Scaling in Socially Driven Computer Networks

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1. INTRODUCTION

This work aims at comparing a typical distributed computer network model with a newly conceived model that introduces principles of social relations in the network design.

Previous research showed that attributes of both biological entities [20] and companies [7] share the same characteristic power law function on their size, with sub-linear scaling. As biological entities and companies grow bigger, their relative growth slows down and they tend to stabilize in size. Without growth, they die.

The context for companies can be set as the hierarchical structures often present in those, which define top down relations between employees. The fixed structure limits the system preventing it from the necessary flexibility to adapt. Cities do not have such strict hierarchies, having connections and flows resembling a network. These networked relations happen regarding social aspects and characteristics of cities. Infrastructural aspects behave the same way as companies and biological systems ("economies of scale" [5]).

Oppositely, cities concentrate creativity, power, and wealth. Recent studies [5, 4] claim that cities all over the world behave similarly, and they all show social related attributes (such as wages) with superlinear power law functions with respect to their size ("increasing returns" [5]). Networked relations in cities' internal elements, the population, drive their growth. Each element in this population is independent and flexible, and their behavior can be defined with superlinear power law functions with respect to their size.

Assuming the growth of computer networks regarding the amount of nodes is related to the one of the companies that create and operate them, would it be possible to create a model for computer networks that could present superlinear scaling? If the growth of computer networks could be defined by the individual interest of people, adhering to a community network, would that type of network have superlinear scaling?

A possible application of this study is in the field of Internet of Things [1] in which advanced communication, node intelligence and social relations are being considered which are part of the exploration in this work.

The preliminary results were obtained under a simplified mathematical restrictions model for Software Defined Network (SDN) wireless mesh networks. They are derived from a network evolution simulation using the restrictions model in order to observe the network node usefulness. It presents the distinct network structure observed under three different artificial intelligence models explored. It is observed that multifunctional node behavior is important and can lead to a setting that is more adaptive, flexible, and prone to innovation.

2. BACKGROUND AND RELATED WORK

In [5], a comparison is presented about the difference between the scaling in biological life and cities, arguing that the pace of social life in the latter is influenced by their population size. Cities concentrate creativity, power, and wealth. For such reason their growth (in terms of social attributes) presents a superlinear scaling as a power law function of its population size with $\beta > 1$, unlike biological organisms which show decreasing dynamics with growth, implying a sublinear scaling. In a super linear growth, the systems under this growth model, such as cities, are destined to collapse. To avoid collapse, the system starts over through major innovations.

The development of SDN protocols such as OpenFlow [6, 9] intended to infuse flexibility in computer networks. The authors argue that controlling performed through software in a centralized manner could foster innovation in networks by providing real experimentation settings for network researchers.

Biological networks often present characteristics such as community structure. This structure reflects nodes that are highly connected internally, but loosely connected to other groups [14]. Other biological networks have been proposed e.g. the Bio-Networking architecture [17]. The main idea is to apply biological concepts to computer networks in order to make the network adaptive, scalable, and autonomous. This work was published in the same year as OpenFlow [9] and there are similarities in the goals, however the former lacks the characteristic of independence between groups that OpenFlow provides with the use of SDNs.

Similarly to this proposed approach, TinySDN [8] works over wireless networks. TinySDN is proposed for the specific environment of sensor networks and even though it allows multiple controllers trying to introduce more flexibility to the standard SDN, some restrictions remain given that nodes are specialized as controllers or forwarding nodes that just perform tasks given by the controllers. Having multiple controllers [15] does not remove the restriction of every node in the network having to agree on common standards, which implies lack of flexibility.

3. APPROACH

Innovations are key to support the start of new growth cycles before singularity events generate a collapse in an exponential growth function [5]. Additionally, an important differentiation between the internal elements of cities and biological systems is their "degree of freedom". The former has more freedom to change functions (elements within their lifetime), allowing exploring more alternatives that can potentially provide better adaptation. Finally, preferential attachment [2, 18, 11] can accelerate the selection of good innovation alternatives, providing faster adaptation.

In a standard distributed control/routing network, nodes need to agree upon a common protocol to allow seamless communication (e.g. the Internet). This standardization implies a drawback: changes (including innovative ones) are hard due to required agreement between all nodes. A more flexible setting is intended using SDNs so that innovations can be supported.

Even though SDNs are more flexible than the current Internet model, there are still some restrictions regarding specialization of nodes: controllers, if more than one, and the regular nodes. This lack of flexibility does not add to increase "degrees of freedom" and, consequently, adaptation. A group (related nodes under common control) assumes at least two different elements: the forwarding nodes, and a controller. How could a model with computer networks under the SDN architecture improve adaptation and innovation?

An innovative but also adaptive SDN network model should assume that any node could become a controller, given its importance in the group, such as a strategic position. The appearance of a new controller with new characteristics (its position on the network, forwarding rules, etc.) can attract nodes, if the change seems beneficial (as in innovations: adoption based on the perception of a benefit). Additionally, there may be changes over time e.g. addition or elimination of nodes. Nodes should decide the best controller given their perception, or a combination of information provided by trusted nodes with which they have communicated before.

The suggested approach is based on the aforementioned customized SDN. Given an area, groups of nodes can be formed having each one controller at most. Groups do not need to have fixed parameters, allowing a higher "degree of freedom". The decision of choosing a controller can be based on many factors such as effectiveness of the controlling algorithm, and centrality within the group. Since the nodes can choose their controller, the system is flexible enough to embrace other criteria.

3.1 Node Behavior Models

Nodes are modeled as "Intelligent Agents" in a Multiagent setting [12]. Nodes are born when visible to the network. Oppositely, they die when their are no longer reachable by other nodes.

A node is a unit that has two functions (management and forwarding), a utility function, a physical position, and a lifetime. Each node is born with a standard lifetime.

The management and forwarding functions are inherited by the standard SDN architecture. The former is the SDN control function responsible for receiving and answering routing requests, while the latter is responsible for sending the message to the node indicated by the current controller.

A node's utility function defines the set of rules which will influence its decision of joining a group, voting for the next controller, and deciding if they are willing to communicate. The utility function centralizes all decisions made by a node regarding their behavior. More generally, the nodes sense the environment around them and apply their action based on the result from such function.

Each node is born in a location within the defined area. This represents the physical position. Such position impacts on the node's chance to survive and its connections given the characteristics of the nodes around them.

As part of the utility function, the node's lifetime may be altered depending on the survival condition. A node needs to communicate as much as possible in order to maximize its lifetime. If it does not communicate enough, the lifetime decreases.

A node executing the management function of a SDN group is labeled controller.

A group is a set of nodes that share the same controller. Each group has only one controller and all nodes within the group can reach the controller directly or indirectly.

The following node models apply the aforementioned concepts in different combinations.

- *Strict* nodes join the closest group based on signal strength. There are no restriction regarding distance to controller. Only a percentage p of strict nodes can operate as controllers.
- *Standard* nodes join the closest group based on signal strength. There are no restriction regarding distance to controller. Any standard node can become a controller.
- *Greedy* nodes join the largest nearby group for which the controller is within a given distance dc. They can change group if a neighboring group is s percent larger than their current one. A regular node can become controller if it is in the largest nearby group and its group controller has stopped.

3.2 Governing Models

Groups can choose their controller, due to the flexibility of the proposed model, by running elections. Elections are different in each governing model, depending on the moment and frequency which they occur. The intended models are described below.

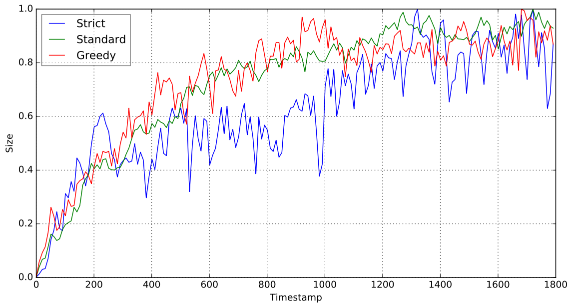

Figure 1: SDN groups' growth for the proposed node behavior models. Curves are regularized by the overall maximum amount nodes of each model. With the addition of restrictions, models present a bounded growth.

- The *Monarchy* model has a controller defined since the beginning of the group existence. The controller only changes if the current controller ceases to exist. It is a more strict model, incapacitating the group to adapt to a better positioned controller, for instance.
- The *Democracy* model has elections at fixed intervals. Controller may change after each election. It adds to the the concept of the "degree of freedom", allowing better adaptation.
- The *Parliamentary* defines that the controller can change at any moment. It is the most flexible model. This adds the highest amount of "degree of freedom" to the nodes.

The elections can only be performed on existing groups. An SDN group only exists if it has a defined controller, by definition. This causes the first controller selection to be random as soon as the group is created.

In the current evaluation, the *Monarchy* model was implemented and analyzed.

3.3 Evaluation

In order to evaluate the proposed model, a specific simulator was implemented. The simulator is event oriented, having its simulated time decoupled from real time. The connectivity model is using real settings in terms of attenuation (modified Friis formula for free space electromagnetic waves attenuation [16]) and wireless protocols (simplified IEEE 802.11 a, b, g, n). Wireless speed calculation is used to determine connectivity between node pairs [19, 10]. Wireless contention and collision are not being considered.

Communication represents the usefulness of the node in the network. Although the communication is not tracked as metric, the mathematical model of lifetime (equations 1 and 2) derives from the possibility of communication. Nodes' lifetime defines group growth, therefore, the size metric is intrinsically related to the desired communication metric.

Equation 1 describes a simple mathematical model that represents both the demand (group size *size*) and the restrictions (node degree dg and node's distance to SDN's group controller dc) in the usefulness of the node. With a larger group size, a node has increased potential of finding nodes to communicate. Oppositely, a large number of connections reduces the time share of communication (competition over free channel). Additionally, the distance to the group's controller adds latency over the set up of new or expired communications [9]. *Alpha* defines how much each factor should be considered when multiplied by the group size.

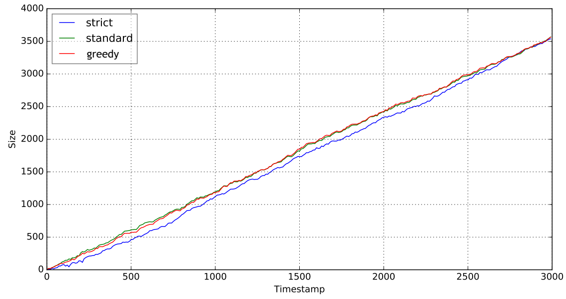

Figure 2: SDN groups' growth for the proposed node behavior models. An unbounded growth is observed in the absence of restrictions.

$$r = size \times \left(\frac{\alpha}{1 + dg} + \frac{1 - \alpha}{1 + dc} \right) \tag{1}$$

Equation 2 describes the application of a node's restriction r in random normal distribution to obtain a node's lifetime.

$$\begin{aligned} lifetime &= offset_{it} + \mathcal{N}(\mu, \sigma^2), \\ \text{with } \mu &= \left(3 - \frac{r}{2}\right) \text{ and } \sigma^2 = (6 + r) \end{aligned} \tag{2}$$

This restriction model is compared with a non restrictive model, which serves as baseline, proving that the restrictions create the expected behavior.

4. RESULTS

Figure 1 shows the result of an experiment using the three node behavioral models described on Section 3 and the restricted lifetime model presented in Section 3.3. The three models present a bound in their growth. This is comparable to results from [20] which show examples of fitted growth of different biological systems.

However, Figure 2 shows the behavior of nodes when Equations 1 and 2 (baseline lifetime model) are not enforced. Lifetime restrictions are fundamental to obtain the expected bounded growth as a starting point (sublinear scaling).

Figures 3, 4 and 5 present the different final topologies of the experiment of Figure 1. The white squares represent the SDN controllers, and different groups have different colors.

The strict model 3 has limited availability of controlling

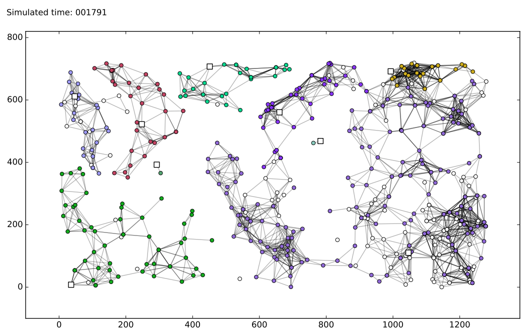

Figure 3: Final topologies showing different coverage and densities given the *Strict* Model.

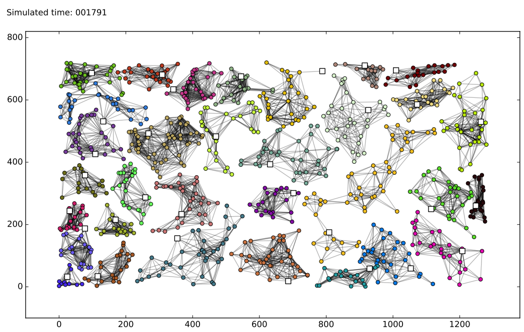

Figure 4: Final topologies showing different coverage and densities given the *Standard* Model.

nodes due to role specialization (only a few nodes can behave as controllers) which penalizes the dispersion of nodes over the simulation area. Since nodes connect to the closest group, there are more and denser groups.

In the standard model, role generalization provides better coverage and the objective of connecting to the closest group reflects in more and denser groups.

In the greedy model, node role generalization (any node can be a controller) allows good coverage. However, unlike the previous models, the greedy approach of finding the largest group within a maximum L2 distance of the controller creates sparse groups.

In addition to the characteristics in the evaluated models, some further exploration can be performed by measuring nodes' communication as scaling metric, analyzing a more complex model that considers behavioral characteristics such as communication with specific nodes, controller decision based on the effectiveness of a controller's forwarding algorithm, managing connectivity degree to influence network contention, analyzing the consequences of having different governing models. Those are some examples of factors that can infuse different "degrees of freedom" and innovation to the network and add on to this work.

In addition to the aforementioned future improvements, us-

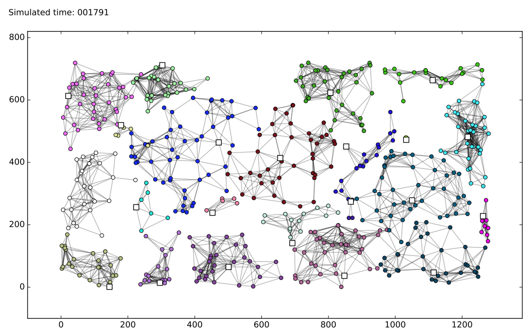

Figure 5: Final topologies showing different coverage and densities given the *Greedy* Model.

ing simulations to achieve a close to real environment has a bound regarding simulation scaling due to machine limits [3, 13]. As a consequence, a parallel approach is necessary in order to achieve the simulation environment desired.

The proposed model offers a computer network that does not need the entire set of nodes to agree on changes. A new group can be created to accommodate changes by establishing a new controller and attracting interested nodes. Networks can be flexible enough to embrace changes and the dynamicity of human creations.

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