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Jamming transition in air transportation networks

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ABSTRACT

In this work we present a model of an air transportation traffic system from the complex network modelling viewpoint. In the network, every node corresponds to a given airport, and two nodes are connected by means of flight routes. Each node is weighted according to its load capacity, and links are weighted according to the Euclidean distance that separates each pair of nodes. Local rules describing the behaviour of individual nodes in terms of the surrounding flow have been also modelled, and a random network topology has been chosen in a baseline approach. Numerical simulations describing the diffusion of a given number of agents (aircraft) in this network show the onset of a jamming transition that distinguishes an efficient regime with null amount of airport queues and high diffusivity (free phase) and a regime where bottlenecks suddenly take place, leading to a poor aircraft diffusion (congested phase). Fluctuations are maximal around the congestion threshold, suggesting that the transition is critical. We then proceed by exploring the robustness of our results in neutral random topologies by embedding the model in heterogeneous networks. Specifically, we make use of the European air transportation network formed by 858 airports and 11 170 flight routes connecting them, which we show to be scale-free. The jamming transition is also observed in this case. These results and methodologies may introduce relevant decision-making procedures in order to optimize the air transportation traffic.

1. Introduction

In the last decades, Physics of Complex Systems and Complexity Science have started to address real-world problems. In particular, much attention has been paid to self-driven particles such as pedestrian and freeway traffic [2,3] or Internet traffic systems [4]. Not that surprisingly, complex features such as the emergence of phase transitions [4–8] or criticality [9] take place in models that characterize these complex collective phenomena. Thereby, the focuses of such complex systems seem to be both a realistic and useful approach when describing the concept of traffic dynamics [2], both in homogeneous and in heterogeneous media.

The first insights considering traffic dynamics from a cooperative phenomenon point of view were developed in cellular automata. In [10] and subsequent works, Nagel and Shreckenberg developed a stochastic discrete model of freeway traffic dynamics which evidenced a free–congested phase transition quite similar to real traffic behaviour. Successive refinements and generalizations of this model such as [5] or [6,8] have been performed so far. All these models focus on how the aggregation of local dynamical rules may generate emergent nonlinear behaviour at the global level, such as travelling jam waves, for instance. Pedestrian dynamics has also been addressed from a complex system point of view. Self-organization

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effects occurring in pedestrian crowds which lead to unexpected mutual disturbances of pedestrian flows, such as panic effects [11], have recently been studied.

On the other hand, in recent years much attention has been paid to another type of traffic dynamics, taking place in heterogeneous media: Internet traffic. Similar insights have been considered: free–congested phase transitions have been observed, explaining the real behaviour of the Internet performance (see, for instance, [4] and subsequent works). Other complexity features such as information transfer in the transition neighbourhood [12] or self-organized criticality [9] have also been addressed in these systems. Some evident analogies between highway and Internet systems have even been put forward [13]. The main difference between both hallmarks is that, in the case of Internet traffic models, the topology of the underlying network of interactions [14] is inevitably coupled to the internal traffic dynamics, in such a way that the emergent behaviour that takes place is related to the interplay between complex collective dynamics and complex interaction topologies. In fact, it is now well known that complex interaction topologies strongly affect the dynamics (for instance, percolation and epidemic thresholds have been found to be highly topology dependent [15–19]), so that proper modelling of such phenomena should take good care of this fact.

Here we will handle a system quite similar to the former ones: the Air Transportation System (ATS). This system is formed by a spatially extended network that physically covers a wide range of the world, made up by weighted nodes (airports of different characteristics) and links (flight routes) through which aircraft flows diffuse. Insofar as the latter system shows striking similarities with the highway system or the Internet, in terms of nonlinear coupling of local dynamics, queuing generation and congestion propagation phenomena, it is clear that the ATS merits a complex system insight. Some recent studies have focused on the air transportation network topology [1] and its structure [20,21] or on its application to real epidemic spreading [22,23]. Much to the contrary, state-of-the-art air navigation modelling is focused on local models and uncoupled network models (see, for instance, [24–27]), rather than global models that take into account the nonlinear coupling effects. While some traffic dynamics systems in complex topologies have been recently performed [28–30], specific systems that address air traffic modelling are somehow lacking. In this paper we present a network-based model of the ATS that simulates the effect of traffic dynamics. In Section 2 we present the model, in terms of the network definition and the local dynamical rules. A random network topology is chosen in a baseline approach, in order to study the effect of local dynamical rules in the global behaviour without any further source of complexity. In Section 3 we point out the emergence of a jamming transition in the dynamics of aircraft diffusion, which distinguishes a regime where the average amount of queues in the network is null (efficient regime) from a regime where this average value is non-null due to bottleneck generation (inefficient regime). Moreover, we show that the transition is critical. In Section 4 we extend the neutral model by embedding the system in heterogeneous networks. To this end we generate the (real) European air transportation network, formed by 858 European airports and 11 170 flight routes connecting them. We first show that this network exhibits a scale-free topology, in good agreement with previous results for the worldwide transportation network [1] (indeed we show that similar exponents appear). The simulations suggest that the dynamics in this real network are qualitatively similar to what is found for the random (neutral) topology, which means that the neutral model is – at least for networks of comparable sizes – robust against changes in the network topology. In Section 5 we provide some conclusions and depict some further work.

2. The model

We will model the ATS as a complex directed network where some dynamics take place. In the network, each node is an airport, and two nodes are linked if there exist a flight route between them (note that, between two linked nodes, both directions are defined). Each node is weighted in order to characterize the airport's design capacity (the design capacity stands for the maximal number of aircraft per time unit that an airport can handle in an ideal situation). Each link will also be weighted in order to implement a metric layer in the network: each link weight characterizes the Euclidean distance between node pairs. Instead of the adjacency matrix alone, which fully characterizes an undirected graph [31], this co-weighted directed network will be characterized by a triple, formed by an adjacency matrix (which describes the topology structure), a distance matrix (which describes the geometric structure and the link weights) and a design capacity vector (which describes the node weights). As a neutral model, we have chosen a random network topology [31]. Observe at this point that while further relaxation of this neutrality will be performed in Section 4 (where we run the model in a realistic non-Poissonian network), it is necessary in a baseline approach to run the model in a network whose topological complexity may not have an effect in the global dynamics. This random network has $n = 100$ nodes, where:

(i) The node's weights (design capacities) are chosen randomly from a uniform distribution $U[1, 1000]$ and are fixed for different network geometries.
(ii) The nodes have been linked randomly, with a link probability $p = 0.2$ (the mean degree is consequently $\langle k \rangle = p(n-1)/2 \simeq 10$).
(iii) The link's weights are integers chosen randomly from a uniform distribution $U[1, 10]$, characterizing the number of time steps that a given flow will need to cover the distance between two given nodes.

In addition, the real capacity RC of each node will be updated each time step as a percentage of its design capacity DC, modelled stochastically in the following way:

$$RC(t) = DC(1 - \xi), \tag{1}$$