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Cascade-robustness optimization of coupling preference in interconnected networks

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ABSTRACT

Recently, the robustness of interconnected networks has attracted extensive attentions, one of which is to investigate the influence of coupling preference. In this paper, the memetic algorithm (MA) is employed to optimize the coupling links of interconnected networks. Afterwards, a comparison is made between MA optimized coupling strategy and traditional assortative, disassortative and random coupling preferences. It is found that the MA optimized coupling strategy with a moderate assortative value shows an outstanding performance against cascading failures on both synthetic scale-free interconnected networks and real-world networks. We then provide an explanation for this phenomenon from a micro-scope point of view and propose a coupling coefficient index to quantify the coupling preference. Our work is helpful for the design of robust interconnected networks.

1. Introduction

Infrastructure systems, such as the World-Wide Web, power grids, communication networks and transportation systems, act an increasingly important role in our everyday life [1]. Normally, these infrastructures are in smooth operation. However, the random malfunction or malicious attack may lead to a collapse of the entire system. In recent years, large-scale communication outages [2], blackouts [3] and traffic congestion [4], which can result in serious economic consequences, receive widespread concerns.

Complex network theory is a powerful tool to evaluate and improve the robustness of networked infrastructures. Numerous previous research can be mainly divided into two aspects: topology robustness and cascading robustness. Albert [5] evaluated robustness based on network topology and found that scale-free networks display a surprisingly high degree of tolerance against random failures, but sensitive to intentional attacks. Different from topology robustness, Motter et al. [6] proposed a load-capacity cascading failure model, in which the load of a node is defined by its betweenness centrality. Wang and Chen [7] investigated the universal robustness characteristic of weighted networks against cascading failures by adopting a local weighted flow distribution rule and obtained an optimal weighting parameter. Wang and Rong [8] investigated the robustness against cascading failures of US power grid and found that the low-load nodes also played vital roles in the cascading propagation.

In spite of significant achievements, most previous works are limited to the case of isolated networks. However, many real networked systems are actually coupled with each other. In 2010, Buldyrev et al. [9] studied the electrical blackout in Italy, and firstly proposed a framework to capture the phenomenon of cascading failures in interdependent networks. Thereafter, the research of coupled networks drew extension attentions from different communities [10–25] and one can have a comprehensive review through the work of Boccaletti et al. [10]. Many crucial influence factors, such as coupling strength [17,18], coupling mode [19–22], coupling preference [23–25] are comprehensively investigated. In terms of coupling preference, Tan et al. [23] studied the cascading failures in interconnected networks under intentional attack and concluded that assortative coupling can better resist the cascades compared to disassortative or random coupling. Peng et al. [24] proposed a cascading model with different load-redistribution strategy on intra-links and coupling links, and drew the same conclusion. Chen et al. [25] further found that assortative coupling performs better for dense coupling, while disassortative coupling is more robust for sparse coupling.

Neither assortative nor disassortative coupling is the optimal strategy. Recently, researchers resort to intelligent optimization algorithms, which has shown outstanding performance in solving

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many realistic problems [26–32], to enhance network robustness [33–35]. Zhou et al. [33] proposed MA to enhance the robustness of scale-free network against malicious attack without changing the degree distribution. Tang et al. [34] introduced a memetic algorithm to optimize the topology of network resisting both targeted and random attacks. Chen et al. [35] applied particle swarm optimization algorithm to search for the most favorable pattern of node capacity allocation to improve the network robustness with the minimum cost. Actually, the configuration of coupling links in interconnected networks is a combination optimization problem with discrete variables. In this paper, we design a specific MA to optimize the coupling links of interconnected networks and compare the MA optimized coupling strategy with traditional assortative, disassortative and random coupling preferences. It is found that the MA optimized coupling strategy with moderate assortative value can better enforce the network robustness against cascading failures. Afterwards, an explanation from a micro-point of view is provided and an experiment on real-world is investigated.

This paper is composed of 5 sections. Section 2 describes the interconnected networks model and three coupling preference strategies as well as the optimization model. Section 3 represents the memetic algorithm and Section 4 shows the simulation results and corresponding analysis. Section 5 summarizes the work.

2. Model

2.1. Network and cascading models

Many real-world networks are found to be scale-free, such as the World-Wide Web [36], Internet [37] and airline routes [38], thus we adopt the well-known Barabási-Albert (BA) model to build each individual network [39]. The BA model starts with a small number (m_0) of vertices, and at every time step a new vertex is added with $m(\leq m_0)$ edges that link the new vertex to m different vertices already present in the model. In the following, the BA model is set to $m_0 = 2$ and $m = 2$. The interconnected network is composed of two BA scale-free networks, A and B. Without loss of generality, these two networks are assumed to share the same network size, $N_A = N_B = N/2$, and the same average degree, $\langle k_A\rangle = \langle k_B\rangle = \langle k\rangle$.

Networks A and B are coupled by interconnected links. Coupling probability $p = 2n_c/N$ is defined as the ratio of the number of interconnected links n_c to the network size $N/2$. Each node has at most one interconnected link.

There are three common coupling preferences, namely assortative, disassortative and random coupling:

Assortative coupling. Couple the heaviest load node in network A with the heaviest load node in network B. Then couple the second heaviest load node in network A with the second heaviest load node in network B, and so on. Repeat this process until $pN/2$ coupling links are added.

Disassortative coupling. Couple the heaviest load node in network A with the lightest load node in network B. Then couple the second heaviest load node in network A with the second lightest load node in network B, and so on. Repeat this process until $pN/2$ coupling links are added.

Random coupling. Randomly choose a node in network A and a node in network B. If neither of them has a coupling link, then couple them. Repeat this process until $pN/2$ coupling links are added.

In the cascading model, the node load can be calculated by betweenness centrality if the traffic flow transmits along the shortest path. The betweenness centrality is defined by Freeman [40] as follows:

$$B(v) = \sum_{s\neq t\neq v\notin V} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

where V is the set of vertices, and σ_{st} denotes the number of shortest paths from $s \in V$ to $t \in V$. For convention, $\sigma_{ss} = 1$ [40]. $\sigma_{st}(v)$ denotes the number of shortest paths from s to t that go through $v \in V$.

The node capacity C_i is the maximum load that the node i can deal with. As in Ref [6], the capacity of node is proportional to its initial load:

$$C_i = (1+\alpha) * L_i \tag{2}$$

where α is the tolerance parameter and L_i is the initial load of node i.

Initially, the highest-load node in the interconnected network is removed. The node load is then recalculated. If one node's load is beyond its capacity, it will be removed from the system and the load will be updated. Repeat this step until there is no more overloaded nodes.

2.2. Optimization model

Following common practices, only nodes in giant component remain functional after cascading process. Therefore, the proportion of the giant component to the initial network size is a natural measure of network robustness, which is defined as:

$$G = \frac{N'}{N} \tag{3}$$

where G represents the network robustness, N is the size of the interconnected networks and N' is the size of giant component after cascading failure.

Our goal is to optimize the robustness of interconnected networks by means of adjusting the coupling preference. For convenience, a coupling matrix M is used to describe the coupling preference.

$$M_{ij} = \begin{cases} 0, & \text{node } A_i \text{ and } B_j \text{ are not coupled.} \\ 1, & \text{node } A_i \text{ and } B_j \text{ are coupled.} \end{cases} \tag{4}$$

where A_i denotes node i in network A, and B_j denotes node j in network B. Then the optimization model of coupling links can be formulated as a combination optimization problem:

$$max \quad G$$

$$s.t. \begin{cases} \sum_{i=1}^{N} M_{ij} = 0 \quad or \quad 1 \\ \sum_{j=1}^{N} M_{ij} = 0 \quad or \quad 1 \\ \sum_{i=1,j=1}^{N} M_{ij} = \frac{Np}{2} \\ 0 < p \leq 1 \end{cases} \tag{5}$$

3. Method—memetic algorithm

Memetic algorithm (MA), which is a hybrid metaheuristic, was first proposed by Pablo Moscato in his technical report [41] in 1989. The term memetic comes from the concept of meme, defined as a unit of cultural evolution that can exhibit local improvement [42]. It is a marriage between a population-based global search and the heuristic local search. It is proven successful in various optimization problems [43–46]. The framework of MA algorithm is presented in Algorithm 1.