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Node ranking for network topology-based cascade models – An Ordered Weighted Averaging operators' approach

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ABSTRACT

The importance of network components under fault conditions has been assessed by different techniques. However, the indicators analyzed in the literature do not consider that some isolated events, such as component outages may trigger other events. For example, in a power system, the outage of transmission equipment (e.g., a power line or a transformer) may cause the redistribution of the power flow and could cause overloading of neighboring elements. These potential cascade effects have been analyzed using several models. Based on different assumptions, these models are able of determining more precisely, the important elements of the network. In this paper, the authors extend a previous non-parametric multicriteria aggregation approach to include the decision-maker preferences. The new approach, based on the use of aggregation rules that relies on parametric Ordered Weighted Averaging (OWA) operators to support the decision-making process, is able to produce a unique ranking of components. The aggregation rule is based on the classic OWA operator that considers decision-maker preferences associated with risk perception, compensation, entropy of information, among other aspects, and the weighted OWA operator (WOWA) for assessing the relative importance of the criteria. To illustrate the approach, the effects of the additional information provided by the decision-maker as well as their variations are evaluated using a real electric power grid under three cascade models.

1. Introduction

During the last decades, interest in understanding how the performance of networks diminishes as a function of component failures (nodes and links) has significantly grown. Several authors have analyzed this problem from different perspective (see [1–4] among others). For example, Ref. [3] analyzes the problem of determining the minimum set of nodes to be removed that produces the maximum reduction of cohesion (i.e., the network fragmentation problem). Other models that have analyzed the effects of deleting nodes and arcs are: the Most Vital Arcs Problem [1]; the k-edge Survivability Problem [2]; the Key Player Problem/Negative [3], and the Critical Node Problem [4], to name a few.

Other authors (see for example [5] and references therein) have used concepts associated with the centrality of a graph. For example, Freeman, as mentioned in [5] defines the betweenness of a node or a link as the degree of participation of each component in all possible paths between pairs of nodes.

Independent of the main concept used, these approaches attempt to determine the set of elements which, when taken out of service, by a fault or an intentional attack, causes network disruption. The magnitude of these disruptions is used subsequently to determine the classification of components or groups of components from the most to least important.

However, such models do not consider that some isolated events, such as the failure of a component, may trigger other events. For example, the outage of a transmission component in an electric power system could produce a redistribution of the power flow and could cause overloading of neighboring elements. Protection devices would disconnect those overloaded components causing the possible start of “the first stage of a cascade” [6]. Indeed, it is possible that the power flow would need to be redistributed again, leading to potential further overload of additional components and their consequent disconnection.

Each cascade stage could worsen the system performance. The process can continue until finally stabilizes (quiescent state): there

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are no longer cascading effects or the system could not perform its intended function.

Several cascade models have been presented in the literature (e.g., [7–9], among others). In general, the failure of a component or set of components could start a cascading sequence. At the quiescent state, the performance of the system, such as the load curtailed or an index related to the network cohesion, is associated to the failed component. Since these cascade models are based on different assumptions, the consequence in the system due to a component failure could be different. Thus, the component importance assessment must be considered as a multi-indicator system: each component is characterized simultaneously by several criteria (or attributes) that represents the consequence in the system.

In order to determine the overall importance of each components based on the results of several cascade models, the decision-maker (DM) could select the decision-making problem defined as "Problematique γ" in [10]: ranking a set of alternatives from the best to the worst ones.

For systems modeled as networks, different aggregation approaches have been proposed in the literature. In general, such studies only consider centrality-based importance measures (e.g., [11–13]).

Recently Rocco et al. [14] presented an approach for the ranking of "components derived from three simple cascade models using a non-parametric technique based on partial order theory" but without considering DM preferences.

This paper proposes an extension of the approach in [14] by considering the use of Ordered Weighted Averaging (OWA) operators [15,16] for identifying critical nodes. The proposed approach structures an aggregation rule, which allows assessing risk appetite, compensatory aggregations, entropy of information (dispersion), and the embedding of experts' preferences over the criteria selected (relative importance) [17–20]. The effects of the relative importance are also analyzed.

The paper makes use of the Hasse diagram (HD) technique as a preliminary analysis tool for assessing the importance of the components of the system under study. HD is a fully non-compensatory graphic technique, based on the mathematical concepts of partial order [21], that produces an aggregated picture of the components to be ranked, and is capable to highlight possible conflicts among them, suggesting a set of components that could be partially ordered. HD is a non-parametric technique that does not require information regarding DM preferences.

The paper is structured in five sections. In Section 2, three cascade models are briefly reviewed. Section 3 describes the fundamental ideas of partial order set, Hasse diagrams and the OWA models for ranking. Section 4 illustrates the proposed approach using a real electric power grid. The final Section 5 presents conclusions and future work.

2. Cascade models

This section briefly reviews the basic concepts of a cascade model and describes the three cascade models to be used in Section 4. It is assumed that the topology of the network is known and could be represented by a graph G (**N, A**), where **N** is the set of N nodes and **A** is the set of A links connecting nodes.

A cascade model evaluates if the outage of a selected component (i.e., the event) is able to trigger additional events and determines the possible cascade sequence. Once the cascade failure terminates (the quiescent state), the performance of the final network topology is assessed. As in Rocco et al. [14] three simple cascade models are described and used to illustrate the proposed approach. However, it is important to realize that any other cascade model could be considered, since the approach presented in this paper assumes that the consequences of the outage of a component are properly evaluated no matter the cascade models selected.

2.1. Model 1: Pepyne et al. [7]

This model simulates cascading effects by defining a probability of propagation for each link as follows. A node is randomly selected for failure forcing the flow to be redistributed among the nearby links, causing potential overload of specific components and triggering protecting devices to disconnect the lines with a probability of failure propagation p_{ij} (this probability is a function of protection enhancements or maintenance actions).

2.2. Model 2: Crucitti et al. [8]

This model considers the $N \times N$ adjacency matrix $\boldsymbol{e}$, where $e_{ij} \in [0,1]$ is a measure of the efficiency in the "communication" along the arc between node i and node j. Initially, at time $t=0$, $e_{ij}=1$ for all the existing arcs. The average network efficiency E is defined as:

$$E = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} \frac{1}{d_{ij}} = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} e_{ij}$$

where d_{ij} and e_{ij} are the geodesic distance and the efficiency between nodes i and j, respectively.

Each node is characterized by a *capacity* defined as the maximum load that node can handle. An efficient path is defined as the shortest path between any two nodes. Then, the number of all of the shortest paths of a network that passes through node i is used as a proxy of the load $L_i(t)$ on node i at time t.

The capacity C_i of node i is assumed proportional to its initial load $L_i(0)$, i.e., $C_i = \alpha L_i(0)$, where $\alpha > 1$ is the tolerance parameter of the network.

The removal of a specific node "starts the dynamics of redistribution of flows on the network" and affects the most efficient paths between nodes. At each time t, the model defines a rule for the time evolution of e_{ij} "that mimics the dynamics of flow redistribution following the breakdown of a node":

$$e_{ij}(t+1) = \begin{cases} e_{ij}(0)\frac{C_i}{L_i(t)} & \text{if } L_i(t) > C_i \\ e_{ij}(0) & \text{if } L_i(t) \le C_i \end{cases}$$

where j extends to all the first neighbors of i. Therefore, if at time t if a node i is congested, the efficiency of all of the arcs passing through is reduced and eventually the new most efficient paths appear.

2.3. Model 3: Wu et al. [9]

In this model, each node i has a weight $\beta_i = k_i^{\Theta}$, where k_i is the node degree and Θ is a selected parameter that controls the strength of the node weight. The cascade effects is simulated by redistributing the flow through a broken node i among its nearest neighboring nodes. The additional flow ΔF_j received by the neighboring node j is:

$$\Delta F_j = F_i \frac{\beta_j}{\sum_{l \in \Omega_i} \beta_l}$$

where Ω_i is the set of neighboring nodes of i.

Each node i in the network can handle a maximum flow Φ_i, which is assumed proportional to its weight $\Phi_i = c k_i^{\Theta}$. If $(F_j + \Delta F_j) > \Phi_j$ then the node j will be broken, and further redistribution is induced.

3. Ranking techniques

Let P define a set of m objects (for example, nodes) to be