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From Reliability to Resilience: Planning the Grid Against the Extremes

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Context

Although extreme events – mainly natural disasters and climate change-driven severe weather – are the result of naturally occurring processes, power system planners, regulators, and policy makers do not usually recognize them within network reliability standards. Instead, planners have historically designed the electric power infrastructure accounting for the so-called credible (or "average") outages that usually represent single or (some kind of) simultaneous faults (e.g., faults on double circuits). A reliable power system would be operated in a secure way if it were able to withstand these faults without threatening the integrity of system operation and preserving continuity of supply to customers. However, the impact of recent extreme events on power systems, e.g., bushfires in Australia, flooding events in the UK, storms in the Americas, and earthquakes in countries located at the edge of the Pacific Ocean, which have even led to chaotic societal situations, goes far beyond N-1 or N-2 outages and clearly highlight the need for rethinking current planning practices. For example, during the last 10 years Chile had annually witnessed more than 300 earthquakes above 4.5Mw, with several hours of interruptions year by year. In the case of the UK, severe storms and floods result in power outages for tens of thousands of customers per year; in 2016, for instance, floods were responsible for power interruptions that lasted up to 56h in North West England. These are only a few examples worldwide where the aftermath of catastrophic extreme events brought resilience into discussions by power system planners, regulators, and policy makers.

In this context, and within the broader framework of low-carbon energy network planning under uncertainty, in this article we analyze a set of key questions pertinent to the resilience debate: How can we incorporate resilience-thinking into power system planning, going beyond traditional reliability-driven planning? Can negative impacts of natural hazards on electricity supply be mitigated through planning measures? What is the optimum portfolio of measures for boosting power grid resilience to such extreme events? How can we build a power grid that is both robust and flexible enough to withstand events that have possibly never been experienced before?

Since such questions are troubling decision makers around the world, our aim is to introduce a general, quantitative framework that can identify optimal portfolios of resilience-enhancing investments and demonstrate them through several illustrative case studies. While doing so, we highlight the fundamental physical and decision makers' risk attitude features that distinguish reliability-driven from resilience-driven investments. Our framework, which was elaborated during a UK-Chile joint project and implemented in actual operation and planning mechanisms in the Chilean power system, can thus be seen as a fundamental development to extend, in a transparent and consistent way, current reliability practices towards more resilient grids.

Incorporating resilience in network planning

With its growing relevance and interest to our Power and Energy Society, many definitions of power system resilience have emerged lately. In the technical report PES-TR65 published by IEEE in April 2018, resilience has been defined as "*the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event*". In general, these resilience definitions mainly focus on characterizing the term "extreme event" that could threaten power systems and on the key features that a power system should possess within the multifaceted concept of resilience in order to minimize the risk exposure to these extreme events. In particular, the following two points provide insight across all definitions and specific relevance to network planners who aim to identify resilient network enhancements:

1. Emphasis on extreme or catastrophic events, formally referred to as high impact and low probability (HILP) (or also as "*black swan*") events, which require some form of hedging;
2. Emphasis on the time-varying nature of resilience, including and quantifying the various phases before and during a severe event, as well as after it (when the system recovers).

Capturing HILP events within network planning: need for risk-averse modelling

Historically, (deterministic) network reliability standards have typically ignored any contingency beyond "credible" ones, e.g., N-1/N-2. This has resulted in a bias towards building more and more infrastructure, mainly to provide redundancy to deal effectively with any outage that might threaten the uninterrupted power supply. However, experience with extreme events clearly shows that this reliability-driven approach of making the infrastructure "bigger and stronger" through redundancy and reinforcements may not be effective to hedge against multiple simultaneous outages or outages occurring in rapid succession. In fact, very extreme events cause outages well beyond credible ones, potentially affecting hundreds of network components. In other words, extreme events typically lead to considering N-X outages, with X greater or much greater than 1 or 2 and even in the order of hundreds or more! Indeed, here lies one of the fundamental differences between reliability and resilience, at least in the context of network planning. Planners may then intuitively realize that, while improving reliability, more redundancy may not necessarily improve system resilience to extreme events. Alternatively, flexible ("smarter") solutions could provide more viable options to enhance resilience by helping to withstand the initial adverse impacts of extreme events as well as by supporting the efficient response and prompt recovery of the system.

In the new context outlined above, could "hybrid" solutions (where "hybrid" refers to both infrastructure/network, i.e., to provide redundancy and robustness, and non-infrastructure/non-network or smart operational solutions, i.e., to provide flexibility) constitute the optimal portfolio to boost resilience to extreme events? While this is still an open research point and likely to be case-specific, if we want to keep the lights on or at least pursue an acceptable level of system operation under a large array of circumstances (beyond the so-called credible contingencies), it is evident that current planning standards need to be modified to allow HILP events to be accounted for within the network design and expansion decision making process. However, the key question here is *how*? While no straightforward answer exists, below we discuss a few possible approaches, also recognizing that it is technically unrealistic (and economically not viable) to consider targets of 100% reliable supply after extreme events and, at the same time, the system should meet classical (deterministic) reliability standards that consider only credible outages.

A first approach to incorporate HILP events within network investment planning could adopt probabilistic (or, in mathematical programming terminology, “stochastic”) models that explicitly consider the associated probabilities and resulting impacts of many states of the system, including the intact system and simultaneous outage scenarios. These impacts are usually measured in terms of energy not supplied (ENS) and valued through economic metrics such as the value of lost load (VoLL). More specifically, in the probabilistic reliability assessment pioneered by Billinton and Allan, the resulting estimated costs from ENS are averaged (weighted by probability) across all modeled scenarios and optimized against additional investment and operational costs. Network investments are thus well justified as a trade-off between economics and security of supply and, if we neglect for simplicity operational costs (e.g., congestion costs, losses, etc.), carried out up to the point where the marginal cost of additional investment equalizes the marginal benefit of enhanced reliability. This is graphically illustrated in Figure 1, where reliability cost is measured as expected energy not supplied (EENS) times VoLL. This probabilistic approach, however, presents a fundamental limitation to properly address HILP events and inform appropriate investment decisions as a hedge against them, as we discuss below.

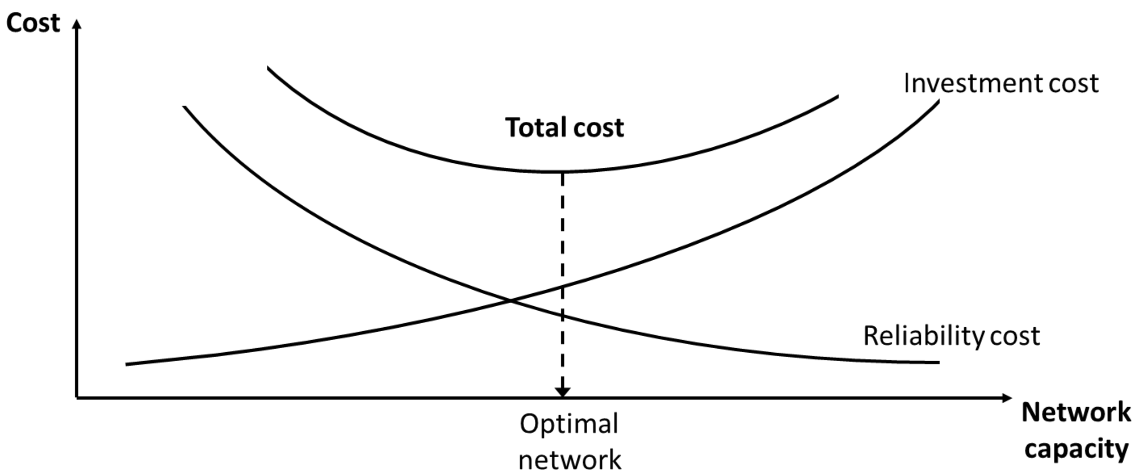

Figure 1: Optimal balance between investment and reliability costs.

HILP events are by definition very rare, and their impact on average indicators such as EENS is therefore very limited. For example, our analysis shows that, on average, it would be economically optimal for Chile’s power system to suffer the consequences of very large earthquakes every 15 years rather than invest in further assets to reinforce and harden the power system. It is therefore worth asking ourselves why we should be concerned about events that, on average, have a relatively small effect. We argue that the answer to this question may be with the *risk attitude* of electricity consumers and policy makers (and therefore network planners too, who somehow “serve” both). In fact, as suggested by empirical evidence, customers and policy makers generally dislike risks associated with the highly adverse consequences often associated with HILP events, and would thus like to reduce them as much as possible. But how can we model this risk attitude, and what is the underlying risk attitude assumption in the probabilistic assessment above?

In risk analysis, attitudes towards risk are usually classified into three categories, which are exemplified as follows. Consider an electricity consumer who is given the choice between the following two options. In the first option, the consumer pays $90 for a network service that hardly ever fails and, when it does, small amounts of energy are unserved, totalizing an associated expected cost of ENS equal to $10. In the second option, the consumer pays $50 for a network service that fails more often and with larger amounts of ENS each time, totaling an associated expected cost equal to $50. Note that, in both cases, the total amount paid by the consumer for network and EENS is the same. In this context, the consumer is said to be:

- Risk neutral: if the consumer is indifferent between these two options;
- Risk averse: if the consumer prefers the first option over the second one;
- Risk seeking: if the consumer prefers the second option over the first one.

The reader can easily deduce that risk neutrality is intrinsically part of traditional probabilistic analysis because the above two options seem equally attractive. In reality, however, consumers are typically risk averse and arguably prefer a more stable and predictable outcome from the electricity network, even if this may (slightly) increase its costs, as mentioned earlier. In fact, as in many other industries, consumers might be willing to pay the price of insurance policies that eliminate (or at least mitigate) the losses associated with some rare but high impact scenarios that may occur. In this context, risk-averse electricity consumers (which we argue represent the majority) might prefer to be hedged against the consequences of HILP events on their electricity supply and pay for the corresponding cost increase, even if these events occur rarely or might not happen at all. Apart from very extreme cases such as earthquakes, which may be life-threatening and for which higher risk aversion may be justified for different reasons in any case, evidence of such a consumer attitude can be seen more and more often even for relatively smaller impact events. For example, heat waves in Australia in January 2019 led to sporadic rolling load shedding events in several areas, including central Melbourne. The relatively short outages were considered outrageous by many consumers, even though they experienced only a minor overall adverse impact.

In addition to the consumer attitude, governments must consider the welfare of their citizens and, understandably, might want to take a risk-averse approach in dealing with HILP events for political reasons, irrespectively of the classical economics associated with traditional power system planning methodologies. That is why specific regulatory and market mechanism responses were called for following the South Australia black system event of September 2016, and more is expected in response to the bushfires that again occurred throughout Australia in January 2020.

In any case, once again the main noteworthy message here is that risk-averse approaches and metrics that should be contemplated for HILP events are typically not present in current system planning practices.

Recognizing the outage-and-restoration evolution: need for time domain modelling

One important aspect of resilience is its time-varying nature. The concept of resilience includes the phases before and during a severe event as well as after the event, when the system recovers. In this context, Figure 2 shows the time-varying, multi-phase resilience trapezoid, which clearly highlights the phases of a power system when exposed to extreme events, namely: pre-disturbance resilient state, disturbance progress, post-disturbance degraded state, restorative state, and post-restoration state. It also clearly highlights the type of actions that can be applied for mitigating the impacts of extreme events during these phases, which refer to preventive, corrective, emergency coordination, restorative, and adaptive, respectively. However, this critical temporal evolution aspect is usually missing in current reliability assessments for planning purposes, which mainly focus on the system response *before and right after* the disturbance occurs (without including system restoration). In contrast, because the impact on the system due to a HILP event is substantial, the explicit modelling of the system response and restoration is key in assessing different options for enhancing resilience at the planning stage, especially those based on flexible and operational non-network solutions. This time-varying characterization also enables modelling targeted optimization of metrics specifically designed for resilience analysis purposes, thus giving the opportunity for decision makers to select specific attributes of resilience that can be enhanced by implementing different operational and investment decisions, which also correspond to different enhancement propositions.

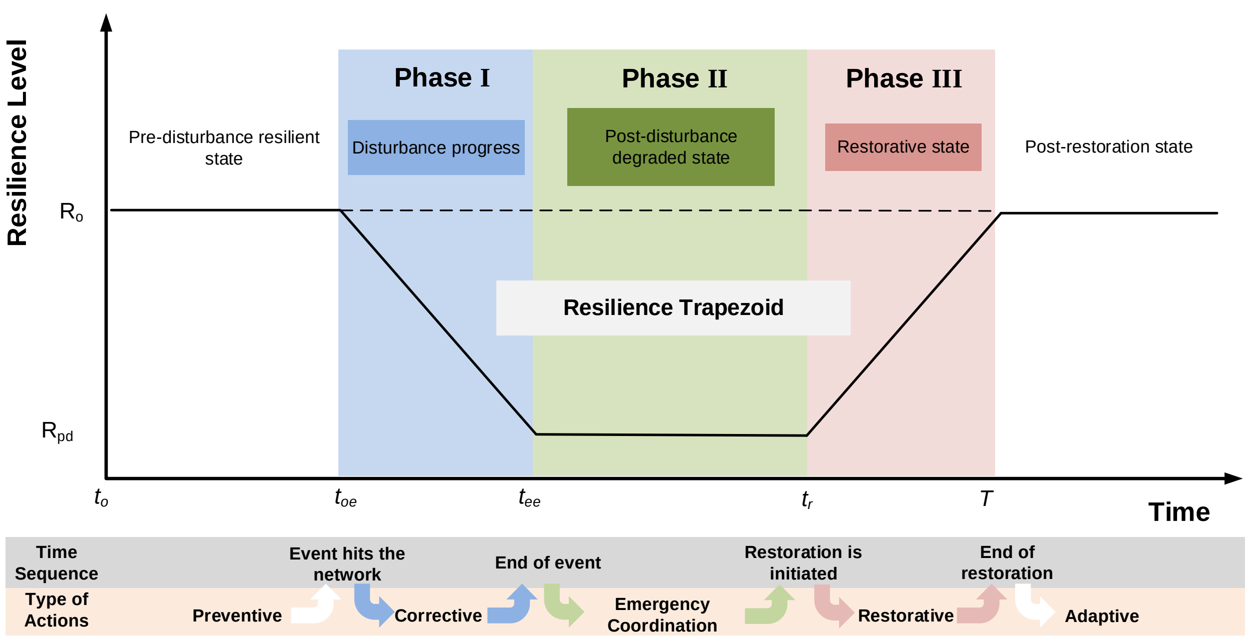

Figure 2: Time-varying, multi-phase resilience trapezoid (Source: Panteli et al., 2017).

Probabilistic risk-averse framework to identify resilient network enhancement options

Based on the above premises, we introduce here a resilience-oriented planning methodology based on a stochastic risk-averse mathematical program for supporting the decision-making process of identifying resilient network enhancements. The proposed two-stage model (Figure 3) intelligently selects, in the first stage, specific network investments out of a set of candidate options, which are, in the second stage, tested through quantification of their resilience benefits in probabilistic outage scenarios originated by stochastic simulation of natural hazards. As a result, the optimal portfolio of network investment decisions as evaluated through a given resilience metric (measured across various scenarios) is identified.

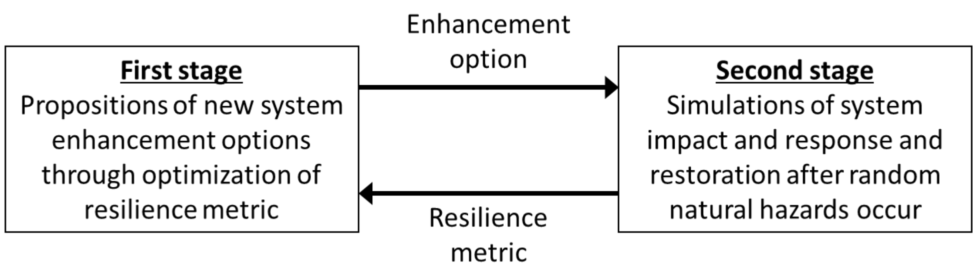

Figure 3: Quantitative approach to identify optimal resilient system enhancement options (Adapted from: Lagos et al., 2020).

The stochastic generation and assessment of hazard and outage scenarios is carried out through the following simulation-based steps:

1. *Hazard characterization*: in the first step, we generate various hazards with random magnitudes and locations (this can be done by respecting historical patterns). Additionally, spatiotemporal profiles may be necessary to model hazards that change position and intensity dynamically (e.g., storms), spread (e.g., bushfires), or attenuate their magnitude with distance (e.g., earthquakes).
2. *Vulnerability assessment of system components:* By using fragility curves (illustrated in Figure 4) and which are assumed to be known for various natural hazards and system components, either through historical data or on the basis of engineering modelling), we determine both (i) the hazard-dependent failure probabilities of every network component (e.g. towers, lines, as well as substation and generation equipment) and (ii) the outage scenarios across the system which are generated from these probabilities.

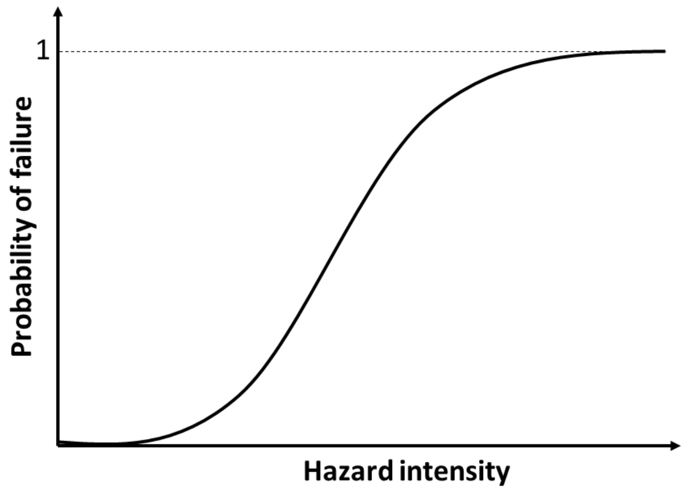

Figure 4: Example of generic fragility curve for a piece of network equipment.

3. *System response*: This is the step where we simulate, for each outage scenario identified above, the potential system cascading from automatic power flow rerouting, load/generation disconnection, and post-contingency redispatch (once cascading has ended). We then assess the spatially resolved volumes of energy not supplied. Importantly, prior to the outage, we assume a normal operation of the system by running an economic dispatch problem, in which the system infrastructure is intact.
4. *System restoration:* We simulate both (i) the reconnection of failed/damaged network components once these have been repaired (whose reconnection times are determined probabilistically assuming that the reconnection events are exponentially distributed) and (ii) the reconnection of load/generation which is obtained by a post-contingency dispatch model.

Figure 5 illustrates the aforementioned process and Figure 6 shows a typical curve for the supplied demand which results from the simulation of the post-fault events associated with a scenario that follows this sequence: a) random generation of hazard; b) random generation of network outage; and c) random generation of equipment repairs. Note that the shape of the curve in Figure 6 can vary and can be hazard- and system-specific. This power supply curve is generated several thousands of times (e.g., 10,000) for different hazard-outage-repair sequences by using Monte Carlo simulation. We consider a large number of simulations so as to adequately capture the potential consequences of a comprehensive set of natural hazards on the power network.

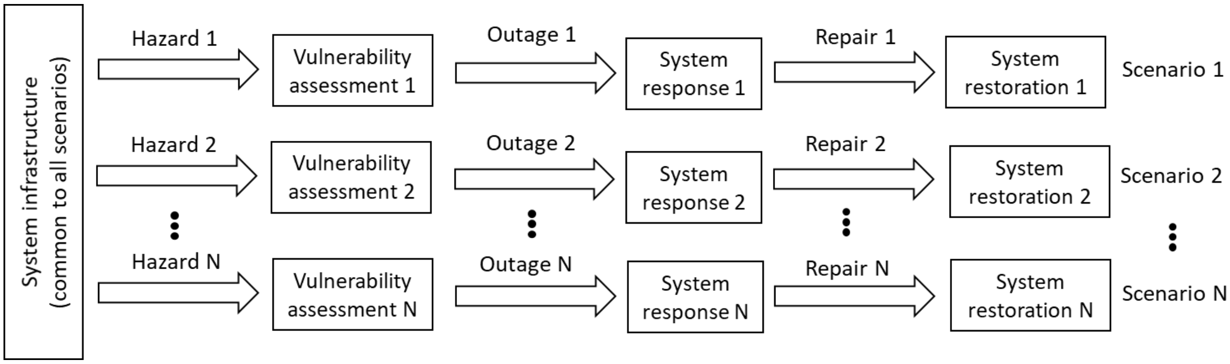

Figure 5: Simulation of hazard-outage-repair scenarios for the system infrastructure under study.

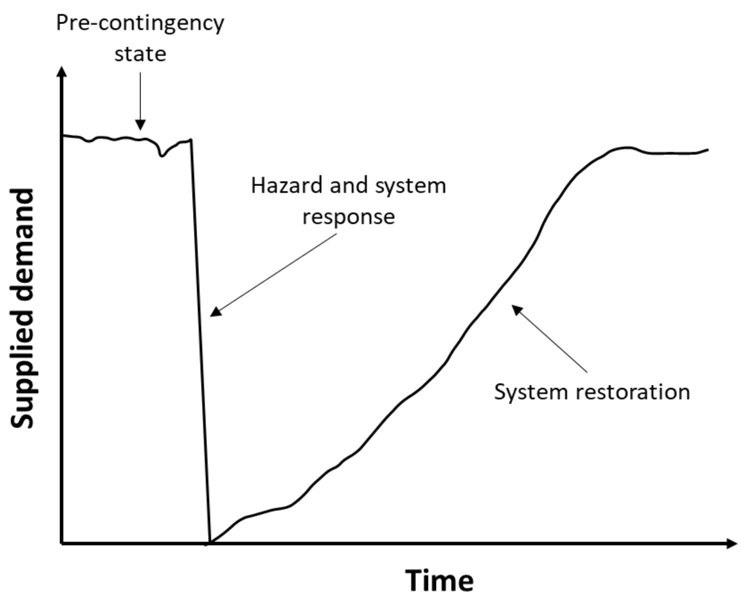

Figure 6: Example of supplied demand curve resulting from each scenario simulated.

After the simulations have been performed under several outage scenarios originated by natural hazards, a suitable resilience metric can be selected and calculated for every scenario. The metric could, for example, be the ENS, or, based on our previous work, one taken from the *FLEP* resilience metric system (the FLEP metric assesses how *fast* resilience drops (*F*-metric), how *low* resilience drops (*L*-metric), how *extensive* is the post-disturbance degraded state (*E*-metric), and how promptly the system recovers (*P*-metric)). After quantifying the effect of each scenario with the selected metric, the optimization problem minimizes risk exposure subject to a budget constraint (representing the total amount available to be invested in resilient network enhancement), thus identifying the optimal portfolio of investment decisions that provides the best hedge against the HILP events simulated. The risk measure being minimized can be determined by calculating the expected value of the selected resilience metric (e.g., ENS) across an appropriately selected *worst* set of scenarios resulting from the stochastic simulation.

To do so, the *Conditional Value at Risk* (*CVaR*) measure can be used so as to consider only those scenarios representing the worst cases. More specifically, CVaR (also referred to as $CVaR_{\alpha}$, although in this article we use CVaR without the subscript to simplify the notation) represents the expected value across a predetermined set of worst cases. An illustrative example of probability distribution function (PDF) and relevant parameters, with the ENS used as the resilience metric, is shown in Figure 7. It should also be noted that the value of the parameter *α* also provides an explicit indication of risk attitude, since 1-*α* indicates the size of the considered set of worst cases. A reliability assessment would use the measure of expected energy not supplied (EENS) by sampling across *all* credible sets of outages. In this averaging, the impact of non-credible worst-case outages would normally be outweighed by the much more frequent credible outages. In the context of our framework, then, this means that in first approximation the mean value (i.e., the EENS) and the CVaR of the PDF shown in Figure 7 could be used as the reliability assessment and the resilience assessment measures, respectively. Furthermore, although optimizing for EENS/CVaR is useful to clearly identify decisions from a reliability/resilience perspective, in practical settings, where planners need to consider both criteria to make tradeoff decisions, optimizing on a linear combination of EENS and CVaR might also be a suitable option.

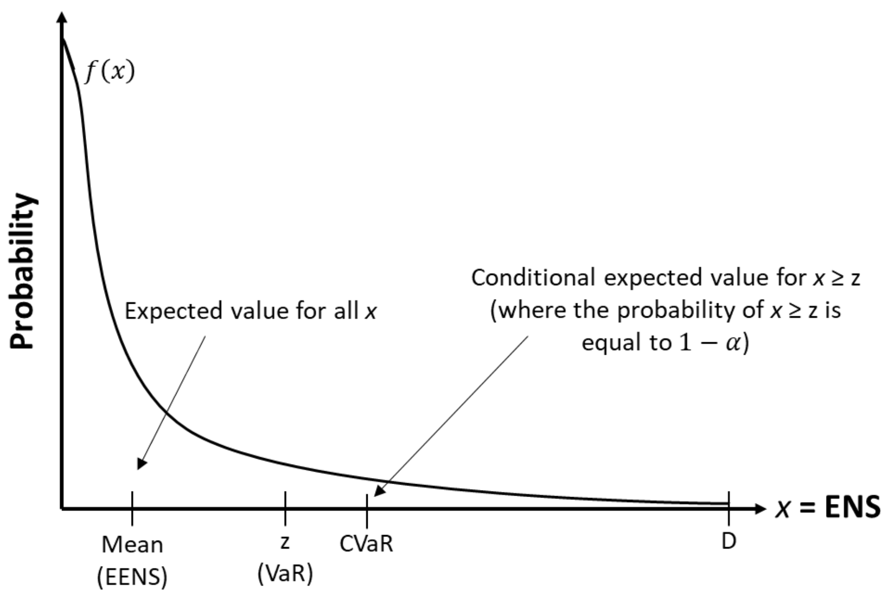

Figure 7: CVaR concept for risk-averse resilience assessment, where 1-α indicates the size of the considered set of worst cases, VaR (or z) is Value at Risk, CVaR is Conditional Value at Risk, D is maximum demand, x is Energy Not Supplied (ENS), and the Mean value is Expected Energy Not Supplied (EENS).

The proposed mathematical framework can be used to select a wide-ranging portfolio of resilient network enhancement options depending on the specific decision variables considered in the problem, such as hardening infrastructure, installation of new assets, provision of better response times for repairing damaged infrastructure, restoring power, etc. This addresses the so-called *resilience trilemma*, that is, the need for balancing the portfolio solution among several options to make the system *stronger*, *bigger,* and/or *smarter* in a resilient and cost-efficient manner. In particular, among the set of investment decisions to enhance system resilience, the following could be considered:

- New lines and transformers, to create alternative “routes” to transfer power and provide redundancy, or additional reactive power to operate the network under “weaker” conditions when several network assets are outaged due to HILP events (“bigger”).
- Substation, tower, and other equipment hardening, to make the system more robust and “stronger” against HILP events.
- Shorten response times by increasing expenditure in enhanced stocks of network assets and equipment, more repair crews, and more online monitoring and control solutions.
- Installation of new flexible network technologies such as special protection schemes, energy storage units, FACTS, HVDC, etc. so as to make the system more flexible to adapt to different conditions post-fault, helping to mitigate consequences of HILP events.
- Installation of distributed energy resources (such as microgrids, distributed generation, etc.), to provide localized energy solutions when the main system fails.

There are several ways to apply this framework, especially to implement the two stages illustrated in Figure 3, by using mathematical programming methodologies. For the analysis in this article, we use Optimization via Simulation (OvS) techniques, which determine the (nearly) optimal portfolio of network enhancements based on a series of simulations (from the optimizer's perspective), which corresponds to the first stage, the simulator is the second stage, assumed to be a black-box model without a known mathematical structure). One of the key advantages of the OvS approach is that it allows inclusion of a great deal of operational details in the simulation stage, e.g., minimum stable generation levels, ramp rate limits, minimum startup and shutdown times, etc., which require a non-convex formulation and are complex and hard to manage in closed form.

Illustrative two-busbar example

This simple example illustrates and demonstrates our proposed framework to identify resilient enhancement options against HILP events in network planning and, crucially, how these differ from other decisions that are more reliability oriented.

“Textbook” illustrative case study

The two-busbar network in Figure 8 features one 500 MW generating unit in node 1, one load in node 2 with a constant demand of 500 MW, and a transmission link between the two nodes. Depending on the configuration (i.e., number of circuits and their capacities) and reliability characteristics of this link, and assuming perfect reliability for the generator, this power network can be adequate, secure and/or resilient. As adequacy and security have been historically part of reliability analysis, we will consider here that a network is reliable if it is both adequate and secure. We also use the DC power flow approximation for the sake of simplicity.

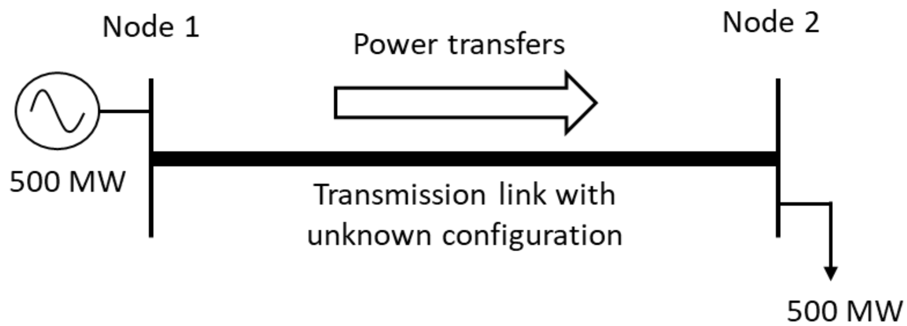

Figure 8: Illustrative two-busbar system.

Reliability I: Adequacy

Considering that adequacy is the ability of a power system (including generation and network capacities) to supply the aggregate electricity demand at all times, the power network in Figure 8 is adequate if the total (thermal) capacity of the link is at least 500 MW. This can be achieved by a number of network configurations, including the option of one single circuit of 500 MW transferring power from node 1 to node 2. This particular option, however, is evidently not N-1 secure.

Reliability II: Security

From our previous work, we distinguish between two types of security: deterministic N-k security and probabilistic security. To comply with a deterministic N-1 security standard for network design, we need two circuits, each of (at least) 500 MW to link nodes 1 and 2. A probabilistic standard, instead, demands an appropriate balance between the cost of improving reliability, here in the form of investment costs, and the associated savings in reliability operational costs, measured through the improvement in EENS (resulting from the new investment) times the VoLL. Let us now assume that there are only two possible "secure" configurations (i.e., number of circuits and their capacities) for the transmission link in question and let us evaluate the cost and benefits of each of them to identify the appropriate, optimal solution. Table 1 provides the basic reliability information and costs of the following two alternatives:

- N-0 option: where 2 circuits of 250 MW are installed
- N-1 option: where 2 circuits of 500 MW are installed

In both cases, the network is 99.976% of the time with full available capacity (further reliability information associated with outage and repair rates is presented later in Table 2).

Table 1: Reliability and cost information associated with two alternative network design options.

Option N-0

Cost of investment calculation	
Unit cost of investment [$/MW.km.yr]	100
Lenght [km]	200
Capacity per circuit [MW]	250
No. Circuits	2
Cost of investment [$]	**10,000,000**

Cost of EENS calculation		Failure states	Circuit 1	Circuit 2	State probability	Available capacity [MW]	Power not supplied [MW]
VoLL [$/MWh]	1000		Available	Available	0.9997629	500	0
Expected power not supplied [MW]	0.06148		Unavailable	Available	0.0001142	250	250
Time horizon [h]	8760		Available	Unavailable	0.0001142	250	250
Cost of EENS [$]	**538,532**		Unavailable	Unavailable	8.782E-06	0	500

Total cost calculation	
Total cost [$]	**10,538,532**

Option N-1

Cost of investment calculation	
Unit cost of investment [$/MW.km.yr]	100
Lenght [km]	200
Capacity per circuit [MW]	500
No. Circuits	2
Cost of investment [$]	**20,000,000**

Cost of EENS calculation		Failure states	Circuit 1	Circuit 2	State probability	Available capacity [MW]	Power not supplied [MW]
VoLL [$/MWh]	1000		Available	Available	0.9997629	1000	0
Expected power not supplied [MW]	0.00439		Unavailable	Available	0.0001142	500	0
Time horizon [h]	8760		Available	Unavailable	0.0001142	500	0
Cost of EENS [$]	**38,464**		Unavailable	Unavailable	8.782E-06	0	500

Total cost calculation	
Total cost [$]	**20,038,464**

In this case, the N-0 solution is determined to be more economically efficient and therefore should be the one selected under a probabilistic security approach. However, this solution is sensitive to an array of economic and reliability parameters. For example, if VoLL is increased from 1,000 $/MWh to 30,000 $/MWh, then the secure option changes from the N-0 to the N-1 design solution.

Resilience

One of the key characteristics of the probabilistic security analysis carried out above is its focus on EENS, which, as discussed, is not suitable for resilience studies dealing with HILP events. For the purposes of assessing resilience, then, let us assume that the (marginal) probabilities of the four states previously evaluated (a no fault state, two single fault states, and a double fault state) are originated from the conditional probabilities displayed in Table 2. More specifically, Table 2 shows the probability of the four states under two different weather conditions, namely, fair and adverse weather, as well as the marginal probability of the four states considering *both* weather conditions.

Table 2: Reliability data and probabilities of failure under fair and adverse weather and marginal probabilities of failure for the four states considered.

	Fair weather	Adverse weather
Failure rate [occ/yr]	0.2	20
Repair rate [occ/yr]	2190	52
Unavailability	9.1E-05	0.27723
Availability	0.99991	0.72277
Duration [h]	8759	1

Failure states

Circuit 1	Circuit 2	State probability (fair weather)	State probability (adverse weather)	State probability (marginal)
Available	Available	0.999817	0.522400	0.999763
Unavailable	Available	9.13E-05	0.200373	0.000114
Available	Unavailable	9.13E-05	0.200373	0.000114
Unavailable	Unavailable	8.34E-09	0.076855	8.78E-06

For illustrative purposes we assume that the failure rate is 100 times higher for adverse weather and that repair times increases from 4 hours under fair weather conditions (i.e., repair rate of 2,190 occurrence per year or occ/yr) to 7 days under adverse weather conditions (i.e., repair rate of 52 occ/yr). Also, adverse weather, in this example, is limited to 1h per year (thus conventionally representing a HILP event), while fair weather conditions occur during the remaining time (i.e., 8,759h).

In order to provide a hedge against such a HILP event, we analyze the three following options within the concept of resilience trilemma (assuming that the initial condition is the same N-0 network configuration selected under the probabilistic security approach described in the previous section):

- N-1 design: where we re-evaluate the option to install two circuits of 500 MW, i.e., making the network “bigger” by adding redundancy;
- N-0 with shorter response times under extreme events: where we evaluate a contract with other network companies to use their repair crews under extreme events, which reduces the repair times from 7 to 3 days (i.e., making the network “smarter”);
- N-0 with underground cables: where we evaluate the option to bury the current double circuits, each of 250 MW of capacity, thus halving the failure rate under both weather conditions, and assuming at the same time, for simplicity, that the repair rate stays the same. This is equivalent to a “stronger” system option.

Table 3 shows the impact of these new options on various average and risk indicators, including:

- EENS: the expected value of ENS across all scenarios (economically valued at VoLL).
- CVaR: the conditional value at risk of ENS, that is, the average ENS across the 0.001% worst cases (economically valued at VoLL).
- Probability of double outage under adverse weather condition, which occurs one hour per year only.

Table 3: Average and risk indicators of the four considered network design options.

Metric	N-0 base case	N-1	N-0 shorter repair time	N-0 underground
VoLL x EENS [$]	538,532	38,464	470,506	280,428
VoLL x CVaR [$]	4,113,206,199	3,846,412,398	2,690,095,838	2,837,833,988
Probability of double outage under adverse weather [%]	7.7%	7.7%	2.0%	2.6%

As it could be expected, changing the network design from N-0 to N-1 provides the best results in terms of EENS cost, reducing it by 93% from approximately 539 k$/yr to 38 k$/yr. However, this decision provides a very limited hedge against HILP events, reducing the CVaR by 6% only from 4,113 k$/yr to 3,846 k$/yr. (Note that in this case and in the following ones, the probability of double outage and CVaR follow a similar pattern, so, for the sake of simplicity, we just focus on CVaR.) Interestingly, reducing the repair time under adverse weather reduces CVaR significantly (by 35%, from 4,113 k$/yr to 2,690 k$/yr) while the corresponding EENS reduction is more limited (only 13%). This exemplifies the fact that one enhancement solution may be preferred from a reliability perspective, while, from a resilience perspective, other options may be more attractive. Interestingly, the option in which lines are underground features an attractive compromise between reliability and resilience indicators, reducing EENS cost by 48% (which is not as good as the 93% reduction related to the N-1 solution, but not as bad as the 13% reduction related to the N-0 case with shorter response times) and reducing CVaR by 31% (which is not as good as the 35% reduction related to the N-0 case with shorter response time, but not as bad as the 6% reduction associated with the N-1 solution). This is particularly important in practice in the presence of budget constraints and under the need for undertaking *both* reliable and resilient enhancements in power networks.

Realistic application to earthquakes in Chile

In order to demonstrate the applicability of the proposed resilience planning framework to the real world, the following case study is used to identify resilience enhancement decisions among an array of multiple candidate solutions to protect against earthquakes in the Chilean transmission system.

Case study description

The Chilean transmission system, which covers more than 3,200 km from Arica to Chiloe, is modeled through an equivalent network composed of 40 nodes/substations and 56 transmission corridors (shown in Figure 9), representing the infrastructure in 2018. For that year, electricity demand was approximately 76 TWh and generation supply included mainly hydro (23 TWh, 30%), coal (30 TWh, 39%), and gas (11 TWh, 15%) units, with minor participation from wind (4 TWh, 5%) and solar resources (5 TWh, 7%) too. The total installed generation capacity was 24 GW.

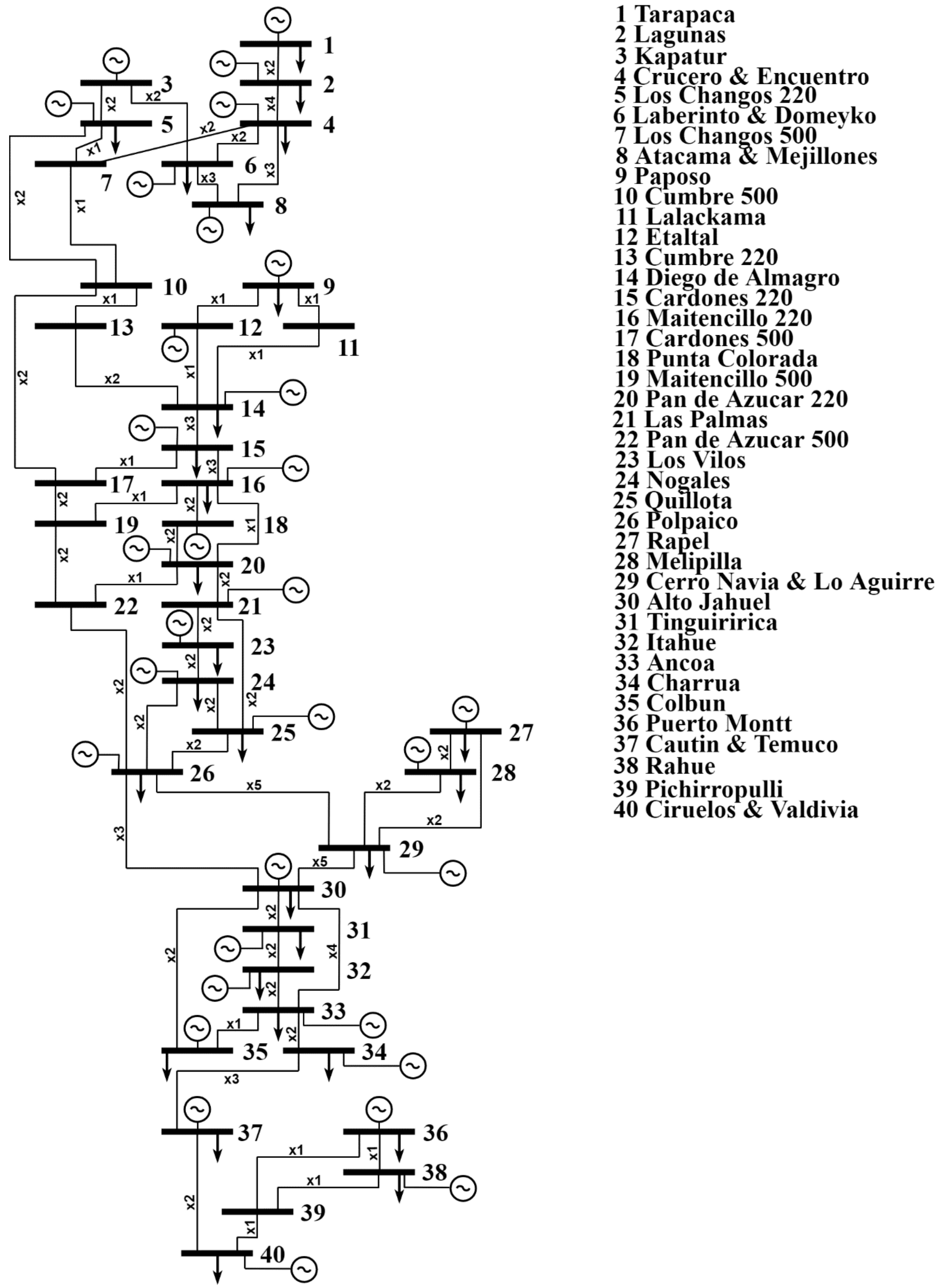

Figure 9: Chilean transmission network model used in the case study, indicating topology, generation and demand nodes, and number of circuits per corridor.

For the purposes of modelling the potential failure of system infrastructure during an earthquake, we have used the fragility curves of towers, generation units, and substations adopted by the Federal Emergency Management Agency, USA (Hazus-MH2.1), which relates probability of failure of these system components with the peak ground acceleration (PGA) at their particular locations.

For the calculation of the peak ground acceleration in different locations following an earthquake with a given epicenter, we have used validated models that could characterize the strong ground motion attributes observed in the 2010 earthquake in Chile.

We then randomly generated a comprehensive set of scenarios (e.g. 10,000) that follows the sequence:

1. *Random generation of earthquakes and PGA calculation*: With random location and fixed intensity equal to 8.5Mw, equalizing the conditions of the most recent 2010 earthquake, which was one of the worst earthquakes experienced in Chile, the PGA is determined at the location of each system equipment.
2. *Random generation of network outage*: Once the probabilities of outages are obtained from the fragility curves, outages are simulated through a Monte Carlo process.
3. Random generation of equipment repairs: Once pieces of equipment fail, they are recovered following a random process.

The system dispatch before, during, and after the earthquake was obtained by simulating 5 days, where the earthquake occurs in the first hour in order to capture the system collapse as well as the system recovery. The analysis captures key features of a resilient power grid.

Results: Portfolio solutions for resilience enhancement

Figure 10 shows the Pareto frontier between the risk measure and the budget used to improve resilience. Here, the risk measure is the Conditional EENS (CEENS), where ENS is averaged across worst scenarios, e.g., all scenarios originated by very large earthquakes with a magnitude of 8.8Mw (in practice we can assume that CEENS ≈ CVaR by an appropriate selection of the value of the parameter α), and the "budget" indicates the number of available investment options allowed as a proxy for their total cost (e.g., budgets equal to 1, 3 and 5 mean that up to 1, 3 and 5 investment decisions can be made, respectively). The figure shows the most economical option (budget = 1) is to invest in an HVDC link connected point to point between the Atacama desert (node 4) and Santiago (node 29). This enhancement option in fact features two main characteristics. First, pre- and post-fault power flows are fully dispatchable due to power electronics equipment that allows system operators to have a higher level of controllability of the power flows, co-optimizing them with other operational measures, e.g., generation (re-)dispatch, exercise of reserve services, etc. The second characteristic is the unique topological connection of this candidate cable, which bypasses most substations between the north and the center of the country, reducing in this way its exposure to earthquakes (note that the main impact from earthquakes is on substation equipment rather than towers and transmission lines). In fact, empirical evidence from past events in Chile, strongly suggests that substations (rather than lines) feature the most severe problems during earthquakes. For example, in the 8.8Mw earthquake in

2010, only 3 towers failed, while 12 (out of 46) substations in the high voltage transmission systems showed some level of damage. For this very same reason, the best complements for this HVDC link are the hardening of substations supplying Santiago, i.e., Alto Jahuel and Cerro Navia (budget = 3).

Interestingly, for budget equal to 5, two storage facilities, each being a pumped-hydro storage unit of 300 MW, are added to the optimal portfolio. In this case, the storage facilities located in Cumbre and Lagunas allow the system operator to more efficiently manage the large amounts of renewable generation located in the north (under any outage conditions, with and without earthquakes), whose production is transferred through the HVDC link to the central area of the country in Santiago, which is in turn supplied by Cerro Navia and Alto Jahuel substations (among others). All of the aforementioned assets are part of the selected portfolio solution, clearly indicating the value of coordinated investment. These five enhancement options selected as a unified portfolio thus act as one synergic multi-asset enhancement, providing the best possible insurance to the main system load center against the occurrence of large earthquakes.

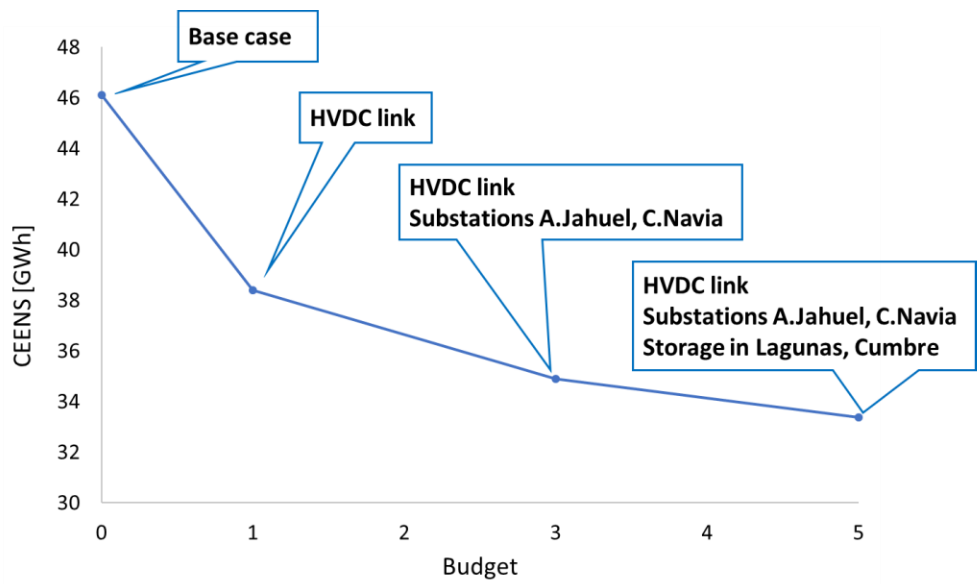

Figure 10: Optimal portfolio solutions for resilience enhancement for different budgets.

Summary and the way forward

In the context of the transition from reliable to resilient power grids, we have demonstrated the need for considering risk-based (rather than average) indicators to identify the necessary enhancements in network and system infrastructure. Importantly, this article has discussed some of the fundamental differences among various investment solutions (e.g., redundancy and substation hardening) compared with more flexible operational solutions, with the overall aim of improving the reliability and resilience of power grids. Although the proposed mathematical framework to determine resilience network enhancements is fully probabilistic, this differs from the classical probabilistic-based decision-making models due to the explicit incorporation of risk aversion, in contrast to the risk-neutral attitude assumed in classical reliability studies. We argue that planning for resilience corresponds to becoming risk-averse so that the resulting network designs are less exposed to HILP events in comparison to designs resulting from (risk-neutral or even simply risk-unaware) reliability studies.

The differences between reliability- and resilience-driven investments were illustrated on both a simple “textbook” two-node example and a realistic 40-node representation of the Chilean power system. While the former was used to clearly explain the fundamental concepts of the framework we propose, in the latter we identified and discussed the best Pareto portfolios of investment propositions that offer the highest level of hedge against adverse impacts of large earthquakes. For this case, we also emphasized the importance of hardening the infrastructure beyond the classical redundancy-based (i.e., adding more and more infrastructure), reliability-driven solutions. Furthermore, we demonstrated how redundancy effectively improves average indicators, while hardening improves risk indicators. Perhaps most importantly, our results also clearly illustrated how additional operational flexibility and responsiveness can play a major role in enhancing system resilience to HILP events.

Looking ahead, in order for planners and regulators to fully consider resilience-enhancement investment solutions once specific hazards or potential HILP events of interest have been identified (which is a non-trivial and case-specific exercise *per se*), the following two questions will need to be more appropriately addressed in the near future:

(i) What is the right level of risk mitigation for HILP events? Or in other words, what is the right level of risk aversion to be considered when determining resilience-based investment propositions?

(ii) How should the costs associated with resilience be allocated among market participants?

Although the latter may arguably be more intuitive to address, for example on a beneficiary-pays basis (i.e., identifying the set of beneficiaries associated with the resilient network enhancements), the former undoubtedly requires a deeper understanding of electricity consumers’ risk attitudes. This is not an easy task and goes beyond the expertise of many members of our IEEE PES community, critically demonstrating, going forward, the need for undertaking and integrating more interdisciplinary work in this field.

Further readings

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