Ecological Uniqueness for Understanding Line Importance in Power Grids

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***Abstract*— The identification of critical components in electric power grids is an important challenge power engineers face. Similarly, many ecologists face the challenge of identifying important species in food web networks. Drawing similarities between power grid networks and food web networks, this study utilizes proposed identification methods from ecology literature to identify critical components in electric power grids. These ecological methods used include measures of Sum of the Trophic Overlap (STO) and Weighted Trophic Overlap (WTO). We also study a method proposed from power engineering literature that uses the Normalized Line Outage Distribution Factor (NLODF) to compare the different methods. The intention of this study is to determine if bio-inspiration in criticality metrics provides a feasible tool to use in power grid analysis. The proposed engineering method utilizing NLODF is found to be more accurate in identifying critical lines in power grids when considering all lines in the grid. However, the ecological metric STO is found to be as good as NLODF when considering the top 10, 20, or 30% of lines. STO was the most accurate metric in the largest grid analyzed, suggesting STO may be more accurate in larger grids. The comparable performance of the ecological and engineering methods suggests the ecological methods can be used to accurately identify critical components in electric power grids.**

Keywords— bio-inspired design, critical lines, power grid design, resilience, trophic overlap, line outage distribution

I. Introduction

Critical power grid components have a significant impact on the grid function. Power lines are of particular interest to power engineers because line failures contribute to major damages and blackouts [1]. The increased complexity of modern power grids exacerbates these negative impacts, increasing the importance of identifying critical lines. Outages result from weather events, cyberattacks, and/or equipment failures and can cost billions of dollars while impacting every aspect of daily life [2, 3]. Failure analyses are needed that are capable of analyzing *large* and *complex* grids quickly to determine areas that need immediate attention.

Current power grid failure analyses centers around *N-x* contingency analyses, where N is the number of grid components (lines, buses, generators, etc.) and x is the number of components that fail, to determine the impact of outages on the overall network [4]. *N-1* is the standard reliability measure used by the North American Electric Reliability Corporation (NERC) and ensures that the grid can survive the failure of one component [5]. Multiple element (x>1) contingency analyses becomes *infeasible* for large grids (for example, the Western Electricity Coordinating Council system with around 20,000 components) due to an exponential increase in the number of possible combinations of outages [6]. Most grids have bus numbers in the hundreds and thousands, meaning that *N-x* is primarily relegated to hypothetical and small-scale investigations. The identification of critical grid components, however, can help focus failure analyses on the most important components, dramatically reducing the computational efforts needed. Critical component identification is still a nontrivial task, with current methods limited by intense computational requirements and a lack of grid physics (represented by the power flow equations) [7]. Identifying critical power grid components will improve planning analyses and protection efforts, for example advanced security or functional redundancy, reducing the need for excessive computational analysis and saving costs with unneeded redundancy.

The method proposed in this paper to identify critical power grid components is based on ecological methods used to identify critical species in ecological food webs. Species in food webs, analogous to the components in power grids, cause cascading extinctions among other issues when harmed [8]. Ecologists identify "keystone" or important species in food webs to understand how best to allocate resources for conservation and protection efforts [9]. Learning from the efforts of ecologists may offer computationally tractable routes

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for identifying important power grid components. The use of analogies with food webs is supported by prior success that modeled grid architecture after the functional and structural characteristics of food webs to improve grid resilience [5, 10, 11].

A. Engineering Method to Identify Critical Actors

No one method for identifying critical components in power grids has been shown to give an accurate ranked list of important power grid components [12]. The use of *Betweenness Centrality* (from graph theory) measures how often a component lies on the path between any two others and has been used to identify more central, i.e. more critical, grid components [13, 14]. This method, however, focuses exclusively on the *structure* of the network and does not account for the flow of power through the grid components. Researchers have studied the inclusion of power flow in Betweenness Centrality, requiring exhaustive tests to determine importance (computationally inefficient) [14].

A common power system sensitivity measure called the *Line Outage Distribution Factor* (LODF [15]) has been used for its ability to find the importance of grid lines and accounts for power flow. LODF is a useful but approximate sensitivity-based method to rank line criticality based on power flow impacts that result from transmission line outages. LODFs are then incorporated to improve Betweenness Centrality calculations and *N-x* contingencies analyses. Eq. 1 shows the calculation for LODF of line *i* due to the outage of line *j* where Δf_i is the change in flow on line i and f_j is the initial flow on line j [16]. The change in flow is calculated by the power transfer distribution factor (PTDF) which tells how a line responds to a change in generation and load.

$$LODF_{i,j} = \frac{\Delta f_i}{f_j} \tag{1}$$

B. Ecological Method to Identify Critical Actors

The need to identify key places to invest limited resources such that the entire network benefits is one that is shared by both power grids and ecosystems. Conservation efforts require the identification of critical species to implement ecosystem conservation efforts. Ecological methods to determine actor importance in a network of species also stem from graph theory [17]. A network structure-focused measure that ranks the functional differences between species as related to their role in the ecosystem (known as 'uniqueness') is the *Sum of the Trophic Overlap* (STO [18]). A modification that includes the proportion of prey in the predators' diets is the *Weighted Trophic Overlap* (WTO [19]). Like LODF, WTO is able to account for both network structure (connectivity) and flow (how much is exchanged between nodes). This paper seeks to benefit from conservation-motivated methods of understanding ecosystem actor importance to identify critical components in electric power grids.

II. Methods To Identify Critical Components

A. Case Studies

Seven publicly available grid case studies are used: 5-, 6-, 7-, 9-, 14-, 37-, and 57-Bus grids from PowerWorld [20]. Smaller cases are chosen as they permit exhaustive calculations of *N-x* violations, enabling the validation to be done using accurate rankings. Fig. 1 shows the 5-Bus grid and Fig. 2 shows the matrix used to calculate WTO. Replacing the nonzero entries with ones results in the matrix used to calculate STO. The entries are the flows between nodes (i.e. grid components, set as the buses, generators, and lines) in the directional graph (digraph). Note: prior work that applied ecological methods to electric power grids did not model transmission lines as nodes [5, 10, 21]. Modeling transmission lines as nodes in our research allows us to treat them as if they were species in a food web for STO and WTO calculations. STO and WTO are calculated for all components in the digraph. Only the lines between buses are of interest because the grid models assume a direction connection between generators and buses (no transmission line). The bus and generator components are ignored in this work as NLODF, our comparison, is only calculated for lines. These exclusions resulted in the analysis of five lines for the 5-Bus grid in Fig. 1 and 7, 10, 9, 20, and 49 lines for the 6-, 7-, 9-, 14-, and 37-Bus grids, respectively.

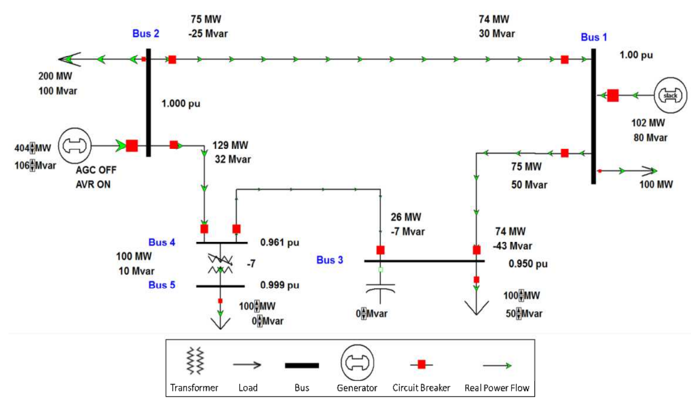

Figure 1. 5-Bus Grid (figure from PowerWorld [20]). The lines, buses, and generators form the directional graph nodes.

$$\mathbf{M} = \begin{array}{c} \\ G1 \\ G2 \\ B1 \\ B2 \\ B3 \\ B4 \\ B5 \\ GL1 \\ GL2 \\ BL3 \\ BL4 \\ BL5 \\ BL6 \\ BL7 \end{array} \begin{array}{c} \begin{array}{cccccccccccccc} G1 & G2 & B1 & B2 & B3 & B4 & B5 & GL1 & GL2 & BL1 & BL2 & BL3 & BL4 & BL5 \end{array} \\ \begin{pmatrix} 0 & 0 & 96 & 0 & 0 & 0 & 0 & 96 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 404 & 0 & 0 & 0 & 0 & 404 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 74 & 0 & 0 & 0 & 0 & 74 & 0 & 0 & 0 & 0 \\ 0 & 0 & 78 & 0 & 0 & 126 & 0 & 0 & 0 & 0 & 78 & 126 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 26 & 0 & 100 & 0 & 0 & 0 & 0 & 0 & 26 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 96 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 404 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 74 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 78 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 126 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 26 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 100 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

Figure 2. Intercompartmental Flow Matrix (M) for the 5-Bus network of Fig. 1. GL and BL represent lines from a generator and bus respectively.

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B. Normalized Line Outage Distribution Factor

Normalized Outage Distribution Factor (NLODF) is a method proposed by Narimani *et al.* that ranks a power system's lines in order of importance, with respect to their influence on contingencies in the rest of the grid [15]. NLODF uses the computation of Line Outage Distribution Factor to determine line importance, predicting the effect of the removal of one line on the distribution of power through the rest of the grid. The distribution factor for each line is calculated for each line removal in LODF, resulting in a vector of distribution factors. NLODF takes this vector output and converts it to a scalar using the average and standard deviation. The calculation for NLODF is shown in Eq. 2. A higher NLODF value means that the associated line has a larger *negative* impact on the network when removed and therefor is more important.

$$NLODF(i) = \frac{mean(abs(LODFs))}{std(abs(LODFs))} \tag{2}$$

C. Trophic Overlap

In ecology, *trophic* refers to a species' relationship with nutrients. Trophic levels in a food web are determined by the way species produce or consume nutrients (e.g. producers, primary consumers, secondary consumers, etc.) [22]. Species in the same trophic level gain nutrients from the same trophic level source. Species that share many interactions will have greater trophic overlap while species that do not will have less trophic overlap [23]. Species in the same trophic level will have a lot of *trophic overlap* because they share many interactions through predation. STO and WTO measure the *uniqueness* of an actor by how unique its trophic interactions are as compared to other species in the food web. This measure of uniqueness is slightly different from the *importance* of a species to the food web, but uniqueness *is* considered when measuring importance because unique species are less replaceable [18, 24]. Higher STO and WTO values indicate that the component is *less* unique, i.e. it has more in common with other components in the network.

The calculation of STO and WTO first requires that the network be modeled as a directional graph (digraph). Ecosystems digraphs select species as nodes and links as their caloric predator-prey exchanges (or mutually beneficial interactions in plant-pollinator networks). The energy transfer between species in a food web is direct through predation. The energy transfer between grid components, such as a bus, happen via transmission lines – also modeled as components here. Interactions are then quantified in an intercompartmental (i.e. doesn't consider flows that cross the system boundaries) flow matrix (**M**), such as the one in Fig. 2.

The calculation of STO considers only the network *structure* and WTO considers the flow magnitude being transferred across that structure, otherwise their calculations mirror each other. STO utilizes an undirected structure matrix (**US**, Fig. 3a) using ones and zeros: one signifies an interaction from actor *i* to *j* and zero no interaction. The weighted matrix (**WF**, Fig. 3b) for WTO contains a flow percentage to represent

US =	G1	G2	B1	B2	B3	B4	B5	GL1	GL2	BL1	BL2	BL3	BL4	BL5
G1	0	0	1	0	0	0	0	1	0	0	0	0	0	0
G2	0	0	0	1	0	0	0	0	1	0	0	0	0	0
B1	1	0	0	1	1	0	0	1	0	1	1	0	0	0
B2	0	1	1	0	0	1	0	0	1	0	1	1	0	0
B3	0	0	1	0	0	1	0	0	0	1	0	0	1	0
B4	0	0	0	1	1	0	1	0	0	0	0	1	1	1
B5	0	0	0	0	0	1	0	0	0	0	0	0	0	1
GL1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
GL2	0	1	0	1	0	0	0	0	0	0	0	0	0	0
BL3	0	0	1	0	1	0	0	0	0	0	0	0	0	0
BL4	0	0	1	1	0	0	0	0	0	0	0	0	0	0
BL5	0	0	0	1	0	1	0	0	0	0	0	0	0	0
BL6	0	0	0	0	1	1	0	0	0	0	0	0	0	0
BL7	0	0	0	0	0	1	1	0	0	0	0	0	0	0

(a)

WF =	G1	G2	B1	B2	B3	B4	B5	GL1	GL2	BL1	BL2	BL3	BL4	BL5
G1	0	0	0.28	0	0	0	0	1	0	0	0	0	0	0
G2	0	0	0	0.50	0	0	0	0	1	0	0	0	0	0
B1	0	0	0	0	0.37	0	0	0	0	1	0	0	0	0
B2	0	0	0.22	0	0	0.5	0	0	0	0	1	1	0	0
B3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B4	0	0	0	0	0.13	0	0.50	0	0	0	0	0	1	1
B5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GL1	0	0	0.28	0	0	0	0	0	0	0	0	0	0	0
GL2	0	0	0	0.50	0	0	0	0	0	0	0	0	0	0
BL3	0	0	0	0	0.37	0	0	0	0	0	0	0	0	0
BL4	0	0	0.22	0	0	0	0	0	0	0	0	0	0	0
BL5	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0
BL6	0	0	0	0	0.13	0	0	0	0	0	0	0	0	0
BL7	0	0	0	0	0	0	0.50	0	0	0	0	0	0	0

(b)

Figure 1. (a) Undirected Structure Matrix (US). (b) Weighted Flow Matrix (WF) based on Fig. 2 network.

flow magnitude in place of the **US** matrix's ones. Energy flow matrices from PowerWorld [20] are used to create **US** and **WF**.

Eq. 3-6 show the calculations for STO. D_j is the degree of species *j* or its total number of interactions. **DUS** is the degree normalized matrix. **IM** in Eq. 5 is the interaction matrix, where *n* is the maximum shortest path in the network plus 1. Once **IM** is found, the strengths of the interactions can be determined using various threshold values ranging from zero to one. If an element in **IM** is greater than the predetermined threshold value that interaction is considered strong. If the element is less than the threshold value, the interaction is weak. The **AM** matrix contains these strong and weak identifiers. Each threshold value has its own **AM** matrix. Looking at a single **AM** matrix, if species *k* and *m* both have strong interactions with species *q* (determined by comparing AM_{kq} vs. AM_{mq}), species *k* and *m* experience trophic overlap. The matrix **TO** summarizes the trophic overlaps for all species/actors in the network. Each **AM** matrix has a corresponding **TO** matrix, used to calculate Eq. 6. STO is calculated for each species in the network using the set of **TO** matrices.

WTO calculates a weighted degree in place of D_j in Eq. 3, found by summing the rows and columns of **WF**. WTO then uses Eq. 4-6 with matrix **DWF** in place of **DUS** and WTO in place of STO. More details behind the derivation of STO and WTO, as well as some worked examples, can be found in Lai *et al.* and Xiao *et al.*, respectively [18, 19].

$$D_j = \sum_{i=1}^{k} \boldsymbol{US}_{ij} \tag{3}$$

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$$DUS_j = \frac{US_j}{D_i} \quad (4)$$

$$IM = \frac{1}{n}(DUS + DUS^2 + \cdots + DUS^n) \quad (5)$$

$$STO_j = \sum_{T=0}^{1} TO(T)_j \quad (6)$$

D. Validation

N-x analyses are run for 5-, 6-, 7-, 9-, 14-, 37-, and 57-Bus network case studies. Smaller case studies are chosen for the ability to exhaustively calculate the *N-x* violations providing an accurate importance ranking of all the grid power lines. *N-1* contingencies are applied to the grids and the impact factor (*IF*) of each line is calculated following Eq. 7, where % Overflow is the amount of power overflow through a line and Bus Low and High Voltages are the amount of voltage at a bus below or above the bus's maximum voltage. Lines with a higher impact factor are more important. If two or more lines are found to have the same impact factor (e.g. *IF*=0 if no violations), then *N-2* is used and so on until there are no more ties.

$$IF = (\%Overflow - 100\%) + (1 - Bus\ Low\ Voltage) + (Bus\ High\ Voltage - 1) \quad (7)$$

The error, defined as the distance in rank from the true rank, of each line is calculated. For example, for the 5-Bus case study NLODF has line b4b5 (the line from bus 4 to bus 5) ranked as second most important, but the "true rank" has it as third yielding an error of 1. Table I shows the line rankings for each metric. From Table I, NLODF rank errors are: b2b4 has an error of 0 and b4b5, b1b3, b1b2, and b4b3 have errors of 1. This gives a total error of 4. When divided by the total number of lines the average overall error is 0.8. Then, the error is normalized by dividing by the largest possible rank error (4 in the 5-Bus grid) so as to compare to larger networks. The results were normalized because larger grids tend to have greater error due to the larger potential difference in rank. The results are shown in Fig. 4.

The accuracy of the top *X*% of lines is also of interest, where *X* is either 10, 20, or 30% (i.e. an analysis of the top 10% of lines in the True Rank). The top 30% of lines in the 5-Bus network is only two lines, while 10% and 20% are only one. The top 10, 20, and 30% of lines were chosen because the smaller networks, like the 5- and 6-Bus, consisted of only one or two lines. As larger grids are studied in future work, e.g., in the 57-Bus network, it is possible that only the top 10% of lines need to be considered. For example: Table I shows the top two lines of the True Rank are b2b4 and b1b3. NLODF accurately ranks one of these two lines as being in the top two, b2b4, meaning it is only 50% accurate. The results are shown in Fig. 5.

TABLE I. LINE RANKS IN 5-BUS NETWORK

Rank	True	NLODF	WTO	STO
1	b2b4	b2b4	b4b5	b4b5
2	b1b3	b4b5	b2b4	b1b3
3	b4b5	b1b3	b1b3	b4b3
4	b4b3	b1b2	b1b2	b1b2
5	b1b2	b4b3	b4b3	b2b4

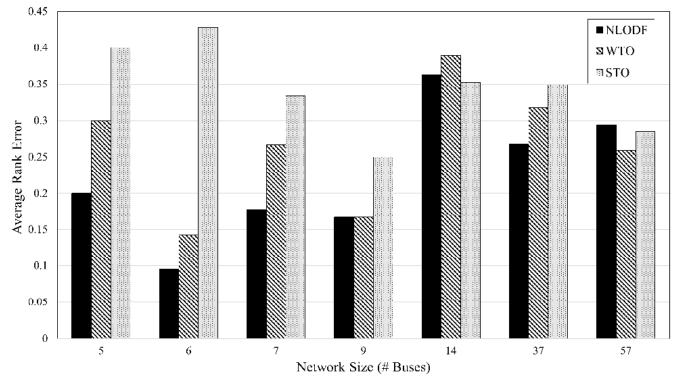

Figure 2. Normalized average rank error in each network. The data is normalized based on network size. The taller the bar the more inaccurate the metric was for that case study.

III. RESULTS

Fig. 4 and 5 show the accuracies found for NLODF, STO, and WTO metrics for each power grid network case study. The *average rank error* represents the overall inaccuracies of the three metrics. This illustrates *on average* how accurate a given metric is and easily compares the three metrics. Fig. 4 shows that, on average, NLODF has the lowest average error among the seven power grid case studies.

Although total accuracy is important, it is not always feasible to calculate, especially in larger networks. The more critical lines will appear at higher ranks. Fig. 5 shows the accuracy of each metric (NLODF, STO, WTO) for the 10%, 20%, and 30% most important lines in the grid. 100% on the y-axis means that all of the lines were correctly ranked within that top percentage. The top % are highlighted because, as can be seen when comparing Fig. 4 and 5, the metric that was able to most accurately rank the top (i.e. most important) lines was not always the same as the metric that had the lowest overall average error in ranking all the lines. Fig. 5 shows that NLODF was found to be the most accurate in three of the seven networks (5-, 14-, 37-Bus cases), STO was also the most accurate in three of the seven networks (7-, 9-, 57-Bus cases), and WTO was the most accurate in only one of the seven networks (6-Bus case).

IV. DISCUSSION

Identifying the most important lines in an electric power gird is critical for grid failure analyses. Instead of running *N-x* contingency analyses on all lines in the grid, computations can focus on only the most important lines – saving time and money. This work focuses on providing accurate and efficient ways of determining line importance through bio-inspiration. The results suggest that ecological methods of allocating conservation efforts in biological ecosystems provides metrics that can be used by grid decision makers. This may open the door to further inspiration for power grids in using ecological conservation methods.

None of the results show a clear winner. The results show that when looking at the *overall accuracy* (Fig. 4), NLODF is the most accurate more often, but NLODF and STO were *each* most accurate in three out of seven cases in the top *X*% analysis

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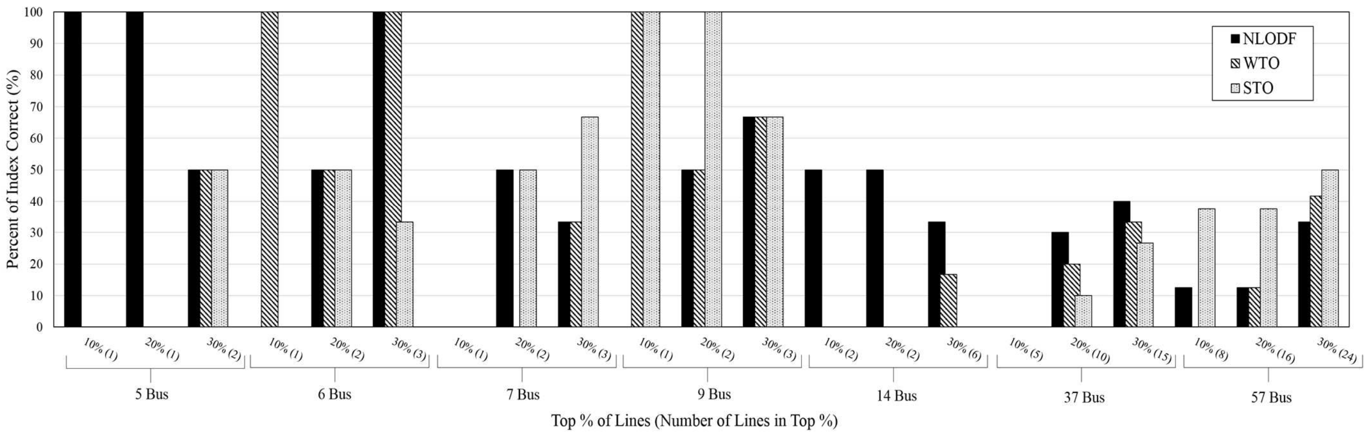

Figure 3. The top 10, 20, and 30% accuracy of each of the three indices (NLODF, WTO, STO).

(Fig. 5). This is interesting for multiple reasons. First, it shows different outcomes depending on the scope of the analysis, highlighting the importance of determining the focus of mitigation/conservation efforts (the entire network or only the top *X*% of lines). Second, this result is interesting because preliminary work suggests that STO is less computationally demanding than NLODF. Only connectivity and flow information are needed for calculating STO and WTO (and STO only requires the former), both are readily available from any code that performs power flow modeling and analysis. Additionally, no sensitivity calculations are required. This reduces the time to complete calculations, suggesting that STO and WTO may be more computationally tractable. Further research must be done to calculate computation times to validate the significance of any differences in calculation time/effort. Comparisons to verify this hypothesis will require implementing and comparing each method using similar software. This study calculated the LODFs using PowerWorld and the STO and WTO metrics in MATLAB. However, knowledge of the calculation requirements supports STO having less computational needs than NLODF, while the results here show it is comparable to NLODF, supporting further investigations into its viability for quickly and accurately estimating important lines. Currently, the times to run STO calculations for the 5-, 6-, 7-, 9-, 14-, 37-, and 57-Bus grids are 0.48, 1.49, 2.66, 1.91, 9.49, 114.62, and 388.39 seconds, respectively. Similar times are found when running WTO calculations. Further work is planned to reduce these times, especially for the larger grids. We also plan to find calculation times for NLODF to compare the results.

Interestingly, STO was most accurate in the largest network (57-Bus) when considering the top *X*% of lines, whereas NLODF was least accurate for this network in both the overall and top *X*% analysis. This may suggest a higher accuracy from STO in larger networks, but more case studies need to be investigated to determine if this trend is statistically significant. Analysis of larger networks is planned for future work.

Another interesting observation from the top *X*% analyses is the consistency of metric performance in a network. When a metric is found to be most accurate in the top 10%, this metric will be as or more accurate than the other metrics at 20% and 30%. This can be seen in the 6-Bus network where WTO is the most accurate at 10% and is just as accurate or better than the other two metrics at both 20% and 30%. This may be useful for analyzing larger grids or greater numbers of lines. A power engineer that wants to determine the most critical top 30% of lines, an analysis at 10% would suggest which metric will be the most accurate at 30%. The engineer can then focus computation on that one metric. The results of this work are limited by the smaller sizes of the grids tested. Larger grid sizes are needed to allow for better comparison between this research and real-world electric power grids. Current efforts are focused on studying larger grids to gain more understanding of the accuracy of NLODF, STO, and WTO.

Future research may present other applications for STO and WTO. One such application may be improved grid resilience. Research has suggested that inspiration from the structure of ecological food webs can suggest design changes to improve the resilience of power grids [10]. An ecological preference for redundancy over efficiency [25-27] has been found to create bio-inspired networks with increased resilience when measured by *N-x* contingency analyses [10]. Future work may show that understanding critical grid components can offer a route to focus added redundancy where it is most needed. Determining the validity of using ecological uniqueness to identify critical components in electric power grids can aid in identifying components best suited for redundancy. Additional future research regarding STO and WTO may also aid in more general analyses of electric power grids. For instance, STO and WTO metrics may help identify vulnerability of electric power grids in terms of voltage instability [28] or provide efficient solutions for the optimal allocation of line capacity [29]. STO and WTO may also aid in the problem of intentional controlled islanding [30].

V. Conclusion

Ecology provides multiple methods to identify the most critical actors in networks. The bio-inspired approach presented here provides a new method for analyzing component importance in electric power grids. Although there are existing proposed methods for identifying critical components in electric power grids, the methods presented here offer comparable

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results while remaining computationally tractable. Planned future work includes further analysis of run times for the various methods discussed, exploring larger grid sizes, and analyzing importance of components other than transmission lines.

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