Complex Networks as Control Paradigm for Complex Systems

Stefan Grobbelaar (1), *Student Member IEEE* and Mihaela Ulieru (2), *Senior Member, IEEE*

***Abstract*—Rooted in a deep understanding of their major properties, a control paradigm for complex systems is proposed based on latest advances in modeling the dynamics of complex networks.**

***Keywords*.** Complexity Science, Future Internet, mobile devices, sensor networks, ad-hoc networks, power grid, deregulated electricity market, power market model, holonic stigmergy.

I. Background

THE foundations of Cybernetics [1] and General Systems Theory [2] developed from two schools of thought:

A. Control and Feedback

The cybernetics group [3] was firmly established in America by 1946. The term Cybernetics was given by [1] as "The science of control and communication in the animal and the machine". Cybernetics offers methods for the study and control of systems that are intrinsically complex through mechanism, variety, regulation and control [4]. Main themes are those of circular causality and feedback control [5].

B. Relationship between parts

The concepts of General Systems Theory evolved from Bertalanffy's work on theoretical biology in Europe [6]. The Society for General Systems Research was established in 1956 after his move to America in the 1950's [7].

The main idea of General Systems Theory [8] is that of interactions between parts. Reductionism [9] refers to the individual analysis of the parts of a system, followed by a theoretical formulation of how the parts of the system interact, and a synthesis of the theoretical interactions in order to derive the higher-level properties of the system. The reductionist approach avoids the study of the real relationships between parts. In contrast, the systems approach focuses on the study of the interactions and relationships between parts.

Following the development of the concepts of Cybernetics and General Systems Theory, System Dynamics [10] introduced a way of describing how systems grow over time, and, more specifically, how interactions between parts of a system develop over time. System Dynamics uses concepts drawn from the field of feedback control to organize available information into models [10].

The combination of Cybernetics, General Systems Theory and System Dynamics culminated in what is known as Systems Theory. The purpose of Systems Theory is to create models for describing the behavior of a related set of natural, physical or social phenomena.

(1) PhD candidate in the ARM Lab
(2) Canada Research Chair and Director, Adaptive Risk Management (ARM) Lab, The University of New Brunswick, Canada (http://www.cs.unb.ca/~ulieru/)

II. Complex Systems

Complex systems refer to a set of systems that share some common behavioral and structural properties. These properties include: non-linear relationships between parts; openness; feedback loops; emergence; pattern formation and self-organization. In this section, we describe these properties on an example complex systems scenario of a future Internet consisting of multiple wireless networks [11] in which constellations of wireless devices (or *ad-hoc networks*) cluster to share Internet access. As parts of a complex system (Fig. 1), the wireless devices represent users, and the bandwidth providers represent service providers, while the interactions between the parts are driven by the need to form communities of networks to obtain access to bandwidth resources.

For the scenario in Fig. 1 we aim to:

1) Control the formation of ad-hoc networks to satisfy the requirements of both users and service providers for bandwidth as shared resource.
2) Maintain network robustness given a large number of networked users and service providers.

In this Section we take a Complex Systems approach to address the control objective. A Complex Networks approach to address robustness will be presented in Section IIIB.

A. Non-linear relationships between parts

In linear systems, effect is directly proportional to cause. Non-linearity of a dynamic system is largely rooted in the *unpredictability* of the system [12]. The unpredictability of a dynamic system is a result of random noise, the effect of the environment on the system, and a lack of knowledge of the system's initial conditions. A system may be viewed as deterministic if the current state(s) of the system determine its future state(s) in the presence of random noise, environmental inputs and unknown initial conditions. The sources of unpredictability may not affect the deterministic nature of a system however they do affect the ease with which the system's behavior can be predicted. A deterministic dynamic system whose behavior is hard to predict is known as a chaotic system. Chaotic systems are hard to predict because their future state(s) are particularly sensitive to the initial conditions of their current state(s). Dynamic systems may either be chaotic everywhere, or chaotic around a central

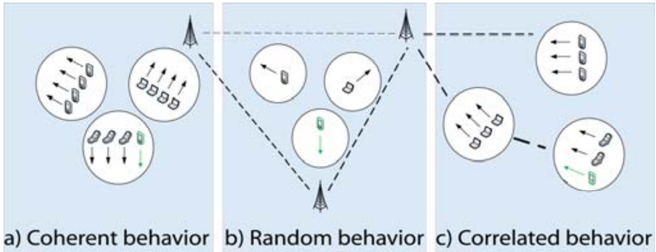

Fig. 1. The logical connectivity of devices in a future Internet

attractor [13].

The initial conditions of our scenario system are random in terms of the locations of existing and new devices joining the system, and their proximity to devices that offer bandwidth access.

1) *Coherent device behavior* (Fig. 1a)*:* Consider a new user may join a system at a location where it is out of range of a bandwidth provider and in range of other wireless user devices. If none of the existing users have access to a service provider, the newly joined and existing users can merely organize themselves into a group where they share access to each other's resources. User behavior is coherent in that they all have a single objective of sharing resources with one another, thereby restricting their functional structure to that of sharing resources with each other. This restriction in functional structure (in the absence of a bandwidth provider) confines the spatial structural organization of the resulting community of devices, and *the devices* in the community become the central attractor points of the system, in other words, the users themselves attract new users.

2) *Random device behavior* (Fig. 1b)*:* If a new user joins a system at a location where it is in range of a service provider and out of range of other users, the user connects directly to the service provider for bandwidth access. If we observe a number of these users, we see that their behavior is not coherent as would be the case where their objective is to share resources with other users. The functional objective of a user differs from that of a nearest other user in that they connect to different service providers. The different functional objectives result in a less restricted spatial organization than in (1), and the *service providers* become central attractors of the system. The combination of central attractors is analogous to chaotic attractors of natural dynamic systems.

3) *Correlated device behavior* (Fig. 1c)*:* A new user joins a system at a location where it is in range of a service provider and in range of other wireless users; hence the newly joined user has a twofold functional objective, i.e. to connect to neighboring users to share their bandwidth resources and to connect to its nearest service provider. The functional objective of the user is less restricted than in case (1), but not as diverse as in case (2). The resulting spatial organization is a combination of those found in cases (1) and (2) above.

B. *Emergence*

General Systems Theory emphasizes a study of the relationship between parts, and emergence emphasizes the interaction between parts to form a coherent whole. The coherent whole maintains a sense of identity or persistent pattern over time [14].

Systems exhibit emergence when there are coherent properties at a macro-level that dynamically arise from interactions between parts of the system at a micro-level [14]. Here, "level" refers to the magnitude of scale at which the system is observed, and emerging properties are novel with respect to the individual parts of the system. The emergent collective behavior of the system is captured by the behavior of its parts, but a description of the collective behavior is not implicitly contained in the behavior of the parts at a particular scale of observation [15].

The micro-level interactions between parts of a system may be either independent or coherent, resulting in different collective behaviors [15]:

- *Coherent interactions* (Fig. 1a) between parts at the micro-level lead to a simple small-scale behavior, however in this case, complex behavior is observed at a large scale.
- *Independent interactions* (Fig. 1b) between parts lead to a simple collective behavior at a large scale, however, the complex behavior of parts at a small scale is irrelevant to the collective behavior of the system at a large scale.
- The *correlated behavior* (Fig. 1c) between parts represents a combination of coherent and independent behaviors to achieve a specific functional goal. The logical and consistent correlation of parts at a large scale is a result of correlated behavior between parts at a small scale.

The introduction and removal of wireless devices (users) and bandwidth providers (service providers) result in an *emergent behavior* of the system.

1) *Coherent device behavior* (Fig. 1a)*:* For the community of users out of range of a bandwidth provider, the behavior of users is coherent at the micro-level (device level) and leads to a simple small scale behavior of the system. As the community of devices grows over time, their coherent behaviors merge into a *complex collective behavior* in which all devices are coherent with regard to their functional objectives, i.e. to interact to share each other's resources.

2) *Random device behavior* (Fig. 1b)*:* When users are in range of service providers, but out of range of other users, the behaviors of the individual users are independent in that they are "attracted" to different service providers. The independent interactions lead to a simple collective behavior at a large scale or, in other words, from the point of view of the bandwidth service providers.

3) *Correlated device behavior* (Fig. 1c)*:* The individual behaviors of users are neither completely random nor completely coherent, but correlated for a specific organizational function i.e. users connect to service providers and neighboring users in a correlated fashion to meet their functional connectivity objectives.

C. Openness

Complex natural systems are usually open [16] i.e. they exist at a dynamic gradient far from equilibrium. This is in contrast to dynamic equilibrium which refers to a state of a system at which it experiences no change when isolated from its environment. Under equilibrium conditions, a system ceases to change over time when observed at a large scale or macroscopic level. However, an open system (not isolated from its environment) under non-equilibrium conditions may experience equilibrium at smaller scales of observation.

Dissipative Systems [17] are open systems, and the processes by which they evolve are governed by the transfer of energy from the environment. Whereas isolated systems (or closed systems in a broader sense) strive to maintain thermal equilibrium, Dissipative Systems have a potential to offset an increase in entropy by consuming energy and using it to export entropy to their environment.

In our scenario, the system of users and service providers has different degrees of equilibrium at different scales of observation. When neither a newly joined or existing users have access to a service provider, the system is in equilibrium when viewed at the level of the community of users. The system is open to growth from this equilibrium in that a service provider may be introduced, resulting in non-equilibrium of the system at a community level, but a potential equilibrium state at a level which includes the newly introduced service provider. As with a Dissipative System, the community of users strives to maintain equilibrium by sharing their resources in the absence of a service provider.

D. Relationships between parts contain feedback loops

The combined study of the concepts of control and feedback found in Cybernetics and Dissipative Structures in far-from-equilibrium thermodynamics have lead to the development of the field of Autopoiesis. *Autopoiesis* [18] refers to a characteristic of natural dynamical systems whereby a system produces the components which make up the system in order to maintain the organized structure that gave rise to the components in the first place. Over time, the structure of both system and environment change as a result of mutual perturbations.

We consider our scenario system at a time when a community of wireless users has had access to at least one service provider for some time. The service provider is then removed from the system. During the time of access to the provider, the community downloaded several resources through the bandwidth connection. When the provider is removed, the community acts as a “bandwidth store”, which may in turn provide resources to existing and newly joining users in the community. The system has produced a new “bandwidth provider” in the form of a community in the same way that a natural system produces the components of the same system through Autopoieses. As with Autopoieses, the new community structure of wireless devices relies on the addition and removal of one or more service providers to maintain an organized “dissipative” system of wireless users and service providers.

E. Self-organization

Self-organization unifies a broad spectrum of theories [19] which include thermodynamic (dissipative structures) and synergetics approaches [20]. A working definition of self-organization is given by [14] as “a dynamical and adaptive process where systems acquire and maintain structure without external control”. Structure can be spatial, temporal or functional.

Self-organization suggests an ability to adapt towards a certain organizational structure or attractor point. Of the various attractor points [21], chaotic attractors allow for a large variety of behaviors or organizations, whereas point attractors allow only single behaviors. The adaptability of a system relies on a balance between a single behavior and a variety of behaviors to achieve control of the system.

Expressed as system behavior, the organization of structure is the arrangement of parts to achieve a specific function. The structural organization restricts the behavior of a system and confines it to a smaller region of its spatial, temporal or functional structure. The smaller region of its structure is representative of a *central attractor* observed at a particular scale. In Fig. 1 the organization results in an *increase in order* of the system behavior to achieve a specific functional or structural goal, and is rooted in the completely random or semi-organized initial conditions of the system.

F. Complex Adaptive Systems

Not all Complex Systems are adaptive. The authors of [22] argue that some complex systems, e.g. soap bubble formations and frost-heaving patterns in tundra soils, arise from self-organization without the benefit of selection or design. Adaptive Systems add to the properties described so far, those of *diversity* and *natural selection* most evident in ecosystems, which are perhaps the best examples of Complex Adaptive Systems [22]. The dispersed and local nature of an autonomous selection process assures continual adaptation, the absence of a global controller, and the emergence of hierarchical organization [23]. An essential characteristic of a Complex Adaptive System [24] is aggregation. For the scenario in Fig. 1, aggregation generates an ecosystem of users and service providers, illustrated in Fig. 2.

G. Aggregation

Aggregation refers to the way users are grouped into communities of users, which in turn are grouped into hierarchical community structures. The users and service providers are not homogenous in that they differ in the

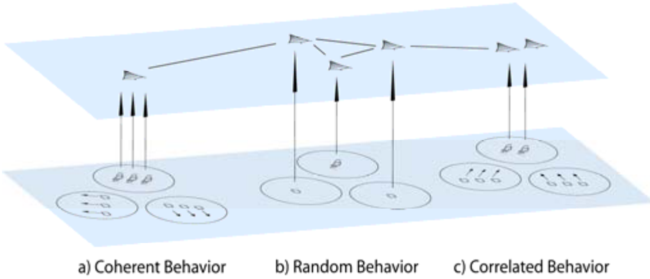

Fig. 2. Hierarchical assembly of users and service providers

amounts of bandwidth they require or are able to share. These differences enable a hierarchical assembly of users and service providers which may either be imposed on the system as a design objective, or emerge through pattern formation [25] of local interactions.

III. Complex Networks

A. Basic Concepts

The study of complex networks [26] aims to create models of networks in order to predict the behavior of networked systems [27]. The parts of a complex system are represented by nodes of a complex network, and the interactions between parts are the links.

An early contribution to the field of complex networks was the discovery that real networks are neither completely ordered nor completely random [28], exhibiting properties of both. These properties can be quantified by a statistical measure of the local density of a network, and the global separation of the network (or path length between the nodes of a network). The "small worlds" model of Watts and Strogatz [29] captures the interplay between order and randomness of a network, where order means every node is connected to its nearest neighbors (high clustering), and randomness refers to the fraction of nodes that are randomly rewired in order to reduce the path length between nodes. Random and small-world models capture the *topological* features of networks.

Erdos and Renyi [30] were the first to study the distribution of the maximum and minimum number of links in a random graph, the full degree distribution being derived later by [31]. Random networks exhibit a low probability of a node exceeding the average number of links of the network, and have a normal distribution [28].

Albert and Barabasi [32] observed that many networks do not in fact have random degree distributions, but display distributions that follow a power law. Power Law distributions point to the likelihood of a network node connecting to more than the average number of links of the network, and have resulted in the construction of scale-free models. In contrast to the random and small world models, scale-free models focus on capturing network *dynamics* rather than topology. The authors of [26] argue that the topology of a network is a result of the dynamic processes of growth and preferential attachment, thus challenging the 'small worlds' model.

- *Growth:* Whereas the random and small-world models assume a fixed number of nodes that are randomly rewired, growth implies that networks are open and that new nodes are added over time.
- *Preferential Attachment:* Random and small-world models assume that links between nodes are placed randomly. Newly arriving nodes will tend to connect to already well-connected nodes, rather than poorly connected nodes.

The dynamic processes that take place on a network (i.e. the interactions between nodes to form links) result in a topological structure that is characterized by a specific degree distribution. The degree distribution may be altered by changing the dynamic processes, or by randomly rewiring the nodes to achieve a desired distribution.

Based on the network models described so far many other models have been developed [27]. For example the Internet [33], World Wide Web and protein interaction networks have power-law distributions, whereas other networks like power grids follow an exponential distribution [34].

These statistical properties, i.e. degree distributions of the network models are important indicators of a network's sense of community structure, robustness, and sensitivity:

1) Community Structure

The community structure of a network is given by an intermediate scale of analysis between local (e.g. clustering) and global (e.g. path lengths) structure [28]. Community structure is determined through hierarchical clustering [35]: a method of partitioning a network into similar subsets of nodes. The statistical properties (degree distribution) of a network are different at different intermediate scales of analysis. Fig. 2 shows two different scales of analysis of our scenario network: a lower scale of communities of users and a higher scale of service providers.

2) Robustness

Network robustness deals with the origins and effects of node failure. A robust network is defined by [28] as a network which can resist failure of its nodes as a result of both random and targeted node removal. More specifically, network robustness refers to the possibility of a small response of a network to large stimuli [36]. As an example, [37] have studied the effect of both types of node removal on the Internet. They conclude that the Internet has a high tolerance for random node removal or failure, but is highly vulnerable to targeted removal (attack) of nodes that have a high number of links.

3) Sensitivity

In contrast to network robustness, network sensitivity refers to the possibility of a large network response to small stimuli. Using a dynamic attractor network model [36], have shown that the scale-free topologies found in nature enable more sensitive response to changes compared to random networks. The authors argue that the functional characteristics of some networks and their topologies are better understood in terms of the system's need to respond with sensitivity to external changes. They identify a consistent pattern of behavior of the network (attractor) with a functional state of a system, and suggest that the architecture of different network topologies affect the properties of robustness and response under changes to the state(s) of the nodes of the network. They specifically contrast the response of random (exponential distribution) and scale-free networks' changes in nodes, considering the size and type of attractor points. The attractor points represent the regions in the space of network states that evolve to a given attractor [36]. The statistical properties of the networks (i.e. their degree distributions) characterize how the networks respond to in terms of robustness and sensitivity.

B. A Complex Networks Approach

The statistical model of a network represents the network as a whole, and as a result, the network is described at a macroscopic or high level of observation.

From a complex networks perspective, both the wireless devices and bandwidth provider(s) are the nodes of a network. The interactions between the nodes of the network are reflected in their drive to form communities of networks to obtain access to bandwidth resources. This view considers the design of the system from the large-scale perspective of the bandwidth provider(s) or communities of devices as a whole.

According to the statistical properties of networks (degree distributions) the robustness and sensitivity of the network depend on the distribution of the number of links connecting the nodes. The desired degree distribution that would give the right balance between robustness and sensitivity is determined by the specific application context.

Consider now an application context extending the scenario in Fig. 1 to a deregulated electricity market (Fig. 3). Within this context we regard deregulated electricity markets as Complex Systems that have rules imposed on them from above (by society) and below (through physical topology). Economic theories claim that deregulated markets lead to increased economic efficiency by offering higher quality services at lower retail prices. However, market participants have unique business strategies, risk preference and decision models [38]. The Electricity Market Complex Adaptive Systems Model (EMCAS) [38] is an agent-based modeling tool that analyzes multi-agent markets and allows for the testing of regulatory structures before they are applied to power grids.

So far, Fig. 1 described the logical connectivity of a future Internet (Fig. 3C):

- The *logical connectivity* represents the abstract relationships between nodes, i.e. the relationships for controlling the network by determining who connects to who to achieve optimum bandwidth usage. Fig. 3A shows that the cumulative degree distribution of the current Internet follows a power law, indicated by the straight-line form on double logarithmic scales [33].
- We extend this scenario by introducing the *physical connectivity* of a power grid (Fig. 3D). The physical connectivity represents tangible links between electricity users and suppliers for transmitting power. Fig. 3B shows that the cumulative degree distribution of the existing Western United States power grid follows an exponential degree distribution [34]. The curve appears as a straight line as a result of the log-linear scale used.

In the extended scenario, the bandwidth users at the logical connectivity level mirror the electricity users at the physical level, and the bandwidth providers at the logical level mirror the electricity suppliers at the physical level.

IV. Control of a Complex System

A holarchy is defined as a nested hierarchy of self-replicating structures (holons) [39]. Holarchies represent patterns of self-organizing structures in which holons at several scales of observation behave as autonomous wholes to achieve a certain cooperative goal. Our scenario's goal is to control the formation of communities of electricity users and suppliers to satisfy electricity market rules while maintaining robustness against failure and attack [40] (Fig. 3D).

1) The higher level holon(s) mirror the service provider(s) of the logical connectivity layer of Fig. 3C, which in turn mirror the electricity supplier(s) of Fig. 3D.
2) The lower level holons mirror the users of the logical connectivity layer of Fig. 3C, who in turn mirror the electricity users of Fig. 3D.

At a small-scale level of observation, the holarchy represents a Complex System with holons that make up the parts of the system.

The holons have

- *intended goals* that are given by a user need, e.g. the geographical grouping of electricity users who would benefit by creating a "virtual energy store", and
- *imposed goals* that are imposed on holons by higher-level neighbors (or by the power market model of Fig. 3E in the case of the highest level holon).

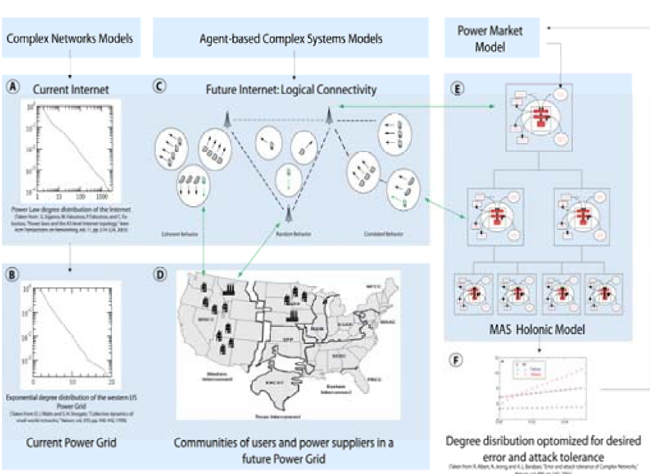

Fig. 3. Complex Networks as control paradigm for Complex Systems.

The rules that govern the relationships between holons are detailed in [40]. The grouping of holons according to these rules results in a 'network of networks' (the holarchy – aka. a Complex Network).

Given a certain combination of intended vs. imposed goals, the holarchy reaches a stable, optimal state that reflects a certain network topology. At this state, the holarchy's network topology is characterized by a particular degree distribution.

This degree distribution may correspond to either a power law or exponential distribution, or a combination of both, i.e. a power law with an exponential tail-end. The resulting distribution would be associated with a characteristic error and attack tolerance.

By sequentially varying the weight of the imposed vs. intended goals of the holons (by adjusting their own needs and that of the market model), the topology of the network (which represents the physical entities of users and service providers/suppliers) may be manipulated to yield a desired degree distribution and associated error and/or attack tolerance (Fig. 3F).

V. Conclusions

Our current efforts are focused on the development of a mathematical model for this paradigm and its implementation using Multi-Agent Systems concepts.

References

[1] N. Wiener, *Cybernetics: Control and communication in the animal and the machine*. New York, NY: J. Wiley, 1948, pp. 194.

[2] L. Von Bertalanffy, "An outline of general systems theory," *The British Journal for the Philosophy of Science*, vol. i, pp. 134, 1950.

[3] S. J. Heims, *The Cybernetics Group*. Cambridge, MA: MIT Press, 1991, pp. 334.

[4] W. R. Ashby, *An introduction to Cybernetics*. New York, NY: J. Wiley, 1956, pp. 295.

[5] G. Bateson, *Mind and nature: A necessary unity (Advances in Systems Theory, Complexity, and the Human Sciences)*. Cresskill, NJ: Hampton Press, 2002, pp. 220.

[6] L. Von Bertalanffy, *Kritische Theorie der Formbildung*. Berlin, Germany: Gebrüder Borntraeger, 1928, pp. 244.

[7] R. H. Abraham and A. Montuori, "The Genesis of Complexity," in *Advances in Systems Theory, Complexity, and the Human Sciences*: Hampton Press, 2002, pp. 1-17.

[8] L. Von Bertalanffy, *General System Theory: Foundations, development, applications*. New York, NY: Braziller, 1995, pp. 295.

[9] A. Scott, "Reductionism revisited," *Journal of Consciousness Studies*, vol. 11, pp. 51-68, 2004.

[10] J. W. Forrester, *Principles of Systems*: Productivity Press, 1988, pp. 387.

[11] D. Raychaudhuri and M. Gerla, Report of NSF workshop: New Architectures and Disruptive Technologies for the Future Internet: The Wireless, Mobile and Sensor Network Perspective [online]. Available: http://www.geni.net/documents.php

[12] S. H. Kellert, *In the wake of chaos : Unpredictable order in dynamical systems*. Chicago, IL: University of Chicago Press, 1993, pp. 190.

[13] D. V. Newman, "Emergence and strange attractors," *Philosophy of Science*, vol. 63, pp. 245-261, 1996.

[14] T. De Wolf and T. Holvoet, "Emergence versus self-organisation: Different concepts but promising when combined," *Lecture notes in Computer Science*, vol. 3464, pp. 1-15, 2005.

[15] Y. Bar-Yam, "Complexity Rising: From Human Beings to Human Civilization, a Complexity Profile: NECSI technical report," in *Encyclopedia of life support systems*. Oxford, UK: EOLSS Publishers, 1997.

[16] F. Mandl, *Statistical Physics*. New York, NY: Wiley, 1971, pp. 402.

[17] G. Nicolis and I. Prigogine, *Self-organization in non-equilibrium systems : From dissipative structures to order through fluctuations*. New York, NY: Wiley, 1977, pp. 512.

[18] F. G. Varela, H. R. Maturana, and R. Uribe, "Autopoiesis: The organization of living systems, its characterization and a model," *Biosystems*, vol. 5, pp. 187-196, 1974.

[19] M. Bushev, *Synergetics: Chaos, order, self-organization*. River Edge, NJ: World Scientific, 1994, pp. 252.

[20] H. Haken, *The science of structure: Synergetics*. New York, NY: Van Nostrand Reinhold, 1984, pp. 255.

[21] F. Heylighen, "The Science Of Self-Organization And Adaptivity," in *The Encyclopedia of Life Support Systems*. Oxford, UK: EOLSS Publishers, 1999, pp. 253-280.

[22] S. A. Levin, "Complex Adaptive Systems: Exploring the known, the unknown and the unknowable," *Bulletin of the American Mathematical Society*, vol. 40, pp. 3-19, 2003.

[23] S. A. Levin, "Ecosystems and the biosphere as Complex Adaptive Systems," *Ecosystems*, vol. 1, pp. 431-436, 1998.

[24] J. H. Holland, *Hidden order: How adaptation builds complexity*. Reading, MA: Addison-Wesley, 1995, pp. 185.

[25] J. H. P. Dawes and M. Golubitsky, Pattern formation in large domains [online]. Available: http://www.newton.cam.ac.uk/

[26] R. Albert and A. L. Barabasi, "Statistical mechanics of Complex Networks," *Reviews of Modern Physics*, vol. 74, pp. 47-97, 2002.

[27] M. E. J. Newman, "The structure and function of Complex Networks," *Society of Industrial and Applied Mathematics Review*, vol. 45, pp. 167-256, 2003.

[28] D. J. Watts, "The 'new' science of networks," *Annual Review of Sociology*, vol. 30, pp. 243-270, 2004.

[29] D. J. Watts and S. H. Strogatz, "Collective dynamics of small-world networks," *Nature*, vol. 393, pp. 440-442, 1998.

[30] M. Karonski and A. Rucinski, *The Origins of the Theory of Random Graphs*. Berlin: Springer, 1997, pp. 351-380.

[31] B. Bollobas, "Degree Sequences of Random Graphs," *Discrete Mathematics*, vol. 33, pp. 1-19, 1981.

[32] A. L. Barabasi, *Linked: The new science of networks*: Perseus Books Group, 2002, pp. 256.

[33] G. Siganos, M. Faloutsos, P. Faloutsos, and C. Faloutsos, "Power laws and the AS-level Internet topology," *Ieee-Acm Transactions on Networking*, vol. 11, pp. 514-524, 2003.

[34] L. A. N. Amaral, A. Scala, M. Barthelemy, and H. E. Stanley, "Classes of small-world networks," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 97, pp. 11149-11152, 2000.

[35] S. F. K. Wasserman, *Social network analysis: Methods and applications*. Cambridge: Cambridge University Press, 1994, pp. 857.

[36] Y. Bar-Yam and I. R. Epstein, "Response of Complex Networks to stimuli," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 101, pp. 4341-4345, 2004.

[37] R. Albert, N. Jeong, and A. L. Barabasi, "Error and attack tolerance of Complex Networks," *Nature*, vol. 409, pp. 542, 2001.

[38] M. J. North, G. Conzelmann, V. Koritarov, C. M. Macal, P. Thimmapuran, and T. Veselka, "E-laboratories: Agent-based modeling of electricity markets," presented at the American Power Conference, Chicago, IL, 2002, pp. 1-3.

[39] M. Ulieru, "Emergence of Holonic Enterprises from Multi-Agent Systems: A Fuzzy-Evolutionary Approach," in *Soft Computing Agents: A New Perspective on Dynamic Information Systems*, V. Loia, Ed.: IOS Press, 2002, pp. 187-215.

[40] S. Grobbelaar and M. Ulieru, "Holonic Stigmergy as a Mechanism for Engineering Self-Organizing Applications," presented at the 3rd International Conference of Informatics in Control, Automation and Robotics, 2006, pp. 1-5.