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Quantifying the resilience of community structures in networks

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ABSTRACT

Many networks contain community structures, or collections of densely connected nodes with sparse connections to other dense groups in the network. Communities may coalesce for a number of reasons, including friendships in a social network, physical connections in an infrastructure network, or spatial distribution in a neighborhood. Several approaches have been proposed to identify communities and compare the partition of networks into communities. This work explores community structures from the perspective of their resilience, or their ability to withstand degradation in network performance and recover to a desired level of network performance. In this context, network performance is defined as the similarity of a network partition (or the characterization of the network into community structures) formed after the disconnection of one or more links to the initial partition. This work provides an approach to measure how the initial set of community structures survive after a disruption and how these structures return after restoration commences. The approach is illustrated with an electric power network case study.

1. Introduction and motivation

In recent years, the concept of resilience, or the ability to withstand, adapt to, and recover from a disruption, has been discussed, measured, and modeled in a variety of perspectives including social science [1–3] and engineering [4–7], as well as the relationship of the two perspectives [8,9]. Resilience-related work published in archival journals has increased significantly in the last decade [10], and guidance and policy dealing with resilience has grown in the government sector as well [11,12].

Among the planning documents by government agencies on resilience is a particular recent emphasis on the resilience of communities, or networks of socially connected individuals [13,14], after a disruptive event. The National Academies of Science [15] suggest "One way to reduce the impacts of disasters on the nation and its communities is to invest in enhancing resilience […]." The National Institute for Standards and Technology [16] defines community resilience as "the ability of a community to prepare for anticipated hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions." Measuring and quantifying this ability to prepare, adapt, withstand, and recover is vital to planning for and implementing community resilience. And doing so requires the identification of how communities are defined and how they emerge.

Quantifying the resilience of community structures in networks is a first step toward quantifying community resilience. Communities are often thought of as entities who group together due to commonalities, such as interests or geography [17]. A more general, network-centric definition is offered by Porter et al. [18] as a network structure consisting of a group of nodes that are "relatively densely connected to each other but sparsely connected to other dense groups in the network." These two concepts of community, one from a social science perspective and one from a network science perspective, are congruent: connectivity is a matter of how relationships are defined. Communities of scholars [19] and actors [20] emerge from thousands of entities based on collaborative relationships. Neighborhood communities are based on geographical relationships [21]. In general, these systems are modeled using the concept of a network, where scholars, actors, are represented by nodes and their relationships as links. At the end, no matter the cohesiveness concept used, a set of initial communities are derived. We distinguish the resilience of the set of initial community structures as being quantified from a network-centric perspective (i.e., the ability of the set to withstand and recover from perturbations), whereas community resilience is a social science realization of that network structure. We

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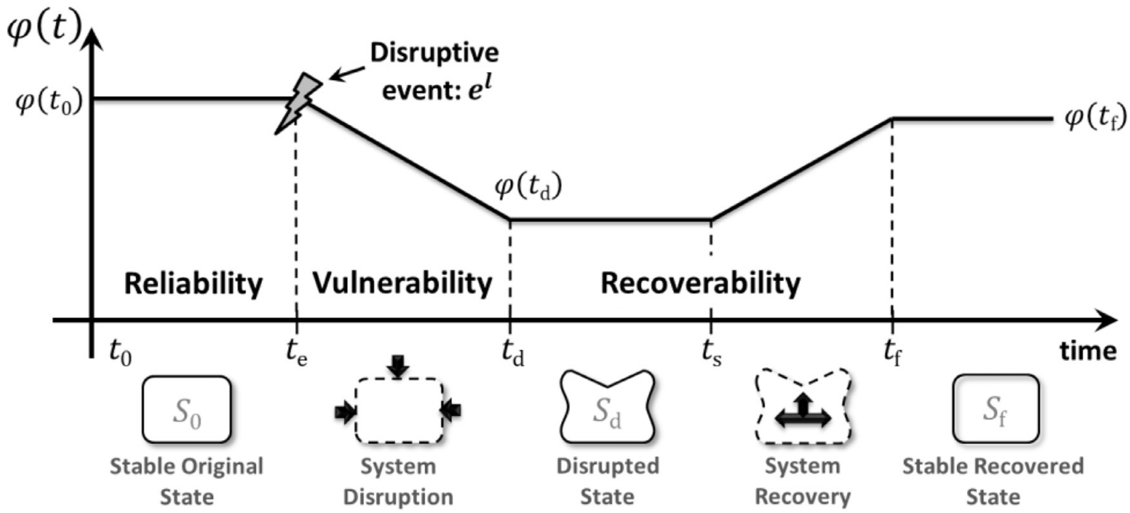

Fig. 1. Graphical depiction of decreasing system performance, $\varphi(t)$, across several state transitions over time [23].

focus on the former in this paper, and the latter could be addressed by applying our proposed approach to social networks and studying what measures could be implemented to reduce social vulnerability to disrupted (network-centric) community structures.

As such, this work analyzes communities from a network perspective and studies relevant community resilience phenomena. Resilience is modeled as a function of the similarity of the initial partition of the network (i.e., the community structure) before and after a disruption, suggesting that community structures that stay intact and recover quickly after a disruption are more resilient. As such, resilience depends on the structure and characteristic of the network and its partition in communities (i.e., our main analysis refers to the partition of the network as a whole). Note that, in some cases, communities could adjust their internal structure to cope with a disruptive event. Such analysis at the community level is also possible but requires the definition of a different performance function. For example, the authors of Ref. [22] consider the effects of a disruption on the performance of the communities in a network, where the assessment is based on a performance function simulating the electricity load in each community as well as the interaction among communities.

While the example illustrated here deals with the topology of an electric power network, the work deals with the general definition of community structures, no matter how they are derived, and the general approach to modeling their resilience, thus, a variety of communities could be described.

The remaining of the paper is as follows: Section 2 offers background to a resilience modeling technique developed by the authors as well as background on community structures in networks. The proposed approach to model community resilience is discussed in Section 3, with a case study of network behavior under disruption is provided in Section 4. Concluding remarks are given in Section 5.

2. Methodological background

This section offers background on the approaches to quantify resilience and identify community structures in networks.

2.1. Modeling resilience

Fig. 1 is a graphical depiction [23–25] of the performance of a system before, during, and after a disruptive event, e^l. The performance of the system is measured over time with function $\varphi(t)$, which reduces after the disruptive event suggesting that a larger value of $\varphi(t)$ is desired (e.g., flow along a network, utilization of an asset, well-being of entities). Fig. 2 depicts a system whose performance measure increases after a disruption (e.g., count of entities without service, delays in flow, unsatisfied customers).

Three dimensions of resilience are exhibited in Figs. 1 and 2: reliability, vulnerability, and recoverability. In the ***reliability*** dimension, the steady-state behavior of the system is exhibited in the time interval $t_e - t_0$. The behavior of the system prior to the disruptive event is typically described with reliability theory [26,27], which provides models and techniques and measure the probability that under normal operating conditions, the common-cause failure time is greater than some value t, $R(t) = P(T > t),\ t \in (t_0, t_e)$. In the ***vulnerability*** dimension, the reduction in system performance in the interval $t_d - t_e$ is compared to its state before the disruptive event [28]. Methods in this area are used to: (i) understand how disruptive events adversely affect the service function (e.g., analyzing probability that a disruptive event e^k does not affect the service function below some threshold b, $P(\varphi(t) > b|e^l)$, and (ii) identifying the components that are critical to the system (i.e., those components that, when degraded, have the most adverse effect on system performance) [26–33]. Finally, in the ***recoverability*** dimension, actions are taken during interval $t_f - t_d$ to restore system performance to a desired level (perhaps similar, better, or worse than $\varphi(t_0)$) in a timely fashion. Recent work in this area has offered optimization models to restore system performance [34–36].

A number of studies have described related resilience metrics. Cimellaro et al. [37] quantify resilience as the “normalized shaded area underneath” the function $\varphi(t)$. Similarly, Zobel [38,39] analyzes the difference between steady-state performance and disrupted performance to measure system resilience to different events. Francis and Bekera [40] offer a similar measure assuming exponential recovery. Sterbenz et al. [41] provide a temporal description of resilience but no mathematical formulation, Nair et al. [42] provide a demand-based perspective, and Rose [43] analyzes at the economic impact of resilience.

Note that Figs. 1 and 2 depict situations where a disruptive event causes an undesirable decrease and an undesirable increase in system performance, respectively. However, situations could arise in noncoherent systems where, for example, disruptions actually improve performance (e.g., the removal of caustic links in a social network), but such work is not addressed here.

2.2. Modeling resilience

Discussed previously, when nodes with similar characteristics have close connections, they form a *community*, and the connections between communities are relatively sparse. A simple illustration of three com-