Journal of
Information Technology & Software Engineering

Deo, J Inform Tech Softw Eng 2013, 3:2
DOI: 10.4172/2165-7866.1000e117

Editorial Open Access

Big-Data-Driven Control Strategies for Complex Networks

Narsingh Deo[1]* and Sumit Kumar Jha[2]

[1]Department of Electrical Engineering and Computer Science, University of Central Florida, Orlando, USA
[2]Department of Electrical Engineering and Computer Science, University of California, USA

Introduction

Spurred by the growth of the World Wide Web and the Internet, and their similarity to numerous other large, dynamic, real-life networks, a truly cross-disciplinary science of complex networks has emerged in the past 15 years [1-12]. Hundreds of studies have been conducted and papers published exploring properties of complex networks—such as, their size, diameter, degree distribution, pairwise-distance distribution, cliques, communities, clustering coefficient, and the like [5-11]. Several growth models of these evolving networks have been proposed and studied [5,6]. However, an area of active interest, which has not been studied adequately, is that of designing control policies to steer the evolution of such a network towards a desired goal [8]. In practical situations, such as controlling the spread of diseases or the formation of opinions, topological properties, of the network, may need to be controlled. It would, therefore, be valuable to have automated synthesis [7] of strategies for controlling relevant topological properties of complex networks described by, for example, a preferential-attachment and preferential-deletion model [6]. We propose that an automated optimal control of evolving complex networks be achieved by leveraging recent results in developing stochastic models for the evolution of complex networks in combination with the classical results on dynamic-programming algorithms for optimal control [2-4].

Complex Networks

Interactions between multiple entities have been modeled and studied as static graphs at small scale for nearly a century. But the study of large, random, evolving graphs as models for the World Wide Web, the Internet, and other real-life networks took off only about 15 years ago. In particular, inspired by the need to understand the evolving interactions among multiple entities in sub-disciplines as different as cyber-security and metagenomics, the study of complex networks has generated a great deal of interest in the computer-science community.

The Erdos-Renyi uniform random graphs exhibit neither the degree distribution nor the clustering coefficient of many naturally occurring real-world networks. The degree distribution of small-world networks is binomial and, hence, disagrees with that of many real-world networks. Likewise, static models are not capable of providing a description of the temporal evolution of real-world networks; thus, the recent emphasis on studying dynamic models of real-world networks. Such models are usually described by a stochastic graph process, where the graph evolves by two broad sets of rules: (i) Preferential attachment of a new node to existing nodes, and (ii) Copying. Most of these stochastic models have focused on the shape of the asymptotic degree distribution of complex real-world networks.

Much of the recent study of real-world networks identifies broad families of complex networks, models their generative processes, and suggests algorithms that exploit the properties of these broad families of real-world networks. The focus of investigation into real-world networks has been on a set of easily measurable properties of graphs: *e. g*, size, diameter, degree distribution, pair-wise-distance distribution, cliques, communities, clustering coefficient, connectivity and the like. Several families of networks, including citation networks, email networks, twitter networks, social networks, peer-to-peer networks, metabolic networks, genetic regulatory networks, and web graphs, have been well studied using these readily measurable properties of graphs.

Big Data

While the interdisciplinary area of complex networks has enabled us to understand, analyze, and predict the evolving complex interactions among the network entities; with the advent of rapid data acquisition techniques in combination with the dramatic drop in cost of sensing, transmitting, storing, and processing data, we are surrounded by Big Data. It has now become possible to track the evolution of interactions among network entities in real-time.

While different models have been proposed to account for the variety of complex networks observed in natural and engineered systems; computational methods for automated synthesis of control strategies to steer such evolving interactions towards a desired goal have not received adequate attention. Problems requiring synthesis of such optimal control strategies for complex networks are all around us [8]. Two representative examples are discussed in the following:

Epidemics on Networks

The spread of infectious diseases is often modeled with dynamic contact networks--where nodes represent infected individuals [9]. As the disease spreads, new nodes are added to this network. The death of a patient results in deletion of the corresponding node from the dynamic network of infected individuals. In such a setting, the probability of a node being added to the network can be controlled through a number of tools: isolation, immunization, and quarantine. While it is desirable to enforce all mechanisms to prevent an epidemic, we seek to optimize the trade-off between the control of the epidemic and the total cost of the control methods employed to achieve such a goal. Using the optimal control synthesis approach envisioned here, we can synthesize optimal strategies for controlling the number of infected individuals in evolving epidemiological networks.

Opinion Networks

The second example of controller synthesis for complex networks is the formation of robust opinion networks. The creation of a stable opinion network may require the formation of a dense network such that the entire opinion network itself is robust and immune to deletion of a few nodes. Thus, the topological property of interest for such networks is the average edge-density of such an opinion network. While the probability of adding a new node can be directly controlled, a key question is how to determine the optimal birth process to ensure that the edge-density of the network reaches a desired threshold.

***Corresponding author:** Narsingh Deo, Department of Electrical Engineering and Computer Science, University of Central Florida, Orlando, USA, E-mail: deo@cs.ucf.edu

Received August 26, 2013; **Accepted** August 26, 2013; **Published** August 27, 2013

Citation: Deo N, Jha SK (2013) Big-Data-Driven Control Strategies for Complex Networks. J Inform Tech Softw Eng 3: e117. doi:10.4172/2165-7866.1000e117

Control Strategy

Here, we propose that dynamic programming based optimal control synthesis for stochastic dynamical systems be used to synthesize control strategies for stochastic models of evolving complex networks. This approach combines the Hamilton-Jacobi-Bellman (HJB) dynamic programming algorithm with a stochastic model for the evolution of complex networks involving the preferential birth and death of nodes in the complex network.

Automated Synthesis of Control Strategy

Recent advances in constraint solving technology have led to renewed interest in the problem of automated synthesis [7]. Synthesis algorithms for systems as varied as software, stochastic models in biology and hybrid and dynamical systems have been developed. However, the automated synthesis of control strategies for stochastic complex networks has not been studied much. Our approach for controlling the dynamics of stochastic complex networks builds on existing work in complex networks theory and in the optimal deterministic control of stochastic dynamical systems. It involves the following three different steps:

1. Based on the interactions observed among the entities being studied, we first choose an appropriate stochastic dynamical model for describing the evolution of these interactions. A variety of existing dynamical models have been proposed and are available in the literature. Some of these dynamic real-world network models include those that only permit birth of new nodes, while others allow both the birth of new nodes and the death of the old ones. Several readily measurable properties of the interactions being studied (*e.g.,* degree distributions, graph diameter, number and size of communities, *etc.*) may be used to determine a stochastic dynamic model appropriate for describing the temporally evolving interactions.

2. When a suitable stochastic dynamical model has been identified using the topological characteristics of the interactions being studied, we still need to determine the numerical values parameters that can fit the behavioral predictions of the stochastic dynamical model to the empirical data corresponding to the observed interactions. For example, a stochastic preferential attachment and deletion model for complex networks is parameterized by the probability that determines the rates of birth and death of nodes in the network. The probability must be chosen carefully so that the predictions of the model are in close agreement with the observed values. A variety of machine learning techniques may be used to compute the numerical parameters of the model. If the observations are available as time-series data; Kalman filtering, Bayesian networks, or evolutionary algorithms may be used to determine the parameters of the stochastic model. If there are additional qualitative constraints on the interactions being studied, parameter synthesis methods based on temporal logic and symbolic algorithms may be used to prune the parameter search space. At the end of this step, a completely defined stochastic dynamical model describing the evolution of the complex network is determined.

3. We then suggest the synthesis of control strategies using dynamic programming based optimal control algorithms for the stochastic dynamical model so as to achieve one or more desired topological properties of complex networks. In order to compute an optimal strategy, we must first define a cost function that approximates the desired notion of optimality. We recommend using a cost metric involving the state of the complex network and the control inputs applied to it, that captures two different aspects of an optimal control strategy for complex networks: (i) the distance between the current topological property of an evolving network and the desired state of the topological property, and (ii) the cost associated with the input being applied to steer the complex network to a desired state. This will drive a complex network to a desired topology and minimize the cost involved with the control inputs that guide the complex network.

Conclusion

In this paper, we have outlined how Hamilton-Jacobi-Bellman style synthesis of control strategies can be applied to the problem of optimal control in complex networks. We have focused on a continuous variant of the preferential attachment and deletion model. In future work, one should investigate the capability of the proposed framework to design control strategies for other stochastic dynamic models of evolving complex networks. Further, as the control law is being applied, additional observations on the evolving complex network may be used to ascertain the efficacy of the control policy. Our ongoing work includes investigating the use of online algorithms for controlling the evolution of complex networks.

As we encounter the flood of Big Data, much of it being unstructured at least on the surface, it is imperative that we seek out hidden structures to manage, understand, and exploit Big Data. Graph theory and complex network may prove to be a very convenient framework for such an undertaking. The optimal control synthesis philosophy discussed here may then be deployed to control engineered and natural systems whose evolution can be described by structured Big Data.

References

1. Albert R, Barabási AL (2002) Statistical mechanics of complex networks. Rev Mod Phys 74:47- 97.
2. Bardi M, Dolcetta IC (2008) Optimal control and viscosity solutions of Hamilton-Jacobi-Bellman Equations. Birkhäuser.
3. Bellman R, Kalaba R (1965) Dynamic programming and modern control theory. 1st edition, Academic Press, New York, USA.
4. Bertsekas DP (1995) Dynamic programming and optimal control.4th edition, Athena Scientific.
5. Cami A, Deo N (2008) Techniques for analyzing dynamic random graph models of web-like networks: An overview. Networks 51: 211-255.
6. Deo N, Cami A (2007) Preferential deletion in dynamic models of web-like networks. Information Processing Lett 102: 156-162.
7. Jha S (2011) Towards Automated System Synthesis Using SCIDUCTION. Lambert Academic Publishing, Germany.
8. Liu YY, Slotine JJ, Barabási AL (2011) Controllability of complex networks. Nature 473: 167-173.
9. Marathe M, Vullikanti AKS (2013) Computational epidemiology. Communications of the ACM 56: 88-96.
10. Newman MEJ (2003) The structure and function of complex networks. SIAM review 45: 167-256.
11. Cohen R (2012) Complex networks: structure, robustness and function. Cambridge University Press, United Kingom.
12. Strogatz SH (2001) Exploring complex networks. Nature 410: 268-276.