Physica A 405 (2014) 114–127

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Network congestion analysis of gravity generated models

Dimitris Maniadakis, Dimitris Varoutas *

Department of Informatics and Telecommunications, National and Kapodistrian University of Athens, Panepistimiopolis, Ilissia GR-15784, Greece

HIGHLIGHTS

- Network congestion is examined under different topology and traffic types.
- Gravity networks suffer less congestion than random, scale-free or Jackson–Rogers ones.
- Gravity traffic pattern causes more severe congestion to all topology types.

ARTICLE INFO

Article history:
Received 22 September 2013
Received in revised form 31 January 2014
Available online 12 March 2014

Keywords:
Complex network
Gravity model
Network congestion
Spatial network
Traffic dynamics

ABSTRACT

The network topology has lately proved to be critical to the appearance of traffic congestion, with scale-free networks being the less affected at high volumes of traffic. Here, the congestion dynamics are investigated for a class of networks that has experienced a resurgence of interest, the networks based on the gravity model. In addition, supplementary to the standard paradigm of uniform traffic volumes between randomly interacting node pairs, more realistic gravity traffic patterns are used to simulate the flows in the network. Results indicate that depending on the traffic pattern, the networks have different tolerance to congestion. Experiment simulation shows that the topologies created on the basis of the gravity model suffer less from congestion than the random, the scale-free or the Jackson–Rogers ones under both random and gravity traffic patterns. The congestion level is found to be approximately correlated with the network clustering coefficient in the case of random traffic, whereas in the case of gravity traffic such a correlation is not a trivial one. Other basic network properties such as the average shortest path and the diameter are seen to correlate fairly well with the congestion level. Further investigation on the adjustment of the gravity model parameters indicates particular sensitivity to network congestion. This work may have practical implications for designing traffic networks with both reasonable budget and good performance.

1. Introduction

Networks have been thoroughly investigated in the last decade with impressive research results on the universality of various topological characteristics [1] and on the mechanisms of topology generation [1–3]. Unexpected similarities and substantial common, but non-trivial, structural features (power-law degree distributions, high clustering coefficient, small geodesic path lengths, etc.) among real-world networks compose the most essential findings indicating a departure from the random network models having being proposed five decades earlier [4]. The contemporary knowledge on the networks' structure can now be used for the understanding of challenging underlying processes that take place on networks. For example, searching, diffusion, spreading, synchronization, traffic flow interactions and other dynamical phenomena have recently been put in the foreground.

* Corresponding author. Tel.: +30 210 7275318; fax: +30 210 7275214.
E-mail addresses: D.Maniadakis@di.uoa.gr (D. Maniadakis), D.Varoutas@di.uoa.gr, dvaroutas@gmail.com (D. Varoutas).

http://dx.doi.org/10.1016/j.physa.2014.03.023

Traffic dynamics in complex networks have been extensively studied lately [5–22] due to their wide applications in telecommunications and transportation and as a result of the novel discoveries on network topology. Recent works focus on the efficiency improvement of traffic systems and bring out a relationship between controllable parameters of network topology and traffic-flow performance. Several of them deal with routing strategies on complex networks [13–16,19,20], some others with the capacity distribution [5,11,21], while others with the cascading failures [8,9] and the congestion on complex networks [6,7,10,12,17,18,22].

Most of the networks examined in the previous studies are random (Erdős–Rényi or *ER* algorithm [4]) or scale-free (Barabási–Albert or *BA* algorithm [1]) and the traffic flows are assumed to be homogeneous between randomly selected source and destination nodes, with barely a few exceptions [17,20]. However, in real networks, especially on spatial ones, the topology can deviate from those derived from the *ER* or *BA* models [23,24] and traffic is more likely to be generated/received unevenly at some nodes than at others, according to their characteristics [25–27]. Therefore, in this paper, gravity topologies are introduced as they have been found to share statistical properties with real-world networks while allowing for optimal expected traffic exchange. Their ability to combine intrinsic attributes and extrinsic features in a simple spatial weighted network model has widely established them in telecommunications and transportation [24,26–33]. Here, their behavior under congestion is compared to the behavior of random, scale-free and Jackson–Rogers (*JR*) topologies. The *JR* topologies are incorporated in the analysis since they can successfully reproduce all of the basic features of real-world networks [3], including a high cliquishness which may be a congestion determinant. In addition, network congestion is studied taking into consideration traffic flows obeying the more realistic gravity-based flow patterns, as recently observed in the related literature [34,35].

The main purpose of this paper is to examine the relationship between the traffic flows and congestion factors in different topologies. Traffic congestion can be improved either by developing better routing strategies or by network restructuring [36] which is more in the focus of this paper. In this analysis a series of implications are derived from what kind of congestion and cost level to expect for a given set of topological and traffic parameters. Thus knowledge is obtained on which way to (re)design a traffic network, e.g. transportation, telecommunications or other network, in order to alleviate congestion effects.

The paper is organized as follows. In Section 2, the network models and the traffic flow types are introduced. In Section 3, the simulation results are presented and discussed. Finally, the conclusion is given in Section 4.

2. Network types and traffic flows

2.1. Network representation

In formal terms, networks can be represented as graphs $G(N, K)$, which are mathematical entities from Graph Theory, defined by two sets, N and K. The first set, N, is a finite set of N elements called nodes or vertices, and K is a finite set of K elements containing unordered pairs of different nodes called links or edges. The graph G can be described by the $N \times N$ adjacency matrix, A, whose entry a_{ij} is equal to 1 if there is a direct edge between nodes i and j, and 0 otherwise. In the case of a weighted network, an additional set of values attached to the edges is characterizing the links. The matrix containing the edge weights could describe the traffic flows, the capacity, the cost, the length, etc. Here, the graph nodes are also considered to have a precise position on a planar map $\{x_i, y_i\}_{i=1,\dots,N}$ and a fitness value $\{f_i\}_{i=1,\dots,N}$.

The basic statistical properties of such a network representation are referred to here; the average shortest path, the diameter, the clustering coefficient, and the degree distribution. The average shortest path or average geodesic path length is defined as the average number of steps along the shortest paths for all possible pairs of network nodes. The diameter of a network is the length (in number of edges) of the longest shortest path between any two nodes in the network. The clustering coefficient measures the density of triangles in the network, and put simply, is the mean probability that the friend of your friend is also your friend. It can be quantified by defining it as $C = \frac{3\times \text{ number of triangles in the network}}{\text{number of connected triples of vertices}}$, where a "connected triple" means a single vertex with edges running to an unordered pair of others [37]. A clear deviation from the behavior of a random graph can be seen in the clustering property, sometimes called transitivity, and suggests that there is a heightened number of triangles in the network—sets of three vertices each of which is connected to each of the others. The degree distribution is the probability distribution function (PDF) of the node degrees k over the whole network, where k is the number of edges directly connected to a node. The PDF is usually well fitted with a Poisson or a power-law distribution.

2.2. Analysis of the main network types

A great variety of network formation models has been proposed in the past years, however studies in traffic dynamics are mainly based on two simple well-known models; the *ER* [4] for random networks and the *BA* [1] for scale-free networks. The network topology has proved to be critical to the appearance of traffic congestion, with scale-free networks being the less affected at high volumes of traffic [6,12,22]. More recently, the *JR* formation model [3] has been proposed, which can successfully reproduce all of the real networks' basic features including a high cliquishness—a possible congestion determinant. Here, one more class of networks that has experienced a rekindling of interest, the class of networks based on the gravity model [24,26–32], is introduced in order to be examined, additionally to the previous three network classes.