DRAFT

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Enriching Policy Analysis: The Role of Agent-Based Models

"The dynamics of public performance management" that the author presents at the 9th Public Management Research Conference is illustrated as an example in this manuscript.

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Abstract

We have long known that public policy problems are “wicked” or complex. However, in order to make them manageable we have “reduced” them to fit linear Newtonian-Cartesian models. Recent advances in complexity theory have given us a conceptual framework, language, and models that provide us the capacity to implement alternative frameworks for studying wicked problems. After a brief overview of the relevance of complexity concepts to public policy analysis, we discuss the role of agent-based models as an enhanced policy analysis tool for dealing with the complexity of policy problems.

Keywords: Complexity, Policy Analysis, Agent-Based Models

INTRODUCTION

There is growing recognition of the limitations of traditional linear views and optimization methods in capturing the complex reality that is the subject of public administration, public policy analysis and management (Moss, 2002; Lempert, 2002; Henrickson & McKelvey, 2002; Moss & Edmond, 2004). “No model less complex than the system itself can accurately predict in detail how the system will behave at future times” (Bankes, 2002, p. 7263). This methodological reinterpretation of Ashby’s principle of *requisite variety* (Ashby, 1957, pp. 206-212) guides us in our reflection on current practice of policy analysis.

While statistical and other modeling techniques have been extensively and successfully used in policy analysis, their shortcomings for policy analysis are well documented (Morçöl, 2002; Fisher, 2003a). These shortcomings are closely related to the complexity of policy problems in the world of politics (Moe, 1989), competing values (Quinn, 1991), interdependency (Pfeffer & Salancik, 2003), and uncertainty (Stacey, 1992). For such problems, the classical approaches of predictive modeling and optimization have limited utility (Schön, 1983; Bankes, 2002).

In recent years, complexity science has made broad claims about its relevance for policy science. However, much of these works lacks the full operationalization of complexity models as a useful tool for policy analysis. In this paper, we explore critiques of traditional policy analysis and discuss the nature of policy problems using the language of complexity. We also discuss agent-based modeling as a methodological supplement or enhancement to the tools and techniques commonly used for public policy analysis.

COMPLEXITY

Complexity Science

While its roots go much deeper (Goldstein, 1999; François, 1999), complexity science emerged as an academic activity in the 1970s, gathered momentum in the early 1980s, and was enveloped in controversy by the mid-1990s (Wilson, 1998). The multidisciplinary research in modern biology, physics, economics, and computer science initiated a renewed interest in complex systems. (Waldrop, 1992). From the outset, complexity science has relied on a process of gaining knowledge from shared ideas, methods, and experiences from diverse disciplines in order to understand the irreducible complexity of reality as a composite whole. According to Weaver (1948), the focus of applied physics, biology, medical science, psychology, economics, and political science is on 'the problem of organized complexity.' These problems "involve dealing simultaneously with a sizable number of factors which are interrelated into an organic whole" (Weaver, 1948, p. 539). The essential nature of complex systems implies that these areas may not be successfully understood when only a small number of variables are considered or explored by standard deterministic techniques.

Complex systems are generally defined as dynamic systems that exhibit recognizable patterns of organization across spatial and temporal scales (Holland & Miller, 1991; Parker, et al., 2003). Organizations and policy systems can also be understood as complex adaptive systems where several elements in society are dynamically and purposefully interrelated.[1] A major interest of complexity science is the study of emergent phenomena in different complex systems and to recognize common patterns and underlying mechanisms.[2] Emergent behavior can not be predicted or necessarily envisioned from knowledge of the system's constituent parts (Casti, 1997). For instance, an atom does not have a temperature, but a collection of atoms does. Each molecule of sugar does not have the sweetness property, but as a whole it does. Similarly, there are no individuals in a mob, but mobs form and their spatio-temporal properties can be studied systematically. Therefore, it is the organization of the components that determines the emergent phenomena of complex systems.

Simon (1996) discussed three important stages in complexity and complex systems and associated keywords within each stage (Table 1).

<Table 1 Here>

In each of these stages, complexity science shares the holistic view of the world that humans are part of a greater whole. This holistic understanding also reflects the frustration with the praxis of modern scientific knowledge and technical solutions. In particular, an essential tenet of social and policy science is the idea of social reform and progress. However, this idea is based on the unrealistic assumption of total predictability which has avoided dealing with unending complexity. These complex and wicked problems require a mediated approach so that yesterday’s solutions do not become today’s problems. Focusing on a single goal mischaracterizes the problems which are essentially multi-objective and subject to multiple constraints. The complex systems perspective holds the promise of an adaptive, intergrated approach to these problems and their contexts.

Complexity of Policy Problems

Scientists who subscribe to complexity view the world through a lens that is different from that of a traditional positivist (Morçöl, 2002; Baets, 2005). A fundamental assumption of the positivist paradigm is that even if we do not know reality in its entirety, it is not inherently unknowable. The role of science is to accumulate the knowledge necessary to make the reality predictable in this context. On the contrary, complexity acknowledges the limited ability of humans to comprehend the complexity of reality and therefore requires humble reflection on the current state of knowledge (Morçöl, 2002). “Our search is ultimately devoted not to a precise knowledge of the universe, but to a grasp of the role which we play in it – to the meaning of our life” (Jantsch, 1980, p. 310).

This leads us to the debate on whether scientific knowledge should be verifiable and empirically testable in order to establish its objectivity or perhaps wonder whether scientific objectivity is something that policy science must pursue.[3] What does scientific objectivity mean in human and social affairs? One cannot see the world without the intervention of the physical senses. The world that one sees reflects the image of one’s sensory interpretation. Our nervous system brings forth a world in the process of cognition. The regularity of the world we experience at every moment is created each time by the neural capacity of the brain. Even if the world is out there, the world has no ‘essence’ to be discovered (Czarniawska, 1997). In that sense, interpretation, subjectivity, and social construction become an inevitable domain for policy analysis.

Recent advances in complexity science have given us a framework and language for discussing such complexity. Below, we discuss some insights that complexity science provides to policy science, along with their critiques of traditional policy analysis.

Actors and Interactions

Complexity defines human beings and entities as situated within the environment that consists of other human beings and entities. They are depicted as adaptive, autonomous, and purposeful actors (Nohria, 1992). These actors are adaptive in that they are “guided by information from the environment, must control its essential variables, forcing them to go with the proper limits, by so manipulating the environment that the environment acts on them appropriately” (Ashby, 1952, p. 82). These actors are also autonomous. They are “situated within a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to affect what it senses in the future” (Franklin & Graesser, 1997, p. 18). Further, these actors are purposive in that they “deal with conscious decisions or adaptations in the pursuit of goals within the limits of their information and their comprehension of how to navigate through their environment toward whatever their objectives are” (Schelling, 1978, p. 18). Therefore, the behavior of these actors is much more complex than physical particles. Human behavior does not usually permit any simple summation or extrapolation to the aggregate (Schelling, 1978).

Traditional policy analysis has implicitly subscribed to the assumption of rational human-beings and mechanistic entities within a de-contextualized situation.[4] Periodicity and generalization play an important role in this approach. Thus, a logical consequence of this approach is to seek the best alternatives and best solutions. From the perspective of complexity, the world is not a collection of isolated rational objects, but a representation of a network of autonomous and purposeful actors who are fundamentally interconnected and interdependent. Understanding human beings and entities as adaptive, autonomous, and purposeful actors highlights the limitation of the traditional view and also acknowledges the importance of the distinction between natural laws and social rules.

Living systems are partially reacting to action due to history, context, and randomness. Change is an inevitable component of living systems. The notion of fundamental laws in human and social systems may be neither feasible nor desirable.[5] The concept of social laws must be interpreted differently than natural laws. “While behavior in the physical domain is governed by cause and effect (laws of nature), behavior in the social domain is governed by rules generated by the social system and often codified into law” (Capra, 1996, p. 211). Social laws are not immutable. They need to be seen as general explanatory statements.[6] This view shifts our conceptual interest from rational objects to the interaction and interdependency among autonomous and purposeful actors in order to refine social rules related to complex human behavior. In other words, human behavior can be perceived as communication. A message is a single unit of communication. A series of messages exchanged among people is called interaction. The higher level of human communication is a pattern of interaction (Watzlawick, Bavelas, & Jackson, 1967). While social rules are designed to deal with certain patterns of human interactions, this theoretical base of social rules has not been properly incorporated in traditional policy analysis. Complexity and human interactions were assumed away in many policy analyses for the purpose of simplicity.

Knowledge and Learning

Complexity shows that systems or processes should not be frozen and need to stay somewhere between too much and too little order. At the ‘edge of chaos’ where complexity exists, human creativity and innovation can thrive.[7] Uncertainty is at the heart of creativity.[8] This provides a perspective on two key components in human understanding and actions, knowledge[9] and learning. Is knowledge a transferable commodity or process? Can interpretation be knowledge? Can knowledge exist independent of the human being who uses it, learns it, and transfers it? How should we understand learning in organizations or learning organizations? What does it mean for analysis?

Knowledge is not something that exists independently from human beings or something that can simply be stored as substance or a framework. Knowledge is seen as an endless process and praxis. There is little use of knowledge in a theoretical framework if it is of no use in the dynamic world. The pragmatics of knowledge emphasizes the relation of signs to users in a context,[10] and behavior can only be studied in the given context. The meaning of the behavior pertains to the context at a certain time. Therefore, the context, dynamic world in which one lives redefines one's knowledge at every moment.

When environments are stable, standards and procedures are valued. Well-defined hierarchy and neutral bureaucracies are highly regarded. Uncertainty and errors are considered as something to be eliminated. When the environment is rapidly changing and uncertainty prevails, creativity and learning are vital for dealing with complexity. One must be free to reflect on perplexity, confusion, or doubt in order to acquire learning. From this learning process, they become reflective practitioners (Schön, 1983) and reflexive practitioners (Cunliffe & Jun, 2005). There is no room for knowledge and learning if all aspects of social activities are pre-specified or pre-determined. Knowledge and learning are crucial to understanding adaptive, autonomous, and purposeful actors.

Organizations that embrace complexity are living (de Geus, 1987) and learning entities (Senge, 1990; Michael, 1997[11]). These organizations value openness and flexibility. They embrace uncertainty and error as learning opportunities. For example, it is suggested that organizations focus on recognizing patterns and building networks to amplify positive feedback rather than trying to achieve optimal performance at all times. In analysis, therefore, an optimal policy based on a best estimate model may not be robust across the range of possible behaviors of complex adaptive systems (Bankes, 2002). These analyses oversimplify issues and limit learning opportunities.

Further, depending upon whether one observes the issues from inside or outside a particular system, the quality of understanding and description are significantly different.[12] When one is part of the system, trial and error, adjustment, and change of one's thoughts and actions become crucial ingredients for better decision-making. Analyses from outside the system may not fully capture the complexity with which these organizations deal.

Process and Emergence

It has been implicitly believed that the basic process of nature is deterministic and reversible. Once the particular state of a system is measured, the reversible laws are supposed to determine its future. Therefore, the emphasis of the studies is on time-independent laws. This concept of the simple world governed by time-reversible fundamental laws has been questioned (Pierce, 1961; Prigogine & Stengers, 1984). Reversibility and determinism may apply only to limiting and simple cases. Data, processes, and issues are dependent upon their epoch and upon the forms of process dominant in the time. Irreversibility and randomness are rules in nature and lie at the origin of most processes of self-organization (Prigogine & Stengers, 1984).

Traditional policy science as a search for simplicity contributed to our understanding of policy-making. Nevertheless, there is a need for comprehending the nature of complexity to improve policy processes. Public policy can be seen as an emergent phenomenon (Morçöl, 2003). During implementation, policy is interpreted and enacted based upon the interpretation. Public policy is not reducible to the original intentions of its initiators or the text of the law. Once it emerges, public policy does not stay the same, but it constantly evolves. This revisit of '*implementation as evolution*'[13] is rooted in the philosophical tradition of Heraclitus who realized that one cannot step twice into the same river.

Advances in modern science such as chaos theory and quantum physics have provided examples that show that one cannot forecast the future based on the past. Two versions of the impossibility of prediction with certainty are found in the literature. One version starts from Poincaré, who said that small differences in the initial conditions generate very large differences in the final phenomena (Merton, 1936; Lorenz, 1964; Baets, 2005). The other version is from Gell-Mann (1994), who stated that even in the classical limit and even when the laws and initial conditions are exactly specified, indeterminacy can still be introduced by any ignorance of previous history… whereby future outcomes are arbitrarily sensitive to tiny changes in present conditions. This implies that there is not always a best solution. Best principles might provide better insights for policy design.

The evolving nature and emergent property of public policy makes us reflect on current practices of policy evaluation and evaluation methods. The causal relationship in nature is considered to be a scientific achievement. The relationship between social programs and outcomes may not be the same because programs and outcomes co-evolve. Even if the causal relationship between a program and an outcome was present at one time, the relationship might be true only in the given time and under the assumption that the context was fully considered. However, we still do not know how to fully include contextual complexity in our studies.

Therefore, some argue that instead of searching for causality, the concept of synchronicity may provide better insights into business dynamics (Peat, 1987, 2002; Baets, 2005). Synchronicity refers to 'meaningful coincidence, significantly related patterns of chance,' (Peat, 1987) or ‘being together in time’ (Baets, 2005). The notion of synchronicity has its roots in *Flatland* (Abbott, 1963; Stewart, 2001) where complex objects that fall through flatland “may look like a correlated series of events that are separated in space” (Peat, 1987, pp. 116-117). Normal events in the three-dimensional world may look like synchronicities in the flat world of two dimensions. One may not be able to draw the whole picture of the complex object at this moment, but one can still catch and follow the flow at the moment of synchronicity. This alludes to the idea that business and organizational performance may be improved by learning how to take opportunities when synchronicity is presented, even if one can not draw the whole picture.

The practice of policy analysis is still under the influence of positivism (Durning, 1999; Fischer, 2003b). However, a massive paradigm shift has conceptually been noticed. This shift implies changes in our world view, from a simple to a probabilistic world, from hierarchy to heterarchy, from mechanistic to holographic universe, from deterministic to indeterministic view, from direct to mutual causality such as symbiosis and nonlinearity, from metaphor of assembly to morphogenesis (creation of new forms), and from pure objectivity to perspectival (Lincoln, 2005). The basic assumptions in complexity are well aligned with the changing world view. The complexity views are compared with the traditional positivistic approach (Table 2).

<Table 2 Here>

MANAGING COMPLEXITY

Over the past few decades, alternatives to the positivist approach have been making some inroads. For example, there has been an effort to understand the argumentative and narrative nature of policy analysis (Fischer & Forester, 1993). What policy analysts do is to provide policy arguments. This argument is not separated from value judgments and is used by policy makers during public debates. Methods and conditions to improve policy debate and discourse are more important than objective measures (Majone, 1989).

While these perspectives are intellectually stimulating, their applicability in policy analysis remains unclear. How can we use some of these ideas on evaluating public programs and processes? We know how to measure efficiency, effectiveness, and productivity within the framework of traditional policy analysis. However, we do not have many clues regarding how to model complexity and design our future in this uncertain world in order to eventually improve future performance.

Social Complexity and Algorithms

In its most simplistic form, complexity science searches for algorithmic rules that can represent complex patterns in reality. Algorithms are a set of simple rules that repeat over and over again (Peat, 2002). Mandelbrot (1997) has shown that algorithms can produce 'fractals'[14] which are scale-free self-organizing complex patterns in nature. Fractal geometry shows that seemingly complicated shapes and patterns can arise from simple and humble beginnings. Coastlines, clouds, and trees are physical examples of fractals. These natural shapes display self-similarity on many scales. They are made up of many smaller copies of themselves (Stewart, 2001). In other words, each part of a shape is geometrically similar to the whole. Although it may not be true for all patterns, simple mathematical rules can lead to such complicated patterns. When we do not know whether there are any underlying rules, patterns will help us to look into them because they are not just a random mess (Mandelbrot, 1977; Grimm, et al., 2005).

> "Patterns are observations of any kind showing nonrandom structure and therefore containing information on the mechanisms from which they emerge." (Grimm, et al., 2005, p. 991)

The notion of fractals may not be limited to nature. We can also draw an analogy of fractals for social complexity. For example, collaboration, coordination, and diffusion present enough complexities and irregularities. Nevertheless, certain mechanisms can be found in these behaviors (Axelrod, 1984, 1997b). For example, the traditional notion of organization has been presented as a black box that has complex impersonal relationships and standardized procedures mainly in a hierarchical structure. Recent studies are opening the black box with relatively simple mechanisms such as 'Sense-and-Respond' (Haeckel, 1999) and 'Request-Execution-Delivery' (Ramanathan, 2005). Organizations are made up of self-similar copies of these mechanisms on many scales. These mechanisms are important to our understanding of the complexity of global supply chains and health service delivery systems.[15]

Computational Social Science Models

Computational social science models are being developed to simulate social complexity using computer algorithms. The original ideas of computational models for social complexity can be found in Weiner (1948, 1954), Ashby (1952, 1957), Newell & Simon (1972), and Simon (1996). In cybernetics, it is assumed that human cognition is not different from information processing in computers. Human cognition works through the manipulation of symbols based on a set of rules. Communication is a transmission of information. This simplistic view of humans has been criticized by biologists in the 1970s (Capra, 1996). Whether human cognition can be duplicated by a computing machine is still in question (Dreyfus, 1972; Casti, 1997).

Newell & Simon (1972) further extended the idea of cybernetics for studying human problem solving. When they explored how integrated activities constitute problem solving in such tasks as chess and puzzles, information processing theory provided a foundation of their understanding of what symbols and symbol manipulation can do for us. Later, Simon (1996) distinguished three important components of 'the artificial' and specified their relationships. The three components are: the purpose (goal), the character of the artifact (inner environment), and the environment in which the artifact performs (outer environment). In Simon's (1996) framework, social complexity is a result of the adaptive interaction between the artifact and its outer environment, rather than from some inner complexity within the artifact.

> "Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves." (Simon, 1996, p. 53)

This idea known as *Simon's Conjecture* is the basis of the epistemology of computational social science (Cioffi-Revilla, et al., 2004). This conjecture allows us to anticipate certain behaviors from the knowledge of goals and its outer environment, even when there is minimal knowledge of the inner environment, such as physical properties and characters of the artifact. For instance, uneven traffic flow as collective behavior emerges, mainly due to the complexity of the environment, such as random positioning, signals, and distance between cars (Resnick, 1994), rather than the capacity of the engines, models, and types of the cars. If the organization of some components, rather than their properties, largely explains social complexity, the consequences of alternative organizational assumptions for human behavior can be explored using computer agents. The computer agents are organized somewhat in the image of man by having properties and showing certain behaviors (Newell & Simon, 1972; Simon, 1996). The behavioral assumptions can be codified into a set of algorithmic rules.

Complexity is a multidisciplinary science. It takes into consideration elements of very different disciplines, such as cybernetics, systems theory, chaos theory, artificial intelligence, artificial life, cognitive sciences, computer science, ecology, economy, evolutionary biology, game theory, linguistics, philosophy, social sciences, and management. In this paper, the notion of complexity in many areas is simplified with fractals. Certainly, social complexity belongs to, overlaps, and goes beyond complex patterns in nature. As several complexity models have been developed and introduced, there has been an effort to simulate social complexity using computational models. In many cases, they aim to understand and model values, interactions, uncertainty, learning, process, and emergence in social complexity using the simulation models (Figure 1).

<Figure 1 Here>

Development of Agent-Based Models

Agent-based modeling is a recently emerging technique within the tradition of computational social science models. Complexity models, computational models, and agent-based models are the same in that they codify organizational assumptions as computer programs (algorithms), and the inference is performed by executing the program (Edmond, 2001). Complexity models are a synonym of complexity science, and they are not separable from each other. Computational models are given explicitly in mathematical terms or implicitly by coding the relationships among the variables and rules constituting a computer program (Casti, 1997). An agent-based model is a computational model in that it implicitly codes the interdependency of agents and action rules using symbols of programming language.

However, agent-based models are different from classical simulation models. Macro-simulation in the 1960s used sets of differential equations for macro-level forecasting. Micro-simulation in the 1970s used the individual as the unit of analysis for macro-level forecasting. However, individuals do not directly interact or adapt in these simulations (Marcy & Willer, 2002). The basic variables determining the outcome of decisions are aggregated quantities rather than the actions of individuals (Casti, 1997). By making agents behave based on their own properties and interaction rules, users of agent-based models are more interested in theoretical bridges between micro- and macro-levels and in gaining insights than in mathematical solutions.

Characteristics of Agent-Based Models

Agent-based models go beyond deductive analysis of closed systems to provide interactive analytic support for inductive reasoning about open systems (Bankes, 2002). Agent-based models can be implemented as a method of exploring complex problems. The advantages of agent-based models include the ability to accommodate various differences among individuals, to simulate complex decision-making by an individual, and to address interactions over time and space (Gimblett, 2002). Repetitive competitive interactions among agents are a feature of agent-based models. Even a simple agent-based model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates (Epstein & Axtell, 1996). Agents may be capable of evolving and allowing unanticipated behaviors to emerge. Sophisticated agent-based models sometimes incorporate neural networks, evolutionary algorithms, or other learning techniques to allow realistic learning and adaptation (Bonabeau, 2002).

Agent-based models consist of agents and action rules. Agents are the basic unit of action in simulations and are specified by defining the complex system studied and specifying the interdependency of system components. Agents can be humans, institutions, robots, computers, objects, concepts, and even ants. They are heterogeneous and autonomous with behavior that can be rational, adaptive, and random in response to the environment. Learning occurs through the adaptive behavior (Ashby, 1952) and thus influences future decisions. Action rules reflect organizational assumptions in complex systems. The rules specify how the agents interact. Flexibility in designing new action rules in a simulation allows researchers to test alternative assumptions underlying complex social phenomena in the simulated reality (Resnick, 1994; Simon, 1996; Marcy & Willer, 2002).

Above all, agent-based models aim to enrich our understanding of fundamental processes that may appear in a variety of systems and to support our intuition on the target system (Axelrod, 1997a; Edmonds, 2001). Once patterns and processes are modeled as a dynamic system, it is possible to test some options for purposeful actions. This will allow us to approach complex issues with the awareness of consequences. **Figure 2** presents a methodological framework within which agent-based models can be implemented. This figure is an adaptation of Drogoul & Ferber's representation (1994, p.134) that contrasts classical stochastic simulation models and agent-based models (James, 1996; Maturana & Varela, 1987; Lash, 1990; Mingers, 1995). Encompassing patterns and process this comprehensive framework shows that agent-based models can incorporate traditional research models within a set of realistic assumptions.

<Figure 2 Here>

Illustration and Examples

Agent-based models have been used for many purposes, such as modeling emergence (Holland, 1998), catastrophic phenomena, far-from equilibrium behaviors (Bak, 1991, 1996), constructivist learning and challenging assumptions (Resnick, 1994), virtual laboratories (Casti, 1997), technological or engineering applications, and planning. Here three policy-relevant examples for which agent-based models were used are presented: Schelling's segregation, Axelrod's computer games, and an artificial world to address traffic congestion.

Schelling's segregation model (1978) represents one of the first constructive models of a dynamic system that is capable of self-organization based on simple rules. In this segregation model an agent is a cell surrounded by other cells. A cell changes color or remains unchanged depending upon the characteristics of their neighbors' colors. In **Figure 3**, the simulation shows that initial random agents that a computer generated (left figure) segregated after a certain time (right figure). Agents were represented using each cell with two different colors. Neighbor cells are environments of agents. The action rule used in the simulation is as follows: "an [blue or red] agent decides whether it wants to move. It scans all of the neighbors and sums the total number of similar agents. If the sum is below the threshold, then it moves." The simulation did not specify detailed properties of the agents other than their colors and the action rule. Yet, the simulation arrives at a segregated equilibrium. This example illustrates an utility of agent-based models for thought experiment or theory testing.

<Figure 3 Here>

In their early stages, some modelers presented complexity without altering the rigid assumptions on agents (Axelrod, 1984; Axtell, 1999). Later, their interests were broadened to organizations and social systems. This resulted in relaxed assumptions regarding rationality (Axelrod, 1997b; Axelrod & Cohen, 2000). For example, Axelrod (1984) studied under what conditions cooperation will emerge when egoists compete in a game without central authority. The study showed that the norm of reciprocity made it possible for cooperation to emerge (Axelrod, 1984). In other words, cooperation emerges because of the possibility that the players will meet again even when the assumption of self-interested rational agents is not abandoned. In a later study on the emergence of norms as solutions to dilemma of collective action, Axelrod (1997b) chose to implement an evolutionary approach. In this simulation, the initial strategies are chosen at random, and strategies also undergo some random mutation. Agents no longer need to be rational. Players are given the opportunity to defect and to punish the defections they observe. The study identified ‘metanorm’ (the treatment of non-punishment as if it were another form of defection) as a mechanism that could sustain a partially established norm. This example shows an applicability of agent-based models for studying traditional social science topics.

If the former focuses on understanding the underlying processes of social phenomena, there are also examples of artificial worlds. Many policy problems require intervention. However, scientific, repeatable, and controllable tests on human subjects are not easy due to ethical, theoretical, and practical issues. Artificial worlds can be a laboratory for testing policy interventions. Chris Barrett at Los Alamos built TRANSIMS in order to tackle Christmas-shopping congestion on Louisiana Boulevard in Albuquerque, New Mexico (Casti, 1997, pp. 131-142). The main questions in the simulation were how a proposed change in the system creates traffic patterns and how these patterns impact the environment. The structure of the artificial world consists of travel demand and transport system data, trip route plan generation, traffic micro-simulation, and environmental simulation.

DeliverySim: The Dynamics of Public Performance Management

The other area that ABM has not been frequently utilized, but has enormous potential is public performance management. The current approach of performance management is to examine who performs better, why they perform better than others, and what are imperatives of high performance organizations. The complexity and dynamics of public management has not been a major concern to this approach, thus provides limited insights on the complex reality of public performance management.

In exploring the dynamics of public performance management, dynamic systems theories provide rich theoretical foundation. For example, human ecology has explored the mutual influence of humans and environments and their adaptive strategies. The properties of complex adaptive systems - irreversibility, coevolution, and synchronicity - provide a fertile area for discussion with regards to performance management. These dynamic systems theories lead us to pay attention on the temporal organization of necessary components and conditions to understanding the dynamics of public performance. There have been a few conceptual applications of dynamic systems theory to management (Dörner, 1989; Kiel, 1994; Quinn, 1991). Built upon their works, we test a research hypothesis on public performance management. The productivity/quality double helix hypothesis suggests that at times productivity and quality will converge and diverge (Kiel, 1994). As managers strive to produce better results in both areas, one element may lag as another improves. In an effort to redirect the current interest of public performance management from ‘who and why’ to ‘when, where, and how’, we built an agent-based model, *DeliverySim*.

DeliverySim consist of two elements: (1) *Agents:* Three different agents are developed in the system of public service delivery. The “client” agent is public service recipients who are supposed to be satisfied by consuming public services. The “local” agent represents local agencies that are responsible for actual service delivery. The “state” agent develops policy and work process as well as monitor overall flow in the system. (2) *Action Rule*s: We have two basic rules: First, we modeled the way that participant agents select the local agents using the Huff spatial interaction model (1964) and communication with neighbors. Second, we modeled how participant agents make decisions on whether they will stay or leave for the search of other local agents by comparing their expectation with the quality of the local agent chosen. The interaction among agents allows the state of agents to coevolve. The state of agents and their decision at time *t* influence future states ($S_{agent}^{t+1} = f(S_{agent}^{t}, D_{agent}^{t})$), where *S* represents state of agents and *D* represents decisions made at time *t*. The field of action is defined by the nature of the work (e.g. public service delivery programs). Public performance is measured using productivity and quality. Being consistent with traditional definitions, productivity (*P*) is defined as $P_{local}^{t} = O_{local}^{t} / I_{local}^{t}$, where *O* is outputs, and *I* is inputs. Quality (*Q*) is defined as an arithmetic mean score of clients’ satisfaction for service delivery in the field over time.

We present our preliminary results of *DeliverySim* in Figure 4 and Figure 5. In Figure 4(a) we recited Kiel’s quality/productivity double helix hypothesis (1994, p. 143); whereas the replication of the double helix in our *DeliverySim* was presented in Figure 4(b). In Figure 5, we examined the performance of “local” agents in terms of quality and productivity as well as customer satisfaction of “participant” agents over time.

<Figure 4 Here>

<Figure 5 Here>

Our next question is how to balance these competing values in public performance management under the different conditions. We would like to test the impact of different resources allocation strategies based on their performance and its impact to the system and their future performance. Ultimately, our goal is to run the simulation with empirical data and to provide context relevant policy recommendations.

Some Perspectives on Policy Modeling

The conceptual basis and models of complexity are discussed for policy analysis. Based on this discussion, we draw some perspectives on policy modeling. Traditional policy analysis has been effective in identifying measurable factors that exhibit regular patterns at a certain time and in a given context. However, many of the underlying processes that give rise to such patterns are unknown. Conventional research methods and tools have limited utility in studying such unknown processes. For example, statistical tools are built on the principle that one can make inferences about a population based on samples. Statistical analysis presents inductive and historical facts with assumptions specific to statistical techniques and data rather than processes. Economic models and techniques are built upon the basic assumptions of economics. The relationships identified using economic theories or tools do not necessarily mean that the process leading to the relationship is based on the underlying assumptions. Linear programming is genuinely solution-oriented in a given context. As the conditions change, the solutions change. What does not change is the assumption underlying this tool, which is to seek optimal solutions subject to certain conditions. By selecting an analytical tool, one implicitly subscribes to the values on which the tool is based. Understanding the process may reveal much richer stories and make individuals reflect on the underlying assumptions.

Given that policy analysis requires substantial contextual knowledge as well as scientific knowledge for conscious action, policy analysis tools need to be flexible in incorporating contextual knowledge in many different policy settings. In other words, policy analysts must build testable models to represent the patterns they observe, and these models must be continuously revised until they align with the observed pattern. Multiple theories and assumptions need to be tested in the process of modeling. This process will improve the analyst's own understanding of the reality as well as its representation for others. Therefore, it provides a chance for policy analysts to reflect on what they believe, what they value, and what they do.

A crucial aspect of policy analysis is to inform practice even when only partial knowledge exists (Murray, 1983). Policy and decision-making cannot be delayed until social science is able to explain all social processes (Moore, 2002). Policy questions do not necessarily go together with analytic questions in a discipline. The fact that there are different views and values surrounding policy and decision-making should not discourage people about the role of policy analysis. It only implies that there is a need for an enhanced analytic and synthetic approach that can incorporate different interests and values into the policy analysis. It must be able to evaluate evidence within a larger spectrum of experience through analysis so as to facilitate dialogue among stakeholders.

CONCLUSIONS

There have been a number of studies on complexity and management (Stacey, 1996, 2000; Amin & Hausner, 1997; Rosenhead, 1998; Battram, 1999; Sanderson, 2002; Baets, 2005), but there has been limited work on modeling complexity for policy analysis and decision support. The prominence of agent-based models is not limited to the fact that they can implement what the traditional approach has successfully addressed. These models can also serve to explore the implications of imperfect rationality (bounded rationality), the effects of learning, and social structure. While these aspects of human and social systems have been well acknowledged in the literature,[16] it is only recently that scholars are able to develop operational models.[17]

Early simulation and modeling had difficulties finding the right agents and describing the interactions among these agents (Casti, 1997), as well in modeling emergence and surprise. However, many of these obstacles are being overcome with the recent advance of technology and the progress in various disciplines. Today, one can create artificial worlds. They can conduct repeatable scientific experiments on complex systems. They can even address the consequences of a policy intervention. It seems that we are ever closer to '*the sciences of the artificial'* (Simon, 1996). This is the right time to bring up this advance in modeling and advantages for the policy community so as to enrich policy analysis.

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NOTES

[1] There have been a number of theoretical studies, which argues the applicability of complex sciences in the field of policy, management, and organizations. This includes, but is not limited to, the application of chaos and complexity theory for public management (Kiel, 1994), management (Battram, 1999), governance (Amin & Hausner, 1997), knowledge management (Baets, 2005), organization (Stacey, 1996), policy evaluation (Sanderson, 2002), and health service delivery organization (Kernick, 2004).

[2] Several efforts have been documented by scholars in different areas. Examples can be found from Casti (1989), Bak (1996), Wilson (1998), Auyang (1999), Buchanan (2002), and Barabasi, (2003).

[3] The objectivity of scientific knowledge is not a settled issue. For example, see Oreskes, Shrader-Frechette, & Belitz (1994) for discussion in natural science and Moore (1983, 2002), Vickers (1970), and Ackoff (1999) in social and policy science. They provide equally good discussions on the limitation of such a concept of objectivity for scientific knowledge. Epistemology based on biology has provided a strong foundation on such an understanding. See Bronowski (1978), Maturana & Varela (1987), Dyke (1988), and Hawkins & Blakeslee (2004). Also, see Casti (1989) and Popper (2002) for the issue approached from the philosophy of science.

[4] One of most recent books on this topic is Talbot (2005).

[5] Vickers (1970) argued that “the only reason why men are by and large more predictable than the weather is that they are concerned to be predictable; concern to meet each other’s expectations by accepting common self-expectations. Also, the web of mutual expectations creates an order of which the regularities obey neither general nor statistical laws. The order is created rather than discovered, imposed rather than induced” (p.101).

[6] For discussion on the difference between natural laws and social rules, see Hon (1999), Capra (1996), and Conte, Hegselmann, & Terna (1997). Hon’s discussion (1999) is particularly concise and insightful.

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[7] See Waldrop (1992) and Lewin (1992) for the 'edge of chaos' and McMaster (1996), Stacey, Griffin, & Shaw (2000) and Desai (2005) for the applications of the concept in management.

[8] Biology has provided a foundation on such a view. See Jacob (1982) and Maturana & Varela (1987).

[9] For discussion on knowledge from the complexity perspective, see Rescher (1996) and Baets (2005).

[10] A long tradition of such a view is found from Morris (1938), Watzlawick, Bavelas, & Jackson (1967), and Maier, Hadrich, & Peinl (2005).

[11] First edition was published in 1973. The second edition is cited here.

[12] This argument is found in critiques of traditional system and management theories (Senge, 1990; Stacey, Griffin, & Shaw, 2000), and in discussions of relativity in physics (Casti, 1997).

[13] Majone & Wildavsky (1973). This paper was republished in *Public policy: The essential readings* edited by Theodoulou & Cahn (1995).

[14] Mandelbrot (1977) coined 'fractals' from Latin adjective, fractus, and verb, frangere, which means to 'break' to create irregular fragments (p.4).

[15] Communications of the ACM (the Association of Computing Machinery) published a special issue on adaptive complex enterprises in May 2005. See Jones & Deshmukh (2005) for the application of complexity to supply chain management and Tan, Wen, & Awad (2005) for the application of chaos theory to health service delivery.

[16] There is no shortage of this understanding in organization literature (Simon, 1955; Argyris & Schön, 1974; Schön, 1983, Senge, 1990; Michael, 1997).

[17] Many of the methodological papers have recently been published (Axelrod, 1984, 1997b; Gilbert & Troitzsch, 1999; Bank, 2002; Lempert, Popper, & Bankes, 2004).

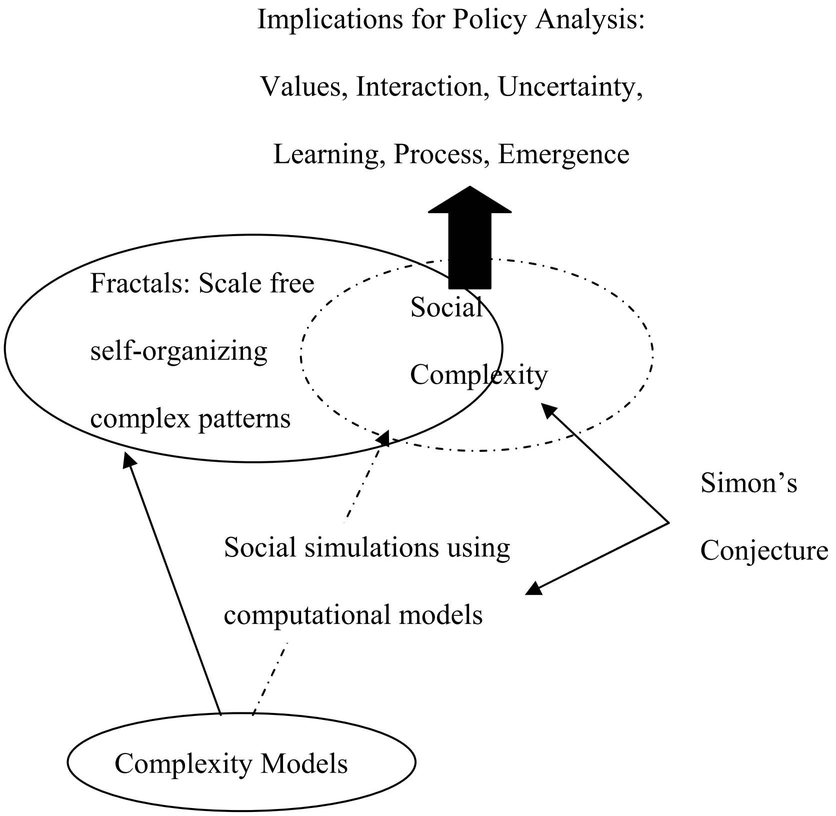

Figure 1: Modeling social complexity to inform policy decisions

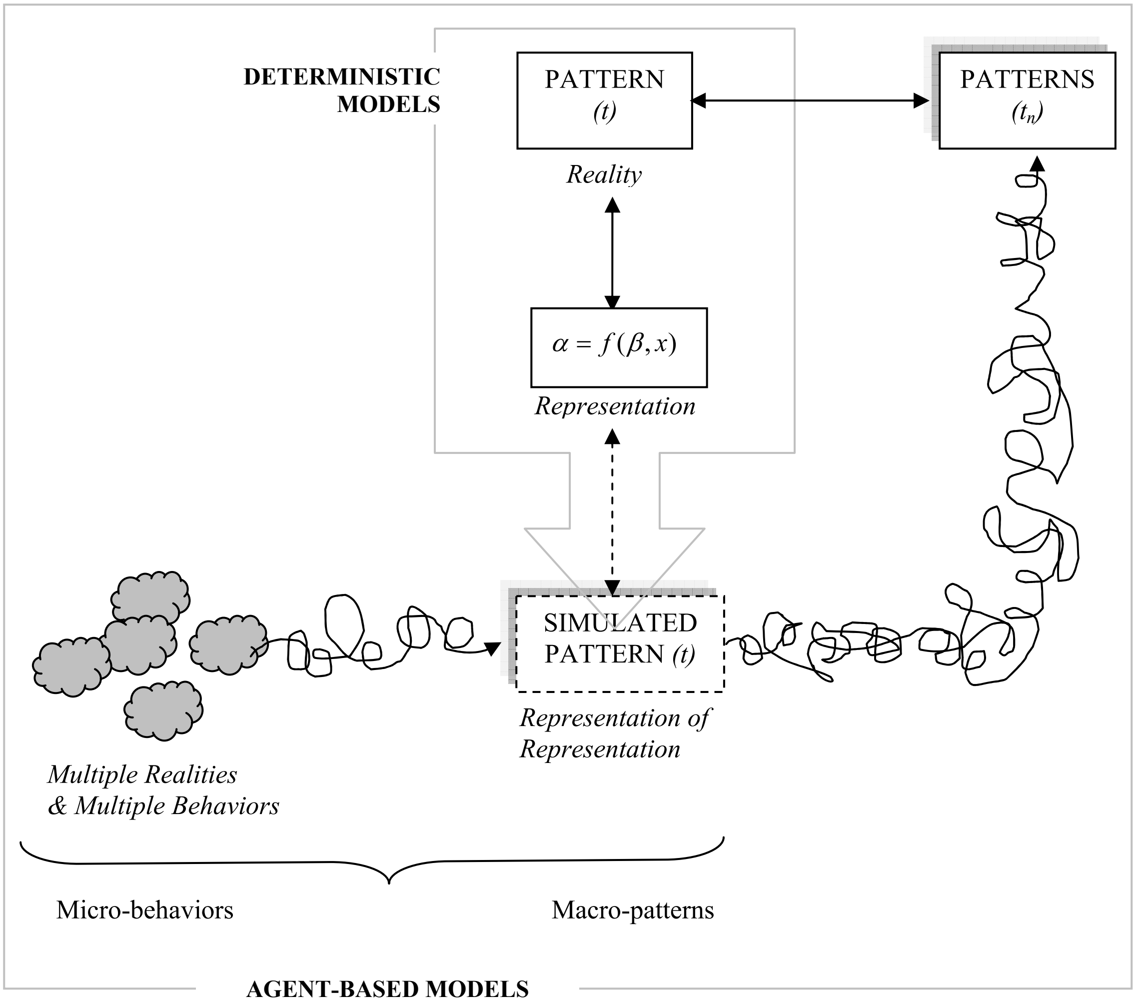

Figure 2: Methodological framework – the smaller box inside the larger box presents the relationship between patterns in reality and their representation using a mathematical formula that has been a general framework in the traditional approach. The larger box presents the framework of agent-based models. Often agent-based models aim to replicate the representation of the reality or one's understanding of reality rather than the reality itself. These multiple representations are achieved by assuming multiple realities and multiple behaviors of agents at micro levels. The model assumes that their dynamic nonlinear interactions self-organize to create certain patterns at macro levels. This also allows to project future patterns based on the nonlinear interactions among heterogeneous agents.

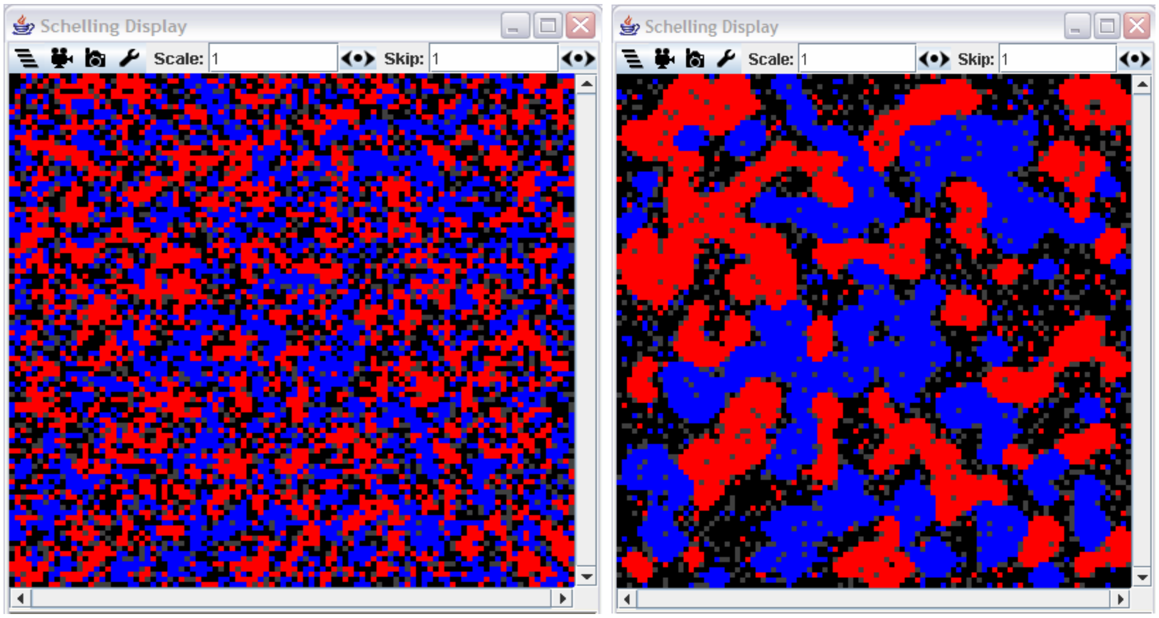

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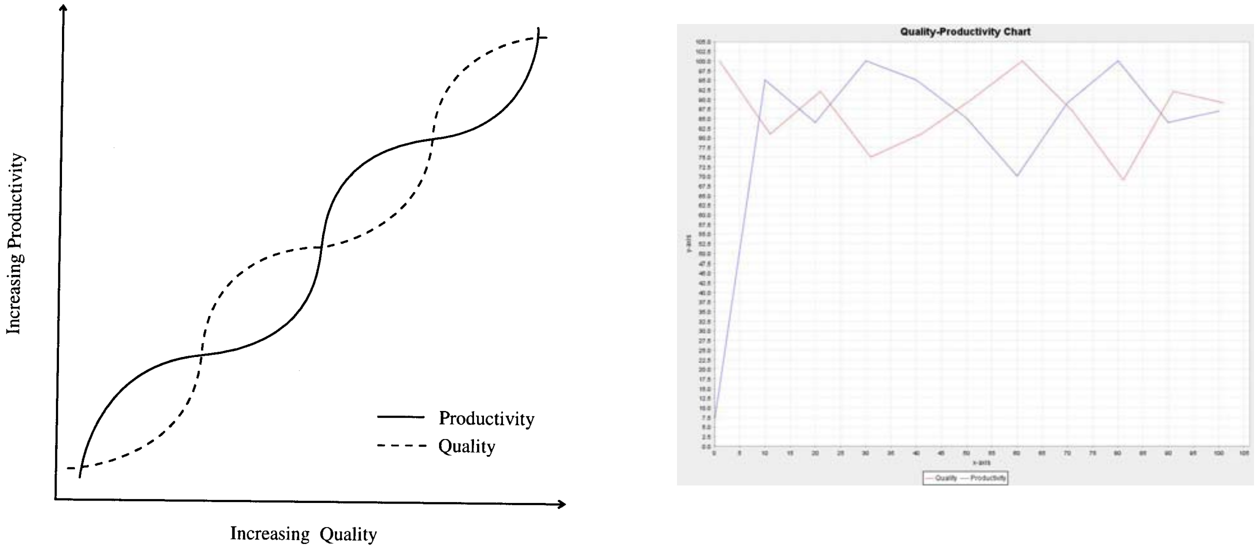
Figure 3: Schelling's segregation model was conceptually introduced in his *Micromotives and Macrobehavior* (1978). The simulation was implemented in MASON version 10.0.



(a) Productivity/Quality Double Helix Hypothesis

(b) A replication of the double helix

Figure 4: The Productivity/Quality double helix hypothesis by Kiel, 1994, p. 143 and a replication of the double helix by *DeliverySim*.

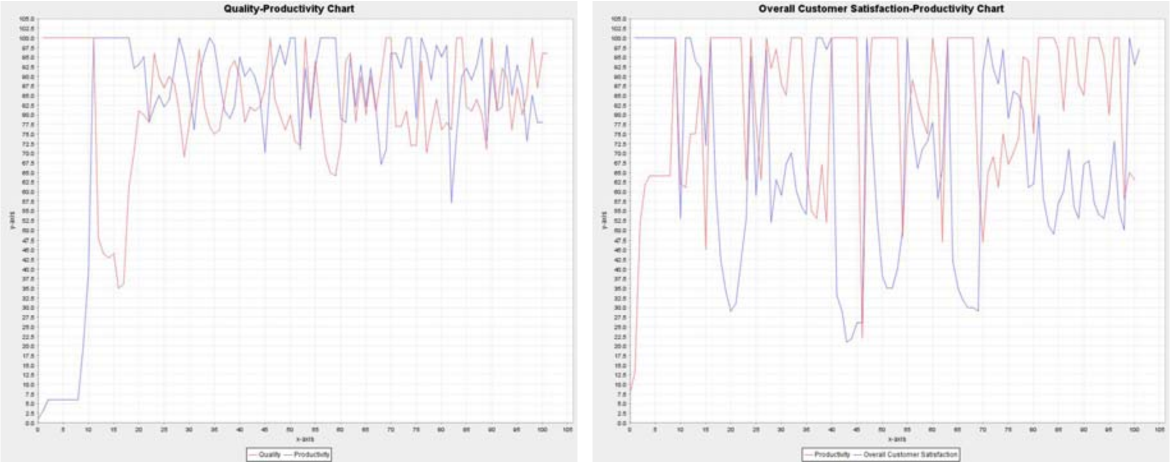


Figure 5: Simulating Quality vs. Productivity Trade-off and Customer Satisfaction vs. Productivity Trade-off using *DeliverySim*.

Table 1: Keywords in three distinct stages of complexity

Period	Keywords
Between World War I & II	Holism, Gestalt, Creative Evolution
After World War II	Information, Feedback, Cybernetics, General Systems
Now	Chaos, Complex Adaptive Systems, Genetic Algorithms, Cellular Automata

Table 2: Basic assumptions of traditional positivistic approach and complexity

	Positivistic Approach	Complexity Approach
Goal	Mastering nature	Conversation with nature (Jantsch, 1975; Prigogine & Stengers, 1984)
Ontology	Substance	Process (Rescher, 1996, 2000)
Assumption	Independence / Invariance,	Connectedness (Whitehead, 1938, 1978; Bronowski, 1978; Bateson, 2002),
	Reversible	Irreversible (Prigogine & Stengers, 1984)
Search	General Law	Principles or Rules (Hon, 1999),
	Causality	Synchronicity (Peat, 1987; Baets, 2005)
Models	To Predict	To Anticipate (Holland, 1998) or understand