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RESEARCH ARTICLE

Electric Grid Vulnerability Analysis to Identify Communities Prone to Wildfires

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ABSTRACT Natural hazards, like wildfires, present various challenges to the electric grid that can leave many communities without power. To identify vulnerabilities in the grid and the corresponding at-risk communities, this work considers the implementation of two Graph Theory assessment approaches, namely betweenness centrality and minimum cut, and combines the results from each with spatial fire probability data to produce a novel assessment of communities at-risk of losing service because of a wildfire. The results from a betweenness centrality analysis identified at-risk communities whose critical lines, necessary for routing power to the community from the numerous generators, were found to be at-risk if they were located within high probability burn zones. Communities at-risk of separation from the grid with one cut (or electrical shorting) of a transmission line due its proximity to a high burn probability (BP) area were also identified using the minimum cut Graph Theory algorithm. When the methodologies were applied to a demonstration transmission grid, the results found that about one third of the 585 substations had centrally located lines in high BP areas. About 46% of the substations require just one cut to be removed from the grid, and the average length of these one-cut segments was 37 km and the longest was 188 km.

INDEX TERMS Electric grid, vulnerability, wildfires, centrality, minimum cut, natural hazards.

I. INTRODUCTION

Power outages are often the result of weather events. Records show that natural hazards, like severe storms, wildfires, and high winds, caused over half of the major power outages in the U.S. between 2000 and 2016 [1]. This will continue to be a problem if current trends persist [2]. Fig. 1, for example, shows that since 1983 the number of fires each year remained relatively constant [3]. However, the total size of the fires increased significantly over the same time period from about 2 million acres in 1983 to around 8.5 million acres in 2021. Fig. 1 depicts the collected fire data and includes a least squares fit line to indicate the general trend of the data.

A system's resilience, or ability to withstand major wildfires, depends on many factors, such as redundancy. Redundancy is one of the resilience components highlighted in [4] and described in [5]. Understanding the grid's ability to maintain operations during an event, like a forest fire, requires a Geographic Information System (GIS) analysis of

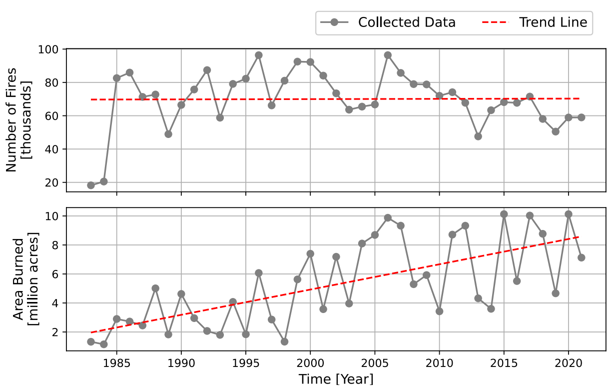

FIGURE 1. Frequency and acres burned from 1983 to 2021 in the U.S.

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its topology and proximity to likely hazard locations. Therefore, this work explores the transmission grid's redundant topological connections to determine at-risk communities prone to long-term outages as the result of a wildfire event near transmission lines.

Abedi et *al.* highlights various approaches useful for performing a vulnerability analysis, which usually includes a topological methodology, flow-based methods, logical reviews, or functional assessments [6]. Each of these methods offer different levels of detail and complexity. For instance, flow-based methods require a detailed physics-based model that simulates the voltage and power flows throughout the grid [7], [8]. Whereas topological and logical methods provide a more simplistic and easier to implement approach because they don't require extensive information, detailed models, and complex modeling software.

Topological and logical methods are useful for assessing the grid's connections [9] and identifying critical elements [10], [11]. Approaches, like minimum cut-set vulnerability analysis, assess cascading failures [12] or identify lines prone to overuse during a contingency event [13], or identify vulnerable nodes using graph theory betweenness centrality [14].

An assessment of electric grid vulnerabilities usually entails metrics that ensure the avoidance of a complete loss of power throughout a system. These assessments often do not focus on the impacts of wildfires on a specific location. This paper, therefore, defines a novel methodology for using existing topological approaches and focuses on identifying a specific risk level of a substation (and its connected community.) More specifically, this paper's contribution is to show how graph theory analysis techniques can be combined with wildfire probabilities to determine the risk of grid outages to a specific location. To do this, the analysis combines a grid topology assessment with spatial wildfire Burn Probabilities (BP.)

The two topological approaches include: betweenness centrality [15] vulnerability analysis and a minimum cut [16] complete separation (or community isolation) analysis. The intent of the centrality analysis is to identify connections (or electrical lines) of greatest importance to each community. Importance, in this case, refers to the lines necessary for continuation of power, or maintaining stable grid conditions for a particular community and the connected generators. An analysis from this perspective is novel. A minimum-cut analysis discovers the lines and their lengths that can separate a community's substation from the grid with one cut, which is commonly left out of typical vulnerability assessments.

II. BACKGROUND

Common methods for assessing the electric grid do not provide a community perspective. The N-1 contingency analysis, for example, involves an iterative power flow simulation that systematically removes a line and checks to see if the system continues to provide stable operations as a whole [17]. It does not, however, require that all loads continue to be served. Thus, the N-1 takes a top-down approach and does not focus on the vulnerabilities of each community. Whereas the proposed methodology intends to assess vulnerabilities from the perspective of the community that is connected to a single substation using topological approaches.

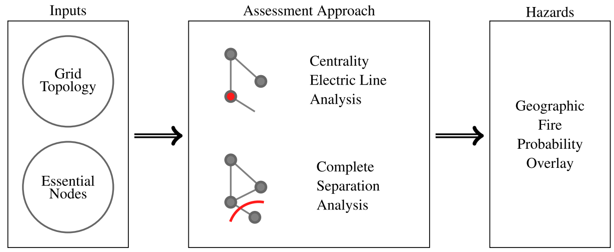
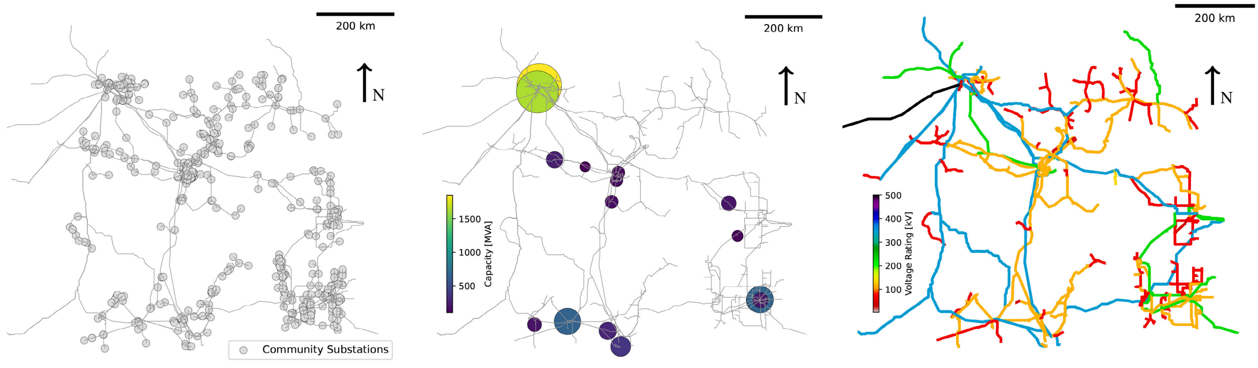


FIGURE 2. Digram depicts the implementation of the topological assessment approaches to identify at-risk critical lines and one-cut sections that serve substations.

Topological analysis approaches identify grid vulnerabilities by evaluating node connections. Historically, betweenness centrality was successfully applied to the electric grid to identify critical lines that would result in the highest percentage of lost load [18] and assess line limits [19]. One research paper found that when using topological procedures, the analysis can consider the system's structures and the connected generators and loads [20], which were included in this analysis. Other topological approaches using betweenness centrality were useful for understanding critical lines necessary for maintaining stable operations when faced with a natural disaster like a hurricane [21]. However, like most of the other studies these documented approaches consider impacts to the system at-large and how to survive an outage by reducing loads or through reinforcement immediately before an event [22]. Yet, none of the past literature used betweenness centrality to identify critical lines for each connected community powered by a substation.

The minimum cut set assessments can also identify grid vulnerabilities. Most use a topological method for large-scale power failures [23]. For instances, one approach used the minimum cut analysis to evaluate the impacts of sequential attacks and the corresponding effect of cascading failures [12]. Again, no papers, to the best of the authors knowledge, applied the technique for individual community vulnerability assessments.

The community centric vulnerability studies that do exist often focus on individual critical services within a community. Tools like the Resilient Node Cluster Analysis Tool (ReNCAT) identify the location and boundaries of a micro-grid useful for maintaining power to critical services [24] in a distribution grid. Some topological approach used to identify community related vulnerabilities include Graph Theory community detection techniques [25]. Community detection was also used to identify critical lines [26], but not for specific substations.



(a) Substations (b) Generation Sources (c) Transmission Lines

FIGURE 3. The analysis includes geographic data: community substation locations (a), generation source locations (b), and transmission line locations and interconnections (c).

Wildfires impact the electric grid significantly. Studies examine the challenges and solutions associated with fires [27]. Modeling attempt to forecast the overall risks [28], but current literature lacks an assessment methodology that identifies and compares critical line segments with a spatial BP. This work, which compares critical lines and BP, provides a specific and actionable results that defines where the system should be hardened to improve resilience for a location or where communities should consider a contingency plan in preparation of an outage caused by a wildfire.

III. METHODOLOGY

Two topological vulnerability analysis approaches were used to identify the locations of at-risk communities connected to the transmission grid via a substation. The approach, depicted by the bock diagram in Fig. 2, includes the gathering of inputs, administration of analysis approaches that utilize the inputs, and a review of the results. The assessment approaches, depicted in the middle block of Fig. 2, were the Graph Theory Betweenness Centrality and Minimum Cut analyses, which are described in Sections III-B2 and III-C2 respectively.

A. GEOSPATIAL INPUT DATA

The spatial data includes location information of communities of interest using the available substation data, grid topology data, and generation source locations [29]. Geospatial data also included hazard probability results provided by other modeling efforts.

The grid topology input data includes the location and information about substations that power local communities (Fig. 3a), generation resources (Fig. 3b), and the transmission lines connecting them all (Fig. 3c).

Fig. 3a depicts the substation locations with the gray circles. Substations connect communities with power from the transmission electric grid and thus a useful proxy for representing a community of people. Areas where there are high concentrations of them likely indicates metropolitan areas. Dispersed or sparse substations often represent communities within rural locations that are more spread out and remote. The generation systems are also dispersed throughout the area of interest, as shown in Fig. 3b. The highest capacity of generation, indicated by the size of the circles, resides in the top left of the map in Fig. 3b.

The transmission electric grid spans significant distances throughout the U.S. The high voltage electric lines transfer power from the generation sources to substations that support rural and urban communities. At the substations, the voltage is reduced and then distributed to individual loads via low voltage distribution lines. The transmission system used in this evaluation is depicted in Fig. 3c. Fig. 3c provides an overview of the topology and depicts voltage for each line with a range of different colors that indicate a voltage between 100 kV to just over 500 kV.

B. CENTRALITY VULNERABILITY ASSESSMENT

The centrality assessment first discovered each substation's dependency on lines that connect it with large-scale generation scattered throughout the grid. Then, it compared the lines of greatest importance with a hazard probability map to estimate each substations vulnerability. Ultimately, the result found at-risk substations that had critical lines within (or passing through) high probability burn areas.

Analysis of centrality, using the Betweenness algorithm, provides a legitimate review of grid vulnerabilities. A comparison of vulnerability techniques in past work includes the same betweenness algorithm and power-flow models. The past work found that the two approaches produce very similar results [30].

1) ANALYSIS OVERVIEW

This assessment calculated the centrality of substation connections to multiple generators. The implementation only considered major generators over 100 MW connected to the transmission system. The approach used a graph (G) of the electric grid and the substation and power generation nodes, represented by S and P in Algorithm 1 respectively.

Algorithm 1 Centrality of Substations & Generators

Input: G, S, P; /*Graph of grid & nodes
Output: C ; /*Substation centrality
Function SubstationCentrality(S,P):
$C \longleftarrow G, S, P$
for all $ns \in S$ **do**
  for all $np \in P$ **do**
    $Path_i = ShortestPath(G, ns, np)$
  end for
  $G_j = CreateGraph(Path)$
  $C_j = Centrality(G_j)$
end for
return C

Algorithm 1 provides a general overview of the centrality function, which involves two for loops that iterate over all of the substation nodes (S) and power generation nodes (P). Within the for loops the shortest path in G between each substation and generator was discovered using the Dijkstra method [31]. The shortest path calculation considered each conductor's voltage rating as a weight. The voltage rating weight meant that the shortest path often followed a higher voltage rather than just the minimum length. Each path (i) was combined into a graph and j graphs were produced for each substation. Finally, the centrality, described in Section III-B2, for each substation graph (G_j) was computed.

2) BETWEENNESS CENTRALITY

Betweenness centrality was used to find the most important lines in each graph G_j, which was a subgraph of G that connected the substation of interest with the generators. Many types of centrality metrics have been used in past work to investigate network resilience [32]. Some were applied to various networks including water distribution systems [33] and the electric grid [34]. The betweenness centrality used in this work was originally defined by [35]. And this implementation used the approach defined in [36] using Python momepy [37] through the Networkx wrapper [38]. The approach identifies the centrality for node v using Eqn. 1:

$$c_B(v) = \sum_{s,t \epsilon V} \frac{\sigma(x, y|v)}{\sigma(x, y)} \tag{1}$$

where V is the set of nodes, $\sigma(x, y)$ represents the number of shortest paths, and $\sigma(x, y|v)$ are the number of paths that pass through a v that are not x or y. In this case, the betweenness values were normalized using:

$$\frac{2}{((n-1)(n-2))} \tag{2}$$

where n is the number of nodes in the graph. The approach added heterogeneity to the analysis by considering weights associated with the graph's edges (or transmission lines). In this case, the weights assigned to each edge were the voltage rating for each line. Therefore, the algorithm assessed each node by summing the weights of all its adjacent edges using Eqn. 3.

$$x_i = \sum_{j=1}^{N} a_{ij} w_{ij} \tag{3}$$

The a and w, in Eqn. 3, represent the adjacency and weight matrices for nodes i and j.

Algorithm 2 Community Separation Algorithm

Input: G, S ; /*Graph of grid & nodes
Output: MC, L ; /*Minimum cuts & length
Function CommunitySeparationRisk(S,P):
$MC, L \longleftarrow G, S$
c = $graphCenter(G)$
for all $ns \in S$ **do**
  for all $an \in atRisk$ **do**
    MC = [*minimumCut*(G,c,ns)]]
    $atRisk \longleftarrow MC = 1$
    for $i \leftarrow 0$ to $len(path)$ **do**
      if $path[i] \ni$ atRisk **then**
        if $G.degree(path[i]) \leq 3$ **then**
          $InPath = path[i]$
        else
          $InPath = path[i]$
          break
        end if
      else
        $InPath = path[i]$
      end if
      $segments_i = computeDistance(path[i], path[i-1])$
    end for
  end for
  $L = [totalDistance]$; /*Minimum cuts & length
end for
return MC, L

C. ISOLATION VULNERABILITY ASSESSMENT

Substations, and their connected communities, at the edge of the grid are prone to separation because of limited connections (or adjacent edges.) This analysis considers this scenario and identifies at-risk substations by first finding the ones that can be disconnected with one cut. Then, the analysis approach computes the distance of all the grid line segments that if cut once would segregate the substation and the community would not receive power from the electric grid.

1) ANALYSIS OVERVIEW

Algorithm 2 describes the iterative process for evaluating the electric grid's graphic representation to identify at risk communities in danger of complete separation. This function uses the inputs G and the substation nodes (S) to find the minimum cuts (MC) for each substation and the length of the lines connecting at risk (i.e., one cut to remove) substations. The iterations start by looping through all the substation nodes. At this stage, the algorithm computes the minimum cuts (described in Section III-C2) and substations with only one minimum cut are found. The second embedded iteration only consideres the at-risk substations and computes the path of each substation to the center of the graph. Then, the algorithm iterated through each path to find the segments of the grid within the minimum cut of one. In this loop, the path point is first evaluated to see if it is within the at-risk data set. If it is considered at-risk, the point is added to the in-path set of data. If not, the point is evaluated further to compute the number of adjacent edges. Adjacent edges less than or equal to 3 meant that the point could be added to the in-path data, but if not the iterative assessment ends and moves to the next at-risk substation. The adjacent edges threshold number of 3 was chosen because it was the maximum number of connections observed in this demonstration grid.

2) GRAPH THEORY MINIMUM CUTS

Partitioning the electric grid into segments that do not have a reasonable power source, or access to a source, results in power outages for customers. This was represented using the Graph Theory minimum cuts analysis [39], where the electric grid was represented by a connected graph G, and a set of cuts will result in two or more partitions (or a disconnected G) [40]. This analysis identifies vulnerabilities in G by finding segments that are removed by cutting the smallest number of edges. It also identifies the length of the single segment that if removed will de-energize a community.

D. WILDFIRE HAZARD PROBABILITIES

The final step in the vulnerability analysis involved a comparison of the centrality and minimum cut results with BP data. The U.S. National Forest Service Research Data Archive provides wildfire risk assessment for all lands throughout the U.S. [41], and plotted for this paper's area of interest in Fig. 4. Scott et *al.* describes how this BP helps characterize infrastructure exposure and potential effects due to a fire [42]. The probability map considers various elements including weather, fuels and topography, large-fire suppression, and fire growth and behavior [43]. The probability was determined using simulation outputs. The BP was computed by dividing the number of times an image pixel section burned by the amount of model runs, and thus provides a relative approximation.

Wildfires in the area of interest often occurred in forested areas in or around mountains. Fig. 5 provides the location, boundaries, and reported burn acres for fires that occurred between 1911 and 2014 [44]. A comparison of the actual burn areas with the BP map shows that many of the historical wildfires occurred within high probability zones - shown in the Fig. 6 map. For instances, fires in the lower left are clearly within the high BP areas. This includes the large fire that burned over 500,000 acres in 2011. There were also many fires in the forested area in the center and lower center of the map that correspond with the high BPs. Some fires occurred in the low probability areas, but most of these events had very small boundaries.

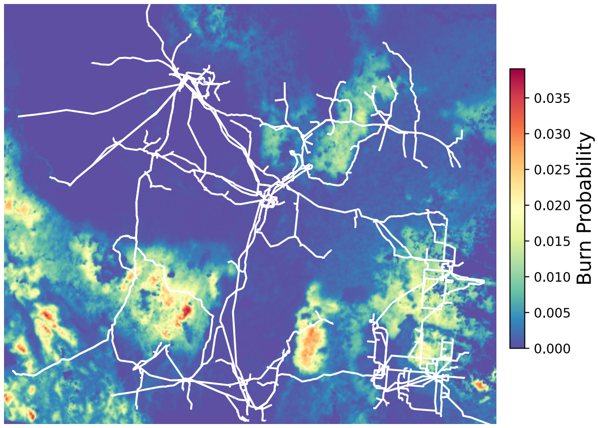


FIGURE 4. Burn probabilities and white lines represent the transmission power lines.

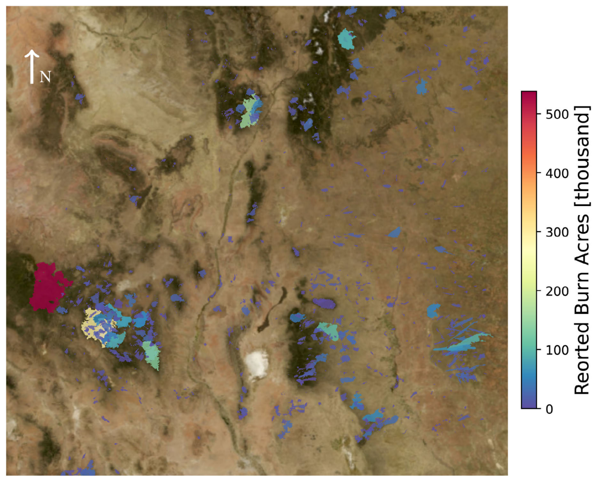


FIGURE 5. Satellite image compares the burned areas with forested areas.

IV. RESULTS

This section reviews the results for the two approaches on an electric grid subject to wildfires. In Sec. IV-A, the centrality of each substations' paths to the generators were identified and compared with the wildfire potential. The final results subsection (Section IV-B) describes outcomes from the isolation vulnerability analysis that identified areas prone to complete separation due to a fire.

A. CENTRALITY VULNERABILITIES

A community substation's ability to remain powered during a contingency event anywhere on the grid may vary depending on how much it relies on one or more line segments. This means that the removal of a line segment, that was centrally located between a substation and multiple genera-

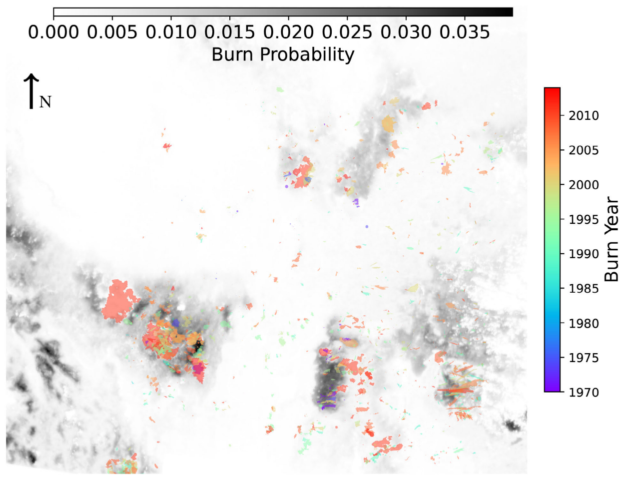
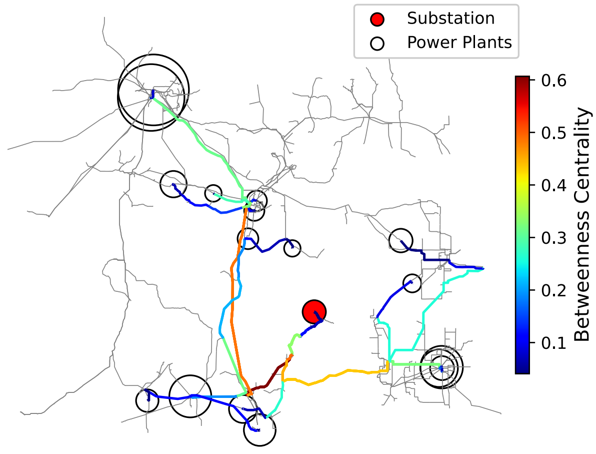


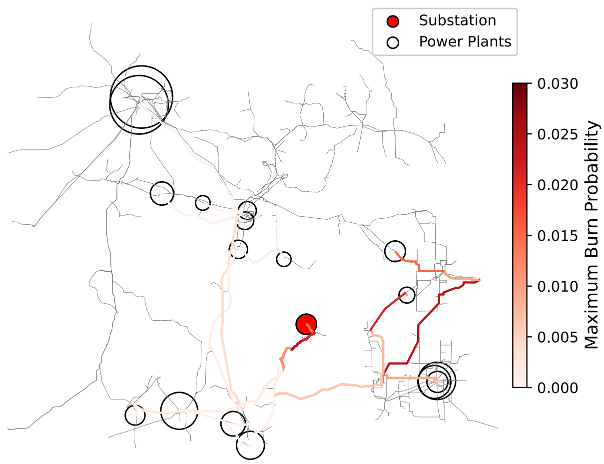
FIGURE 6. **Map that compares past fires with the estimated burn probabilities.**

TABLE 1. **Betweeness burn probability statistics.**

	Betweenness Metric	Burn Probability
Mean	0.29	0.003
Standard Devaiation	0.18	0.0046
Minimum	0.033	0.0
25%	0.11	0.0004
50%	0.28	0.001
75%	0.46	0.004
Maximum	0.67	0.027



(a) Betweenness Centrality



(b) Burn Probabilities

FIGURE 7. **The maps in (a) and (b) depict one of the 585 substation subgraphs. (a) describes the results from the betweenness centrality and (b) shows what burn probability areas the lines in this subgraph pass through.**

tors scattered throughout the grid, may result in inadequate power flows that will require the disconnection of the substation.

This analysis iterated through all of the 585 substations to discover the lines that each depend on the most. The analysis took about 300 seconds (5 minutes) to execute. Fig. 7a depicts an example substations grid connectivity. The graph, depicted with the colored lines describing each segments centrality, connects the sample substation (shown with the red circle) with the many generators (black circles). The colors of the lines in this graph depict the betweenness centrality results, which describe which lines are most important for maintaining system operations in this subgraph. The lines most important to this sample substation pass through areas with varying burn probabilities as indicated by Fig. 7b.

A summary of the betweenness and BP values in this area of interest are provided in Table 1. This table describes the average, minimum, and maximum betweenness metric values and the BP. Betweenness values ranged between 0.033 and 0.67 and observed BP were between 0 and 0.027.

The results from each of the 585 substation subgraphs were aggregated and summarized in Fig. 8 and Fig. 9. An overview of the maximum centrality results for all of the substations is shown in the Fig. 8 map. This map describes the dependence of each substation on a centrally located line as: high dependence using orange and red colored circles; medium dependence with circles colored in yellow; and low dependence using green and blue circles. Visual inspection of the map indicates that sections of the grid tended to have similar results, which was expected since substations close by one another will likely depend on the same lines and also located in the same area of the grid.

Fig. 9 describes the final step in the centrality analysis, which was to identify the maximum BP for each of the most centrally located lines. The map in Fig. 9 indicates that substations located in the middle of the grid were subject to lower BP crossing their most centrally located lines. Substations located in the lower right portion of the map had centrally located lines that crossed areas with slightly higher probabilities than the middle ones. And the substations located in the top and left areas of the map had centrally located lines that crossed the highest BP areas.

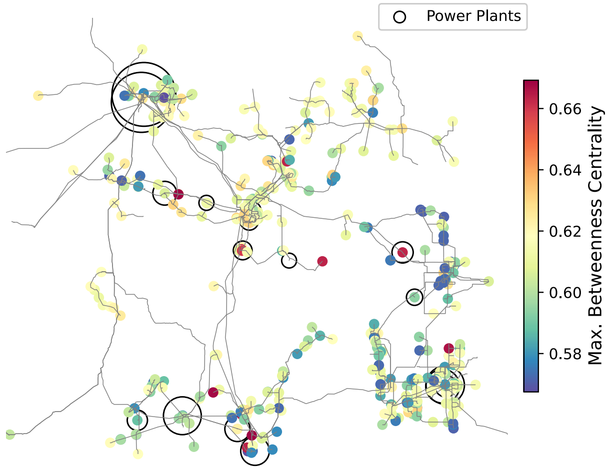


FIGURE 8. This map indicates how much each substation relies on a centrally located line segment by plotting the maximum betweenness centrality value.

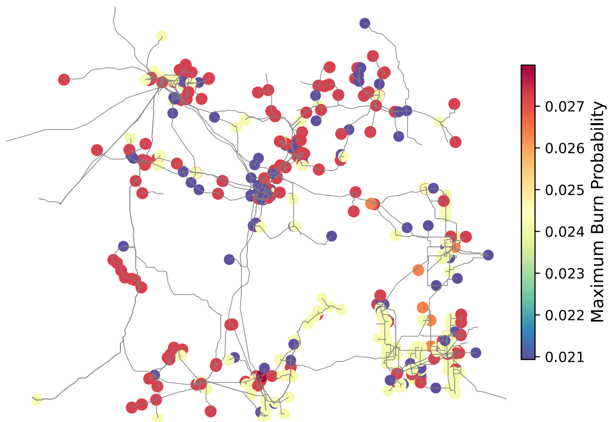


FIGURE 9. The substation colors, shown in this map, indicate the maximum burn probability that the most centrally located lines for each substation cross.

B. ISOLATION VULNERABILITIES

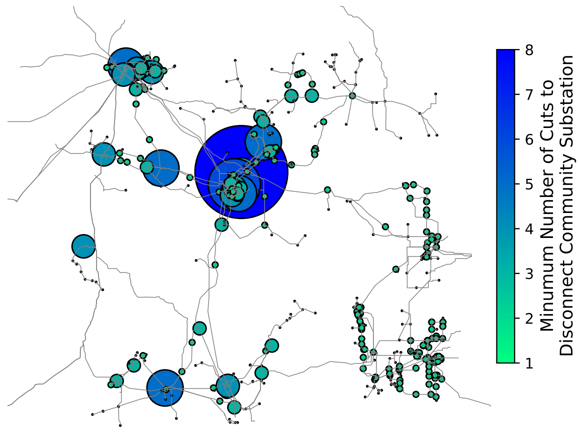
An evaluation of each substation isolation potential involved the identification of single cut line segments prone to wildfire damage. This analysis took about 1.22 seconds. Similar to the centrality analysis, this approach iterated through all of the substations to find lines that could disconnect the substation with one cut.

The isolation vulnerability statistics are described in Table 2. The average number of edges needed to cut to disconnect a substation was 1.69. The electric conductor line segments ranged from 0.02 to 188 km, but most remained below 58 km. And the BP in and around the electric grid ranged from 0 to 0.027.

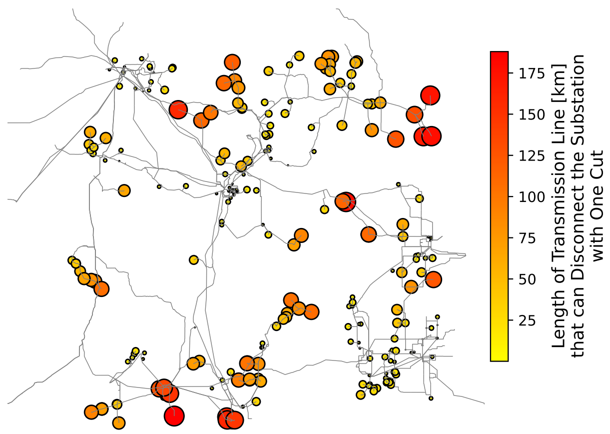
The multi-step process included the analysis of all of the substations. Fig. 10a provides a map of each substation where the size and color represents the number of minimum cuts needed to disconnect it from the grid. The maximum cuts required to remove a substation was 8, as indicated by Fig. 10a, which exists in the center of the map.

TABLE 2. One-cut burn probability statistics.

	Number of Edges to Cut	Edge Distance [km]	Burn Probability
Mean	1.69	37.44	0.0043
Standard Devaiation	0.83	42.65	0.0062
Minimum	1	0.02	0
25%	1	5.27	0.0004
50%	2	20.33	0.001
75%	2	58.41	0.004
Maximum	8	187.9	0.027



(a) Minimum Cuts to Isolate Substation



(b) Length of section that with one cut will isolate a substation

FIGURE 10. The two maps depict the number of cuts it takes to remove the substation (a) and the length of the one cut section (b).

After identifying the total number of cuts required to isolate each substation, the next step identified all those that only required one cut to remove. About 255 (46%) of the substations require one cut to remove and are colored in the Fig. 10b map. This map also indicates the length of the transmission line that if damaged could disconnect a substation completely. The lengths ranged from 0.021 km to about 188 km. The average substation that could be removed with one cut was connected to line segments that on average

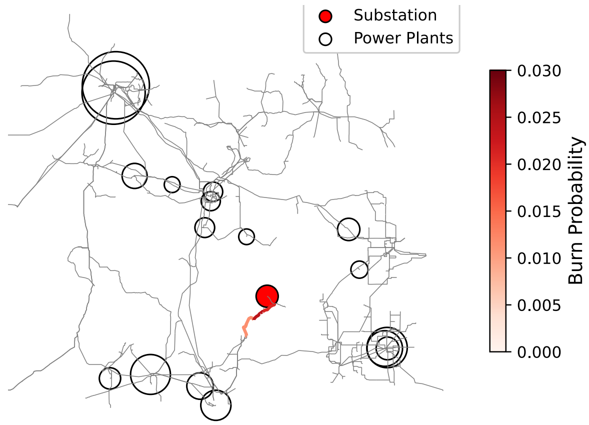


FIGURE 11. This figure depicts the burn probability for the line segment that with one cut can remove the substation from the electric grid.

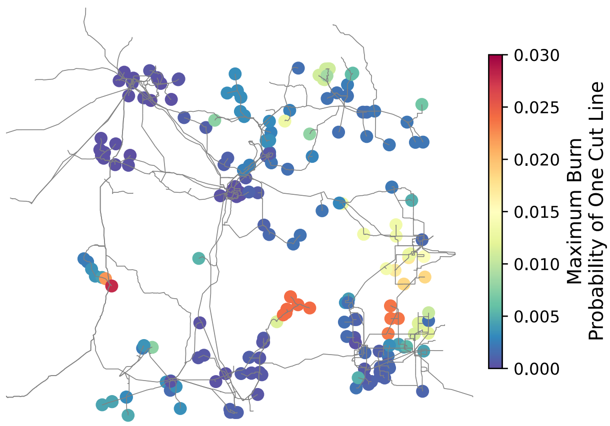


FIGURE 12. The substation colors, shown in this map, indicate the maximum burn probability for the line segments that if cut once could disconnect the substation completely from the grid.

were 37 km long. The top 75% were found to be 58 km and above, while the bottom 25% were below 5 km.

The next step in the analysis compared the segments of the transmission line that can be cut once to remove a substation with the BP map. Fig. 11 indicates which line segment would have to be cut only once to eliminate power to the sample substation. For this substation, the one cut line segment happens to be within an area that has a high BP.

Fig. 12 depicts where the single cut lines for each substation reside in relation to the estimated BP. Some substations have long single cut lines, as discussed earlier and displayed in Fig. 11, that pass through low risk burn areas. There are also some substations with short single cut lines in the lower left of the Fig. 12 map that pass through high probability burn areas.

V. CONCLUSION

The two assessment approaches identified critical lines and their proximity to high probability wildfire burn locations. The community centric betweenness centrality assessment approach found the most critical lines that connect each substation to the major generation sources. Many of the communities in the center of the grid were fount to be at a lower risk due to the proximity to likely wildfires than those on the outer parts of the grid. This was because the communities in the center had critical lines that did not pass through high probability burn zones, whereas communities on the out sectors were near forested areas with high BPs.

The minimum cut analysis found at-risk communities that could be separated from the grid with one cut. The assessment also identified the length of the one cut section, which provided further information on the community's risk. Then, after comparing the one cut sections with the BP a few communities stood out. As expected, the highest vulnerabilities were located in isolated areas that included minimum adjacent edges. Also, the electric lines pass through high forested areas with high BPs.

This study reviews the potential for two topological approaches to identify grid vulnerabilities from the perspective of each connected community. Further studies can elaborate on this work and incorporate power flow models to confirm and complement the topological methods.

ACKNOWLEDGMENT

The paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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