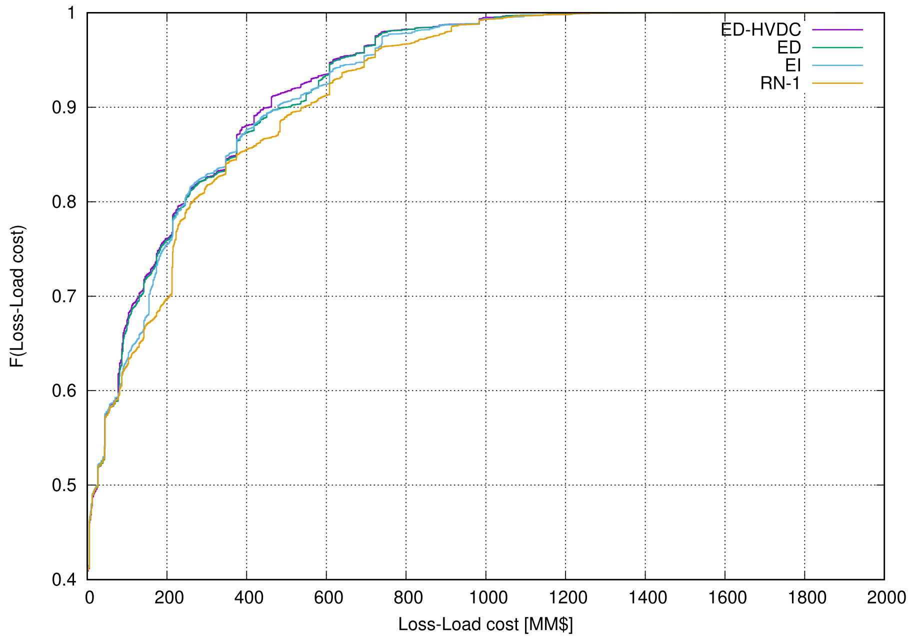


Fig. 7. Empirical cumulative distribution function of the Lost-Load costs.

grids. Earthquakes, hurricanes, and extreme weather events increase the likelihood of spatially-correlated failures of grid components and often result in major power outages [4–7]. Recent studies in the US conclude that the economic impact of grid outages due to natural disasters can be as high as $75 billion in a single year [10]. Consequently, new planning methods for power grids that reduce the risks of major outages due to natural hazards could yield large economic savings.

Existing planning standards and methods to assess the reliability of power grids present various limitations when systems are exposed to natural hazards. For instance, power grids that are planned and operated using deterministic standards such as the $N-k$ criterion can effectively withstand simultaneous outages of any subset of k components of the system, with minimum or no curtailment of demand. However, in systems exposed to natural hazards, not all correlated outages of k components will occur with the same probability. For this reason, it is possible that networks that are planned using an $N-k$ criterion will be able to stand correlated outages that are unlikely to occur (e.g., simultaneous outages of geographically distant components), but will be ill-prepared to handle correlated outages in a geographical region due to a natural hazard. Increasing the security level k used in the $N-k$ criterion could reduce the downside risk of a major power outage due to correlated component failures, but at the expense of implementing network redundancies that will not provide enough benefits to the system (e.g., avoided demand curtailments) to justify their cost.

Probabilistic approaches are an improvement upon deterministic methods. Unlike the $N-k$ criterion, in a probabilistic model it is necessary to consider the likelihood of all possible component failures and the social cost of curtailing demand, which yields an optimal strategy that balances the benefits and costs of different types of network reinforcements. Nevertheless, most of the existing probabilistic approaches assume that the probabilities of individual component failures are statistically independent. This is a convenient assumption in practice because it helps to keep computational models tractable. The downside is that, under this assumption, there is no guarantee that a network that was planned using a sophisticated probabilistic model will fare much better than a network planned based on a deterministic criterion when exposed to a natural hazard.

Our experiment shows that the assumption of statistical independence of component failures can result in planning models that underestimate the likelihood of simultaneous outages when the grid is exposed to natural hazards. In our case study, we find that the probability that at least two lines in the network fail simultaneously due to a simulated earthquake can be up to 15 times higher than the theoretical probability of a simultaneous failure assuming independence. This difference is proportional to the correlation of a simultaneous failure of network components and inversely proportional to the root of the marginal failure probabilities. Consequently, planners aiming to achieve high levels of resilience in power grids that are exposed to natural hazards cannot ignore the likelihood of spatially-correlated failures when evaluating the benefits and costs of different network designs.

We demonstrate that an incorrect assessment of the probability of spatially-correlated outages—by assuming statistical independence of component failures—results in investments in network assets and pre-fault generation levels that are different to the ones that we find that are optimal when we explicitly consider dependent failures. As expected, the network that is planned using a probabilistic model that assumes independent component failures performs rather poorly when tested against an earthquake that causes spatially-correlated outages of network elements, resulting in high levels of expected energy not supplied.

Overall, we find that ignoring correlations of component failures is similar to underestimating the actual risks posed by high-impact and low-probability events that can cause major power outages. This is because the probability that multiple components fail at the same time is artificially low in the planning model where we assume independent component failures. Consequently, the scenarios that ultimately drive investment decisions are those that have a high enough chance of occurrence, which are similar to those that are considered when using the deterministic N-1 criterion. However, we find that the latter is even more conservative than a probabilistic model that assumes independent component failures. Recall that the $N-1$ criterion requires that the system must be able to supply all demand in all scenarios of individual failures, which leads to unnecessary investments in network assets. We confirm this intuitive behavior in our experiments, where we observe that investment costs increase significantly when we plan the network using the N-1 criterion, but without effectively reducing the amount of expected energy not supplied in settings where the system is exposed to natural hazards.

We also use our case study to assess the value of flexible transmission assets. In our study, we consider the option of substituting AC for HVDC transmission lines. HVDC lines are much more expensive than conventional AC lines, yet, they have the added benefit that power flows in HVDC lines are controllable and not constrained by Kirchhoff's Voltage Law. We find that when the probabilistic model that considers spatially-correlated failures has the alternative to invest in flexible HVDC transmission assets, it replaces some investments in AC lines for HVDC links. It also adds additional transmission lines, changing the topology with respect to the optimal investment strategy when only AC lines are considered. This change in the investment strategy results in higher investment costs than in the model that only considers AC investment alternatives. However, this increase in investment costs is more than compensated by the decrease in expected cost of operating the system and curtailing demand. Therefore, flexible network assets, albeit costly, can both reduce operating costs under regular operating conditions and impart flexibility to meet demand in contexts where the system is exposed to natural hazards that cause spatially-correlated failures of network components.

Finally, we want to highlight that the insights from our analysis can be useful for systems exposed to other types of natural hazards that can also cause spatially-correlated failures. For example, a recent heat wave in the state of California resulted in the de-rating of 1870 MW of capacity of gas plants due to ambient temperature, which contributed to the demand curtailments experienced in the state during the summer of 2020 [49]. Around the same period, 55 high-voltage transmission towers were knocked down by conductor galloping [50] as a result of abnormally-low temperatures, heavy snow, and strong winds during a storm in Southern Argentina [51]. Since forecasts indicate that these types of extreme-weather events will increase both in frequency and intensity due to climate change [52], we believe that planning models that consider the impact of spatially-correlated component failures will become valuable tools for designing and operating resilient networks in areas that are exposed to the physical risks posed by natural hazards.

CRediT authorship contribution statement

Javiera Barrera: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Supervision, Project administration. **Pauline Beaupuits:** Methodology, Investigation, Software, Validation, Visualization. **Eduardo Moreno:** Methodology, Validation, Formal analysis, Data curation, Visualization. **Rodrigo Moreno:** Conceptualization, Methodology, Formal analysis, Writing - original draft. **Francisco D. Muñoz:** Formal analysis, Writing - original draft.

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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Appendix A. Stochastic model

This section describe the stochastic optimization model utilized for the computational experiments. It is a modified version of the model presented in [19].

Sets L is the set of transmission lines, N is the set of busbars, and G is the set containing generators. T is a set of time periods and S is the set of scenarios or operating states, which includes the special scenario $s = 0$ where no component failure occurs.

Variables Binary variable $\mu_l \in \{0, 1\}$ indicates if an additional transmission line l is constructed or not. Variable θ_{nts} is the voltage angle at busbar n during time period t at scenario s. f_{lts} is the power flow in line l during time period t at scenario s. ll_{nts} is the lost load at busbar n during time period t at scenario s. Finally, p_{gts} is the output level of generator g during time period t at scenario s and v_g is the binary on/off commitment status of generator g at time t.

The main constraints of the model include:

Kirchoff Current Law

$$p_{nts} + \sum_{l \in \delta^+(n)} f_{lts} + ll_{nts} = \sum_{l \in \delta^-(n)} f_{lts} + d_{nt} \tag{A.1}$$

At each busbar n, time period t and scenario s, there must be a balance between supply and demand. The total generation at n (we denote p_{nts} the sum of p_{gts} for all g in busbar n), plus the incoming power flow must be equal to the demand d_{nt} at the busbar plus the outgoing power flow. $ll_{nts} > 0$ if there is not enough generation and/or transmission capacity to meet demand.

Kirchoff Voltage Law (linearized)

$$-M(1 - \mu_l \cdot A_{lts}) + \frac{\theta_{o(l)ts} - \theta_{d(l)ts}}{x_l} \leq f_{lts} \leq \frac{\theta_{o(l)ts} - \theta_{d(l)ts}}{x_l} + M(1 - \mu_l \cdot A_{lts}) \tag{A.2}$$

$$A_{lts} \cdot \mu_l \cdot \left(-\overline{f}_l \right) \leq f_{lts} \leq \overline{f}_l \cdot A_{lts} \cdot \mu_l \tag{A.3}$$

For each line l, time period t and scenario s, if the transmission line is constructed ($\mu_l = 1$) and it is available ($A_{lts} = 1$), then the power flow f_{lts} over the line must be equal to the difference of voltage angles between its connecting busbars ($\theta_{o(l)ts}$ and $\theta_{d(l)ts}$) divided by the reactance of the line x_l.

Additionally, the power flow over the line cannot exceed its limits $[-\bar{f}_l, \bar{f}_l]$. In case the line is not constructed ($\mu_l = 0$) or is not available ($A_{lts} = 0$), the power flow f_{lts} is zero. In this expression, M is a sufficiently large number, from the classical *Big-M* modeling technique.

Ramp-up and down constraints

$$(1-\varepsilon)\cdot p_{gt0} \le p_{gts} \le (1+\varepsilon)\cdot p_{gt0} \tag{A.4}$$

For each generator g, time period t and scenario s, the generation output level p_{gts} cannot be higher than $(1+\varepsilon)$ times the *default* generation level chosen for the scenario $s = 0$ where no failure occurs.

Bound of variables

$$0 \le ll_{nts} \le d_n \tag{A.5}$$

$$\underline{p}_g\cdot v_{gt} \le p_{gts} \le \overline{p}_g\cdot v_{gt} \tag{A.6}$$

For each scenario s and time period t, the amount of lost load ll_{nts} cannot be higher than the demand at each busbar n, and the production level p_{gts} cannot be lower/higher than its minimum/maximum output $\underline{p}_g$ / $\overline{p}_g$ at each generator g if such generator is dispatched ($v_{gt} = 1$).

Objective Function

$$\begin{aligned} \min & \sum_{l\in L}\pi_l\cdot\mu_l \\ & + \sum_{s\in S}\sum_{g\in G}\sum_{t\in T}\pi_g\cdot\left(p_{gts}\cdot\alpha_t + p_{gt0}\cdot\beta_t\right)\cdot\rho_s \\ & + \sum_{s\in S}\sum_{n\in N}\sum_{t\in T}\pi_n\cdot ll_{nts}\cdot\alpha_{st}\cdot\rho_s \end{aligned} \tag{A.7}$$

The objective function has three components. The first component is the sum of the annualized construction cost π_l for each transmission line. The second component includes the generation costs π_g of each generator in each time period, over the different scenarios $s \in S$. For each scenario, it is assumed that the output level in period t is at a default level p_{gt0} during the time β_t representing the intact system. An output level p_{gts} is generated during the extension of the failure, which is represented by the time α_t. The third term includes for each scenario the cost of the lost load π_n of each demand busbar. We also assume a failure time given by α_{st}. To compute the expected cost over all scenarios, the last two terms are multiplied by the probability ρ_s of the scenario s.

Bus failures Substation failures result in derated capacity. This is modeled by limiting the capacity of all lines connected to the substation, which is obtained by replacing parameter A_{lts} by the corresponding fraction of the total capacity in the scenario s. This affects the bounds of the variable f_{lts}.

Investment in HVDC lines HVDC lines can be included using an extra variable $\widehat{\mu}_l \in \{0,1\}$ for each transmission line. The first term of the objective function must include the additional cost of these lines, by adding the term $\sum_{l\in L}\widehat{\pi}_l\widehat{\mu}_l$, and the constraint $\widehat{\mu}_l \le \mu_l$ for each line $l \in L$. Since an HVDC transmission line is not constrained by the linearized KVL constraints, we add an additional term to the Big-M constraint resulting in (in other words, we "pay" an extra cost to neglect KVL):

$$-M\cdot\widehat{\mu}_l - M(1-\mu_l\cdot A_{lts}) + \frac{\theta_{o(l)ts}-\theta_{d(l)ts}}{x_l} \le f_{lts}$$

$$f_{lts} \le \frac{\theta_{o(l)ts}-\theta_{d(l)ts}}{x_l} + M(1-\mu_l\cdot A_{lts}) + M\cdot\widehat{\mu}_l$$

Additional constraints for the N-1 robust model For the $N-1$ security criterion, the model only considers scenarios where at most one line fails, and the resulting network must withstand each of these outages. Hence, to fulfill this criterion, we add for each busbar with demand the following constraint

$$ll_{ns} = 0 \qquad \forall s \in S, \forall n \in N$$

.

Appendix B. Details of the test case instance

Table B1
Geographical coordinates of the power network busbar are shown in Table B1.

Busbar	Latitude	Longitude	Busbar	Latitude	Longitude
1	–23.650883	–70.397563	8	–23.423331	–68.311097
2	–24.452434	–70.112106	9	–23.244066	–68.614204
3	–24.555276	–68.704701	10	–23.216861	–69.104226
4	–23.650136	–68.787245	11	–23.083895	–69.390199
5	–23.870859	–69.854716	12	–22.930360	–70.029442
6	–23.441645	–69.666275	13	–22.732063	–69.588221
7	–23.460900	–68.593079	14	–22.958990	–69.139022

Table B2
Demand, generating capacities and generation costs at each busbar, marginal failure probabilities for each percentage of the original capacity from the scenario generation. Also, the resulting mean (μ) and standard deviation (σ) values of the original capacity are shown in Table B2.

Busbar	Max. Demand	Max. Gen.	Gen. Cost	Marginal Failure Probabilities						
	[MW]	[MW]	[$/MWh]	100%	95%	60%	30%	0%	μ	σ
1	0	332.4	50	92.6%	4.8%	2.3%	0.3%	0.0%	98.6%	7.3%
2	21.7	140	80	99.9%	0.1%	0.0%	0.0%	0.0%	100.0%	0.4%
3	94.2	100	80	97.2%	1.7%	1.0%	0.1%	0.0%	99.4%	4.6%
4	47.8	0	-	87.6%	5.2%	4.1%	3.1%	0.1%	95.9%	14.5%
5	7.6	0	-	98.1%	1.6%	0.3%	0.0%	0.0%	99.8%	2.2%
6	11.2	100	50	90.6%	4.6%	3.0%	1.8%	0.0%	97.3%	11.5%
7	0	0	-	84.4%	4.5%	3.2%	5.5%	2.4%	92.2%	22.4%
8	0	100	50	83.2%	3.3%	2.4%	9.4%	1.7%	90.6%	24.2%
9	29.5	0	-	80.8%	5.2%	4.9%	8.0%	1.0%	91.1%	22.3%
10	9	0	-	91.6%	4.7%	1.9%	1.7%	0.1%	97.8%	10.7%
11	3.5	0	-	91.7%	5.4%	2.6%	0.3%	0.0%	98.5%	7.4%
12	6.1	0	-	75.9%	6.5%	5.6%	10.9%	1.1%	88.7%	24.7%
13	13.5	0	-	90.6%	4.1%	2.9%	2.3%	0.1%	96.9%	12.6%
14	14.9	0	-	91.6%	4.2%	1.9%	2.2%	0.1%	97.3%	12.2%

Table B3
Network line capacities, reactances and investment costs of each line, and its resulting marginal failure probabilities from the scenario generation.

Lines	Capacity [MW]	Reactance [p.u.]	Investment Cost [$/year]	Marginal Failure Probability
1 - 2	65	0.1069	-	0.03%
1 - 5	35	0.0689	-	0.09%
2 - 3	59	0.1629	-	0.49%
2 - 5	29	0.0795	-	0.01%
3 - 4	41	0.1152	-	1.01%
4 - 7	40	0.0329	-	1.08%
4 - 9	10	0.0553	-	1.56%
5 - 6	29	0.0587	-	0.10%
6 - 11	26	0.0556	-	0.35%
6 - 12	10	0.0774	-	3.12%
6 - 13	26	0.0904	-	1.32%
7 - 8	80	0.0331	-	3.10%
7 - 9	59	0.0276	-	1.94%
9 - 10	17	0.0572	-	1.02%
9 - 14	17	0.0711	-	2.53%
10 - 11	19	0.0374	-	0.13%
12 - 13	15	0.0574	-	2.55%
13 - 14	16	0.0599	-	0.24%
1 - 12	85	0.1009	752,475	3.41%
2 - 4	37	0.1841	597,415	2.45%
3 - 6	75	0.1798	1,183,211	2.60%
3 - 8	80	0.1506	1,056,819	1.44%
4 - 5	56	0.127	623,870	1.52%
5 - 10	55	0.1204	580,696	0.15%
8 - 14	80	0.113	793,262	6.09%
11 - 12	50	0.0771	338,182	2.22%

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