Complex Systems Techniques applied to Transmission Expansion Planning.

Part III: Using Topological Information to Build More Robust Networks

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***Abstract*—Reliability is one of the main objectives that should be considered in Transmission Expansion Planning. However, the high computational demands of traditional approaches mean that they may be unmanageable in real case studies. We propose a simple reliability measure that can be easily calculated based on topology and basic power system information. The measure is easily calculated and has no need for power flow calculations. The use of this measure has been demonstrated in a case study using data from the Spanish power grid.**

***Index Terms*— Transmission Expansion Planning, Reliability, Network Topology**

I. Introduction

RELIABILITYis one of the main objectives that should be taken into account when proposing network designs: demand should be satisfied not only in a base case but also when one or more system elements are unavailable. In general, power systems are built with redundancies in the form of extra generation capacity and transmission facilities. This ensures continuous supply in the event of failures or forced outages of a plant or the removal of facilities for scheduled maintenance (R. Allan, 2013). This redundancy has a cost, and therefore a good network design should carefully weight this cost against the benefits of redundancy.

However, reliability is difficult to assess, as it involves evaluating the sufficiency of network facilities across many different failure or maintenance scenarios (R. Allan & Billinton, 2000). This means that optimal Transmission Expansion Planning (TEP), that is, designing the transmission grid via optimization methods, is challenged by the inclusion of reliability considerations.

In order to overcome this limitation –which also applies to other types of networks – there has been a substantial amount of literature exploring the possibility of using simplified methods to evaluate robustness. Ideally, these metrics could be calculated independently from the complexities of the power system, such as Kirchhoff's Laws (which describe the power flows). The simplest robustness metrics ignore power flow altogether and only consider the topological configuration of the grid. This information can easily be added to an optimization model for Transmission Expansion Planning.

This paper reviews the topological metrics that have been proposed in the literature, proposes a new one and applies it to a real power system. The main contributions of our work are the following:

- We systematize the existing literature, which focuses on *evaluating systems* rather than *designing them*. We give insights on how to use the metrics for network design.
- We propose a measure that combines network topology and basic power system information. No power flow calculations are necessary.
- We demonstrate its use in a real case study.

The rest of this paper is organized as follows. First, section II reviews current approaches of introducing reliability in TEP. Then, section III describes the current topological measures used in this context. Section IV then proposes the measure that will be used in our analysis. Section V and VI present the case study and our results respectively. Section VII concludes and outlines future lines of research.

II. Reliability in TEP

This section describes concisely the main existing approaches for measuring reliability and introducing is an optimization criterion in a TEP model.

1) *Measuring reliability*

The reliability of power systems is usually assessed by means of indices that express the ability of the system to satisfy its loads in the event of failures or maintenance. These indices can be included as an optimization objective in the grid design

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problem. The main ones are divided in two types: deterministic and probabilistic.

The main deterministic indices are:

- Generation Reserve Margin (RM): expresses the ratio between the maximum generation capacity and the peak load.
- Largest Unit loss (LU): expresses the ratio between the reserve margin and the largest generation unit.

The main probabilistic indices are:

- Expected Energy Not Supplied (EENS) is an energy-oriented index that declares the cumulative amount of energy that is not provided to customers across the scenarios considered.
- Loss of Load Expectation (LOLE) is the number of days, hours or minutes in a period where there will be interruptions for some of the customers.
- Loss of Loss Probability (LOLP) gives the probability of not serving the full load across the scenarios considered.

As can be seen from the above, deterministic indices study reliability in terms of generation adequacy only, while stochastic indices consider the full system. Our work aims to better power networks. This is different from expanding the system generation, which we consider to be decided by the generation companies (GenCos) in a liberalized energy market. Therefore, we only consider the family of probabilistic indices. These probabilistic indices are calculated across a range of different scenarios.

- Different hydro inflows or renewable generation availability. For the sake of simplicity, we will consider only one expected scenario in our calculations, although any results should be generalizable to several of such scenarios as a sum by scenario weighted by probability.
- Different conditions for the load. For the sake of simplicity, we will deal with the peak demand scenario only. This is consistent with a wide array of literature on this topic.
- Different failures for the system elements. Most of the literature and the practical applications consider the individual failures of individual elements (generators or transmission lines), known as the *N-1* criterion. This criterion is reasonable in the sense that, failure probabilities being low themselves, the probability of joint unavailability is negligible. This, however, leads to ignoring important events such as cascading failures. When there are too many N-1 scenarios to be taken into account comprehensively, some works resort to considering only the ones with the highest impact or the highest probability.

An exhaustive account of these concepts can be found in reference (R. Allan, 2013).

2) Incorporating reliability into TEP optimization

The indices presented above can be used to measure the performance of the power system as a whole or of parts of it. As such, the indices can be used to determine incentives for the private companies that build, operate or maintain the power system. This is particularly important in the case of Transmission System Operators (TSOs) or power distribution companies. The indices can also be used to compare different network designs.

However, when evaluating reliability of a power grid during TEP, we should include reliability indices in the optimization model. If we choose to do that directly, we can do it in two main ways:

- As a partial objective in the optimization function, so that reliability is measured against other considerations such as investment or operation cost.
- As a constraint, so that a minimum value for the indices is established. In the latter case, the constraint can be either deterministic (it needs to be abided in all the cases) or probabilistic (also known as a *chance constraint*, it only needs to be abided in a given percentage of cases).

These two options imply a considerable size increase in an already large optimization problem, so that other solutions must be investigated.

There are some heuristics that have been proposed as rules to guide the network solution process. For instance, reference (McCalley, Aliprantis, D., Dobson, A., Li, & Villegas, 2013) propones to determine the number of redundant transmission lines by fixing the maximum percentage of flow that is allowed to be lost as a result of a line failure. Reference (Lumbreras, Ramos, & Cerisola, 2013), by some of the authors of this paper, follows a different approach and develops a progressive contingency incorporation algorithm that ensures that only the minimum possible number of failure scenarios is taken into account while ensuring an optimal solution

Along the same lines, reference (Lumbreras, Ramos, & Sánchez, 2014), also by some of the authors of this paper, reduces the size of an optimal TEP problem by introducing only the candidate transmission lines that were selected automatically as the most promising. In that work, the selection of candidates was performed based on the marginal impact of the transmission line on the efficiency of the network. The focus was not on reliability but on network efficiency (the ability to use cheaper generators and therefore reduce operation costs).

In the present work, our objective is to identify ways to assess the robustness of the network quickly, so that we can:

- Introduce them as an efficient approximation of reliability as an optimization objective.
- Identify the transmission lines that are potentially promising candidates for improving system reliability.

As explained above, these measures should be ideally accurate (that is, to reflect the reliability indices EENS, LOLP or LOLE as close as possible) and as simple as possible, where the simplest measures possible would only take into account the topology of the network.

Our work reviews the main topological measures that have been proposed and extends them, as well as applying them to a real case study based on the Spanish power system.

III. Topological Robustness Measures in the Power Transmission Network

Given the importance of this topic, there has been some considerable work in the following areas:

- General frameworks for the topology of supply networks (G. Li, Xuan, Song, & Jin, 2010; Xuan, Du, Li, & Wu, 2011).
- General studies of network vulnerability based on topological network metrics (Dwivedi, Yu, & Sokolowski, 2010; Kasthurirathna, Piraveenan, & Thedchanamoorthy, 2013; T. Li, Pei, Wang, & He, 2008; Manzano, Marzo, & Calle, 2012; Zhou, She, Xu, & Yokoyama, 2009).
- Relationship between connectivity and robustness to node and link failures (Chen & Hero, 2013; Jamakovic & Uhlig, 2007)
- Studies of the power grid from a complex networks perspective (Bai et al., 2006)(G. Li et al., 2010).
- Studies of power grid vulnerability based on topological network metrics (Bompard, Pons, & Wu, 2012; Koç, Warnier, Kooij, & Brazier, 2014; LaRocca, Johansson, Hassel, & Guikema, 2014; Pahwa, Hodges, Scoglio, & Wood, 2010; Wang, Zhang, Zhang, Yin, & Wang, 2011), in particular focusing on the effect of to cascading failures or to targeted attacks (Koç, Warnier, Kooij, & Brazier, 2013).
- Topology modeling using mixed-integer inequalities (Hassaïne, Delourme, Sidorkicwicz, & Walter, 2004), which is a way of including reliability constraints into an optimal TEP problem.

Among these papers, the most closely related to our work is the recent reference (LaRocca et al., 2014), which reviews and evaluates many different topological measures that can be used as surrogates for the calculation of the full physical power flows. The topological measures they study are the diameter, the largest connected subgraph, and various versions of network efficiency (also known as average inverse path length). They propose different versions of these measures where the different nature of demand and generation nodes as well as the impedance or capacity of links, are introduced progressively. They compare their estimates of EENS based on these metrics to the exact values obtained with a linearized, approximate DC load flow and with an AC Load flow, the most accurate model that can be used to simulate the power system. They find –quite intuitively- that the higher the degree of detail included in the metric, the more accurate the results obtained are, and that several measures used together are more informative than individual ones.

There are three main differences between (LaRocca et al., 2014) and our approach:

- Our ultimate goal ultimately optimal grid design rather than assessing the reliability of a given network.
- The metrics we survey are different, as will be seen below.
- We validate these concepts using a real case study (the Spanish power system).

IV. Proposed Measure

Topological measures of power grid robustness are attractive because they allow evaluating the strengths and weaknesses of a power grid without needing complicated models of how power flows through the network. Essentially, the assumption made by purely topological analyses is that the only features needed to understand robustness is the network connectivity – how power lines connect different sites to one another.

Following initial proposals that topological robustness could be successfully applied to the analysis of power grid robustness, it was determined that purely topological measures of robustness were insufficient because network topology contains no information about the physics of transferring power from one side of the network to the other. For instance, topological measures like the network diameter or average inverse path length are easy to calculate but lack a clear connection to the fundamental physics that governs current flow (Hines, Cotilla-Sanchez, & Blumsack, 2010; LaRocca et al., 2014).

In particular, the main qualitative reason for why purely topological measures of robustness do not succeed here is that they do not account for or predict nonlocal cascading failures. In reality, the delivery of currents from one part of the power grid to another does not just depend on the shortest path, but on multiple available paths. As a result, currents may be rerouted non-locally through a new part of the network following a single component failure. This rerouting may in turn cause overloading and non-local failures of further components. Purely topological measures cannot account for this, and therefore fail to predict the full extent of cascading failures.

For this reason, we move beyond purely topological models and incorporate into our analysis information both from the power grid topology as well as the amount of power generated and demanded by each node in the network. With this, we are able to make claims about the network's capability to satisfy demand for power. We apply our methods to the specific real-world case of the Spanish power grid. Our aim is to establish efficient ways of evaluating the robustness of this power network, so we wish to avoid the computationally expensive procedure of simulating the full AC power flow dynamics.

We define robustness in terms of the network's response to failures in one or more components. Ideally, following component failure the network should still be able to supply enough power to meet demand. Our objective is to minimize Power Not Supplied (PNS) in many different possible scenarios. PNS incorporates information about the power generated and demanded at different nodes inside our network, as well as topological information about how those sites are connected to one another in the network by power lines (edges). Our basic contribution is that we approximate PNS by the margin between generation capacity and demand in each disconnected component when simulating the loss of elements in the network. This measure combines topology and basic information on the system in an easy-to-calculate way.

We will assume that as long as two nodes belong to the same connected component (i.e., there exists a path of finite length that connects the two), it is possible for power to flow from one node to the other, and vice versa. We acknowledge that with this assumption we make it impossible to create non-local cascading failures in our power grid model. However, it does allow us to evaluate scenarios in which the network becomes disconnected and certain groups of nodes become isolated from the rest of the network. It is especially problematic if a component failure creates one or more isolated components that cannot sustain themselves without external connections. Component failures that lead to the creation of isolated components represent an important vulnerability in the power grid that we can identify and evaluate using PNS (Figure 1).

We begin by examining the complete, undisturbed network and seeing how much power is generated in excess of demand. We then simulate component failures by removing one or more nodes or edges from the network. Removing an edge or node results in a new network topology, one that may have disconnected certain subcomponents from the rest of the nodes in the network. We will refer to the largest resulting subcomponent as the *bulk* and to the disconnected subcomponent(s) as *isolated subcomponents* (Figure 2). We then compute the change Δ in the amount of power generated in excess of demand inside the bulk.

Mathematically, for each failure scenario we calculate the following:

$$\Delta = \sum_{n \in N'} g_n - d_n - \sum_{n \in N} g_n - d_n$$

Where:

N: undisturbed network

N': bulk component of network after nodes or edges are removed

g_n: power generation at node n

d_n: power demanded at node n

We propose using this incremental measure on the margin between generation and demand to identify potential problems in the system and evaluate robustness.

Two things can cause a large change in generation in excess of demand: either the removal of a node that has large generation or large demand or the creation of an isolated subcomponent that in total has a large generation or large demand. The latter case, where we have created one or more isolated subcomponents, is of greater concern to us. The nodes in the isolated subcomponents are physically separated from the bulk. In the case when $\Delta > 0$ there is excess (unmet) demand in the isolated subcomponent. In the case when $\Delta < 0$, we have disconnected an important generator from the bulk. If Δ is small, then it means that there has been no significant change in the network's capability for connecting generators with demand.

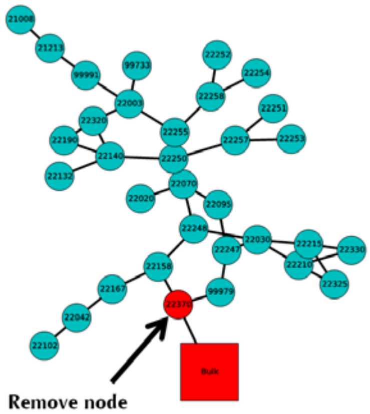


Figure 1. Node removal example.

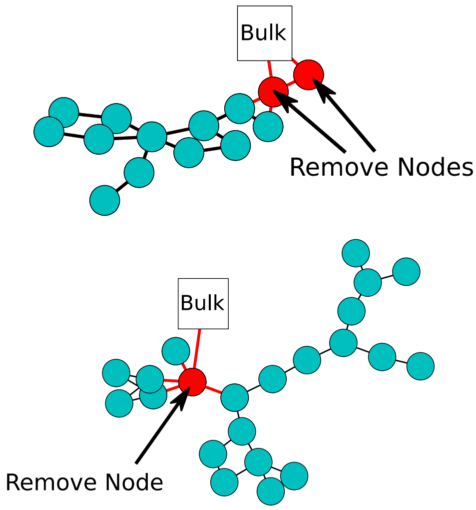


Figure 2. Examples of creation of isolated components.

V. CASE STUDY

We will demonstrate this method in the case of an area of the Spanish power grid, represented by a network containing 372 nodes and 460 edges. Before undergoing node or edge failure, the generators in this network have a peak supply of 8321 MW in total. In addition, there are 7534 MW of intermittent sources of energy. The total peak demand in the network is 15,140 MW, meaning that the power generated in excess demand at peak generation and peak demand is 715 MW.

We will now test the robustness of the Spanish power to component failure by systematically removing nodes and edges, looking at whether or not the network breaks up into components, and calculating Δ, whether the power generated can satisfy the demand in the bulk and in any isolated subcomponents. There are five types of failure scenarios we will consider (Figure 3):

- *n-1 node removal* (failure of a single node)
- *n-1 edge removal* (failure of a single edge, but not the nodes at its endpoints)
- *n-2 local node removal* (failure of two neighboring nodes connected by one edge)
- *n-2 local edge removal* (failure of two neighboring edges

sharing a common node)

- *n-3 local node removal* (failure of three neighboring nodes connected by 2 or more edges)

Edge removal represents the failure of a transmission lines. Node removal might correspond to the failure of a power station or a substation. In the latter case this would represent the total loss of the substation (all positions). This would correspond to an extreme case of losing all positions and also –probably, more interesting- to a case where either the substation has been deliberately attacked or it has suffered from a software failure, situations that are becoming more and more relevant.

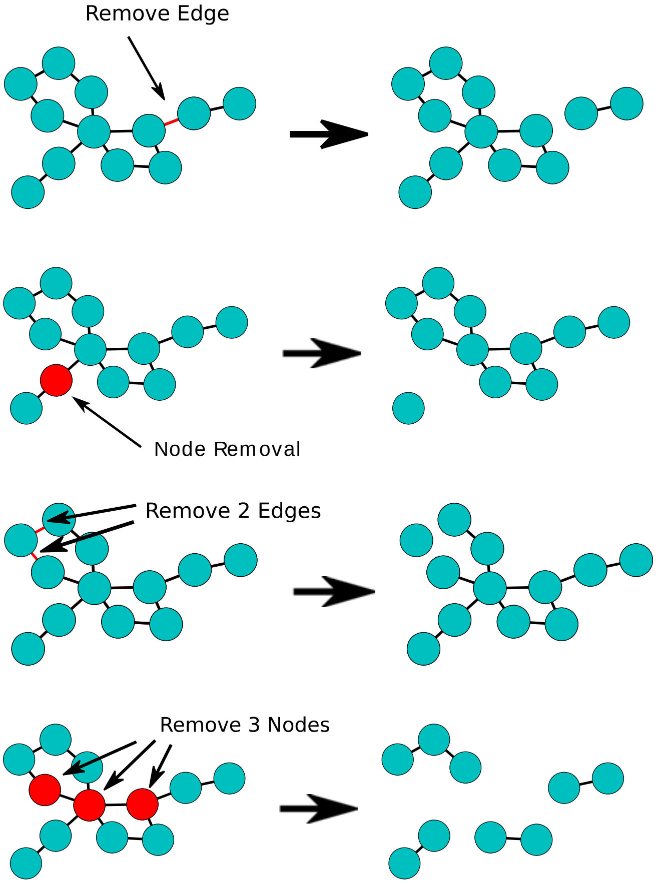


Figure 3. Component Failure Contingencies.

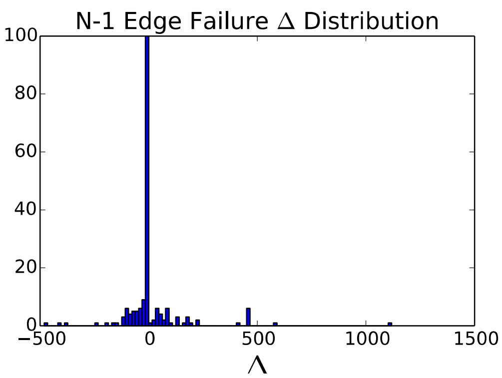
When removing multiple components, for now we restrict ourselves to locally-correlated removal of nodes or edges. This allows us to evaluate the robustness of the network against geographically-correlated component failures (e.g., in the case of weather-related line power line failures confined to a localized region of the country). This is, at best, a very crude approximation of cascading failure, where the failure of one node or edge leads to the failure of another neighboring node or edge. This framework can also be applied to simultaneous failures defined in a nonlocal way (i.e., substations that use the same technology).

VI. Analysis

To examine the n-1 node scenarios, we iterate through all nodes in the network, removing each node one by one and measuring Δ each time (removed nodes are replaced after each measurement). As a result, we can see which nodes, when removed, cause the greatest change to the amount of power generated vs. the amount of power demanded. We plot a histogram below of the distribution of Δ.

We first observe that the bulk of the distribution is centered close to Δ= 0, meaning that the majority of node failures will result in only a small change in the amount of power generated in excess of demand. This is a sign of power grid robustness. Far to the left and to the right of 0, however, we do observe a few outliers in the distribution. These outliers represent cases where are large changes to the available power in the bulk of the network. The highly positive outliers correspond to cases where large isolated components become disconnected from the network. These isolated components do not generate enough power to satisfy demand on their own. **Error! Reference source not found.** shows one such case corresponding to the rightmost outlier in the Δ histogram, in which node failure creates 3 isolated components that have a considerable unsatisfied demand. The highly negative outliers correspond to cases where single nodes that generate a high level of power are removed from the network.

We can also examine other component failure contingencies, each time computing the distribution of Δ and examining the outliers of the distribution. The other histograms in Figure 4 show that, for the most part, the other component failure contingencies do not result in qualitatively different Δ distributions. The histograms for the removal of edges are narrower than the histograms for the removal of nodes. This is expected, simply because by design the removal of nodes is more disruptive than the removal of edges (removing one node has an effect that can be equivalent to removing many edges). Examining the outliers of all of these distributions, we do not find many new cases of creating large isolated components: most of the isolated components created by single node removal are also created by multiple node removal. Again, this is a sign of network robustness, at least in the case of locally correlated component failure.



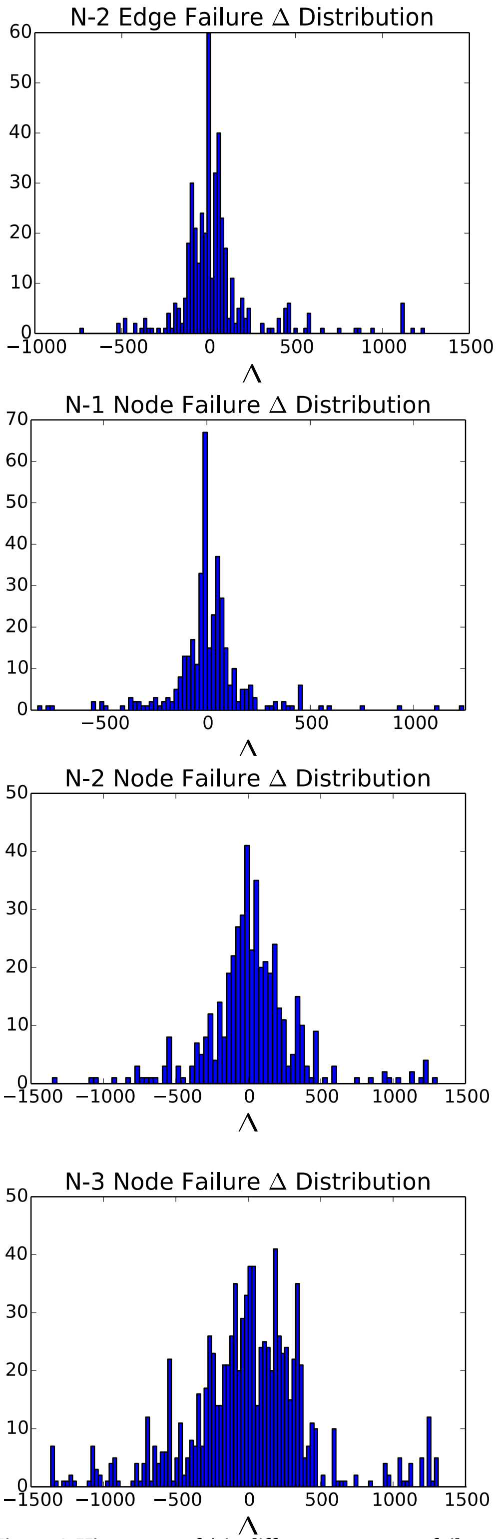


Figure 4. Histograms of Δ in different component failure scenarios.

VII. Conclusions and Further Work

Overall, we have demonstrated the usefulness of Δ ,a simple variation on the Power Not Supplied or EENS, for quickly evaluating power grid robustness and identifying vulnerabilities in the networks. We chose this particular robustness metric because it combines both information about the network topology and the key node properties of power generated and power demanded. This is easy to calculate, and so will be easy to integrate into an optimization procedure. Furthermore, by examining the distribution of Δ for a large number of component failures, it becomes clear which nodes and edges make the network vulnerable. In the real-world case of the Spanish power grid, we have used this procedure to show that the network is largely robust to most node failures and have identified the outlier cases that create a large change in the network's capability to satisfy its demand for power.

Further research should focus on:

- Testing the accuracy of this method compared to other, more sophisticated approaches.
- Introducing it in TEP optimization models.

Additional analysis are therefore needed in order to confirm whether this measure can be effectively applied to facilitate the process of building more robust networks in Transmission Expansion Planning.

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