Disaster Management in Scale-Free Networks: Recovery from and Protection Against Intentional Attacks

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Susceptibility of scale free Power Law (PL) networks to attacks has been traditionally studied in the context of what may be termed as instantaneous attacks, where a randomly selected set of nodes and edges are deleted while the network is kept static. In this paper, we shift the focus to the study of progressive and instantaneous attacks on reactive grown and random PL networks, which can respond to attacks and take remedial steps. In the process, we present several techniques that managed networks can adopt to minimize the damages during attacks, and also to efficiently recover from the aftermath of successful attacks. For example, we present (i) compensatory dynamics that minimize the damages inflicted by targeted progressive attacks, such as linear-preferential deletions of nodes in grown PL networks; the resulting dynamic naturally leads to the emergence of networks with PL degree distributions with exponential cutoffs; (ii) distributed healing algorithms that can scale the maximum degree of nodes in a PL network using only local decisions, and (iii) efficient means of creating giant connected components in a PL network that has been fragmented by attacks on a large number of high-degree nodes. Such targeted attacks are considered to be a major vulnerability of PL networks; however, our results show that the introduction of only a small number of random edges, through a reverse percolation process, can restore connectivity, which in turn allows restoration of other topological properties of the original network. Thus, the scale-free nature of the networks can itself be effectively utilized for protection and recovery purposes.

PACS numbers:
Keywords: growing networks, power law, attacks, peer-to-peer(P2P), scale-free, preferential deletion, compensation, ad hoc networks

I. INTRODUCTION

A large number of networks in different contexts have been found to have scale free structures (see [1] and references there in) characterized by Power-Law degree distributions. For a power-law (PL) degree distribution, the probability of a randomly chosen node to have degree \( k \) scales as \( P(k) \propto k^{-\gamma} \) for large \( k \); \( \gamma \) is referred to as the exponent of the distribution. Moreover, a PL distribution is considered to be heavy tailed if \( 2 < \gamma \leq 3 \), i.e., when the mean is bounded but the variance is unbounded. While many of these networks have evolved naturally, driven by dynamical processes over which we do not have much control, there are several classes of other networks, where the underlying dynamics can be altered to make sure that the resulting networks not only have scale-free structures, but are also resilient to external attacks. Examples of such designer complex networks include, the Internet, national power grids and other infrastructure related networks, computer and communication networks, and more recently Peer-To-Peer (P2P) networks. With the economy going more global every year, the emergence of different kinds of complex networks that interconnect distributed centers of communication, finance, and manufacturing, will only see a rapid growth. In such networks, attacks are a fact of life, and simple attacks, such as Denial-of-Service (DOS), can cripple hubs and other nodes, leading to severe disruptions of services. Understanding the effect of attacks, and mechanisms to respond to attacks is thus of great practical importance to many network based systems.

As reviewed in the following, the study of attacks, including both targeted and random, in scale-free PL networks have been mostly restricted to the case of instantaneous or massive attacks carried out on passive networks. In this paper, we shift the focus to the study of progressive and rapid attacks on networks that can respond in an active fashion. In the process, we design several techniques that managed networks can adopt to minimize the damages, and also to efficiently recover from the aftermath of successful attacks. We find that the scale-free nature of the networks can be judiciously utilized for such protection and recovery purposes.
A. Instantaneous vs. Progressive Attacks and Reactive Vs. Non-Reactive Networks

Susceptibility of networks to attacks has been traditionally studied in the context of what may be termed as instantaneous attacks, where a randomly selected set of nodes and edges are deleted while the network is kept static. Hence, for all purposes, the targeted nodes and edges are deleted simultaneously. The effect of such instantaneous attacks is then studied in terms of the connectivity structure of the network that is left behind after the attack, i.e., how many connected components are there in the compromised network, and if there exist giant connected components that contain a constant fraction of the remaining nodes. It is well known, for example, that in random Erdős-Rényi (ER) networks, it is sufficient to remove nodes independently with a probability above a certain threshold in order to break up the network into many subnetworks that are all small in size. Thus, random ER networks are considered susceptible to random deletions of nodes, or just instantaneous random attacks (IRAs). The case where the deleted nodes are picked non-uniformly randomly (e.g., preferentially with respect to their degrees) has also been studied; for the purposes of this paper, such attacks will be termed as Instantaneous Targeted Attacks (ITAs).

From a network management perspective, a key feature of such attack models is that the network remains passive or non-reactive during an attack: the removal of nodes and edges occurs without allowing the network to take actions (for example, inserting extra edges or allowing a deleted node to rejoin the network) to minimize the disruptive effects of the attacks. We shall refer to such networks as non-reactive networks. On the other hand, if a networked system takes active compensatory measures to maintain its integrity during an attack, or if it takes measures to recover from the damages inflicted by an instantaneous attack, then we will refer to such networks as reactive networks. Moreover, an attack that takes place at rates comparable to the response time of a network will be referred to as a progressive or gradual attack (as opposed to instantaneous attacks). In this paper, instead of only studying the case of instantaneous attacks on non-reactive networks, we explore the cases of both progressive and instantaneous attacks on reactive and dynamic networks, and study how the underlying networks can protect against, and recover from such attacks.

B. Instantaneous Attacks on Random and Grown Scale-Free PL Networks

Both IRAs and ITAs have been studied using the concept of percolation theory. Consider a network of size $N$ in which the largest connected component comprises a fraction $\lambda$ of the nodes. The site percolation process proceeds as follows: Take a constant probability $0 \leq p \leq 1$ (i.e., independent of the size parameter $N$) called the percolation probability. Delete each node in the network independently with probability $1 - p$ and retain it with probability $p$. For large $N$, the resulting network will have almost $pN$ nodes. Out of these $pN$ nodes, a set of $S(N,p)$ nodes will form a single connected component of the largest size. The main lesson of percolation theory is that for many families of graphs there exists a $p_c > 0$, such that if $p > p_c$ then $\lim_{N \to \infty} \frac{S(N,p)}{N} = X(p) > 0$, and if $p < p_c$, then $\lim_{N \to \infty} \frac{S(N,p)}{Np} = 0$. The critical percolation probability, $p_c$, is called the percolation threshold. This uniform instant site percolation process is a particular case of IRAs introduced earlier.

One can generalize the above-mentioned percolation concept of picking nodes randomly but uniformly, to where the nodes to be deleted are picked randomly, but with a distribution based on their degrees. For example, the case of targeted instant site percolation process (or ITA’s) might consist of (i) deleting all nodes of degree greater than a pre-specified value of say $k_0$, or (ii) if the fraction of nodes with degree $k$ in the original network is $p_k$, then the fraction of nodes of degree $k$ after the attack is reduced to $p'_k = bk^{-\gamma}p_k$, where $b$ is a normalization constant. In both cases, the high-degree nodes are the targets of severe attacks, and the low degree nodes are mostly left alone.

The percolation properties of random heavy-tailed scale-free Power-Law networks have been studied extensively and provide a mixed message when it comes to their vulnerabilities to IRAs and ITAs. For IRAs, the percolation theory reveals a very promising fact: The percolation threshold of these graphs is zero. That is, no matter how small the percolation probability, $p$, is, the remaining nodes in the percolated network has a giant connected component. Thus, random PL networks can withstand IRAs with arbitrarily high rates. Previous studies, however, have also shown that the random PL networks are more vulnerable to ITAs, e.g., removal of a large number of only high degree nodes from scale-free networks is enough to fragment the network such that a giant connected component does not exist. Thus, by removing a constant fraction of all nodes preferentially, one can destroy the connectivity of the network; note that the attacker still has to remove almost all the high-degree nodes to do so, which might be a difficult task to accomplish.

In many situations, however, the scale-free PL networks are not truly random, but can be modelled as being grown by dynamical rules, where nodes and edges are added at certain rates. Such networks will be referred to in this paper as grown scale-free networks. For example, the simple preferential attachment dynamic and its variants can give rise to scale-free grown networks with several tunable topological characteristics. Unlike the case of the random scale-free networks, currently there is no instantaneous percolation theory for these grown
scale-free networks. Nevertheless, empirical studies suggest that these networks are also both resilient to random deletions of their nodes (IRAs), and vulnerable to targeted attacks just as in the case of random scale-free networks [8].

For both random and grown PL networks, while we know that they are vulnerable to severe ITAs, the issue of how to recover from such attacks and glue the fragmented network back together efficiently has not been addressed. We show in Section IV how the PL structure of the network can in fact be an asset in this recovery process.

C. Progressive Attacks and Grown Scale-Free Networks

Recall that in progressive or gradual attacks, the deletions of nodes and edges take place at rates comparable to those at which the dynamics of the grown network itself operates at. For example, a progressive attack might correspond to a scenario, where randomly chosen existing nodes in the network (picked preferentially or uniformly with respect to the degree of a node) are removed at the same rate at which the new nodes join in. What do such progressive attacks do to the grown networks as opposed to the well studied case of instantaneous attacks?

Consider the simple case of linearly preferentially grown network, where in addition to a node joining the network at each time step, a uniformly randomly chosen existing node in the network is deleted with probability $c$ at each step. Such a dynamic is considered in detail in [10, 11]. It turns out that unlike the instantaneous attack case, where a grown network is resistant to IRAs, a grown network is very vulnerable to random progressive attacks. However, the connectivity structure of the attacked network is no longer a relevant measure to study the effect or severity of the progressive attacks; the network almost always remains connected, or has a giant connected component. As shown in [12], the damage to the network manifests itself by forcing the network to rapidly lose its heavy-tailed distribution (i.e., the PL exponent becomes much greater than 3, even as $c$ increases only marginally), and the resulting grown network starts resembling networks with exponential degree distributions under the attack.

A reactive grown network, however, may take remedial actions, and one might ask if there exist compensatory dynamics that will restore the heavy-tailed distribution even in the presence of the random progressive attack. It was shown in [12] that indeed the linear-preferential attachment dynamics can be modified in a very simple and local fashion to preserve the heavy-tailed degree distribution and the scale-free nature of the grown network. The compensatory procedure is intuitive and greedy: whenever a node loses a connection, which can only happen when a neighboring node is deleted due to the progressive attack, it compensates for it by making a new preferen-tial connection with a certain probability $n$. Thus, the dynamics remain strictly local (each node reacts only if it is directly impacted by the attack dynamic) and yet, the end result is that the damages to the global topological properties of the network are repaired, even in the limit of extremely high deletion rates (i.e., $c \to 1$).

This particular case study brings out two important differences between instantaneous and progressive attacks: (i) While a grown network might be resistant to IRAs, it can be extremely vulnerable to progressive random attacks. The damage to the network is no longer in terms of a loss in connectivity, but rather in terms of other topological properties of the network. (ii) It is, however, possible to make the dynamical rules of the grown networks to be reactive, and generate networks that are extremely resistant to both gradual and instantaneous random failures and attacks.

D. Protecting Against and Recovering from Attacks in Reactive Scale-Free Networks: A Summary of Results

We first consider protection against progressive or gradual targeted attacks in grown networks. The need to address this type of intentional attacks is particularly urgent in designer complex networks, such as the P2P networks, where performing a comprehensive large-scale attack on all the high-degree nodes is an expensive, and often, a very difficult task. However, gradual deletions of high-degree nodes by first crawling the network and identifying the high-degree nodes that serve as conduits for communication among low-degree nodes, and then attacking some of these nodes might be quite feasible.

Clearly, if no precaution or compensatory action is taken against such an attack, then as exemplified in the case of progressive random attacks [12], one would lose key topological features, including a loss of its heavy tailed degree distribution. How to equip the network with proper feed-back strategies to mitigate the damaging effects of the attacks and failures? These feedback strategies, moreover, must obey some stringent criteria: They must be local, in the sense that they should be triggered and adjusted only based on first neighbor information. In Section IV we introduce one such dynamical compensatory algorithm to mitigate the effect of linear-preferential attacks. In particular we show that, only with simple local modifications to the dynamics, the network can restore much (but not all) of its heavy-tail. The resulting degree distribution is shown to be a power-law with an exponential cutoff at a point that is inversely proportional to the rate of the targeted attack. Again, there is always a giant connected component, and the main effect of the attack is to introduce an exponential cutoff, and lower the PL exponent marginally. Thus, while the attacked network does lose its unbounded variance, the compensatory dynamics manage to preserve the overall PL degree distribution, and as shown next, keep the
network in a state, from which it can recover in a local fashion.

We next show in Section III A that a preferentially attacked network can perform large-scale network repairing and maintenance operations and selectively add edges, so as to increase the $k_{\text{max}}$ by any desired scaling factor; thus, this can repair the cutoff problem resulting from linear-preferential attacks. The recovery procedure is local, in the sense that each node independently decides how many preferential connections to create, and no global coordination is necessary. This procedure retains the exponent of the PL distribution, and only increases the maximum-degree of the distribution, so that the exponential cut-off point is not a limiting factor.

Next, we consider the case of recovery from a large-scale targeted attack. A heavy enough and instantaneous targeted attack will finally fragment any static or dynamic network. In Section IV we for the first time consider the challenging problem of repairing a complex network fragmented by targeted attacks. The disaster recovery consists of two distinct phases, and the first is to recover the lost connectivity. We show that with only a few essential communication paths one can create a giant connected component and glue the network fragments. In particular, we first show (both analytically and numerically) that when scale-free networks are fragmented due to targeted attacks, it results in small-size connected components, the size distribution of which is again heavy-tailed. This allows us to prove that the connectivity of the whole fragmented network can be restored with only a few successful random connections, via the process of reverse percolation. Thus, the nodes of the network will be able to communicate to each other to transfer vital "low-rate" messages, as long as a few random connections among the nodes can be established. Recovery of the topology, can then be achieved, once connectivity is established. Such a recovery step could consist of applying one of the many dynamical rules \cite{1, 9, 12} that would allow it to regain its scale-free structure.

\section{Reactive Grown Networks in Presence of Linear-Preferential Attacks and Compensation}

This section considers a progressive attack, where at each time step in addition to a node joining the network, a preferentially chosen node is deleted with probability $r$. Nodes that lose neighbors to attack don’t sit still, instead they react and replace those lost neighbors; moreover the attacked nodes rejoin the network as new nodes. We show that such a compensatory dynamic in the presence of linear-preferential progressive attacks naturally leads to a PL degree distribution with an exponential cutoff, where the cut-off depends on the preferential deletion rate. Thus, while the attack bounds the maximum degree of the distribution, the compensatory protocol is able to preserve the exponent of the PL distribution. Moreover, as shown in our simulations, as long as each incoming node makes $m \geq 2$ random preferential connections, there always exists a giant connected component, even for very high rates of preferential attacks (see Fig. II for an example); thus the loss of connectivity is not one of the damaging effects of such progressive attacks.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{fig1.png}
\caption{The fraction of nodes in the largest connected component for various rates of targeted attack when $m = 4$. Even for rates as high as 30\%, more than 97\% of the nodes belong to a single component.}
\end{figure}

Our model is a time dynamic one. At each step:

1. A new node $s$ is added to the network and makes $m$ preferential attachments.

2. With probability $r$ a preferentially selected node $w$ is chosen. The preferential selection procedure selects the node $w$ with degree $k(w, t)$ with probability $k(w, t)/\sum k(i, t)$. The selected node $w$ is then deleted from the network, were deletion process is:
   - Delete node $w$ and all its edges. Then $w$ starts as a new node and makes $m$ preferential attachments.
   - For all nodes $z$ that were connected to $w$ and have lost an edge, each one compensates by adding an edge preferentially.

\subsection{Analysis}

We adopt the same rate equation approach as \cite{12, 13} for our analysis. Label each node with its insertion time to network, $i$. Define degree of $i^{th}$ node at time $t$ as $k(i, t)$. When a node is deleted its joining time is reset. Let $S(t) = \sum k(i, t) = 2E(t) = 2(m + r)t$ and total number of nodes at time $t$, $N(t) = t$. The mean degree is $\langle k \rangle = 2(m + r)$. We want to find $P(k)$, i.e. probability that a randomly chosen node has degree $k$ at steady state ($t \rightarrow \infty$). We also define $f(t)$ as average number of edges deleted at time $t$ when a node is deleted preferentially,
that is the average degree of a node chosen preferentially: 
\( f(t) = \frac{(k(i,t))^2}{k} \). Note that obviously \((k) \leq f(t) \leq E(t)\). 

Define the probability that \(i^{th}\) node is not deleted before time \(t\) (is still in the network) as \(D(i,t)\). The initial conditions are \(D(i,i) = 1\), and \(k(i,i) = m\). Next we write master equations for \(k(i,t)\) and \(D(i,t)\)

\[
\frac{\partial k(i,t)}{\partial t} = m \frac{k(i,t)}{S(t)} + rm \frac{k(i,t)}{S(t)} + rf(t) \frac{k(i,t)}{S(t)} \tag{1}
\]

where the first term corresponds to \(m\) preferential attachments, the second term corresponds to deleted node rejoining the network, and the last term represents preferential compensation of on average \(r f(t)\) edges. Note that since each node compensates for lost edges there is no negative term in the equation. Also at time \(t + 1\) the probability that \(i^{th}\) node still exist in the network is given by:

\[
D(i,t+1) = D(i,t) \left(1 - \frac{i k(i,t)}{S(t)}\right)
\]

\[
D(i,t+1) - D(i,t) = -rD(i,t) \frac{k(i,t)}{S(t)}
\]

\[
\frac{\partial D(i,t)}{\partial t} = -rD(i,t) \frac{k(i,t)}{S(t)}
\]

\[
\ln \frac{D(i,s)}{D(i,t)} = - \int_t^s \frac{r k(i,t)}{2(m+r)} dt
\]

\[
= -\frac{r}{\langle k \rangle} \int_t^s \frac{k(i,t)}{t} dt
\]

\[
D(i,s) = \exp \left( -\frac{r}{\langle k \rangle} \int_t^s \frac{k(i,t)}{t} dt \right) \tag{2}
\]

Define \(\tilde{k}(i,s) = \int_s^t \frac{k(i,t)}{t} dt\), then \(D(i,s) = \exp(-r\tilde{k}(i,s)/\langle k \rangle)\). Note if \(k(i,t)\) is lower bounded by \(Ct^\beta\) then \(k(i,t) \geq \frac{1}{\beta} k(i,t)\):

\[
k(i,t) \geq Ct^\beta
\]

\[
\tilde{k}(i,t) \geq \frac{k(i,t)}{\beta} \tag{3}
\]

In order to solve for \(k(i,t)\), we need to know \(f(t)\), which depends on \(k(i,t)\):

\[
f(t) = \frac{(k(i,t))^2}{k} = \frac{1}{N(t)\langle k \rangle} \sum_{i=0}^t k(i,t)^2 D(i,t) \tag{4}
\]

When Equation 4 is valid then:

\[
f(t) = \frac{1}{N(t)\langle k \rangle} \sum_{i=0}^t k(i,t)^2 D(i,t)
\]

\[
= \frac{1}{t\langle k \rangle} \sum_{i=0}^t k(i,t)^2 \exp \left(-\frac{r}{\langle k \rangle} k(i,t)\right)
\]

\[
\leq \frac{1}{t\langle k \rangle} \sum_{i=0}^t k(i,t)^2 \exp \left(-\frac{r}{\beta\langle k \rangle} k(i,t)\right)
\]

Since \(x^2 \exp(-\alpha x) \leq \frac{4e^{-2}}{\alpha^2}\):

\[
f(t) \leq \frac{1}{t\langle k \rangle} \sum_{i=0}^t \left(\frac{\beta\langle k \rangle}{2}\right)^t 4e^{-2}
\]

\[
= \frac{4e^{-2}\beta^2(k)}{\beta^2}
\]

Thus we see that if \(k(i,t)\) is a finite polynomial of positive powers of \(t\), then \(f(t)\) is a constant.

We know that \(f(t) \leq E(t) = (m+r)t\), but edge deletion may reduce it further. Hence we consider the case where \(f(t) = at^b\). We consider this for two cases, first where \(b = 0\), and second where \(b > 0\). If \(f(t) = a\) then Eqn. 4 becomes:

\[
\frac{\partial \tilde{k}(i,t)}{\partial t} = (m+1+r) \frac{k(i,t)}{S(t)}
\]

\[
= (m+r+r(m+a-1)) \frac{k(i,t)}{2(m+r)t}
\]

so, using \(\epsilon = \frac{r(m+a-1)}{2(m+r)}\)

\[
\frac{\partial \tilde{k}(i,t)}{\partial t} = \left(\frac{1}{2} + \epsilon\right) \frac{k(i,t)}{t}
\]

\[
\ln \frac{k(i,t)}{k(i,i)} = \left(\frac{1}{2} + \epsilon\right) \ln(t/i)
\]

\[
k(i,t) = m \left(\frac{t}{i}\right)^{1/2+\epsilon} \tag{6}
\]

Eqn. 5 already showed that if \(k(i,t)\) grows as a power of \(t\), \(f(t)\) is constant. The above shows that when we assume that \(f(t) = a\), we see that \(k(i,t)\) grows as a power of \(t/i\).

We calculate \(P(k,t)\) from \(k(i,t)\) and \(D(i,t)\) using Eqn.

\[
D(i,s) = \exp \left( -\frac{r}{\langle k \rangle} \int_t^s \frac{k(i,t)}{t} dt \right)
\]

\[
= \exp \left( -\frac{r}{\langle k \rangle} \int_t^s \frac{m \left(\frac{t}{i}\right)^{1/2+\epsilon}}{t} dt \right)
\]

\[
= \exp \left( -\frac{rm}{i^{1/2+\epsilon} \langle k \rangle} \int_t^s t^{-\beta} dt \right)
\]

\[
= \exp \left( -\frac{r}{(1/2 + \epsilon) \langle k \rangle} (k(i,t) - m) \right)
\]

\[
P(k,t) = \frac{1}{N(t)\sum_{i:k(i,t)=k}^t D(i,t)}
\]

\[
= \frac{1}{t D(i,t)} \left| \frac{\partial}{\partial k} \right| \tag{7}
\]
If \( k(i, t) = m(t/i)^{1/2+\epsilon} \):

\[
k(i, t) = m(t/i)^{1/2+\epsilon} \quad \text{and makes } m = 2 \text{ preferential attachments. Then with probability } r \text{ we delete a node, choosing a node to be deleted preferentially. Fig. 2 shows the effect of low rate preferential deletion as imposing an exponential cutoff on the scale-free degree distribution.}
\]

We consider a connected PL network where the tail (i.e., the set of high degree nodes) is removed. We first show how a local compensation process, involving the creation of new links, can restore the maximum degree to a multiple of the existing cutoff. Each node decides randomly and independently how many preferential edges to insert, and thus the healing process does not need any central coordination mechanism. Such a healing process can be periodically applied by, for example, a network created by the dynamics described in the previous section, where a cutoff in the degree distribution is naturally introduced.

### III. DECENTRALIZED AND DISTRIBUTED HEALING OF SHARP CUTOFFS IN PL NETWORKS

We consider a connected PL network where the tail (i.e., the set of high degree nodes) is removed. We first show how a local compensation process, involving the creation of new links, can restore the maximum degree to a multiple of the existing cutoff. Each node decides randomly and independently how many preferential edges to insert, and thus the healing process does not need any central coordination mechanism. Such a healing process can be periodically applied by, for example, a network created by the dynamics described in the previous section, where a cutoff in the degree distribution is naturally introduced.

#### A. Healing Process

Consider a short tailed power-law network of exponent \( \alpha \) and maximum degree \( k_0 \). The objective of the healing process is to increase the maximum degree of the distribution by a stretch-factor \( w = k_{max}/k_0 \), so that the maximum degree after the healing process will increase from \( k_0 \) to \( k_{max} \), while the power-law exponent remains the same.

#### B. Simulations

We have performed extensive Monte Carlo simulations. We grow the network where at each step a node is added

Thus:

\[
P(k, t) = \frac{1}{t} D(i, t) \left| \frac{\partial i}{\partial k} \right|
\]

We grow the network where at each step a node is added
Healing Algorithm Given a PL network with exponent $\alpha$, each node $i$ independently decides to compensate with some probability $p$. The compensation process involves making $(w-1)k_i$ new preferential connections where $k_i$ is the degree of the $i^{th}$ node.

Let $P(k)$ and $P'(k)$ be the degree distributions before and after the healing process respectively, then one can easily show that given $P(k)$ is a short tailed power-law with maximum degree $k_0$ and $p \approx w^{-\alpha}$, $P'(k)$ follows a power law distribution as $\lambda(w, \alpha)k^{-\alpha}$. Where $\lambda$ is a constant depending on $w$ and $\alpha$ and cut off is increased to $k_{\max}$. In other words, the effect of the healing process is simply to stretch the degree distribution by a linear factor. Now since the degree distribution is scale-free to begin with, such stretching will not change the distribution. Thus power-law degree distribution of the original network is the key for the simple healing process to succeed.

B. Autonomous Healing

So far we have considered a static case, i.e., we are given a network with a sharp cutoff, and the nodes randomly decide to introduce new edges to restore the cutoff to a desired value, $k_{\max}$, while retaining the same PL exponent, $\alpha$, as before. One can modify this static scenario to an adaptive version, where instead of all the nodes acting at once, each node reacts whenever it loses an edge unannounced, i.e., due to an attacked node going down. The idea is to naturally detect a heavy attack and initiate the healing process.

Feedback Algorithm: Each node $i$ when losing an edge without prior notice performs the healing algorithm of Section II A with probability $1/k_i$, where $k_i$ is the degree of the $i^{th}$ node.

Clearly any targeted deletion of nodes in the tail of the degree distribution, i.e., high degree nodes, will result in the deletion of a constant fraction of the edges of the system. If we further neglect the degree correlation of the nodes, the probability of any edge being deleted when nodes of degree greater than $k_0$ are deleted will be given by:

$$\tilde{p} \approx \frac{\Sigma_{k_0} k P(k)}{E} = \lambda k_0^{2-\alpha}. \tag{8}$$

for some constant $\lambda$ in the order of 1. Then, the probability of a node with degree $k$ losing an edge is $\tilde{P}_k \approx k \tilde{p}$. Thus the probability of a node initiating the healing process is approximately $\tilde{P}_k/k = \tilde{p}$, a constant depending on only the intensity of the attack: We must re-state that we have not considered second order effects and degree correlations here. This algorithm is basically intended to detect any large scale instantaneous deletion of a fraction of network edges. Thus, the algorithm ensures that a constant fraction of the nodes will always perform the healing algorithm in the case of a large enough attack.

We have performed the Monte Carlo simulations of the healing and feedback algorithm. Fig. 5 shows how the healing algorithm works for different values of $\alpha$.

IV. RESTORING CONNECTIVITY IN A FRAGMENTED POWER-LAW NETWORK

Any network will breakdown under a sufficiently heavy targeted attack, and the question we ask is how many random connections among the nodes in the fragmented network do we need to establish before a giant connected component emerges. The goal of this section is to show that both grown and random power-law networks, are very amenable to quick bootstrapping from an attack, and with almost no global coordination. In particular, we will show that even under very intense attacks, only an infinitesimally small probability of success for new connections is enough to quickly reconnect most of the broken network.

For example, consider a linearly preferentially grown PL network of size 50,000 and average degree 4, that has undergone a very heavy targeted attack in which all nodes of degree more than 50 are lost. For a particular simulation, the size of the largest component was only 371 after the attack. Now assume that all the nodes try to initiate only one random connection to some other node in the network in a hope to restore the connectivity. If the probability of success of each of these attempts is only 5%, our simulations show that a very large component of size more than 20,000 forms. This probability of success will go asymptotically to zero as the network size increases. Of course, other reconstruction algorithms will be required to repair the topological damages to the network, as was the subject of the algorithms in Section III A.

The results in this section will follow the following pattern: First we will argue that grown PL networks fragmented under a targeted attack, have components whose size distributions are heavy-tailed PL’s. Thus, even though the average size of the connected components is bounded, the variance is unbounded (or very large). While a proof for grown networks is difficult in general, we show analytically that for a linearly preferentially grown tree network (i.e., each node joining the network makes exactly one preferential connection) the removal of the highest degree node indeed creates disconnected components with a PL size distribution. We then show, using the generating functions formalism, that the same phenomenon can be observed in random PL networks for special forms of targeted attacks.

Next, we prove that as long as we have components with heavy-tailed size distribution, then only a vanishingly small number of random connections will glue the fragments together into a giant connected component.
A. Distribution of the size of components after attack: Grown Power-law graphs

Generally, instantaneous percolation (and hence attack) on grown graphs is hard to analyze. For some special cases however, the statistics of the connected components after a preferential attack can be tracked. In this subsection, we compute the distribution of the sizes of the connected components for graphs grown under the preferential attachment (Barabasi-Albert graphs) with \( m = 1 \): At each time step, a new node is added to the network and initiates one preferentially targeted link. The probability that the \( i^{th} \) node receives this link is \( k(i, t)/\sum_{j=1}^{t} k(j, t) \), where \( k(i, t) \) is the degree of the \( i^{th} \) node at time \( t \).

At some time \( t \gg 1 \), a preferential attack occurs, and deletes the oldest node \( i = 1 \). As a result of such attack, the network will be fragmented into many connected components. We now show that the size of these components have a power-law distribution, and in particular, the probability that a randomly chosen component has size \( C \) is \( \propto C^{-3/2} \).

Before continuing, we need the following observations: (i) Since \( m = 1 \), the network topology is a tree. (ii) Take any node \( i \) and consider the subtree rooted at \( i \) and consisting of all the nodes younger than \( i \). The size of this subtree, denoted by \( T(i, t) \) can be calculated as follows: At time \( t = i \), this subtree has had only one node (with one link to some other node \( j < i \)), thus \( T(i, i) = 1 \), while there has been \( i \) other links in the network. The rate of change of \( T(i, t) \) can be written as:

\[
\frac{\partial T(i, t)}{\partial t} = \frac{(2T(i, t) - 1)}{2t}
\]

If 1 can be neglected compare to \( 2T(i, t) \) (which is certainly true when \( t \gg i \)), one gets: \( T(i, t) = (t/i) \).

Now, note that from the rate-equations, the degree of a node inserted at time \( i \), at a later time \( t \) is given by:

\[
k(i, t) = (t/i)^{\beta}
\]

for \( \beta = 1/2 \). Thus the degree of the first node is around \( k(1, t) = t^{1/2} \). Thus, once the first node is deleted, exactly \( k(1, t) \) connected components will be created (remember the network is tree). Lets enumerate these components by the sets \( C_1, C_2, ..., C_{k(1,t)} \). Let \( \kappa_j, j = 1, 2, ..., k(1, t) \) be the oldest node in each \( C_j \). By construction of the network, the node \( \kappa_j \) must have been connected to the first node \( (i = 1) \). Now note that the size of the subtree \( C_j \) is simply \( |C_j| = T(\kappa_j, t) = (t/\kappa_j) \). This will allow us to find the probability that a randomly chosen connected component has size \( C \) as follows:

\[
P_C = \frac{\# Components of size C}{k(1, t)} \propto \left( \Pr(\kappa connected to 1) \right) \frac{\partial k}{\partial C} \left| \kappa: T(\kappa, t) = C \right. \\
\propto \left( \frac{\kappa^\beta}{\kappa^*} \right) \frac{\partial k}{\partial C} \left| \kappa^*: T(\kappa^*, t) = C \right.
\]

FIG. 3: Degree distribution before and after healing for various values of power-law exponent \( \alpha \) and stretch factors \( w \).
Now, note that $T(\kappa^*, t) = (t/\kappa^*) = C$, and $|\partial \kappa / \partial C| = tC^{-2}$. Therefore:

$$P_C \propto \frac{C^{-\beta}}{C-1} \times C^{-2} = C^{-3/2}$$

In [12], Newman et. al, have shown that for any static random graph, the distribution of the size of the components just before the phase transition and the appearance of a giant connected component obeys the same scaling law as $P_C \propto C^{-3/2}$. So interestingly, while the deletion of a key node (the first node) fragments the network into many components (around $t^{1/2}$ different pieces), the distribution of the sizes of these components obeys a power-law.

For more complex randomly grown graphs, no theory of percolation currently exists to obtain the distribution of the connected components. Simulations however indicate that the same observations still hold for many such networks. One such simulation is reported for networks grown with the deletion compensation protocol introduced in [12], and is reported in Fig. 4.

![Graph](image)

**FIG. 4:** The distribution of the size of the connected components for heavily attacked networks of size 50,000 after a targeted attack that deleted all the nodes with degree greater than 50. (top) Linearly preferentially grown PL network (Barabasi-Albert model) when the average degree is 4. (bottom) Deletion-compensation networks of [12], with $\gamma \approx 2.3$ and average degree 6.

### B. Distribution of the size of components after attack: Static Power-law graphs

We now show that the same observations hold for some form of random targeted attacks on static power-law networks as well. The size distribution of the connected components of any static random network on a given degree distribution can be found analytically using the generating functions formalism [12]. In particular, the variance of the distribution of the size of these components are derived analytically in Appendix A, which also contains a brief introduction to generating functions formalism.

Consider the generating functions of an attacked network:

$$G_0(x) = \sum_{i=1}^{K} q_k p_k x^{-k}$$

(9)

$$G_1(x) = \frac{G'_0(x)}{G_0(1)}$$

(10)

where $q_k$ is the probability that a node with degree $k$ is deleted through the attack. This would define a form of targeted attack if $q_k$ decreases with $k$. In particular, we examine a targeted attack for which $q_k = bk^{-q}$ where $q$ is a measure of the how targeted the attack is and $b$ is a normalization constant. Then, the generating functions of the attacked network for an original power-law graph with exponent $\tau$ are:

$$G_0(x) = \sum_{i=1}^{K} c_1 k^{-\tau-q} x^{-k}$$

(12)

$$G'_1(1) = c' \sum_{k=1}^{K} k^{-\tau-q+2} = O(K^{-\tau-q+3})$$

(14)

for some positive constants $c, c'$ when $\tau + q \geq 2$. In particular, for the linear targeted attack, $q = 1$, this value is always finite for any $\tau > 2$.

It should be noted that such preferential attack would in effect increase the value of $\tau$ by an amount of $q$. Thus following the approach of Aiello et. al. [16], one can show that no giant connected component will exist when:

$$\tau + q > \beta_c \approx 3.478.$$  

Although the network might not have any giant connected component, the variance of the distribution of the sizes might still diverge. This is shown through $G''_1(1)$ (see Eqn. A4):

$$G''_1(1) = \sum_{k=3}^{K} k(k-1)(k-2)bk^{-\tau-q} \propto K^{-\tau-q+4}$$

which diverges for any $q$ provided that $q < 4 - \tau$. In particular for the linearly targeted attack, $q = 1$, the
The variance of the size of connected components diverges if \( 2 < \tau < 3 \), even though the average component size is finite at least when \( \tau > 2.349 \).

### C. The Reverse Percolation Process

The main idea behind the results in this section is what we will refer to as the reverse percolation process: Consider an attacked network, as in Fig. 4. Now let’s start adding random edges between the nodes of this network of many small components. As the number of such random links increases, different component of the network will start to glue together until a giant connected component occurs which contains most of the nodes of the network. Let’s call \( Q(k) \) the distribution of the sizes of these small components, that is, \( Q(k) \) is the fraction of these components that have size \( k \). We claim that the reverse percolation process corresponds to a percolation on a random graph with degree distribution \( P(k) \equiv Q(k) \). To see this we need to recall the method with which a random graph with a prescribed degree distribution \( P(k) \) is built on \( N \) nodes (see Fig. 5).

To construct a random graph with degree distribution \( P(k) \), one can proceed as follows [18]: for any \( k \), there will be \( N P(k) \) nodes of degree \( k \) in the network, labelled as \( V^k_1, V^k_2, \ldots, V^k_{NP(k)} \). For each of these nodes create \( k \) dummy duplicate nodes. To be specific, call the duplicates of the \( i^{th} \) node as \( V^k_{i1}, V^k_{i2}, \ldots, V^k_{ik} \). Now on this hyper graph, one can start a random matching. After the matching, one will collapse the duplicates of a node \( i \) into one node, and therefore all the links to the duplicates will now be links to the collapsed node itself. A reverse percolation process with probability \( p \) can be interpreted as introducing random edges, i.e., doing the random matching with a fraction \( p \) of all the links in the hyper graph.

With this construction in mind, the validity of our claim is readily understood. In the connectivity restoration process, any connected component can be viewed as the duplicate nodes of a single node, and the insertion of random edges can be viewed as a (reverse) percolation process on a graph whose degree distribution is equal to the distribution of the component sizes of the real broken graph (see Fig. 4). In the usual percolation process, you keep each edge with probability \( p \), which in the random graph construction process, basically involves doing random matching with probability \( p \), in the network with duplicated nodes. With this correspondence, many of the well known results for the percolation process on random graphs with a given degree distribution can be readily applied to the gluing process.

In particular, the percolation threshold, corresponding to the probability of successful attempts required for a giant component to appear can be calculated as: \( q_c = \frac{\langle C \rangle}{\langle C^2 \rangle} \), where \( \langle C \rangle, \langle C^2 \rangle \) are the average and variance of the distribution of the connected components (see for instance for [8]). While the average size of the connected components in a heavily attacked network is finite, it is possible for the variance of this distribution to be very large. In which case, the corresponding percolation threshold will be small. In other words, one would only require an infinitesimally small fraction of random links to glue most of the disjoint components together. In particular, if the distribution of the size of the connected components follows a power-law distribution with exponent \( 2 < \alpha < 3 \) and maximum component size \( C_{\text{max}} \gg 1 \), then only \( O(C_{\text{max}}^{-\alpha+3}) \) successful random links per component is enough to ensure that most of the disconnected components are reconnected.
FIG. 6: Percolation and Reverse Percolation Process: Bond percolation corresponds to random deletion of the links of a network. In the top figure, 4 out of 10 links of the random network generated in Fig. 5 are deleted, resulting in the middle graph. This was equivalent to doing the random graph matching on the hyper graph with only 10-4=6 links instead of 10 links (the bottom figure).

V. CONCLUDING REMARKS

We have addressed the issue of attack management in scale-free PL networks that are reactive, and can take local steps to combat attacks. In particular, we have shown how grown networks can cope with both random and linear-preferential progressive attacks, where nodes are deleted as the network grows. We also presented a number of recovery schemes, including repairing of sharp cutoffs in PL degree distributions, and restoration of connectivity in networks fragmented by large-scale targeted attacks. All these compensatory mechanisms are shown to be local, in the sense that global coordination among the nodes is not required, and the nodes initiate new edges only in reaction to changes in their immediate environment.

There are several interesting implications of the results presented in this paper in terms of complex network theory as well. For example, Section II presents a network dynamic that leads to the emergence of PL degree distributions with exponential cutoffs; perhaps, such a mechanism can model existing networks where such degree distributions have been observed empirically. Similarly, when one studies the distribution of the size of the connected components in the networks generated by the dynamic in Section II, then one observes that there is always a giant connected component, but more interestingly, the rest of the components have a power-law size distribution. Such a component size distribution has been observed, for example, in the world wide web (WWW) network, and one wonders if a low-grade preferential deletion of high-degree nodes in the web is one of the dynamical forces shaping the underlying connectivity structure.

APPENDIX A: VARIANCE OF THE DISTRIBUTION OF THE SIZE OF CONNECTED COMPONENTS IN STATIC RANDOM NETWORKS

Consider a random network on a given degree distribution \( P(k) \), that is the probability that a randomly chosen node has degree \( k \) is \( P(k) \). Define
\[
G_0(x) = \sum_{i=1}^{K} P(k)x^{-k} \\
G_1(x) = \frac{G_0'(x)}{G_0'(1)}
\]
as the generating functions of the degree of a node arrived at by choosing a random node or link respectively.

Similarly, one can define \( H_1(x), H_0(x) \) as the generating function of the size of the connected components arrived at by following a random link and node respectively.

When a giant connected component does not exist and therefore the graph is tree like, these four functions should be related through the following consistency equation:
\[
H_1(x) = xG_1(H_1(x)) \\
H_0(x) = xG_0(H_1(x))
\] (A1) (A2)

The average distribution of the sizes of the connected components are:
\[
\langle s \rangle = H_1'(1) = 1 + \frac{G_1'(1)}{1-G_1'(1)}
\]
The phase transition happens when \( G_1'(1) = 1 \) and a giant connected component appears (or disappears).
The known literature has always been interested in the average size of the connected components due to its phase transition and physically measurable properties. We will however examine the properties of the second moment of the distribution of the size of the connected components.

Twice differentiating $H_1(x)$ in (A1):

$$H_1''(x) = G_1'(H_1(x))H_1'(x) + H_1'(x)G_1'(H_1(x)) + xH_1''G_1'(H_1(x)) + x(H_1'(x))^2G_1''(H_1(x)) \quad (A3)$$

Once differentiating $H_1(x)$ in (A1) results in:

$$H_1'(1) = \frac{2}{1-G_1'(1)} \quad (A4)$$

Plugging this into (A4) evaluated at $x = 1$ will result in:

$$E\{size^2\} = H_1''(1) = \frac{4G_1'(1)}{(1-G_1'(1))^2} + \frac{4G_1''(1)}{(1-G_1'(1))^3} \quad (A4)$$

This second moment can diverge in two cases. First, if $G_1'(1) \to 1$, and second $G_1''(1) \to \infty$. When a giant connected component does not exist, $G_1'(1) < 1$, the second moment can still diverge provided that $G_1''(1)$ diverges.

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