A Markov Chain Approach for Cascade Size Analysis in Power Grids based on Community Structures in Interaction Graphs

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***Abstract*—Cascading failures in power grids are high impact societal and economical phenomena. Local interactions among the components of the system and interactions at-distance, based on the physics of electricity, as well as various stochastic and interdependent parameters and factors (from within and outside of the power systems) contribute to the complexity of these phenomena. As such, predicting the size and path of cascading failures, when triggered, are challenging and interesting research problems. In recent years, interaction graphs, which help in capturing the underlying interactions and influences among the components during cascading failures, are proposed towards simplifying the modeling and analysis of cascades. In this paper, a Markov chain model is designed based on the community structures embedded in the data-driven graphs of interactions for power grids. This model exploits the properties of community structures in interactions to enable the probabilistic analysis of cascade sizes in power grids.**

***Index Terms*—power grids, cascading failures, interaction graph, community structure, Markov chain, cascade size**

I. INTRODUCTION

Cascading failures in power transmission networks are complex and high impact phenomena. Understanding and mitigating cascading failures are challenging due to the large number of components and their complex interactions that affect the cascade process. Various studies over the past decades have focused on understanding different aspects of these phenomena using methods including power system simulations as well as probabilistic and deterministic modeling [1].

Understanding cascade size distribution in power grids and predicting cascade size when it gets triggered, have also been extensively studied in the literature. For instance, in the study in [2], blackout data from historical sources as well as from simulations revealed the power-law behavior in the blackout size distribution (e.g. measured in terms of unserved energy or number of tripped transmission lines). This suggests that the likelihood of the occurrence of large blackouts is more than what is traditionally expected. Additionally, prediction of cascade sizes given an initial triggering event, can help in estimating the risk of large blackouts and control and mitigate the spread of failures during cascade processes. It also allows for the characterization of the contributions of components of the system towards large cascades.

In recent years, interaction graphs constructed based on cascading failure data have helped in modeling and analyzing cascading failures in an abstract and simple manner. Various methods have been proposed in the literature to construct graphs of interactions (refer to [3], for a survey). Unlike physical topology-based graphs of power grids, where the edges in the graph represent actual physical connections, edges in the interaction graphs represent interactions among the components during cascading failures. In such interaction graphs, failure propagation is local, i.e., failure of a node can cause probabilistic failure of directly connected nodes.

In our preliminary studies in [4] and [5], we studied the structures and patterns of interactions using the community structures in the interaction graphs constructed based on the influence-based [6] and correlation-based [7] methods. Communities are defined as densely connected groups of components with scarce connections to components of other groups [8]. Community structures in the interaction graphs are important as they tend to trap failures within the communities while exhibiting a lower likelihood of spreading failures outside the community. In this study, we use the community structures that are present in the interaction graphs to study the failure propagation between communities and to characterize the likelihood of various cascade sizes. For this purpose, we formulate a Markov chain (MC) model based on the community structures in the interaction graphs of the power grid. This model exploits the properties of overlap and bridge nodes of communities (i.e., nodes that belong to multiple communities or have connections to other communities) as well as the strength of influences/interactions of the components to characterize transition probabilities in the MC. The states of the community-based MC model allow the tracking of the size of cascades. The main idea behind this model is that the groups of components that form the communities provide an estimated measure of cascade size, as a cascade entering a community is likely to spread failures to other components within the community and less likely to spread outside the community. Thus, using the community-based MC, the distribution of cascade sizes can be characterized using the size of communities. Additionally, depending on the initial conditions such as the community from which the cascade starts, cascade size distribution can be characterized. As suggested by historical data and previous studies of cascading failures, we observe power-law behavior in the distribution of cascade sizes, which suggests the importance of community structures of interaction graphs in cascade behavior.

II. Related Work

In this section, we briefly review the probabilistic [9]–[14] and graph-based models [7], [15] related to this work that focus on characterization and prediction of cascade sizes.

In a group of works in literature, it has been discussed that the branching process [9], [10] can provide an abstract model for outage distribution in cascading failures. In branching process models, outages are grouped into *generations*, where each generation is a sequence of components that failed within a short time-frame. Each component in a generation can independently produce a random number of child outages based on a Poisson offspring distribution, with a specific propagation rate. Thus, historical transmission line outage data was used to estimate static propagation rates for all generations [9] and varying propagation rates for each generation [10] to predict the probability distribution of subsequent line outages given distribution of initial failures.

Probabilistic models in the studies in [11]–[14], are used for stochastic modeling of cascading failures. In the study in [11], a regeneration-based probabilistic approach was used for characterizing the probability of reaching an arbitrary blackout size at any time given the initial power grid conditions, which included loading level, maximum capacity of the set of failed lines, and the number of failed lines. In the extended study in [12], an analytically tractable Markov chain model was developed, in which the states represented the critical grid conditions identified in the study in [11]. Additionally, operational characteristics i.e., loading level, load shedding constraints, and line tripping threshold were also considered for determining transition rates. This model was used to analytically predict the probability of blackout in time and also asymptotically determine the probability mass function of blackout size. The study in [13] extended the Markov model in [12] to consider the effect of interdependencies between power and communication systems on cascade size distributions. In the study in [14], the operational characteristics discussed in [12], was used to study specific conditions which led to power-law behavior on the probability mass function of blackout size.

In addition to probabilistic models, graph-based models [7], [15] have also been used for analyzing cascades and their size distribution. In the study in [7], a correlation matrix constructed using cascade data of failure/functional statuses of transmission lines, is used for predicting the distribution of cascade sizes. And in the study in [15], a Markov chain constructed using transmission line outage data, where states represented *generations* of line outages, was used to predict distribution of cascades of varying sizes.

The work presented in the current paper, belongs to both of the aforementioned categories as it provides an MC model based on the structures embedded in the interaction graphs of power grids for analysis of cascading failures.

III. Interaction Graphs

In this section, we briefly review two models: influence-based and correlation-based, for deriving interaction graphs of power grids. For a comprehensive review of models and analysis of interaction graphs, refer to [3]. We denote an interaction graph by $\mathcal{IG} = (V_{IG}, L_{IG})$, where V_{IG} represents the set of vertices in the graph. Similar to our previous works [4], [5] and as transmission line failures are critical in cascading failures, vertices represent the transmission lines of the power system. The set L_{IG} represents the set of interaction links and the weight of the links represent the strength of interactions.

A. Influence-based Interaction Graph

In this method, interactions among lines are derived in two steps using the pairs of consecutive *generations* in the overall cascade dataset. Note, the cascade dataset consists of sequences of line failures. In the studies in [4]–[6], [15] as well as in this study, all components in the current generation m are assumed to have interactions with all components in the next generation $m+1$. Thus, in the first step, using the branching process framework [10], propagation rate $\lambda_{i,m}$, is used to specify the average number of failures in generation $m+1$ given failure of component i in generation m. In the second step, the conditional failure probability of component j, given failure of component i in the previous generation, is assumed to be $g[j|i]$ and is found by statistical calculation of the number of times that component j failed in the next immediate generation after failure of component i. In the final step, the propagation rates and conditional failure probabilities are combined together using the influence model [16] to form the influence interaction graph H whose i,j element is calculated as $1 - e^{-\lambda_i g[j|i]}$ for $i \neq j$ and zero otherwise. The i,j element is also the weight of the interaction between the components i and j. Thus, matrix H can be viewed as a directed and weighted interaction graph.

B. Correlation-based Interaction Graph

Correlation-based approach [7] simply considers the pair-wise correlation among the failed components during cascades without grouping failures into generations. The i,j element of a correlation matrix CR is the Pearson correlation coefficient between the failed components i and j in the overall cascade dataset. Since the sequence of failed components in a cascade is not considered, the correlation matrix is symmetric and can be viewed as an undirected but weighted interaction graph.

IV. Community Structures in Interaction Graphs

Community structures identified in graphs can be of two types (1) *overlapped*, such that a component may be a member of more than one community and (2) *disjoint*, such that a component is a member of a single community. Community structures are identified in graphs using community detection techniques (see [8] for a survey of such approaches). These approaches utilize the inherent patterns and properties of the graph, such as the weights of the links and their directions.

Community detection algorithms identify the set of communities, $\mathcal{C} = \{C_1, C_2, \cdots, C_n\}$, where *n* is the number of communities in the graph. Each community C_i consists of a set of components with $|C_i|$ representing the community size or the number of nodes in the community. Membership labels to the vertices in the graph V_{IG} are also assigned. The set of membership labels for vertex $v_i \in V_{IG}$ is denoted as $ML(n_i) = \{C_a, \cdots, C_b\}$, where $C_a, C_b \in \mathcal{C}$. For the overlapped community structures $|ML(v_i)| \geq 1$, while for disjoint community structures, $|ML(v_i)| = 1$, where $|.|$ is the cardinality of the set.

In our studies in [4] and [5], Infomap community detection [17] enabled us to identify both overlapped and disjoint community structures present in the interaction graph $\mathcal{IG}$ using variations of its random walk algorithm. In overlapped communities of directed/undirected interaction graphs, *overlap* nodes (nodes that belong to multiple communities) contribute to the spread of failures during cascades. In disjoint communities of undirected interaction graphs, *bridge* nodes (nodes that have links to components in other communities) contribute to the spread of failures during cascades. In the case of directed interaction graphs with disjoint communities, there are two types of bridge nodes: *o-bridge* nodes that have outgoing links towards nodes of other communities and *i-bridge* nodes that have incoming links from nodes of other communities. We consider the former as the initiator of failure propagation during cascades. Note, a node may have both incoming and outgoing links, however, the spread of failures to other communities occur through the outgoing links only.

V. Markov Chain Formulation

Using the concepts discussed in the previous sections, we propose a Markov chain (MC) framework to model the cascade size evolution using the community structures in the interaction graph of the power grid. As mentioned earlier, communities tend to trap failure propagation inside and thus, provide an estimate on the likelihood of various cascade sizes depending on the size of the community, where the failures started, and the communities that failures can propagate to.

We define the state space of the MC based on all possible combinations of the set of communities $\mathcal{C}$ in the interaction graph $\mathcal{IG}$. We consider two variables as the state variables of the MC: (1) variable S representing the set of communities, which have been involved in the cascade process (communities with failed components) and (2) a binary variable I representing the condition that the cascade is contained within existing communities and thus, cascade stops with an absorbing state for MC (i.e., $I = 1$) or not (i.e., $I = 0$). Let $X(t)$ denote the state of the MC at time $t \geq 0$ using pair $(S(t), I(t))$.

To illustrate the MC model and its state space, consider the example interaction graph for a power grid shown in Fig. 1-a. Assume that applying a community detection algorithm on this graph identifies three disjoint communities, named C_1, C_2, and C_3, as shown in the figure. Given these communities, there are fourteen possible states for the MC in which, half of the states are transient and half are absorbing (due to binary variable I) as below. Thus, the state space of the MC for the system in Fig. 1-a is: $\mathcal{S} = \{(\{C_1\}, 0), (\{C_1\}, 1), ((\{C_2\}, 0)), (\{C_2\}, 1), (\{C_3\}, 0),$ $(\{C_3\}, 1), (\{C_1, C_2\}, 0), (\{C_1, C_2\}, 1), (\{C_1, C_3\}, 0), (\{C_1,$ $C_3\}, 1), (\{C_2, C_3\}, 0), (\{C_2, C_3\}, 1), (\{C_1, C_2, C_3\}, 0), (\{C_1,$ $C_2, C_3\}, 1)$. For an interaction graph with n number of communities, the number of transient states in the MC is $\sum_{r=1}^{n} \frac{n!}{(n-r)!r!}$, where r represents the number of communities involved in the cascade process. While the number of states can be large for large values of n, the number of communities in interactions graphs are generally much smaller than the number of nodes in the graph and thus, state space explosion will not occur for interaction graphs of power grids.

We define the transitions among the MC states by exploiting the connections among the communities. Specifically, as the connections (overlap and bridge components) among the communities result in propagation of failures among the communities, they can cause the state of the MC to change by involving more communities in the cascade process. In this paper, we assume that in each transition of the MC, at most one new community will get involved in the cascade process (cascade will propagate to a new community through the connections with communities in the current state of the MC). This simplifying assumption can be justified by considering that time has been divided into small instances and only one new community can get involved at each time instance. This assumption will help in characterizing the transition probabilities and make the transition matrix of the MC sparse. We also assume that if the cascade gets contained in the communities that have already been involved in the cascade process based on the current state of the MC, then the MC will transit to an absorbing state with the same set of communities. Thus, in our MC, three types of state transitions are possible: (1) transition from a transient state to another transient state with one additional community when failures propagate to a new community, (2) transition from a transient state to an absorbing state with the same set of communities when cascade stops, and (3) finally, transition from an absorbing state to itself representing that the state of the system will not change with regard to cascading failures when it stops. Note, the set of communities in each MC state provides an estimate of the cascade size. Specifically, we assume that the number of failed components at each state of the MC can be found by adding up the sizes of the set of communities in that state.

To formulate the transition probabilities among the states in the MC, we utilize the sizes of the communities, the number of overlap/bridge nodes among communities, and the weight of influences/interaction links between communities. As the first step towards formulating the transition probabilities, we define the contribution of a single node $u \in C_i$ that has interaction links to nodes in community C_j (i.e., node u is an overlap or bridge node), in the propagation of failure from community C_i to community C_j as

$$CFP(u) = \frac{\sum_{v \in C_j, j \neq i} w_{u,v}}{\sum_{q \in L_{\mathcal{IG}}} w_{u,q}}. \quad (1)$$

In the context of various types of communities, in equation (1) we have: (i) *for the case of disjoint communities of directed interaction graphs:* $w_{u,v}$ is the weight of the interaction link from o-bridge node u to i-bridge node v and $w_{u,q}$ is the weight

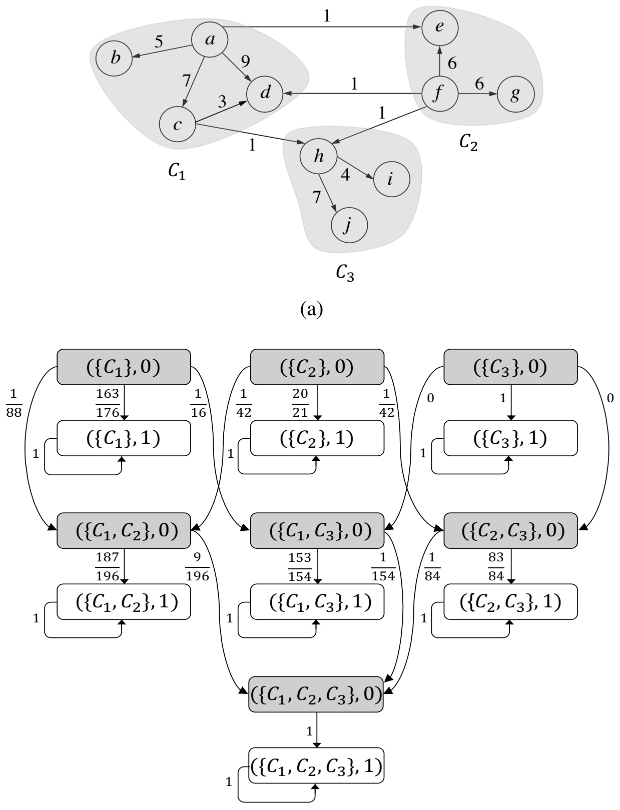

Fig. 1. (a) Example of three disjoint communities. (b) Markov chain of community structure with three disjoint communities shown in (a).

of the interaction link from o-bridge node u to node q, (ii) *for the case of disjoint communities of undirected graphs:* $w_{u,v}$ is the weight of the interaction link connecting bridge node u to bridge node v and $w_{u,q}$ is the weight of the interaction link connecting bridge node u to node q, and (iii) *for the case of overlapped communities of directed as well as undirected graphs:* $w_{u,v}$ is the weight of the interaction link connecting overlap node u to overlap node v and $w_{u,q}$ is the weight of the interaction link connecting overlap node u to node q. Note, for all the above-discussed cases, node q can be a member of any community including communities C_i and C_j.

In the next step towards formulating the transition probabilities, we need to consider the cumulative effect of all the overlap/bridge nodes among the communities. Specifically, the contribution of: (i) all o-bridge nodes in community C_i in the case of disjoint communities of directed graphs, (ii) all bridge nodes in community C_i in the case of disjoint communities of undirected graphs, and (iii) all overlap nodes in community C_i in the case of overlapped communities of both directed and undirected graphs; will be added up. For the case of transitioning from a state with a single involved community to a state with two involved communities we have:

$$p((\{C_i\},0) \rightarrow (\{C_i,C_j\},0)) = \frac{\sum_{z\in C_i} CFP(z)}{|C_i|}, \qquad (2)$$

where $|C_i|$ is the size of community C_i and $p((\{C_i\},0) \rightarrow (\{C_i,C_j\},0))$ is the probability of transition from transient state $X(t) = (\{C_i\},0)$ to transient state $X(t+1) = (\{C_i,C_j\},0)$ with one new additional community. E.g., in the MC of Fig. 1-b, contribution of o-bridge node f to failure propagation in community C_1 i.e. $CFP(f)$ is 1/(1+1+6+6) = 1/14 and probability of transition from transient state $(\{C_2\},0)$ to transient state $(\{C_1,C_2\},0)$ is $1/(14\times 3) = 1/42$.

To generalize, the probability of transition from a transient state $(\{C_i,C_j,\cdots,C_r\},0)$ to a transient state $(\{C_i,C_j,\cdots C_r,C_{r+1}\},0)$ with one new additional community can be defined as:

$$p((\{C_i,C_j\cdots C_r\},0) \rightarrow (\{C_i,C_j,\cdots,C_r,C_{r+1}\},0)) = \frac{\sum_{z\in O_{\{C_i,C_j,\cdots,C_r\}}} CFP(z)}{|\{C_i,C_j,\cdots,C_r\}|}, \qquad (3)$$

where $O_{\{C_i,C_j,\cdots,C_r\}}$ is the set of all o-bridge, bridge, or overlap nodes of the set of communities $\{C_i,C_j,\cdots,C_r\}$, which have interaction links to nodes in community C_{r+1}; and $|\{C_i,C_j,\cdots,C_r\}|$ is the sum of sizes of all communities in the set $\{C_i,C_j,\cdots,C_r\}$. Note, for calculating the sum of sizes of overlapped communities, repeated entries of overlap components are counted only once.

The probability of transition from a transient state $X(t) = (S(t),0)$ to its associated absorbing state $X(t+1) = (S(t+1),1)$ (i.e., absorbing state with the same set of communities as that of the transient state, i.e., $S(t) = S(t+1)$), describes the probability of failure of *non-overlap/non-bridge* nodes (i.e., nodes that belong to a single community). This type of transition implies that failure of non-overlap/non-bridge nodes of a community spreads failures to other components within the community itself only and failures are contained within involved communities. The probability of transition from transient state $X(t) = (S(t),0)$ to its associated absorbing state $X(t+1) = (S(t+1),1)$ will be the complement of probabilities of transition to all other transient states from state $X(t)$. Finally, the only possible transition from an absorbing state will be to itself, such that $p((S(t),1) \rightarrow (S(t+1),1))$ for $S(t) = S(t+1)$ is one.

VI. RESULTS

In this section, we first introduce the cascade dataset generated for the IEEE 118 bus system using MATPOWER simulations. Then, we briefly discuss our interaction graphs constructed using the influence-based and correlation-based techniques. We also briefly discuss the community structures identified in the interaction graphs using the Infomap disjoint and Infomap overlap algorithms. More details of these results can be observed in our previous studies in [4], [5]. Finally, our main focus and discussion is on the characterization of cascade sizes using our community-based MC.

A. Cascade Dataset

We used the IEEE 118 bus system with 118 buses, including substations and generators, and 186 transmission lines. We used MATPOWER [18] to simulate cascading failures of transmission lines based on a quasi-static approach by solving DC optimal power flow equations. The main mechanism of line failures in the cascade process is due to the overload of

TABLE I
PROPERTIES OF THRESHOLDED INTERACTION GRAPHS [5]

Interaction Graph $\mathcal{IG}$	No. of vertices in LCC	No. of edges	No. of communities: Infomap Disjoint	No. of communities: Infomap Overlap
$H \geq 0.6$	143	1160	12	12
$H \geq 0.7$	57	612	4	7
$CR \geq 0.7$	59	636	5	5

the lines caused by the redistribution of power flows after the occurrence of two or three initial random failures. We generated around 16,000 cascade failure scenarios.

B. Interaction Graphs and Community Structures

The generated cascade dataset for IEEE 118 bus system was used to construct the influence-based H and correlation-based CR interaction graphs, discussed in Section III. Each interaction graph had 186 vertices representing the transmission lines of the IEEE 118 bus system. We observed 32,504 and 34,396 number of interaction links in the H and CR graphs respectively. Both H and CR are dense graphs; however, numerous interactions have insignificant weights. Including the contribution of such interaction links in analyzing community structures reduces the quality of identified communities as many such interactions act as noise [19]. Thus, we thresholded the graphs such that interaction links with stronger influences are the ones considered during community detection [20]. As the thresholded graphs can create disconnected graphs, our focus is on the Largest Connected Components (LCC) of the thresholded graphs. We observed the threshold of 0.6 to be the most qualitative for identifying communities in H interaction graph. To make a comparable case for the H and CR interaction graphs, we considered the threshold of 0.7, where the threshold yielded an LCC with 57 and 59 components respectively. Then, we applied the Infomap disjoint and Infomap overlap community detection algorithms, discussed in Section IV, over the LCC of the thresholded interaction graphs. Based on the threshold as well as the type of interaction graphs, the properties of the graphs differ as shown in Table I. Table II presents more details on the structure of the communities and the overlap and bridge nodes.

C. Distribution of Cascade Sizes

To characterize the contribution of community structures in the distribution of cascade sizes, we use the MC formulation discussed in Section V. We numerically calculate the average steady state distribution of the MC as well as cascade size distribution for various initial states of the system depending on where the failures started.

First, we look at the steady state distribution of the MC for the average case when the cascade can start from any community with equal probability. We evaluate this probability distribution for three interaction graphs including interaction graphs based on $H \geq 0.6$, $H \geq 0.7$, and $CR \geq 0.7$. These results are presented in Fig. 2. The y-axis in Fig. 2 shows the log scaled distribution of the probability of occurrences with respect to various cascade sizes in the x-axis. The range of

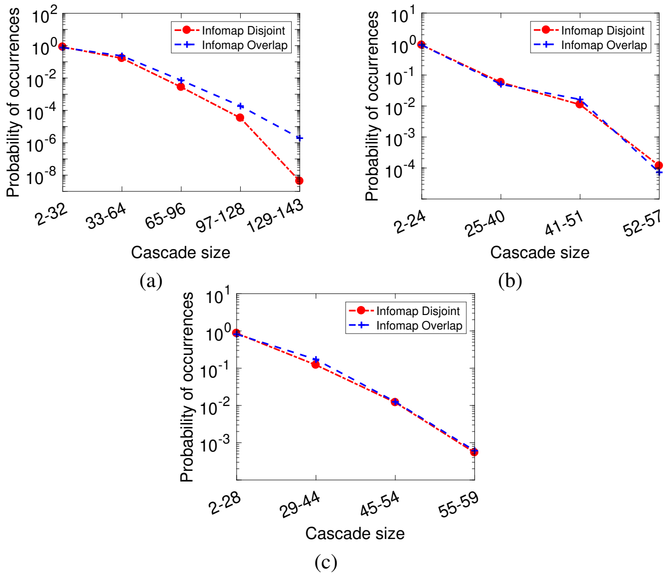

Fig. 2. Log scaled probabilities of cascade sizes when cascade has equal probability to start from any community, for communities identified using Infomap disjoint (in red) and Infomap overlap (in blue) over the interaction graph of (a) $H \geq 0.6$, (b) $H \geq 0.7$, and (c) $CR \geq 0.7$.

TABLE II
COMMUNITY AND OVERLAP/BRIDGE SIZES FOR $H \geq 0.6$

Community	Infomap Disjoint		Infomap Overlap	
	No. of nodes	No. of bridges	No. of nodes	No. of overlaps
1	31	14	32	13
2	17	7	17	7
3	16	5	18	6
4	21	11	29	16
5	26	12	28	14
6	7	3	7	3
7	3	3	6	6
8	2	1	3	3
9	6	3	3	1
10	5	5	8	5
11	6	6	6	6
12	3	3	5	4

cascade sizes in the x-axis shown in Fig. 2 correspond to the LCC of the thresholded graphs shown in Table I. Based on these results, we observe that small cascade sizes are more probable compared to large cascade sizes. For example, in Fig. 2-a for $H \geq 0.6$, the probability of occurrence of cascade size in the range of 2 to 32 failures is 0.83 (seen as 10^0 due to log scale), while the probability of occurrence of cascade size in the range of 129 to 143 is small. These results are in agreement with the cascade size distributions found based on other historical and simulation data in [2]. This power-law based distribution of cascade sizes suggests that large cascade sizes are rare but their occurrence cannot be neglected. These large cascade sizes can be attributed to failure propagation caused by the size of overlap/bridge nodes as well as the strength of interaction of these nodes with other communities.

Next, we look at the cascade size distribution conditioned on the community that failures started in. In Fig. 3, for communities identified using Infomap disjoint for $H \geq 0.6$, we observe that each community has a distinct role in the

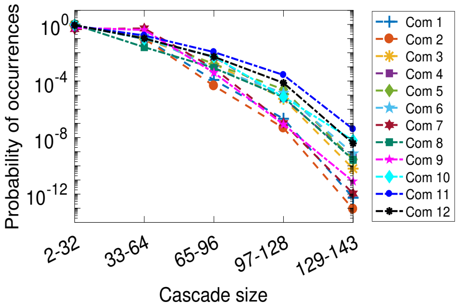

Fig. 3. Log scaled probabilities of cascade sizes when cascade initiates from any community, for communities identified using Infomap disjoint over the interaction graph of $H \geq 0.6$. (Com = community.)

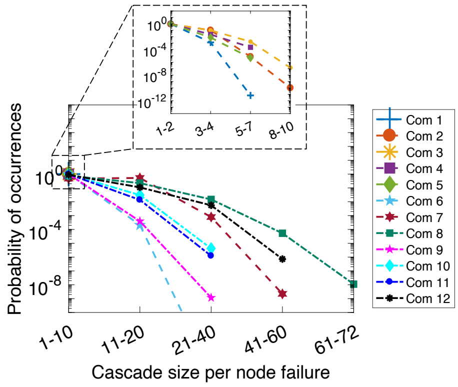

Fig. 4. Log scaled probabilities of cascade sizes induced by failure of one component belonging to different communities, for communities identified using Infomap disjoint over the interaction graph of $H \geq 0.6$.

probability of occurrence of various cascade sizes. For example, the probability of occurrence of large cascade size of range 129 to 143 is highest for community 11 compared to other communities. This can be attributed to the large number of bridge nodes compared to the community size and the strong weight of the interaction links of the bridge nodes. As seen in Table II, community 11 has 6 nodes and all 6 nodes are bridge nodes, as such failures in community 11 has a very high likelihood of spreading to other communities. We observe similar results for other interaction graphs with different thresholds and community structures as well.

To normalize the effect of the size of the initial community on cascade size, we also look at the number of ultimate failures per node failure in the initial community. As shown in Fig.4, for both Infomap disjoint and Infomap overlap, we observe that communities 1 to 5 induce smaller cascade sizes (from 1 to 10) shown in the expanded figure on the top, whereas communities 6 to 12 induce larger cascade sizes (from 1 to 72) shown in the main figure. This behavior is due to the larger size and smaller number of overlap/bridge nodes for communities 1 to 5 and the vice versa situation for communities 6 to 12, as shown in Table II. Thus, the contribution of nodes in smaller sized communities in causing large cascades are more prominent compared to nodes in larger sized communities.

VII. Conclusion

In this paper, we developed a Markov chain model to track the evolution of the cascading failures through communities embedded in interaction graphs. We discussed that the communities in interaction graphs can reveal important properties related to cascading failures as they tend to trap failures. We used this property and showed that the probability distribution of cascade sizes exhibited power-law behavior as observed in previous studies and historical data. This suggests that the community structures can be used to predict cascade sizes and estimate the risk of large blackouts.

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