Proceedings of the 2004 Winter Simulation Conference
R. G. Ingalls,M. D. Rossetti, J. S. Smith, and B. A. Peters, eds.

DATA FARMING COEVOLUTIONARY DYNAMICS IN REPAST

Brian F. Tivnan

The MITRE Corporation
Woodbridge, VA 22192, U.S.A.

ABSTRACT

This paper describes the application of data farming techniques (Brandstein and Horne 1998) to explore various aspects of coevolutionary dynamics (McKelvey 2002) in organization science. Data farming is an iterative process using high-performance computing to execute and vary agent-based models, collect and explore statistical results, and integrate these results for the purposes of growing more data by virtue of generative analysis. The tool of choice for creating these agent-based models is the University of Chicago's Social Science Research Computing's (2004) REcursive Porous Agent Simulation Toolkit (RePast). The paper concludes with a brief description of Tivnan's (2004) Coevolutionary model of Boundary-spanning Agents and Strategic Networks (C-BASN), an extension of Hazy and Tivnan's (2004) Model of Organization, Structural Emergence, and Sustainability (MOSES).

1 DATA FARMING

The following discussion provides a general overview of data farming. For in-depth reviews of data farming, the reader should refer to Horne (2001) and Horne and Meyer (2004). Broadly defined, *data farming* is an iterative process using high-performance computing to execute and vary distillations, collect and explore statistical results, and integrate these results for the purposes of growing more data by virtue of generative analysis. Figure 1 depicts the iterative process of data farming.

To clarify this definition of data farming, two additional definitions are required. *Distillations* are fast, robust, transparent simulations that use agent-based modeling to focus attention on specific aspects of a research problem. *Generative analysis* consists of automated methodologies to drive parameter and rule variations in the iterative data farming process.

1.1 Motivation Behind Data Farming

Brandstein and Horne (1998) describe the motivation for developing the data farming process. Records of historical events are often rich in detail and fascinating to examine, but each is essentially only one data point on the landscape of possible outcomes. Large, twentieth-century computer models are used by the analytic community to run specific scenarios with many details. But they take many hours to set up for what again essentially amounts to one data point on the landscape of possible outcomes. Thus, what if we want to take a look at questions of interest from the perspective of many data points? Have not the recent advances in complexity theory shown that the insight gleaned from the analysis of large data sets can possibly differ significantly from that of smaller samples of the same solution space? The meta-technique of data farming provides a framework to perform the analyses of complexity theory.

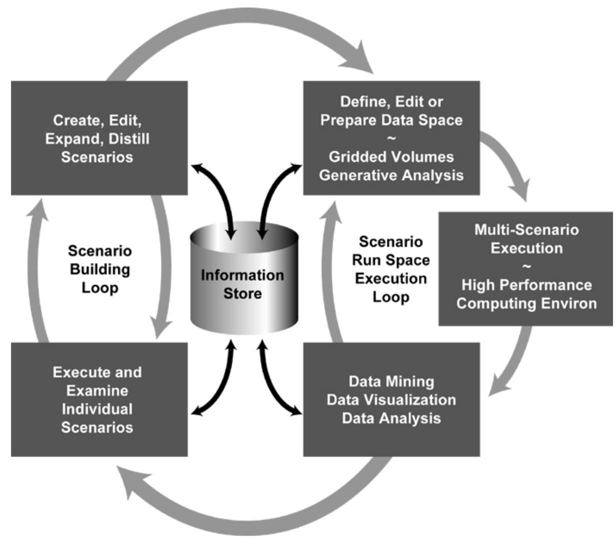

Figure 1: Data Farming Loop

1.2 Designing Simulation Experiments

At this point, the reader will likely be asking the question: "How can the techniques of data farming be efficiently and effectively applied?" The answer: The orthogonal Latin-Hypercube (OLH) design. The OLH design provides an efficient alternative to the full factorial design (Cioppa and

Lucas 2004; Kleijnen, Sanchez, Lucas, and Cioppa Forthcoming). For example, a full factorial design with seven parameters (i.e., design factors) with at least 10 levels (e.g., 10, 20, 30, …, 100) for each parameter generates at least 10^7 or 10 million parametric combinations (i.e., design points). In order to assume a normal distribution for the measured data, the Central Limit Theorem (Larsen and Marx 1986, Larson 1995) requires at least 30 independently seeded replications of the simulation for each design point. Hence, the full factorial design requires at least 300 million runs of the simulation!

However, an OLH design requires only 17 independent design points to comprehensively explore up to a seven-dimensional parameter space (i.e., no correlation between any of the parameters for each of the design points). Hence, the OLH design requires only 510 runs of the simulation (i.e., 17 design points multiplied by 30 independently seeded replications of the simulation for each design point) – clearly an efficient and effective exploration of the parameter space.

2 COEVOLUTIONARY DYNAMICS

This section describes empirical and theoretical research to support the application of coevolutionary dynamics to organization science. The support stems from the following logical progression: (a) organization science theorists have explored, and in many instances, acknowledged the applicability of complexity theory to organization science research; (b) much of the acceptance for complexity science applications follows from the conceptualization of an organization as a Complex Adaptive System (CAS); (c) complexity science offers a robust explanation of order in natural and social systems; (d) coevolutionary dynamics provide the mechanisms with the highest explanatory power for describing order-creation in social systems. The discussion in this section supporting the assumption of coevolutionary dynamics continues with an overview of the literature for each element of the preceding logical progression.

2.1 Complexity Applications to Organization Science

As complexity theory extends the scientific frontiers in many other disciplines such as physics, chemistry, biology and other natural sciences; the concept of the applicability of complexity theory to organization science has recently generated much debate. Specifically, many theorists (for example, Anderson (1999), Brown and Eisenhardt (1997), Carley and Prietula (1994), Gell-Mann (1994), Gersick (1991), Lissack (1999), Mainzer (1997), McKelvey (1997; 1999b), Stacey (1995), and Thietart and Forgues (1995)) have argued convincingly in support of the applicability of complexity theory to organization science. In addition to this support for the theoretical efficacy of complexity science applications to organization science, other theorists (Carley 1997, Carley and Svoboda 1996, Dooley 1997, Kauffman and Macready 1995, Levinthal 1997, Levinthal and Warglien 1999, McKelvey 2002, Siggelkow 2001 and 2002, Sorensen 1997) have detailed the non-linear adaptive capacity of organizations and the non-linear complexity of organizational dynamics (Dooley and Van de Ven 1999).

2.2 An Organization as a CAS

Central to the research exploring the non-linear adaptive capacity of organizations and the non-linear complexity of organizational dynamics lays the conceptualization of an organization as a Complex Adaptive System (CAS). For simplicity in introducing the reader to this study, an earlier consideration of CAS (i.e., Chapter 1 – Complexity of Organizational Dynamics) described it as a system: (a) consisting of many interacting components, (b) constituting more than the sum of these interacting components and (c) possessing some capacity to adapt to its external environment. To facilitate a more comprehensive analysis, the subsequent discussion first describes Holland's (1995) widely held definition of CAS in greater detail and then identifies the direct correlation between his definition and the organization science theories supporting this research.

2.3 Holland's Complex Adaptive System

Holland (1995) describes a CAS according to what he refers to as the "seven basics" - four properties and three mechanisms; when simultaneously occurring, this set of seven basics constitutes the necessary and sufficient conditions of all CAS. The four properties consist of (a) aggregation, (b) nonlinearity, (c) flows, and (d) diversity. The three mechanisms consist of (a) tagging, (b) internal models, and (c) building blocks. More than their distinction as properties or mechanisms, Holland emphasizes the importance of the interrelations between the seven basics.

Aggregation represents both the standard process in modeling of focusing on the salient issues and simplifying all other aspects of the system, as well as, the behavior of CAS: namely, the emergence of large-scale behaviors from the aggregate interactions of less complex agents. Tagging, the mechanism for aggregation and boundary formation in CAS, facilitates selective interaction among agents which ultimately leads to hierarchical organization. CAS possess nonlinear properties, in that agent interactions make the behaviors of the aggregate more complex than can be predicted by summing "typical" agent behavior (i.e., a linear assumption would hold if system behavior was fully deducible from summing or averaging the behavior of the system's components). Flows describe CAS as a network representation of processing nodes (i.e., agents) and connectors (i.e., possible interactions). Two properties of economic flows are important to all CAS: (a) a multiplicative effect – if an agent injects additional resources at a particular node and (b) a recycling effect – the effect of cycles in the network, especially those that extend the utility of resources.

Diversity describes the many different types of agents within a CAS. Each type of agent is intended to fill a unique niche which is defined by the interactions centering on that focal agent. Diversity also arises from the emergence of a new niche to be exploited by adaptations of competing agents. Agents that increase recycling flows discover and exploit new niches, which therefore enhances diversity and leads to perpetual novelty - the hallmark of all CAS.

Another source of diversity within a CAS stems from the idiosyncrasy of agent's internal models. Virtually synonymous with Gell-Mann's (1994) "schema," internal models provide the CAS with a mechanism for anticipation. By eliminating details so that selected patterns are emphasized, internal models provide an agent with a mechanism with which it can detect and then "select patterns in the torrent of input which it receives and then convert those patterns into changes in its internal structure (Holland 1995, p. 31)."

But an agent develops its internal model based only upon its unique experience in a "perpetually novel environment (p. 34)." Therefore, an agent reduces the complexity of a given situation by searching for familiar elements that it is has learned through experience or by natural selection to be effective in similar situations. Holland refers to these familiar elements as building blocks and argues that "this use of building blocks to generate internal models is a pervasive feature of CAS (p. 37)."

2.4 Complexity Science as Order Creation Science

The research of the pioneers in complexity theory has led to the modern understanding of order as an emergent phenomena stemming from complex, seemingly random events (Holland 1995, Kauffman 1993, Prigogine and Stengers 1984). Building on the conceptualization of an organization as a CAS, several organization scientists (Mainzer 1997, McKelvey 2001 and Forthcoming, Stacey 1993) have explored the emergence of order within as well as between organizations. Most notably, McKelvey (2001b, p. 137) argues that complexity theory is "really order-creation science" by first recounting the literary perspectives and definitions of order and then detailing the recent scientific advances in understanding order and its root causes. The discussion of complexity theory as order-creation science continues with a brief summary of McKelvey's (2001b and Forthcoming) analysis.

Following in the Darwin-Wallace model (Darwin 1859) of natural selection and its explanation of speciation in the biological world, order first came to be understood as the emergence of differentiated entities (Durkheim 1893, Spencer 1898). More than half of a century later, Ashby (1956) extends the understanding of order with his concept of requisite variety.

Ashby (1956) does not define order as the emergence of entities but in terms of the *connections* between those entities. He describes his "law of requisite variety" in terms of the connection between two entities (e.g., *A* and *B*). Order exists between *A* and *B*, if and only if, the connection between *A* and *B* is "conditioned" by a third entity, *C*, which is external to the connection between *A* and *B*. Therefore, an entity can only adapt effectively when the variety of its internal order matches the variety of its environmental constraints (Ashby 1956). Of particular note, Ashby's description of order as a function of environmental context fits with Prigogine's (1955) research and the work of other physicists to be described below.

But as McKelvey (2001b and Forthcoming) highlights, Ashby (1956) describes the phenomenon of order but says nothing about what causes order to emerge. McKelvey (Forthcoming, p. 3) describes mature science, "Orthodoxy," as being founded on the equilibrium principle at the core of the 1st Law of Thermodynamics. The 1st Law states that energy itself cannot be created nor destroyed; though its forms may change, the sum of all energy remains fixed (Chaisson 2001). McKelvey (Forthcoming) asserts that since "normal science [or Orthodoxy] accepts order as a given in the universe…this leaves the thermodynamics of order translation as the defining dynamic of science (p. 3)." However, the Nobel-Laureate, Ilya Prigogine, has shown that the 1st and 2nd Laws of Thermodynamics differ on the aspect of reversibility (Prigogine 1955, Prigogine and Stengers 1984).

Prigogine demonstrated that the 1st Law is time-reversible (i.e., the Newtonian processes of classical physics are bi-directional and thus reversible), while also demonstrating the irreversibility of the 2nd Law. The 2nd Law states that any system not in a state of equilibrium will expend energy in an attempt to move toward equilibrium and this loss of energy is called entropy production (Bar-Yam 1997). Prigogine along with his colleagues (1989, 1984, 1997) argues that entropy production is an irreversible process. The foundation of Prigogine's argument rests on Eddington's (1930) "arrow of time" - that nowhere in the Universe can we observe randomness dissipate into order; whereas, we frequently observe order dissipate into randomness.

With Prigogine's research at its core, McKelvey (Forthcoming) references several advances in physics, particularly thermodynamics, as well as biology that contribute meaningfully to our understanding of and support his assertion for Complexity Science as order-creation. Table 1 provides a brief overview of McKelvey's (Forthcoming) assessment of the supporting, order-creation literature.

2.5 Coevolution as the Mechanism of Order-Creation

As the concept of coevolution continues to draw more and more attention from organization scientists as evidenced by a dedicated issue in *Organization Science* (Lewin and Volberda 1999), several leading researchers consider coevolution as a principal mechanism of order-creation in organizational ecology (e.g., Baum and Singh (1994), Lewin and Volberda (1999), and McKelvey (1997, 1999a, 2002)). This discussion of coevolution as the mechanism for order-creation continues with a description of the properties, types and damping mechanisms of coevolution.

2.5.1 Essential Properties of Coevolution

While arguing for coevolution as a unifying framework for research in strategy and organization science, Lewin and Volberda (1999) list the essential properties of coevolution as: (a) multi-levelness / embeddedness, (b) multi-directional causality, (c) nonlinearity, (d) positive feedback, (e) path and history dependence. A brief summary of these properties follows.

McKelvey (1997, 1999a, 2002) asserts that coevolutionary dynamics occur at multiple levels of analysis; within an organization (i.e., microcoevolution) and between organizations and their respective environments (i.e., macrocoevolution) which is similar to Granovetter's (1985) notion of embeddedness. McKelvey (2002, p. 3) asserts that an organization's ability to macrocoevolve with its competitors depends on its microcoevolutionary processes. An excellent example of this multi-level nature is March's (1991) study of environmental turbulence and the corresponding adaptation at the levels of the organization and the organizational microstate.

Because organizations coevolve with each other and with a perpetually altering environment (Holland 1995, Kauffman 1995, McKelvey 1997), the distinction between dependent and independent variables becomes problematic since variables are sensitive to endogenous effects (i.e., multi-directional causality). Consistent with Holland's (1995) description of the nonlinear properties of CAS, Lewin and Volberda (1999) describe the nonlinear properties of coevolution as producing counter-intuitive changes in one variable from presumably insignificant changes in another variable. Similar to Weick's (1979) concept of enactment, an organization influences its environment and is influenced by its environment; these recursive interactions and the resulting interdependency are summarized as positive feedback. Unlike the population ecologists (e.g., Hannan and Freeman (1984)) who point to variations in the environment, coevolutionary theorists (e.g., McKelvey (2002) and Lewin and Volberda (1999)) point to an initial heterogeneity between the organizations to explain the varying effectiveness of organizational adaptability (i.e., path dependence).

2.5.2 Types of Coevolution

After describing the similar properties of all coevolutionary processes, the discussion now briefly shifts to a description of the kinds of coevolutionary dynamics. Maruyama (1963) described four kinds; namely, (a) mutation rate and the environment, (b) predator / prey, (c) supernormal, and (d) inbreeding and population size. McKelvey (2002) offers another kind of coevolution: symbiotic.

The coevolution of mutation rate and the environment addresses the interdependence between the rates of change of an organism and its environment. Similarly, predator / prey coevolution describes the respective rates of change of competing populations. Supernormal coevolution describes the "snowballing" (i.e., nonlinear) effect of a favored characteristic as a tag governing the interaction of agents within a population (e.g., McKelvey (2002) relates this to the propensity for good-looking, intelligent people to attract other good-looking, intelligent people and produce still more good-looking, intelligent people). Inbreeding within a small population rapidly leads to the isolation of the small population from other populations (i.e., diminished embeddedness and few, if any, structural holes); the more isolated the population, the more likely inbreeding will occur and lead to further differentiation. Symbiotic coevolution describes the cooperative and mutually beneficial interdependence of two dissimilar agents.

3 OVERVIEW OF REPAST

An agent based simulation is required to fully explore the coevolutionary dynamics described above. The University of Chicago's Social Science Research Computing (2004) developed the *REcursive Porous Agent Simulation Toolkit* (RePast) as a software framework for creating agent based simulations in JAVA. The goal of RePast "is to move beyond the representation of agents as discrete, self-contained entities in favor of a view of social actors as permeable, interleaved and mutually defining, with cascading and recombinant motives (Computing 2004)."

Borrowing much from other simulation toolkits such as SWARM (Group 2004) and ASCAPE (Institution 2000), RePast essentially consists of a compilation (i.e., library) of computer programs (i.e., classes) that enable a researcher to create, run, display and collecting data from agent-based models. Figure 2 demonstrates some of the features RePast (clockwise from the top right): namely, a toolbar for running RePast, a graphical user interface for manipulating the parameters of the model, some sample output data in the form of a histogram, a display of the agents interacting on the model surface, and another output example in the form of a chart of time-series data.

Researchers interested in agent-based modeling benefit from RePast's vibrant user-community (e.g., the developers at University of Chicago Social Science Research

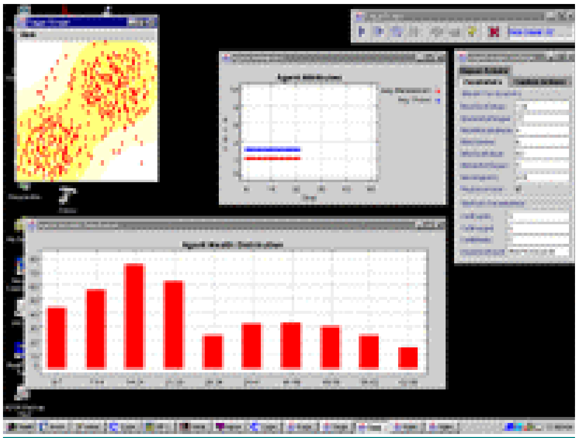

Figure 2. Screenshot of RePast (Computing 2004)

Computing and fellow researchers) and the enhancements to the framework that the community develops. In its efforts to expand both the reach and the capabilities of RePast, the RePast user-community continues to produce helpful RePast tutorials (e.g., (Murphy 2004)) to complement that of the RePast homepage.

4 CURRENT MODELING EFFORTS

At present, the author is using RePast to data farm over different aspects of coevolutionary dynamics between firms collaborating and competing within the same resource niche (Tivnan 2004). This study extends the model of boundary-spanning activity of a single organization (Hazy and Tivnan 2003, Hazy and Tivnan 2004, Hazy, Tivnan, and Schwandt 2003) to a model that will permit the exploration of the collaborative efforts of organizations in a competitive, coevolutionary context; namely, the emergence of strategic networks. This new model is called the **C**oevolutionary model of **B**oundary-spanning **A**gents and **S**trategic **N**etworks (C-BASN; pronounced "Sea Basin").

The type of coevolution that C-BASN will explore is the coevolution of mutation rate and the environment. All the more applicable in high-velocity environments (Eisenhardt 1989) and hypercompetitive contexts (D'Aveni 1994), what an organization has learned (Schwandt and Marquardt 1999) and the rate at which it learns (McKelvey 2002) offer the organization its best source of sustainable, competitive advantage (McKelvey 2001a). That is, an organization must learn faster and more effectively than its competitors to establish an initial competitive advantage, and then that same organization must continue to learn faster still if it is to sustain its competitive advantage. This dynamic is known as an "arms race" or the "Red Queen effect", adopted from Carroll's (1946) Red Queen when she says to Alice, "[i]t takes all the running you can do, to keep in the same place."

To take advantage of the strengths of RePast and its ability to data farm over coevolutionary dynamics such as the previously mentioned Red Queen effect, the author and a colleague, Stephen Upton, have recently undertaken a modeling effort to simulate two opposing military forces (i.e., warring armies), each employing new tactics to counter those of its enemy (Holland, Michelsen, Powell, Upton, and Thompson 1999). This effort will employ the techniques of data farming over an OLH design of a RePast model to explore the predator / prey coevolutionary dynamics of this scenario.

ACKNOWLEDGMENTS

The author has been the recipient of a wealth of insight from his MITRE colleagues: particularly, Philip Barry, Brandy Goff, Gary Horne, Sarah Johnson, Matthew Koehler, Theodore Meyer, and Stephen Upton; as well as his colleagues at the George Washington University: particularly, James Hazy and David Schwandt. Any lingering errors remain the sole responsibility of the author.

REFERENCES

Anderson, P. (1999). Complexity Theory and Organization Science. *Organization Science, 10*(3), 216-232.

Ashby, W. R. (1956). *An Introduction to Cybernetics*. London: Chapman & Hall.

Bar-Yam, Y. (1997). *Dynamics of Complex Systems*. Reading, MA: Addison-Wesley.

Baum, J. A. C., & Singh, J. H. (1994). Organization-Environment Coevolution. In J. A. C. Baum & J. H. Singh (Eds.), *Evolutionary Dynamics of Organizations* (pp. 379-402). New York: Oxford University Press.

Brandstein, A. G., & Horne, G. E. (1998). Data Farming: A Meta-technique for Research in the 21st Century, *Maneuver Warfare Science 1998* . Quantico, VA: Marine Corps Combat Development Command.

Brown, S. L., & Eisenhardt, K. M. (1997). The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations. *Administrative Science Quarterly, 42*, 1-34.

Carley, K. M. (1997). Organizational Adaptation. *Annals of Operations Research, 75*, 25-47.

Carley, K. M., & Prietula, M. J. (1994). ACTS Theory: Extending the Model of Bounded Rationality. In K. M. Carley & M. J. Prietula (Eds.), *Computational Organizational Theory* (pp. 55-88). Hillsdale, NJ: Lawrence Erlbaum Associates.

Carley, K. M., & Svoboda, D. M. (1996). Modeling Organizational Adaptation as a Simulated Annealing Process. *Sociological Methods & Research, 25*(1), 138-168.

Carroll, L. (1946). *Through the Looking Glass & What Alice Found There*. New York: Grosset & Dunlap.

Chaisson, E. J. (2001). *Cosmic Evolution: The Rise of Complexity in Nature*. Cambridge, MA: Harvard University Press.

Cioppa, T. M., & Lucas, T. W. (2004). Efficient Nearly Orthogonal and Space-filling Latin Hypercubes. *Naval Postgraduate School Working Paper*.

Computing, U. o. C. S. S. R. (2004). RePast: An Agent-Based Modeling Toolkit for JAVA (Version 2.2). Chicago: University of Chicago.

Darwin, C. (1859). *On the Origin of Species by Means of Natural Selection*. London: Murray.

D'Aveni, R. A. (1994). *Hypercompetition: Managing the Dynamics of Strategic Maneuvering*. New York: Free Press.

Dooley, K. J. (1997). A Complex Adaptive Systems Model of Organization Change. *Nonlinear Dynamics, Psychology and Life Sciences, 1*(1), 69-97.

Dooley, K. J., & Van de Ven, A. H. (1999). Explaining Complex Organizational Dynamics. *Organization Science, 10*(3), 358-375.

Durkheim, E. (1893). *De la division du travail social: etude sur l'organization des societes superieures*. Paris: F. Alcan.

Eddington, A. (1930). *The Nature of the Physical World*. London: Macmillan.

Eisenhardt, K. M. (1989). Making Fast Strategic Decisions in High-Velocity Environments. *Academy of Management Journal, 32*(3), 543-576.

Gell-Mann, M. (1994). *The Quark and the Jaguar: Adventures in the Simple and Complex*. New York: W. H. Freeman.

Gersick, C. J. G. (1991). Revolutionary Change Theories: A Multilevel Exploration of the Punctuated Equilibrium Paradigm. *Academy of Management, 16*(1), 10-36.

Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology, 91*(3), 481-510.

Group, S. D. (2004, July 28, 2004). *SWARM*. Available: <`http://www.swarm.org/`> July 10, 2004].

Hannan, M. T., & Freeman, J. (1984). Structural Inertia and Organizational Change. *American Sociological Review, 49*, 149-164.

Hazy, J. K., & Tivnan, B. F. (2003, December 7-10, 2003). *Simulating Agent Intelligence as Local Network Dynamics and Emergent Organizational Outcomes.* Paper presented at the Winter Simulation Conference 2003, New Orleans, LA.

Hazy, J. K., & Tivnan, B. F. (2004). *On Building an Organizationally Realistic Agent-Based Model of Local Interaction and Emergent Network Structure.* Paper presented at the 2004 Winter Simulation Conference, Washington, D. C.

Hazy, J. K., Tivnan, B. F., & Schwandt, D. R. (2003). The Impact of Boundary Spanning on Organizational Learning: Computational Explorations. *Emergence: A Journal of Complexity Issues in Organizations and Management, 5*(4), 86-124.

Holland, J. (1995). *Hidden Order: How Adaptation Builds Complexity*. Reading, MA: Addison-Wesley.

Holland, J. V., Michelsen, R. E., Powell, D. R., Upton, S. C., & Thompson, D. R. (1999). *Generative Analysis* (LAUR 99-4715). Los Alamos, NM: Los Alamos National Laboratory.

Horne, G. E. (2001). Beyond Point Estimates: Operational Synthesis and Data Farming. In G. E. Horne & S. K. Johnson (Eds.), *Maneuver Warfare Science 2001* . Quantico, VA: Marine Corps Combat Development Command.

Horne, G. E. & Meyer, T. E. (2004). Data Farming: Discovering Surprise. Paper presented at the 2004 Winter Simulation Conference, Washington, D. C.

Institution, B. (2000, October 12, 2000). *ASCAPE*. Available: <`http://www.brook.edu/es/dynamics/models/ascape/README.html`> July 10, 2004].

Kauffman, S. (1993). *The Origins of Order: Self-Organization and Selection in Evolution*. New York: Oxford University Press.

Kauffman, S. (1995). *At Home in the Universe*. Oxford: Oxford University Press.

Kauffman, S., & Macready, W. (1995). Technological Evolution and Adaptive Organizations. *Complexity, 1*, 26-43.

Kleijnen, J. P. C., Sanchez, S. M., Lucas, T. W., & Cioppa, T. M. (Forthcoming). A User's Guide to the Brave New World of Designing Simulation Experiments. *INFORMS Journal on Computing*.

Larsen, R. J., & Marx, M. L. (1986). *An Introduction to Mathematical Statistics and its Applications*. Englewood Cliffs, NJ: Prentice-Hall.

Larson, H. J. (1995). *Introduction to Probability*. Reading, MA: Addison-Wesley.

Levinthal, D. (1997). Adaptation on Rugged Landscapes. *Management Science, 43*(7), 934-950.

Levinthal, D., & Warglien, M. (1999). Landscape Design: Designing for Local Action in Complex Worlds. *Organization Science, 10*(3), 342-357.

Lewin, A. Y., & Volberda, H. W. (1999). Prolegomena on Coevolution: A Framework for Research on Strategy and New Organizational Forms. *Organization Science, 10*(5), 519-534.

Lissack, M. R. (1999). Complexity: the Science, its Vocabulary, and its Relation to Organizations. *Emergence, 1*(1), 110-126.

Mainzer, K. (1997). *Thinking in Complexity: The Complex Dynamics of Matter, Mind and Mankind* (3rd ed.) (Vol. Springer-Verlag). New York.

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science, 2*(1), 71-87.

Maruyama, M. (1963). The Second Cybernetics: Deviation-Amplifying Mutual Causal Processes. *American Scientist, 51*, 164-179.

McKelvey, B. (1997). Quasi-Natural Organization Science. *Organization Science, 8*(4), 352-380.

McKelvey, B. (1999a). Avoiding Complexity Catastrophe in Coevolutionary Pockets: Strategies for Rugged Landscapes. *Organization Science, 10*(3), 294-321.

McKelvey, B. (1999b). Complexity Theory in Organization Science: Seizing the Promise or Becoming a Fad? *Emergence, 1*(1), 5-32.

McKelvey, B. (2001a). Energizing Order-Creating Networks of Distributed Intelligence. *International Journal of Innovation Management, 5*, 181-212.

McKelvey, B. (2001b). What is Complexity Science: It is Really Order-Creation Science. *Emergence, 3*(1), 137-157.

McKelvey, B. (2002, July 4-6, 2002). *Managing Coevolutionary Dynamics.* Paper presented at the 18th EGOS Conference, Barcelona, Spain.

McKelvey, B. (Forthcoming). Social Order-Creation Instability Dynamics: Heterogeneous Agents and Fast-Motion Science - on the 100th Anniversary of Benard's Dissertation. *Journal of Bioeconomics*, 17.

Murphy, J. T. (2004, July 8, 2004). *A RePast Tutorial*. Available: `<http://www.u.arizona.edu/~jtmurphy/H2R/HowTo01.htm>` July 10, 2004].

Nicolis, G., & Prigogine, I. (1989). *Exploring Complexity: An Introduction*. New York: W. H. Freeman.

Prigogine, I. (1955). *An Introduction to Thermodynamics of Irreversible Processes*. Springfield, IL: Thomas.

Prigogine, I., & Stengers, I. (1984). *Order Out of Chaos: Man's New Dialogue with Nature*. New York: Bantam Books.

Prigogine, I., & Stengers, I. (1997). *The end of Certainty: Time, Chaos, and the New Laws of Nature*. New York: Free Press.

Schwandt, D. R., & Marquardt, M. J. (1999). *Organizational Learning: From World-Class Theories to Global Best Practices*. Boca Raton, FL: St. Lucie Press.

Siggelkow, N. (2001). Change in the Presence of Fit: The Rise, the Fall and the Renaissance of Liz Claiborne. *Academy of Management Journal, 44*(4), 838-857.

Siggelkow, N. (2002). Evolution Toward Fit. *Administrative Science Quarterly, 47*(1), 125-159.

Sorensen, O. J. (1997). *The Complexity Catastrophe in the Computer Industry: Interdependence and Adaptability in Organizational Evolution.* , Stanford University, Palo Alto, CA.

Spencer, H. (1898). *The Principles of Sociology*. New York: D. Appleton & Co.

Stacey, R. (1993). Strategy as Order Emerging from Chaos. *Long Range Planning, 26*(1), 10-17.

Stacey, R. (1995). The Science of Complexity: An Alternative Perspective for Strategic Change Processes. *Strategic Management Journal, 16*, 477-495.

Thietart, R. A., & Forgues, B. (1995). Chaos Theory and Organization. *Organization Science, 6*(1), 19-31.

Tivnan, B. F. (2004). Coevolutionary Dynamics of Strategic Networks: Weak Ties and Boundary Spanning. Washington, DC: Working Paper - The George Washington University.

Weick, K. (1979). *The Social Psychology of Organizing* (Second ed.). New York: McGraw-Hill.

AUTHOR BIOGRAPHY

BRIAN F. TIVNAN is an engineer with The MITRE Corporation. Additionally, Brian is a doctoral candidate in the Executive Leadership Program at the George Washington University. He has a B.S. in mechanical engineering from the University of Vermont and an M.S. in operations research from the Naval Postgraduate School. Prior to joining the MITRE Corporation, Brian served for ten years on active duty in the United States Marine Corps. Brian's current research interests include the use of agent-based models to explore the application of complexity theory to organization science. His e-mail address is `<BTivnan@mitre.org>`