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Engineering structural robustness in power grid networks susceptible to community desynchronization

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Abstract

Networked power grid systems are susceptible to a phenomenon known as Coherent Swing Instability (CSI), in which a subset of machines in the grid lose synchrony with the rest of the network. We develop network level evaluation metrics to (i) identify community substructures in the power grid network, (ii) determine weak points in the network that are particularly sensitive to CSI, and (iii) produce an engineering approach for the addition of transmission lines to reduce the incidences of CSI in existing networks, or design new power grid networks that are robust to CSI by their network design. For simulations on a reduced model for the American Northeast power grid, where a block of buses representing the New England region exhibit a strong propensity for CSI, we show that modifying the network's connectivity structure can markedly improve the grid's resilience to CSI. Our analysis provides a versatile diagnostic tool for evaluating the efficacy of adding lines to a power grid which is known to be prone to CSI. This is a particularly relevant problem in large-scale power systems, where improving stability and robustness to interruptions by increasing overall network connectivity is not feasible due to financial and infrastructural constraints.

Keywords: Power system simulation, Community structure, Network fault tolerance, Stability

Introduction

Disruptions of power grid systems can have a severe, negative impact on performance and lead to *Coherent Swing Instability* (CSI) (Susuki and Mezic 2011; Susuki et al. 2011; Susuki and Mezic 2012), whereby a subset of machines in the grid lose synchrony with the rest of the network, thus shutting the entire network down and leading to unacceptable black-outs. CSI is in essence a manifestation of community structure in a networked system, a collective dynamical divergence of one subgroup of nodal oscillations from another. Instigated by the work of Girvan and Newman on modular structures in networks (Girvan and Newman 2002; Newman and Girvan 2004; Newman 2006), a great deal of attention has been devoted to the development of methods for identification and characterization of modular components. *Community detection* has become a broadly-defined term which is used to refer to a variety of such approaches. A comprehensive review of its uses is presented by Schaub et. al. (Schaub et al. 2017). Much of the prominent work in the field has focused on topological approaches, i.e. methods which take as input an adjacency matrix describing a (weighted or unweighted, directed or undirected) graph. As Schaub

notes, however, dynamics on a network are constrained by topology but cannot be fully described by it.

This distinction has led to work on community detection methods which place primary importance on dynamics. However, as many networks of interest lack a known set of laws governing their evolution (e.g. neurological, social, transportation, epidemiological, etc.), much of this research has modeled dynamics with Markovian diffusion processes describing random flows on the network (Delvenne et al. 2010; Rosvall et al. 2014; Bacik et al. 2016). Power grids have an advantage over these systems in that the physics of generator oscillations and current transmission are well-understood: taken in isolation, each node of the network behaves predictably. Only when they are combined on a complex and non-symmetric graph structure do they begin to exhibit the group behaviors which resist simple characterization. In this work we seek to capitalize on this property by applying a dynamics-focused community detection perspective to simulation data generated by a realistic, machine-level power grid model.

Previous work on applying network-topological analysis to real-world power grids has met with mixed success. The extensive theoretical framework that has been developed in the field of Complex Networks has given rise to a variety of methods which assess functional properties of power grids directly from their network topology, using metrics such as node centrality, betweenness, degree distribution, community structure, and clustering coefficients (Cuadra et al. 2015; Albert et al. 2004; Bompard et al. 2015; Solé et al. 2008; Zhou et al. 2015; Xu et al. 2014; Pagani and Aiello 2014; Pahwa et al. 2013). However, topological methods alone have consistently failed to fully account for observed network vulnerabilities (Bompard et al. 2009; Bompard et al. 2010; Pagani and Aiello 2013; Hines et al. 2010). This has led to a variety of hybrid approaches which incorporate electrical properties of the system not captured by its graph structure, often by using them to assign edge weights or to compute modified versions of existing topological metrics (Nasiruzzaman et al. 2011; Hines et al. 2010; Yan et al. 2013; Bompard et al. 2010; Bompard et al. 2012). The goal of these studies has generally been to develop a heuristic to estimate a power grid's vulnerability to failure, which they then validate using historical data or numerical simulations. In this work we present an alternative method which evaluates the functional consequences of structural modifications directly from simulation data. While this approach has previously been applied to steady-state systems (Baldick et al. 2009), its use for grid disturbances has generally been dismissed as infeasible due to the combinatorially large search space of possible faults and network structures (Hines et al. 2010). Our contribution is a methodology for incorporating topological properties (specifically, community structure) and statistics on measurement data to significantly reduce this space. Our technique identifies a set of candidate locations for single-line additions to an existing network; this is a small structural perturbation relative to the size of the full grid and therefore unlikely to significantly change its global topological characteristics, such as degree distribution. Robustification occurs not by directly tuning some topological (or hybrid topological/electrical) metric, but rather by using such a metric to inform a minor structural modification. This lends itself to practical engineering application, as it suggests an inexpensive change that could be made to an existing grid rather than a design principle for the construction of a new grid from the ground up.

Our data-driven approach is motivated by the proliferation of real-time monitoring strategies for power grids that have been deployed in recent years (Messina and Messina

2015; Kezunovic et al. 2013; Barocio et al. 2013), with event location strategies gaining increasing attention in order to localize pernicious effects (Li et al. 2010; Mei et al. 2008; Bhui and Senroy 2016). These strategies are directed to provide a system-wide awareness of events such as faults and other disturbances, taking advantage of the increasing coverage of *wide area measurement systems* (WAMS) technology which enables the implementation of wide area emergency and restorative control applications (Li et al. 2010; Mei et al. 2008; Bhui and Senroy 2016). Even though these strategies have achieved positive results, additional technical challenges arise as the modern WAMS-generated data become high dimensional and more distributed thorough large areas of the system. We propose an additional technique for power grid network robustification. Specifically, we show that the robustness of the network can be diagnosed from ensemble fault simulations. Moreover, the power grid can be made significantly more robust to disturbances with proper engineering of the network design and attention to the community structure observed in instances of CSI. Such considerations are critical in considering future power systems deployments, or for upgrading current networks in order to circumvent susceptibility to CSI.

In this paper, we detail a simulation model used for characterizing the power grid dynamics and disruptions. We further introduce a procedure for dynamics-based community detection based on the results of these simulations, showing through diagnostic tools that the network's sensitivity to CSI depends on the location and severity of a fault. This allows us to provide an engineering approach capable of characterizing network connectivity modifications capable of robustifying the network to decoherence.

Numerical Simulations of Power Grids

In this section, we highlight the numerical simulation architecture used to evaluate power grid systems and their connectivity structure. Importantly, a prescription of the disturbances applied to the network to induce CSI is considered in order to evaluate the network robustness in a principled way.

The Power System Toolbox

Power grid simulations for this study were produced using Power System Toolbox (PST), a Matlab software package originally developed by Kwok W. Cheung and Joe Chow of Rensselaer Polytechnic Institute (Chow and Cheung 1992). Supplied with both the topological structure of a power network and the specific electromechanical parameters of the grid's generators, nodes, and lines, PST performs dynamic simulations of both steady-state and nonequilibrium dynamics. In this study we employ system fault simulations structured as follows:

1. The system is initialized in a steady state for power flow through the network by solving the nonlinear algebraic network equations which specify the load flow problem.
2. The dynamic portion of the simulation is initiated by applying a transient three-phase fault to a single line in the network, as though the line were brought into momentary contact with a grounding object such as a tree.
3. When a fault occurs, power system protection equipment acts to isolate the disturbance. If the fault is transient, the line can be reconnected after a short time. PST treats this as a two-step process, clearing the fault first at the near end and then at the remote end of the line. These two time intervals, labeled in this paper as

τ_1 and τ_2 , are supplied as input parameters in simulations. Figure 1 illustrates the two time scales, τ_1 and τ_2 , for a simulation of the northeastern power grid system. Our interest is in the dynamics following the fault application and fault clearing time scales.

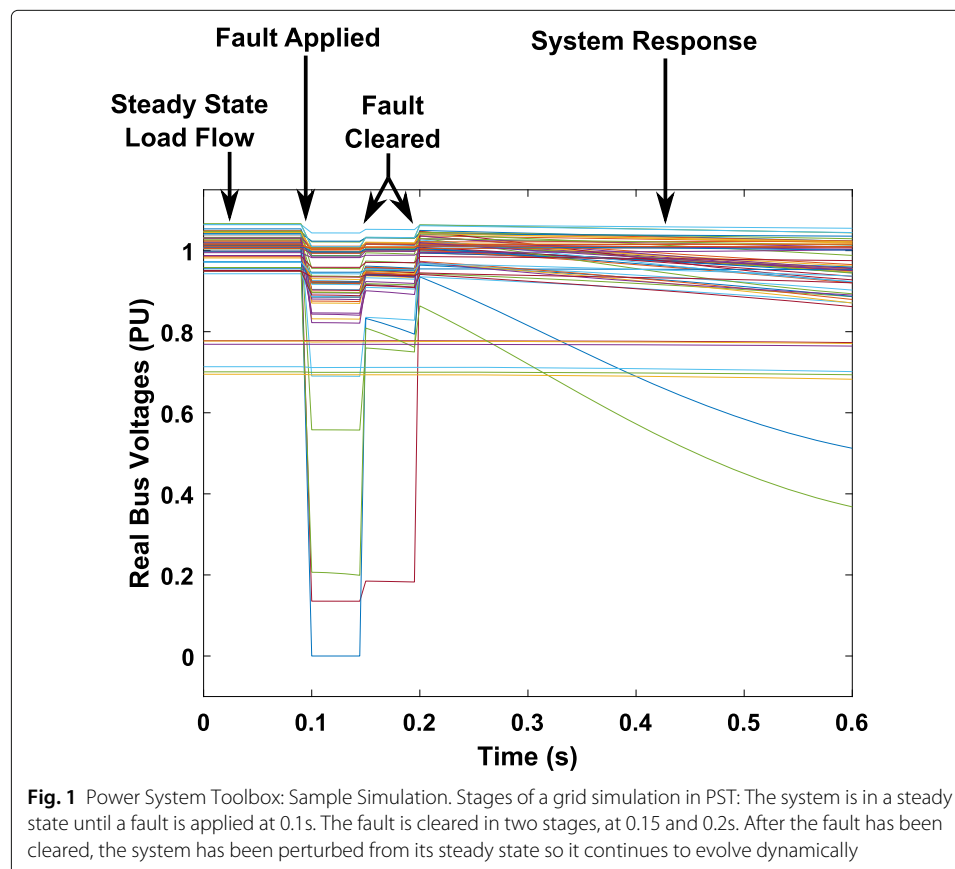
4. When the fault is cleared, the grid recovers its full original network structure. The fault has perturbed it from its initial steady-state configuration, so dynamic evolution continues. We continue the simulation for a long time (relative to the fault duration) and analyze the network's response to the disturbance. The CSI often is induced by a disturbance event (fault application) for which the power grid system does not recover to its original stable (steady-state) behavior.

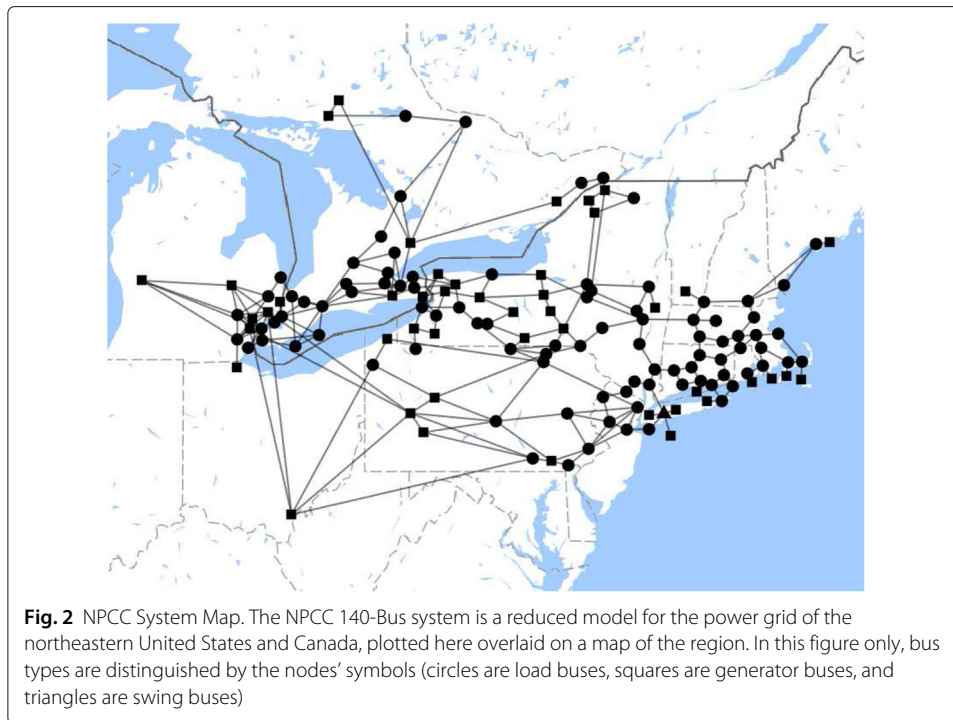
The NPCC 140-Bus System

Simulations in this study are carried out on the NPCC 140-bus test system, which is a reduced model based on the power grid of the North American northeast (Fig. 2). This network was chosen because its machine parameters are representative of those in a major real-world grid and its graph structure is sufficiently large and complex that it gives rise to coherent dynamics at subnetwork level.

Discovering Community Structure in the Grid

Simulations of the northeastern power grid are sufficient to illustrate many of the key features of power grid networks and their induced CSI. By perturbing the various





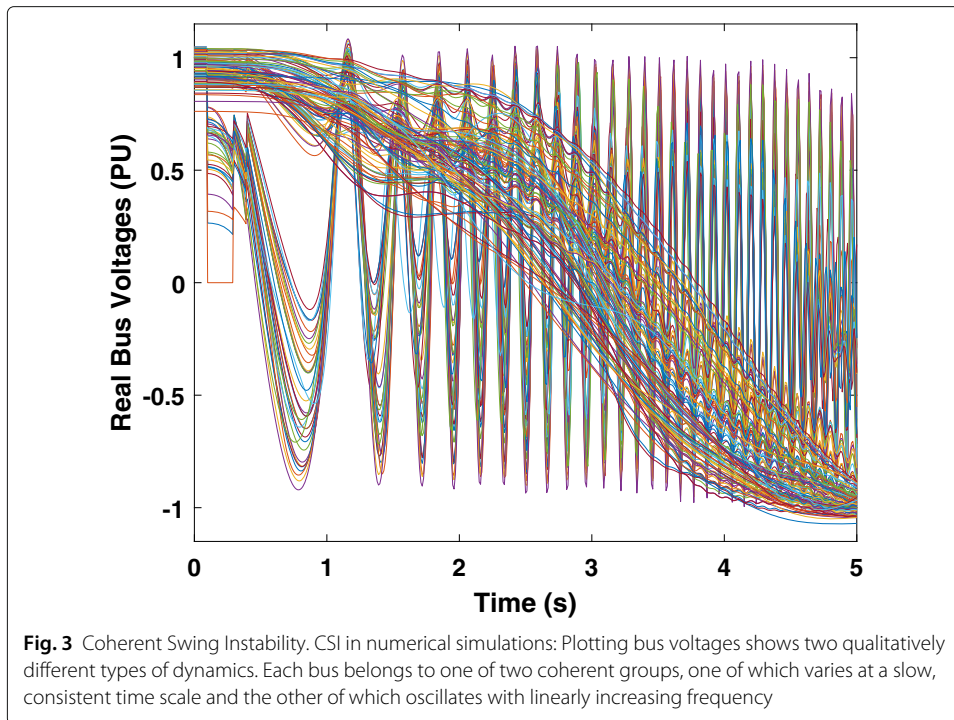
nodes of this specific network, we can characterize the instability structures, and their commonalities, induced in the power grid dynamics.

Identifying Coherent Swing Instabilities

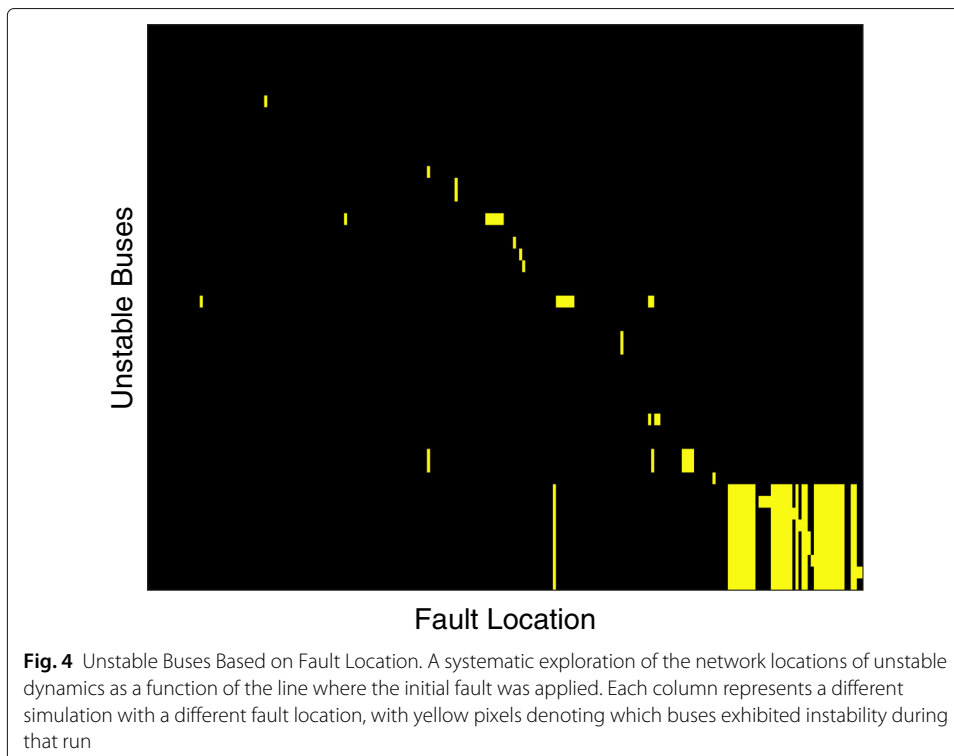
The focus of this specific study is the phenomenon of CSI, in which a subgroup of buses which are strongly coupled to one another, but only weakly coupled to other nodes, collectively lose synchronicity with the remainder of the network. Real-world power systems implement controllers to damp the oscillations of relative rotor angles which give rise to CSI, but no such safeguards are implemented in the PST simulation toolbox. The onset of CSI therefore is manifested as a clear qualitative transition in the dynamics of a subset of the buses. Specifically, a group of machines will begin to oscillate with linearly increasing frequency while the remainder of the network continues to evolve with dynamics on a slower and roughly constant time scale (Fig. 3). Although the PST model does not accurately model the behavior of the unstable network, since local controllers would activate to dampen growing oscillations, it does highlight the lack of robustness of the network to the intrinsic dynamics induced by the disturbances. By engineering a more robust system, the intrinsic dynamics itself acts to stabilize the system. This aspect of engineering a power grid network is considered below in the section entitled *Engineering Network Structure to Reduce CSI*.

Community Detection

We begin by investigating the incidence of CSI by systematically applying faults to each line of the network in succession and tracking which buses (if any) exhibit unstable dynamics as a result. The results, plotted in Fig. 4, suggest that the majority of instabilities



take place in a particular subgroup of buses. To formally characterize this structure we approach it as a network community detection problem: by treating the buses and fault locations as two disjoint populations of nodes with (unweighted, undirected) connections given by the nonzero elements in Fig. 4, we build a square adjacency matrix which casts the results as a bipartite instability matrix (with $N_{\text{bus}} + N_{\text{line}}$ rows and columns).



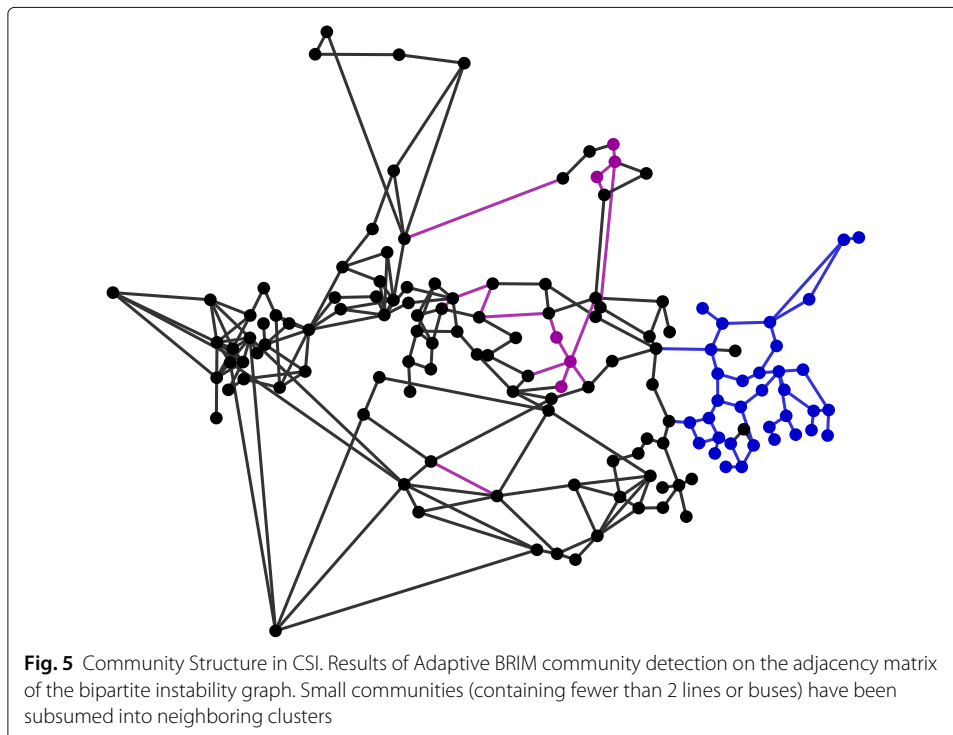
In this form, the results are amenable to any network-topological community detection scheme desired. Results presented in this paper use the Adaptive BRIM algorithm, developed by Michael J. Barber for modularity-based community detection in bipartite networks (Barber 2007). Very similar results were obtained using other bipartite algorithms, including those introduced in Newman (2008) (Newman 2006) and Liu and Murata (2009) (Liu and Murata 2009).

The Adaptive BRIM algorithm detected 12 distinct communities from the bipartite instability matrix. However, many of these were quite small. In the interest of restricting focus to network-wide swing instabilities, communities containing fewer than 2 buses or lines were reassigned to a neighboring cluster based on a vote of graphical nearest neighbors. This led to a reduced population of 3 dominant communities, plotted in Fig. 5.

The blue community, which corresponds geographically to New England, is a contiguous and highly interconnected nodal group with few connections to the rest of the network. A simple topological community detection scheme applied directly to the NPCC-140 graph would almost certainly have identified it as a highly modular cluster. The purple group, however, is thoroughly embedded within the larger black nodal population. This is a testament to the importance of our dynamics-based approach to community identification: modular graphical structure does not necessarily equate to dynamical coherency.

The Sensitivity of Network Connections

Given the diversity of dynamics observed for disruptions of the network, our analysis aims to understand the sensitivity of each node in the power grid to fault tolerances. By varying the fault severity, we can rank the nodes and their susceptibility to CSI.



Varying Fault Severity

To identify the lines where a system fault is most likely to generate CSI, we measure responses to faults of varying intensity. Faults in PST simulations are parameterized by two time durations: τ_1 from the application of the fault to the clearing of the near end, and τ_2 from the clearing of the near end to that of the remote end. Generally speaking, a longer fault duration drives the system farther from its initial steady-state configuration, increasing the likelihood of instability. Indeed, the parametrization of faulty intensity through the (τ_1, τ_2) parameter space allows us to characterize the robustness of each node.

Ranking Lines by Sensitivity

Working in (τ_1, τ_2) parameter space, we identify a domain which captures the onset of instability for most fault locations. This gives a range of values broad enough so that the lowest values of τ_1, τ_2 yield fully stable dynamics, while the highest values of τ_1, τ_2 lead to instability at many fault locations. The precise choice of bounds is somewhat arbitrary as long as they meet these criteria; the performance over the specified (τ_1, τ_2) region will only ever be used as a relative metric for comparing lines. For each fault location, we repeat simulations over a grid in this domain of parameter space. The performance of each run is quantified by determining the number of buses which go unstable.

The result of this analysis gives an “instability frontier” in the space of (τ_1, τ_2) . As visualized in Fig. 6, the more sensitive lines of the network (e.g. Fig. 6a) have a frontier which extends farther down toward the bottom-left corner, whereas more robust lines (e.g. Fig. 6b) are fully stable until comparatively high values of (τ_1, τ_2) . In the former case, we observe that a small perturbation to the fault parameters can lead to a big jump in the number of unstable generators. This foreshadows the crucial role of community structure in understanding this behavior: instability often occurs collectively in coherent subnetworks.

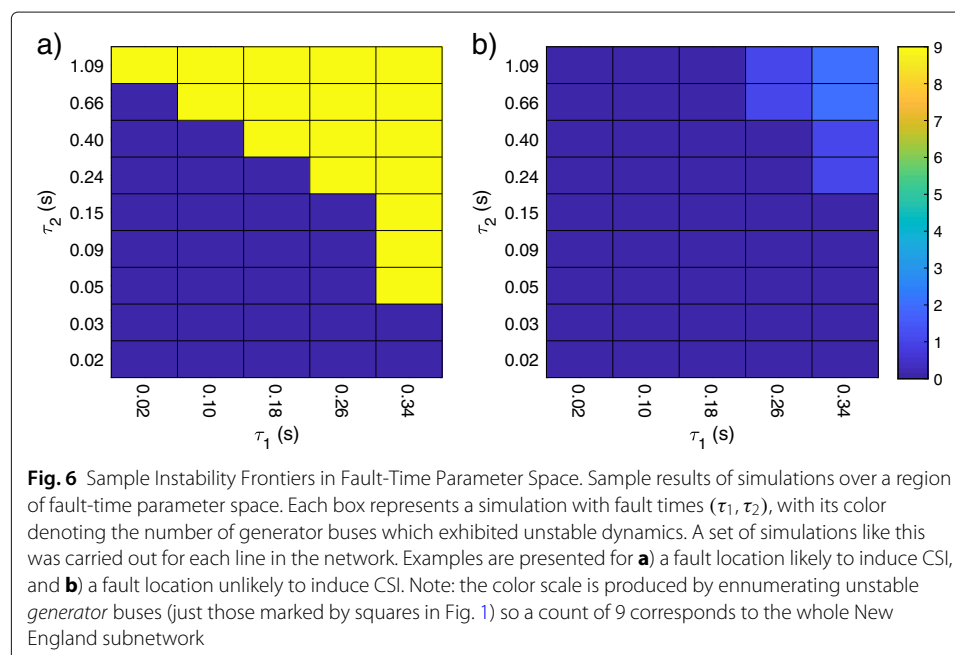
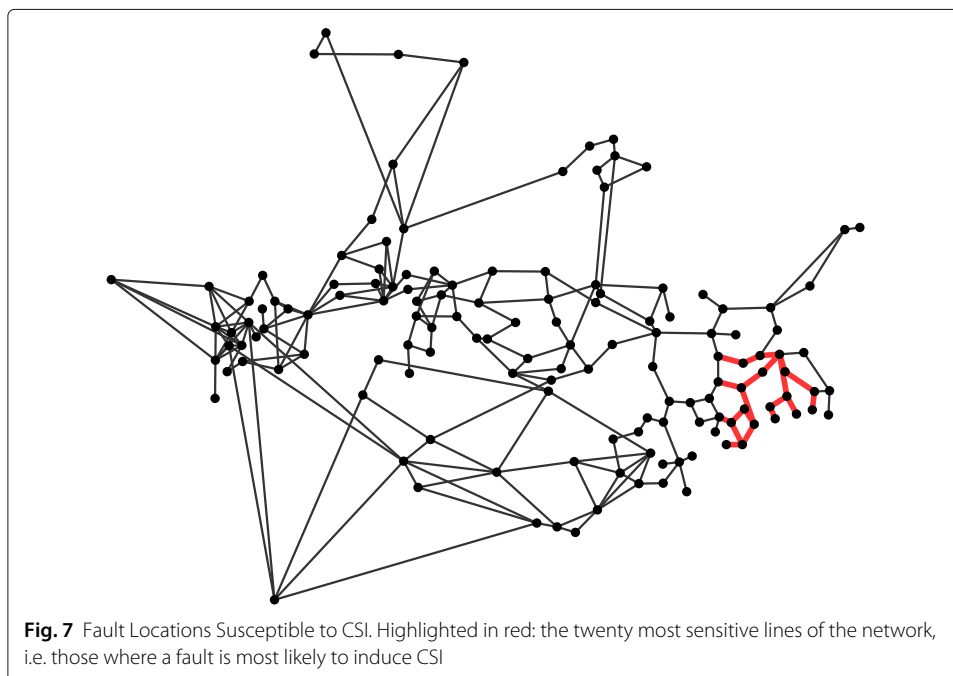


Fig. 6 Sample Instability Frontiers in Fault-Time Parameter Space. Sample results of simulations over a region of fault-time parameter space. Each box represents a simulation with fault times (τ_1, τ_2) , with its color denoting the number of generator buses which exhibited unstable dynamics. A set of simulations like this was carried out for each line in the network. Examples are presented for **a**) a fault location likely to induce CSI, and **b**) a fault location unlikely to induce CSI. Note: the color scale is produced by enumerating unstable generator buses (just those marked by squares in Fig. 1) so a count of 9 corresponds to the whole New England subnetwork

Having performed exhaustive simulations for all possible fault locations, we rank lines according to sensitivity by averaging over the unstable nodes obtained at all (τ_1, τ_2) parameter combinations. The numerical values obtained are of course sensitive to our choice of the fault-time domain, but they serve as a functional metric of comparison between different lines tested on this domain. Figure 7 illustrates the results of this process, with the 20 most sensitive lines highlighted in red. These are the lines whose performance we seek to improve through the remainder of this study. The network modifications we consider in the next section belong to a combinatorially large space, so it is necessary to restrict the scope of our analysis wherever possible to avoid having to do a prohibitively large number of simulations. Restricting simulations to these “worst offender” fault locations allows us to constrain the parameter space while still treating the cases which are of greatest practical concern with respect to grid stability.

Engineering Network Structure to Reduce CSI

Although the specific criteria which lead a subgroup of buses to coherently desynchronize in a given network are not generally well understood, it is clear that the observed phenomenon of community structure is intimately related to the connectivity configuration of the network. Grids are prone to CSI when they contain a subnetwork which is relatively weakly coupled to its surrounding nodes. Thus a naive approach to engineering network stability would be to simply add connections between nodes inside and outside this instability prone community. The results we present in this section not only support this intuition, but also show that not all inter-community line additions yield significant improvements to stability. As such, the full simulation-based approach implemented here is necessary to determine *which* inter-community connections contribute the most to the grid’s structural robustness.



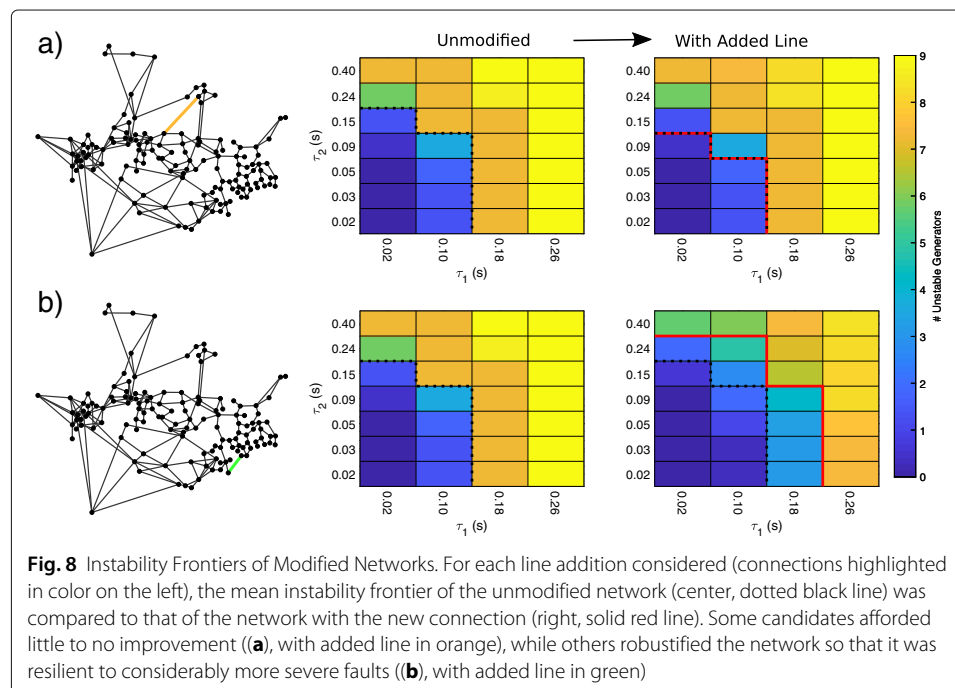
Network Modification Protocol

The approach for assessing how the addition of a transmission line affects the incidence of CSI is as follows:

1. A line connecting the two chosen buses (with resistance and reactance specifications taken to be the median of those of the existing lines) is inserted into the PST network specifications.
2. For each of the most sensitive lines in the unmodified network (i.e. those highlighted in Fig. 7), simulations are carried out for all (τ_1, τ_2) fault-time combinations in the domain identified previously to obtain an instability frontier (denoted in Fig. 8 by a black dotted line).
3. Overall performance for each fault location is again obtained by averaging over the sum of unstable generators. These values are then averaged over all tested fault locations to obtain a single plot of the modified network's susceptibility to CSI (shown in the right column of Fig. 8).
4. The result of this process is compared to that of the unmodified network to obtain a ratio measuring the stability improvement afforded by the added connection.

The set of possible single-line additions to the network is combinatorially large ($N_{\text{additions}} = N_{\text{bus}}(N_{\text{bus}} - 1) - N_{\text{line}} = 19367$, in the case of the NPCC-140 system). The number of simulations necessary to carry out the above steps for a single network modification is such that it is not computationally feasible to test all possible cases.

We present results on a semi-randomly selected subset of these possibilities ("semi-random" because they were chosen with a penalty on geographic distance between the buses to be connected, so as to better conform to practical engineering considerations). These candidates are separated into two groups: those which run between two distinct communities, and those which are internal to a single community.



Network Modification Results

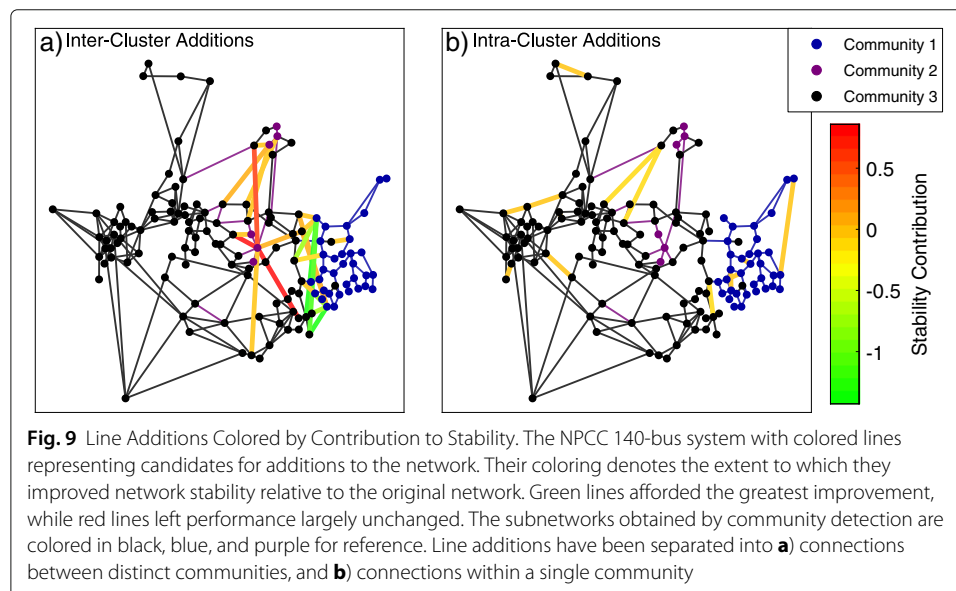
The candidate lines tested using the above protocol are pictured in Fig. 9, colored according to their performance relative to the original network configuration. Additionally, the distributions of the stability change parameter for each of the two populations of line candidates are presented as histograms and box plots in Fig. 10.

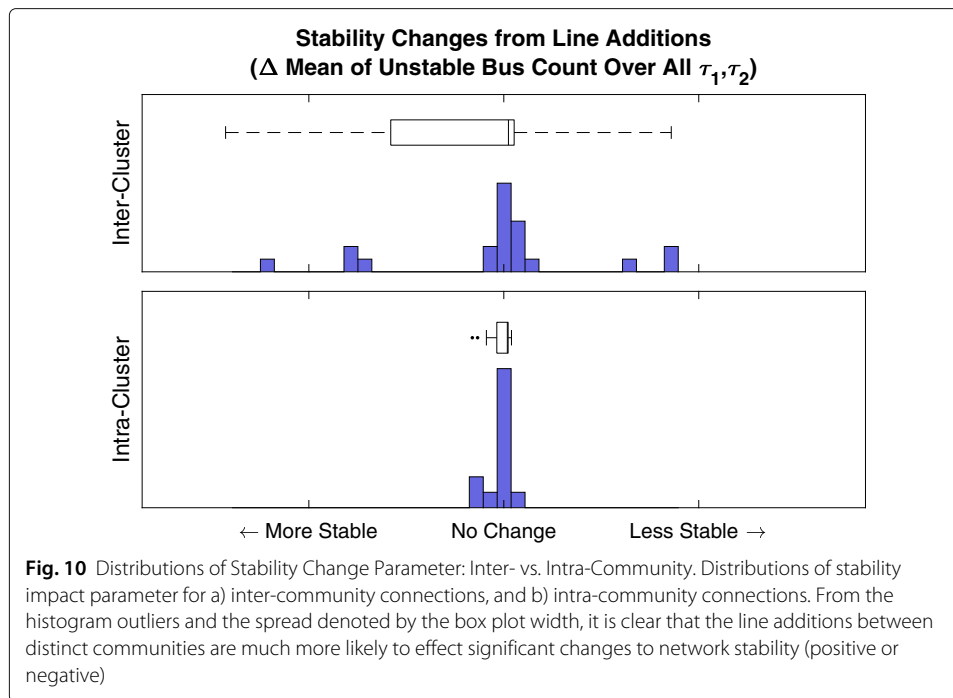
We observe that every line addition that significantly impacted the network's susceptibility to CSI is one that connects two distinct communities. This suggests that understanding the network's community structure is crucial to identifying candidates for new lines to robustify the grid. The search space of inter-community lines is substantially smaller ($N_{\text{additions}} = \frac{1}{2} \sum_i^{N_{\text{community}}} [N_{\text{bus}}^i (N_{\text{bus}}^{\text{tot}} - N_{\text{bus}}^i)] - N_{\text{line}}^{\text{inter}} = 4191$, in the case of the NPCC-140 system, which represents a 79% reduction of the search space). Coupled with practical distance considerations (and any other logistical criteria such as local topography or infrastructure), the number of line candidates for which this extensive simulation process must be carried out becomes much more tractable.

Within the inter-community population of line candidates, the criteria for significant robustification are not obvious. Examining the relationship between performance and common topological metrics such as betweenness and degree centrality reveals little to no correlation, which supports the literature consensus (Bompard et al. 2009; Bompard et al. 2010; Pagani and Aiello 2013; Hines et al. 2010) that these measures are insufficient as predictors of behavior in real power systems. Nonetheless, we have successfully identified a number of lines which do offer a marked improvement even by testing a very small subset of all possible inter-community connections. This shows that our approach to evaluating robustness of the network can effectively identify potential connections capable of robustifying the power grid network.

Conclusion

We propose a computational framework for the analysis of the network level dynamics and stability of power system disturbances. Our analysis is critical for understanding how





the network architecture itself can lead to subgraphs (communities) that are highly susceptible to CSI. By systematically parametrizing disturbances according to the temporal parameters τ_1 (the time of the fault until it is cleared) and τ_2 (from the clearing time of the near end to that of the remote end), we can assess the effect of each node on the overall stability of the power grid network.

We specifically develop evaluation metrics to (i) identify dynamics-based community substructures in the power grid network, (ii) determine weak points in the network that are particularly sensitive to faults, and (iii) produce an engineering approach for the addition of transmission lines to maximally reduce the incidence of CSI. For our example of the Northeast power grid, we identify a strong dependence of line sensitivity on the New England subnetwork. We show how modifying the network's connectivity structure can robustify the network to CSI. The space of possible connectivity changes is combinatorially large, so we restrict modifications to a tractably small subset of single-line insertions to the original network. We show that community detection can be used to substantially reduce this search space, as line additions which connect separate communities tend to much more significantly impact global stability. We find that the addition of a line can markedly improve the grid's resilience to CSI, but the success is highly dependent on location within the network.

Our analysis provides a versatile diagnostic for the efficacy of adding a particular line to a power grid which is known to be prone to CSI. This is a particularly relevant problem in large-scale power systems, where improving stability by increasing overall network connectivity is not feasible due to financial and infrastructural constraints. Our approach focuses principally on network topology, so its results are fairly robust to small variations in the model parameters used in simulation. This makes it a strong candidate for use in

analyzing real-world power systems, as connectivity structure is a characteristic which can be perfectly reproduced in the translation from physical system to simulation model.

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Availability of data and materials

All data analyzed in this study was generated using the publicly-available Power System Toolbox for Matlab, which can be downloaded by request from http://www.eps.ee.kth.se/personal/vanfretti/pst/Power_System_Toolbox_Webpage/PST.html. The parameter definitions for the NPCC-140 Bus System are bundled with the toolbox in the file `pst.dat/data48em.m`.

Authors' contributions

DD was lead author and conducted the computational analysis under the supervision of PhD advisor JNK. All authors participated in conceiving and designing the study. All authors read and approved the final manuscript.

Competing interests

The authors have no competing interests to declare.

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