# Organic Complex Systems: A stochastic dynamical systems theory of living and lifelike organization

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## Abstract

Recent decades have seen exponential advances along many of the frontiers in biology, some of which challenge long-held beliefs about the fundamental nature of biological systems. Active research now concerns issues such as life in extreme environments here on Earth, the possibilities of life forms in outer space or on other planets and whether or not non-carbon-based molecules, or cells that function using substitutes for DNA, could be the basis for new life forms. Similarly, much attention has been devoted to possible artificial life in the form of computational software and emergent, self-organizing mathematical models and "organisms." These thrusts return us once again to the question of "what is life?" and whether we understand its fundamentals well enough to model known biological phenomena and to predict as yet unknown biological systems and behaviors.

The purpose of this paper is to describe, in outline form, a mathematical theory of Organic Complex Systems (OCS) that is intended to be a very broad modeling platform for biological systems. The theory takes as fundamental the well-known axioms that (1) life is largely about the storage, preservation, interpretation and flow of massive amounts of statistical information; (2) that, as such, a full accounting must be taken of the random, probabilistic nature of biological processes; and (3) that these processes are controlled by the fundamental laws of physics and chemistry. In what follows, we build the theory of OCS on the statistical and information theoretic ideas of Boltzmann, Gibbs, Tolman, Shannon, Khinchin and Jaynes.

OCS is based on seven concepts that define a class of dynamical systems that is considered to be *lifelike*. It includes, but is not limited to, biological organisms. The concepts (*organization, emergence, compositeness, reorganization, autocoorganization, uncertainty* and *persistence*) are intended as organizing principles of living and lifelike systems. OCS intends to bring alternative insight as to what it means to be "living."

As a conceptual theory, OCS requires a mathematical underpinning through which it can formally articulate its principles. It would be ideal if an existing mathematical systems theory could perform this task. Nonlinear dynamics seems an obvious candidate for this role, since it formally articulates some of the seven concepts of OCS. However, as a deterministic system, nonlinear dynamics cannot account for the crucial role that uncertainty and randomness play in biology. Consequently, we have developed the theory of Organodynamics – a complex adaptive systems theory – to fill this void.

# 1. Introduction

In recent years, much research has been focused on entities that exhibit lifelike characteristics but which lie beyond the realm of conventional biology. Examples include:

(1) Organisms living in extreme environments that have been discovered on Earth in hydrothermal vents [Zierenburg, et. al 2000] or in other locales not heretofore considered to be capable of supporting life.

(2) Complex organic molecules, including amino acids, that have been detected in interstellar dust clouds within our own galaxy [Chalmers 2003]. Could these molecular structures lead to complex chemical organizations whose emergence might lead to a living organism? Space scientists must anticipate the possibility of encountering such novel systems in their interplanetary exploits [Hazen 2005].

(3) Synthetic biological systems that can be created by assembling naturally occurring biomolecules in new ways [Ardejani and Orner 2013; Fletcher, et. al. 2013], thereby developing systems that do not exist in nature [syntheticbiology.org 2012]. Synthetic biologists are now able to alter complex biomolecules in order to develop novel forms of life that exhibit different traits or attributes (*e.g.* the absence of DNA) from their naturally occurring biological "cousins."

More generally, the field of *artificial life* proposes to engineer lifelike systems from non-biological components [ALIFE 2012; ECAL 2012; IEEE ALIFE 2012].

(4) Autonomic software entities exhibiting lifelike traits that are indistinguishable from those of certain biological systems. Well beyond the considerations of computer viruses and other "intelligent" malware, enterprise-class computer manufacturers have been experimenting for years with self-authoring, self-healing and self-regulating operating environments [Ayodeji and Laster 2007]. At the beginning of the present century, researchers at IBM [IBM Autonomic 2001] developed the autonomic computing manifesto to address the development of this kind of software. Other researchers in both industry and academia have been similarly engaged. How will we know if and when such a software entity (or hardware/software hybrid) has achieved the level of organization that it should be considered "lifelike?"

Indeed, all these examples call out for criteria specifying what it means to be considered *lifelike*. For *biological life,* there is some consensus among life scientists that it exhibits metabolism, reproduction and evolution [Hazen 2005]. But are these the only criteria needed, or only characteristics of biological entities on earth? What is missing is a formal generalization of the concept of "the living" that includes but goes beyond biology as we presently understand it.

Like any area of scientific investigation, a programmatic foundation is needed that ranges from conceptual to practical. In particular, needed are: a conceptual theory (collection of structured ideas), a formal theory (mathematical formalization of the structured ideas), a mathematical modeling paradigm (model building blocks) and an *in silico* implementation (software package) to support the research.

Where are we now in terms of providing a theory of "the lifelike" that is sufficient to support research activities like those identified above? We first note that some of the more disruptive fields of science in the past 150 years – statistical mechanics, quantum mechanics and information theory – incorporate as a core foundation the mathematics of uncertainty and a theoretical and practical treatment of the tension between determinism and randomness. More recently, scientific disciplines that had been firmly entrenched in a strictly deterministic perspective have seen the increasing incorporation of the mathematics of uncertainty in the form of probabilistic mathematical treatments. In the biological sciences, for example, systems biology has led with applications of probability theory and stochastic processes into the 21st century [Wilkinson 2006].

The research introduced in this article postulates that the kind of uncertainty represented by these scientific advances is essential to the idea of "livingness." Darwin, Mendel, Monod, Prigogine ([Darwin 1859], [Monod 1972], [Prigogine 1977]) and others have promoted *chance* to a prominent role in the origin and evolution of life. But a formal program has yet to be presented that shows how the mathematics of uncertainty – probability theory, stochastic processes and information theory – can provide a comprehensive model and explanation of the origin and evolution of self-adapting dynamical systems.

Scientists often presume that high degrees of uncertainty can only lead to more uncertainty. But probability and information theories demonstrate – based strictly on probabilistic reasoning – that there are conditions under which randomness inevitably generates regularity. (See [Shannon 1948, p. 10], [Kleeman 2009, Lecture 3], [Khinchin 1957, Chapter 2] and [Thomas and Cover 1991, Chapter 4].) The research introduced in this article needs a mathematical systems theory that investigates the conditions under which very high degrees of uncertainty lead to very high degrees of certainty.

In addition, the desired theory needs to go beyond the considerations of probability that occur in evolutionary scenarios to investigate other lifelike qualities such as self-organization and the ability to adapt to a changing environment. Contemporary dynamical system theories that model self-organization and adaptation are often referred to as *complex adaptive systems* (CAS).

Thus, it is desirable to identify an existing complex adaptive systems theory that can serve as the mathematical foundation of OCS. Such a theory must be based on the mathematics of uncertainty that incorporates the conditions under which very high degrees of uncertainty can lead to very high degrees of certainty. Some conspicuous candidates include a legacy of dynamical systems theories that can be traced from general systems theory and cybernetics in the middle of the twentieth century up to and including the *complex adaptive systems* theories (CAS theories) of the last four decades. In addition to modeling the dynamics of complex systems, CAS theories feature systems that are *self-organizing* and that can *adapt to changes in their environments*.

One of the most successful and broadly adopted of the CAS theories is *nonlinear dynamics* [Strogatz 1994], sometimes called *chaos theory* because of the sensitivity of its subject systems to initial conditions. In addition, there are other dynamical systems theories that also deserve consideration. These include *system dynamics* [Forrester 1989] and *evolutionary dynamics* [Nowak 2006]. Unfortunately, none of these specifically proposes a generalization of biological life.

More significantly, each is strictly deterministic and is not based on the mathematics of uncertainty. For example, Strogatz [Strogatz 1994] describes *chaos* as "aperiodic long-term behavior in a deterministic system that exhibits sensitive dependence on initial conditions." He explains that "deterministic" means that "...the system has no noisy or random inputs or parameters." "Sensitivity," then, is not randomness[1]. These theories do not support uncertainty in the sense of statistical mechanics, quantum mechanics or information theory.

At this time, we lack a mathematical theory of complex systems that embodies these foundations. While there is nothing wrong with a complex adaptive systems theory that is strictly deterministic, there is also the need for one that is not.

## 2. What Do We Want to Achieve?

The research paradigm outlined here – *Organic Complex Systems* (OCS) – is the development of a new systems theory of the "lifelike." OCS is a dynamical theory of complex adaptive systems that generalizes biological organisms to a larger class – to systems that exhibit lifelike properties whether or not they are biological. We refer to them as *organic complex systems* or simply *organic systems*.

This work intends to present an alternative systems-oriented interpretation of what it means to be "alive". It addresses a number of basic questions. Must *aliveness* be restricted to carbon chemistry? Or can certain notions that we associate with biology be generalized to a broader class of systems – ideas such as growth, reproduction and evolution? Are metabolism and genetics fundamental concepts, or are they only two of many possible manifestations of more primitive principles of organization that can be generalized beyond biochemistry? Is there some foundational set of systemic properties that if exhibited by any entity we would reasonably deem it to be "lifelike?"

A differentiating aspect of OCS theory, in distinction to existing CAS theories, is its focus on the integration of *determinism* and *randomness* (or *certainty* and *uncertainty*) within and among dynamical systems. "Random" and "deterministic" have many definitions. OCS chooses "random" to mean "uncertain" and "deterministic" to mean "certain" – a position consistent with their usage in information theory [Vedral 2010].[2] Distinct from existing dynamical systems theories, OCS establishes its foundations on the mathematics of uncertainty: probability theory, stochastic processes and (statistical) information theory.

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[1] Dictionaries often define "chaos" using the terms "chance", "random" or "unpredictable". For example the Merriam Webster online dictionary offers this definition of *chaos*: "a state of things in which chance is supreme." So, popular usage of the term *chaos* appears somewhat inconsistent with the use of the term by nonlinear dynamics, which defines *chaos* to mean "…behavior in a deterministic system that exhibits sensitive dependence on initial conditions [Strogatz 1994]." This choice of definition by nonlinear dynamics may have led to confusion. This leaves the question in the minds of many readers, "Is chaos random or is it deterministic?" Strogatz, as quoted above, specifies that chaos is deterministic; but lexical definitions of chaos say that it is random.

[2] The significance of representing the interplay of certainty and uncertainty in any theory of living systems is expressed well by [Vedral 2010]. "Note that without randomness this process [natural selection] would not work, given that it is random changes in our DNA that provide the variety on which natural selection operates, selecting mutations that lead to organisms better suited to their environment. As a general theme, we shall see that meaningful information necessarily emerges only as an interplay between random events and deterministic selection."

We can characterize the OCS foundations as an alternative to nonlinear dynamics. OCS and nonlinear dynamics are alike in that they both bring unique and important perspectives to the investigation of complex adaptive dynamical systems. But in other ways they are complementary. The mathematical foundations of OCS are probability and information theories, whereas those of nonlinear dynamics are deterministic nonlinear functions. Also, OCS emphasizes a generalization of living systems. But the purview of nonlinear dynamics is more general.

Another goal of this work is to compare and contrast differing views and definitions of the concept of *entropy* - perhaps most importantly that of classical thermodynamics with those of statistical mechanics and of information theory. We are seeking an overarching theory that is firmly grounded in the mathematics of probability, and which reconciles the powerful earlier conceptualizations of entropy by Clausius [Lawden 1987, pp. 14-17] with those of Gibbs [Tolman 1938, pp. 538-9; Lawden 1987, pp. 56-57] and later Shannon [Shannon 1948, pp. 10-12].

As indicated above, the OCS research program includes several related activities in addition to basic systems theory development – namely a mathematical modeling paradigm as well as modeling and simulation software. The four major activities that comprise the OCS program are summarized as follows:

The ***conceptual theory*** is the natural language articulation of a collection of organizing principles that must be exhibited by an entity to qualify as an “organic complex system.”

The ***formal theory***, named *Organodynamics*, is a mathematical embodiment of the conceptual theory. It is based on the mathematics of probability theory plus Shannon's definition of entropy in information theory [Shannon 1948, pp. 10-12]. Organodynamics establishes the necessary rigor and detail to lead to the construction of practical artifacts such as modeling and simulation software. *Organodynamics is the heart of OCS* since it is the formal basis for the other three activities.

The ***modeling paradigm*** is a toolset of building blocks for constructing models of organic systems without having to refer directly to the mathematics of Organodynamics. The toolset works by using the analogy of a “directed graph” from graph theory as a simplified representation of the mathematical constructs of Organodynamics.

The ***in silico implementation*** is a library of software that implements the OCS modeling paradigm. Its purpose is to increase significantly the speed of designing and implementing OCS models.

The present paper provides a brief introduction to OCS, Organodynamics, the modeling paradigm and software package. For details of current developments, refer to the OCS web site [HollandJG 2013] and the OCS working documents [HollandJG-I 2011; HollandJG-II 2011; HollandJG-III 2011; HollandJGa 2012].

## 3. Some of The Finer Details

The four OCS research activities just described are interrelated and build upon each other. The *conceptual theory* identifies properties that any organic system must exhibit. In so doing, the *conceptual theory* establishes the specific set of systemic properties that any underlying systems theory must model with mathematics, and thus establishes the

criteria for which mathematical discipline(s) can provide the foundation of the *formal theory*. In turn, the *formal theory* provides the rigor that is necessary to develop the two more practical activities – the *modeling paradigm* and the *in silico implementation*. These four thrusts are described more fully below.

### *3.a. The Conceptual Theory*

The conceptual theory identifies seven systemic properties that function as *organizing principles* for organic complex systems. Any entity that satisfies these seven principles qualifies for membership in the class of *organic complex systems*. These properties, named *organization*, *emergence*, *compositeness*, *reorganization*, *autocoorganization*, *uncertainty* and *persistence*, are introduced below.

1. **Organization**. OCS is primarily interested in how a system is, or can be, *organized*. In systems theory, a *system* is not merely a collection of components, but also includes some description of the interrelationships among those components [Meadows 2009]. In OCS, these interrelationships describe the *organization* of an organic complex system. We formally define an organic system as consisting of two distinct parts: its *components* and their *interrelationships*. Since these two distinct parts of a system are of the utmost significance in OCS – and are what qualifies OCS to be labeled a systems theory – we codify that fact in the language of set theory. The set of components is called the *population* of the system. The set of interrelationships is called an *organization* of the system. (Precisely how an "organization" is defined in the language of set theory is left to the formal theory.) Since an *organic system* in OCS consists of a *population* "P" and an *organization* "O", for brevity we denote such a system as an ordered pair (P, O). This notation of an organic system comprising a *population* and an *organization* permeates all seven of these organizing principles. Therefore, this notation (P, O) will appear often in their definitions and characterizations. Of course, a given population can be organized in multiple ways. In light of this, OCS defines the *state* of an organic system as its population and exactly one of its organizations. That is, the *state* of an organic system in OCS is defined as a pair (P, O'), where O' ("O prime") is one of the organizations of P.

2. **Emergence**. All organic systems exhibit at least one systemic property that none of its components exhibits. This is called *systemic emergence*.

3. **Compositeness**. All organic systems are "nested". That is, they have at least one component that also has its own components and their interrelationships. This nesting may occur to any finite number of levels of organizational depth.

4. **Reorganization**. OCS focuses on how an organic system's *organization* changes over time. In other words, OCS is focused on a *change in the interrelationships* among the components of a system. *State change* in OCS is *reorganization*. In OCS, organic systems change their organizations over time in a manner that enables them to continue to exhibit these seven systemic organizing properties. Thus, "aliveness," or "lifelikeness," in OCS is a process of reorganizing in a manner that preserves these seven OCS properties. This aspect is called *OCS property preservation* (that is, if the reorganization does not preserve all seven properties, then the system ceases to be an organic system). A *change of state* of a dynamical organic complex system in OCS is defined as a *change of organization* ("O") of the system. When the *state* of the system changes, the population P is not required to change, but its organization O is.[3]

[3] This description means that OCS chooses to define the state of its dynamical systems in a considerably different manner than does classical, statistical and quantum mechanics. Whereas physics uses conjugate variables such as *position* and *momentum* to define system state, OCS chooses *system organization*, defined in terms of component interrelationships, to define system state. (It also implies that Hamiltonian

5. **Autocoorganization**. How do organic systems accomplish the reorganization of their components in such a way that all seven of these systemic properties are preserved? The answer is that each component participates in reorganizing the other components - resulting in a reorganization of the system. Of course, it is the specific interrelationships among those components (their *organization*) that enable them to change their organization in such a way that the seven systemic properties of OCS have a sustaining probability of being preserved in the resulting reorganization. Thus, it is reasonable to say that the system has a propensity to continuously reorganize itself over time through its components and their relationships in a manner that preserves all seven systemic properties of OCS. These organizational dynamics manifest as the creation, organization, reorganization, replacement, repair, transformation and regulation of the system by itself. And, since OCS uses the term "organization" in a broad meaning to include all of these activities, then it is reasonable to use the term *autocoorganization* to name this systemic behavior.

6. **Uncertainty**. Organic systems exhibit varying degrees of certainty/uncertainty concerning which of their organizations O will be realized at the next reorganization. These degrees of certainty/uncertainty range along a spectrum from completely certain (deterministic) to completely uncertain (random) as well as a continuum of values between these two extremes. However, there is a general tendency for the degree of uncertainty of the organization of an organic complex system to gravitate somewhere between these two poles. Yet at every level of organization within the composite (nested) organization of an organic system, the degrees of uncertainty are generally ever changing.

7. **Persistence**. Persistence is the continued exhibition of all seven of these organizing principles by an organic complex system. The nature of the autocoorganization and uncertainty of an organic system is that it engenders the limited ongoing existence of these systems in a manner that preserves all seven principles of organization. Taken together, all of these static and dynamic organizing principles can result in, at least, a limited persistence of organic complex systems. Once any one of these principles fails to be preserved, then the organic system ceases to qualify as an organic system.

These seven organizing principles *do not* stand independently as axioms; rather, they enjoy certain essential interdependencies. The first three of these properties are static in nature; the final four are dynamic. The major themes that run through these seven properties are: *organization*, *uncertainty* and *persistence*. It is the central task of OCS to explore the conditions under which the interplay of *organization* and *uncertainty* results in qualified *persistence* – and the mathematical mechanisms that underlie these dynamics.

While other collections of systemic properties may also result in reasonable theories of lifelike systems, these seven properties have been selected as defining a style of "livingness" that fits the applications and interests described above. That is, these seven properties are not unique, but they are a pertinent and efficient basis from which to proceed. They also highlight two major concepts that have reappeared time and again throughout the history of western thought and which have provided the basis of sometimes-conflicting intellectual and scientific movements.

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principles are not considered in OCS.) This is a significant change of mathematical focus from physics. The reason for this departure on the part of OCS is simply because its interests and concerns are focused on system organization rather than the position, velocity, mass, momentum or other classical mechanical properties of its systems-of-interest.

Capra [Capra 1996] calls these two concepts *substance* and *form*. *Substance* is concerned with the *elements* that constitute an entity, and therefore is equivalent to the OCS idea of a population of *components*: the "P" in the pair (P, O). On the other hand, *form* refers to the *interrelationships* between the elements of an entity, and is therefore equivalent to the OCS concept of the *organization* of an entity: the "O" in the pair (P, O). In the above discussion these two ideas are introduced in the first OCS organizing principle ("Organization") and permeate the other six.[4]

OCS drives toward a comprehensive theory of living systems by synthesizing these two concepts from the very beginning, within its foundational organizing principles.

### *3.b. The Formal Theory: Organodynamics*

The formal theory of OCS, *Organodynamics*, is a mathematical articulation of the OCS conceptual theory. In order to develop a formal theory of OCS, we must identify a mathematical framework that embodies *uncertainty*, *organization* and *persistence*, the three themes of OCS mentioned above. In fact, the mathematics of OCS must rigorously embody all seven of the organizing principles of the conceptual model.

#### A Complex Adaptive Systems Theory for OCS

It was indicated above that nonlinear dynamics is an obvious candidate for such a foundation. Unfortunately, however, nonlinear dynamics does not provide the probabilistic foundation needed for the sixth OCS principle – *uncertainty*. We thus must look elsewhere.

We begin by noting that such a novel systems theory must be a *complex adaptive systems* (CAS) theory, because of the necessity that it model self-organization and adaptation. However, any systems theory that we use as a foundation of OCS must depart from existing CAS theories (*e.g. nonlinear dynamics*) by replacing a deterministic mathematics with a probabilistic (stochastic) one. Consequently, we characterize Organodynamics as a *stochastic CAS theory*. In this regard, Organodynamics can be understood as an alternative to nonlinear dynamics.[5]

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[4] Capra amplifies the significance of these ideas as follows: "We have seen that throughout the history of western science and philosophy there has been a tension between the study of substance and the study of form. The study of substance begins with the question, What is it made of?; the study of form with the question, What is its pattern [of organization]? These are two very different approaches, which have been in competition with each other throughout our scientific and philosophical tradition… [Capra, p.80]."

He continues, "I shall argue that the key to a comprehensive theory of living systems lies in the synthesis of those two very different approaches, the study of substance…and the study of form (or pattern)…. The study of pattern is crucial to the understanding of living systems because systemic properties…arise from a configuration of ordered relationships. Systemic properties are properties of a pattern." [Capra, p.81].

[5] We have three levels of theory involved here, each of which builds upon the other. OCS is a theory that represents living and lifelike systems. But OCS requires a CAS theory as its theoretical underpinnings. There is no existing CAS that fits the needs of OCS, so we must invent *Organodynamics*. As a CAS, Organodynamics needs a suitable mathematical foundation. Information theory supplies this need. So, OCS is founded on Organodynamics, which is founded on information theory. Attention to Organodynamics occupies more space in this article than does OCS, because it is more complex (it also has applications other than OCS, but that issue is beyond the scope of this article).

## Supporting Uncertainty in Organodynamics

Nonlinear dynamics is a successful, broadly adopted, CAS theory because it utilizes a mathematical foundation based on *nonlinear functions*, including nonlinear systems of differential and integral equations.

Likewise, if Organodynamics is going to succeed as a CAS theory that centralizes the notion of uncertainty, then we must choose a mathematical foundation designed to do that. Information theory, initially described by Claude Shannon in 1948, [Shannon 1948, pp. 10-12], is completely adequate for this task. An inspection of information theory reveals it as an extension to probability theory, with special emphasis on stochastic processes and their asymptotic behavior [Cover and Thomas 1991; Kleeman 2009].

Shannon added a significant new mechanism to probability theory when he invented information theory. This mechanism is a *functional* (maps elements to numbers) that *measures the degree of uncertainty inherent in a probability distribution*. Shannon explained that this measure is defined for any situation that "has a set of probabilities." He pointed out that his mathematical definition for the measure of uncertainty is precisely the same, except for a scaling factor, as the mathematical definition given earlier by J. W. Gibbs for both equilibrium and non-equilibrium statistical mechanics. Therefore, Shannon gave his measure of uncertainty the same name as had Gibbs – *entropy* [Shannon 1948, pp. 10-12].

Information theory is applied to any scientific or other application domain by first identifying one or more aspect of the application that exhibits chance variation under specified conditions – especially chance variation over time. In evolutionary biology, an example would be genetic traits. In finance, an example would be stock market prices. In thermodynamics, an example would be the spread of energy. For each application domain, the meaning of the word "uncertainty" – as measured by entropy – often has a more specialized articulation or implication. For the stock market, it may be "volatility." For engineering, it may be "stability." For ecology, it might be "sustainability."

Information theory then characterizes the patterns of behavior of chance variation for selected traits, or for joint traits, of the application. It does this in terms of the probability distribution describing the chance variation as well as how this probability distribution changes over time for the specific application. Information theory performs this characterization based upon the entropies of those probability distributions, and how they change over time.

As a mathematical discipline, information theory has determined the entropy (degree of certainty/uncertainty) of various patterns of chance variation. Depending on the application, this degree may be anywhere from "unpredictable" to "completely determined." So, depending on the degree of uncertainty inherent in the chance variable of interest, information theory can assist in making predictions.

We shall occasionally refer to the concept of entropy defined by both statistical mechanics and information theory as "statistical entropy" in order to distinguish them from the entropy of classical thermodynamics. The reason for this is that the mathematical definitions for the first two are – except for a scaling factor (or "unit of measure") – exactly the same [Shannon 1948, p. 11], while both differ significantly from the mathematical definition for entropy in classical thermodynamics. This significant difference in mathematical definition between classical thermodynamics entropy and

statistical entropy casts suspicion that there is a significant difference in semantic meaning.

While the meaning of the entropy of classical thermodynamics has been characterized as a measure of "energy spread" in a thermodynamic system [Leff 2012], the meaning of statistical entropy is defined by Shannon as "a measure of the uncertainty" inherent in a probability distribution [Shannon 1948, p. 10]. On its face, it is not clear that these two meanings are the same, and there is very good reason to argue that they are different. One difference is that classical thermodynamic entropy is deterministic, while statistical entropy is probabilistic. It is left to Organodynamics to show that they are at least correlated – an argument already presented by Tolman [Tolman 1938, pp. 9-10, p. 524, pp. 538-539].

Shannon's entropy for a given state space integrates randomness and determinism onto a *spectrum* whose minimum value is complete determinism, whose maximum value is complete randomness, and whose possible values range between the two. Along with probability distributions and stochastic processes, Shannon's entropy has become the central, characterizing element of information theory.

Shannon makes it clear that randomness is not simply a binary phenomenon where an event must be either totally random or totally deterministic. Rather, information theory says that phenomena are most often partially random or partially uncertain. This results in an entropy value that is somewhere between the minimum and the maximum. The question "Just how random is it?" is a meaningful one. The value of the entropy gives the answer to such questions in information theory. This point is often missed.

Anytime one encounters a distribution wherein the probabilities are equally likely (the *uniform distribution*), then the assumption of complete randomness has been made – possibly an unconscious choice that may not be warranted. While philosophers have argued for centuries over whether "the universe is random or deterministic," information theory resolves the issue by dealing in varying degrees of randomness that includes "none," "all" and any degree between the two.

Let's characterize this situation a little further. Recalling that entropy is a measure of the degree of randomness (uncertainty) of a probability distribution, it can be shown for any discrete sample space there is a particular probability distribution on that sample space that has minimum entropy (the *constant distribution*[6]) and another particular probability distribution that has maximum entropy (the *uniform distribution*). All other probability distributions (on that sample space) exhibit an entropy value that lies between the minimum and maximum – and thus exhibit an intermediate degree of randomness. These include most discrete distributions used in science experiments.[7]

[6] *Constant distribution* is the name that is sometimes used for a probability distribution that assigns a probability of 1 to exactly one of its sample points, while assigning the probabilities of 0 (zero) to all of its other sample points. This distribution has entropy of zero since there is zero amount of uncertainty regarding the outcome of any trial governed by this distribution. Thus, the *constant distribution* has minimum entropy 0.

[7] We can see an intuitive recognition of partial randomness (or partial uncertainty) on the part of popular culture by considering a game of "Russian Roulette." The longer such a game continues, the degree of certainty increases that the bullet that has been randomly placed in the pistol barrel will be promoted to the firing chamber. Thus, the longer such a game lasts, the more the degree of randomness and uncertainty

Kleeman [Kleeman 2009, Lecture 1, p. 1] says, "The central idea of information theory is to measure the uncertainty associated with random variables." This characterization may come as a surprise to many readers who may confuse "information theory" with "information technology" (*e.g.* databases), and who might also expect that "information theory" must be concerned mostly with certainty.

But Kleeman's characterization implies that unless uncertainty is involved – as measured by Shannon's definition of entropy, there is no "information" in the sense of information theory. In fact, Shannon specifically states that entropy is simultaneously a measure of "information, choice and uncertainty" [Shannon 1948, p 11] – and therefore equates the three concepts. Khinchin explains how *information* and *uncertainty* enjoy this equivalence in information theory: "Thus we can say that the information given us by carrying out some experiment consists in removing the uncertainty which existed before the experiment. The larger this uncertainty, the larger we consider the amount of information obtained by removing it [Khinchin 1957, p 7]."

Thus, *information theory* is the mathematics of the interplay, the dynamics, between *uncertainty* and *information* (the removal of uncertainty). And, for any happening (event), the *value* of its degree of information is defined to be the same as the value of its degree of uncertainty whose removal would produce that information. This value for both uncertainty and its concomitant information is measured by Shannon's formulation of *entropy* – which is a function only of the probabilities involved.

In OCS, the sixth organizing principle, "uncertainty," speaks to this interplay between uncertainty and information. Organodynamics can be understood as a complex adaptive systems theory that has been constructed to investigate these dynamics in living and lifelike systems.

## Applying Shannon's Information Theory to OCS

We shall now introduce our strategy for applying information theory to OCS in such a way as to result in Organodynamics as the formal theory of OCS.

Jaynes has given a procedure that shows how to apply information theory to any application domain [Jaynes 1957]. The basic requirement is that probabilities are involved. In other words, some aspect of the application must have "chance variation" which is represented by a probability distribution. We shall now outline the elements of information theory and Jaynes' procedure for applying it.

The essential elements of information theory are (1) a probability distribution, representing the possible states (a state space) of a system; (2) the entropy of that distribution – a number measuring its degree of uncertainty; (3) a sequence of such probability distributions (a stochastic process) representing how the system changes state over time, and 4) a sequence of the entropies of that stochastic process – characterizing how the degrees of certainty/uncertainty of the process change over time.

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diminishes. Since the degree of uncertainty is decreasing with each step, then we have partial uncertainty, partial randomness.

(Of course, the probability distribution in the first step must comply with the rules of a probability space [Ash and Doleans-Dade 2000, section 4.2].)[8]

An example of applying information theory to a scientific investigation is presented in Appendix 2, *Applying Information Theory to Science*.

Biological systems exhibit seemingly boundless proliferation. But, in actuality, there are limitations and constraints on how they can grow, reproduce and evolve. Biophysics accounts for these limits in a number of ways. In particular, many of these limitations amount to constraints on energy – or, more accurately, energy delivery and energy spread. So too must OCS explain how dynamical organic systems are ultimately constrained. The approach taken by Organodynamics pertains to a correlation that exists [Tolman 1938, pp. 9-10, p. 524, pp. 538-539] between the entropy of classical thermodynamics (which, according to Leff [Leff 2012, "Key Point 1.4"] measures "energy spread") and the entropy of information theory (which, according to Shannon, measures "uncertainty").

A principal task of Organodynamics is to describe this correlation and to show that statistical entropy represents a generalization of classical thermodynamic entropy that preserves the necessary constraints on proliferation within OCS that we see in biophysics. In fact, the mathematics of information theory employed by OCS provides its own constraints through a number of mechanisms. When the conditions are right for these mechanisms to obtain, they come into play, and then a number of behavior-constraining phenomena occur. Among these is asymptotic behavior wherein chaotic conditions tend toward stationarity in the limit. Loosely speaking, this is chaos moving to order.

Other examples of constraining mechanisms within random processes (whose statistical entropy decreases over time) in biochemistry are found in the dynamics of protein folding and the statistical stability of enzyme function. In such molecules, the relatively predictable (low statistical entropy) internal forces of the protein molecule combine with the Brownian motion (random walk) behavior of the molecule's surrounding environment [Gulukota and Wolynes 1994], [Karplus and Weaver 1994]. This results in a protein folding process that is neither totally random nor totally predictable. It is of "intermediate-degree statistical entropy." Even so, the process is ultimately biased toward the protein being able to perform its function [Austumian and Hanggi 2003], [Haws 2007, pp. 161-168]. Other effects, such as *stochastic resonance* (SR), also produce stochastic processes involving intermediate-level entropies. In SR, predictable forces combine with stochastic ones (noise), resulting in processes in which "cooperation between signal and noise" can introduce coherence into a system; whereas the "signal" alone does not [Bulsara and Gammaitoni 1996].

[8] The interested reader can explore these elements by referring to [Shannon 1948, pp. 10-12], [Khinchin 1957, p. 7], [Cover and Thomas 1991, chapters 4, 5 and 6] and [Kleeman 2009, Lectures 1, 2 and 3]. From these sources it is seen that information theory begins with these probability elements and then immediately leverages them to proceed to the consideration of stochastic dependency and predictability. Building upon the *statistical entropy* of probability distributions, information theory then develops a set of constructs that characterize the degree to which one chance variable portends the behavior of another. Some of these constructs are named *conditional probability distribution*, *conditional entropy*, *relative entropy*, *mutual information* and *entropy rate*. (Especially refer to [Cover and Thomas 1991] and [Kleeman 2009] for a the development and application of these constructs.) From this description, it is easy to see why an application domain must "have probabilities" in order to be addressable by information theory.

Classical thermodynamics uses causal relationships among its various elements to characterize the constraints imposed upon their behaviors and to foster predictability of their future behaviors based upon their initial conditions. On the other hand, probability and information theories do not directly model causality. Rather, they use other ideas to characterize constraints on the behavior of their elements and foster predictability. These concepts, already mentioned above, include *conditional probability*, *stochastic dependence*, *relative entropy*, *mutual information* and *entropy rate* [Cover and Thomas 1991, chapters 2, 3 and 4]. In particular, *entropy rate*, which describes how entropy changes, is useful in characterizing constraints on the behaviors of stochastic processes over time [Kleeman 2009, lecture 3].

In effect, these measures of stochastic conditionality and dependency – particularly mutual information and entropy rate – represent the interrelationships and influence among the time steps of a stochastic process and how their outcomes at each of the steps affect each other. Therefore, Organodynamics leverages all of these information-theoretic mechanisms to characterize the dynamics of organic complex systems.

These information-theoretic mechanisms that drive chaos to order come into play under conditions when stochastic independence ceases to hold sway, and stochastic dependence arises. This fact is often missed. Many of the examples encountered in scientific literature make the (perhaps unconscious) assumption of stochastic independence – which, while it makes things easier to calculate, is often unwarranted. As long as stochastic independence is the case, then chaos need not move to order and can persist. However, when stochastic dependence takes hold, then chaos can move to order under the right conditions. One can test whether a given example assumes stochastic independence by asking if the probabilities are being multiplied in order to calculate joint probabilities. If so, then stochastic independence has been assumed.

## Information Theory in Organodynamics

Organodynamics introduces these information-theoretic ideas by the use of a relatively simple type of dependent stochastic process called the *Markov chain.* What makes Markov chains relatively simple is that they limit their consideration of dependency to just two adjacent time steps – the current and the previous. That is, the probabilities describing time step N depend *only* on the outcomes of time step N-1. For Markov processes, the consideration of any time steps further in the past than step N-1 does not change the probabilities for step N, and can therefore be ignored. If the outcome of some other step earlier than the previous *does* change the outcome of step N, then the process is more complex and does not qualify as Markov.

Initially restricting the use of stochastic processes in Organodynamics to Markov chains simplifies the modeling solutions quite a bit. Of course, this “Markov property” does not hold for all organic systems. And when it does not, then Markov chains may not be sufficiently accurate representations. In those cases, Organodynamics needs more general forms of dependent stochastic processes. Initially, though, Organodynamics will focus on Markov chains as a first approach.

## The Organodynamic Web

So far, we have described a rich mechanism for modeling sequential states of living systems using stochastic processes. But sequential state representation is not enough.

We know that concurrently existing biochemical systems (and their components) coexist and carry on as concurrent processes. To make matters even more complex, we also know that biochemical processes intermingle – they join (in multiple ways) into single processes, and then they split (in even more ways) again into multiple concurrent processes.

Consider for example a typical chain of oxidation-reduction reactions where molecules frequently encounter, sometimes bond and then often split. Or consider higher levels of biological organization – *e.g.* metabolic pathways – where it is routine for entities to combine and then divide. Not only does this "joining and splitting" occur – it occurs at all levels of biological organization. For example, meiosis at the level of the zygote involves both splitting and joining operations, as does conception and child bearing at the level of organisms in sexual species.

These splitting and joining processes occur even at the elementary molecular level – and in Organodynamics constitute their biochemical reorganization. At all these levels of organization in nature, this splitting and joining occurs probabilistically. An encounter may or may not occur; and, if it does, the actual joining (bonding) may or may not occur. These "join" and "split" occurrences are generally stochastic.

So, Organodynamics must define mechanisms to represent the joining of multiple concurrent stochastic processes into one (at certain time steps), and the splitting of one stochastic process into many (at other time steps). In between these join and split events, these processes are continuing to operate concurrently. And this co-operative stochastic intermingling is occurring at all levels of biological organization. Clearly, our stochastic process model, at least as so far presented in this paper, does not model this joining and splitting. Therefore, in Organodynamics, we must add that capability.

Thus Organodynamics defines the concept of joining stochastic processes, specifically Markov chains, by presenting some *algebraic operations* on Markov chains. But these algebraic operations on Markov chains are more general and will function at all levels of organodynamic organization. Such an operation could, for example, represent an oxidation-reduction reaction wherein two molecules coexist concurrently for some time and then encounter and bond to result in a single molecule, which then exists for some amount of time before again joining (bonding) with other molecules or splitting into several new ones.

Of course, there are multiple ways in which processes can combine. Accordingly, Organodynamics identifies a significant number of these ways, and defines each as a unique algebraic operation, or *transform*, on Markov chains. For example, some of these organodynamic transforms on Markov chains are named *Catalyze*, *Unite*, *Divide* and *Integrate*.

This set of operations will constitute an *algebraic structure on Markov chains*. Within this "algebra" we must also represent the splitting of a Markov chain into multiple chains in order to represent such phenomena as cell division. Specifically, this algebra of Markov

chains must provide a framework for representing a number of mechanisms for growth, reproduction and evolution – the hallmarks of biological systems.

The algebra on Markov chains is at the center of the OCS formal theory. With its joining and splitting of process segments, it provides *network semantics* for stochastic processes. This culminates in a comprehensive network construct named the *Organodynamic web*. A single organodynamic web structure is capable of modeling an organic complex system instance in its entirety – regardless of its complexity or number of levels of nested organization. The *Organodynamic web* construct, like the general concept of "circuit" in electronic switching networks, provides the grand scheme of Organodynamics for modeling an organic complex system - or community of such systems.

Markov chains and their algebra form the information theory dynamics that constitute Organodynamics, the formal theory of OCS. We have at this time done considerable theoretical work in this area [HollandJG-I 2011; HollandJG-II 2011; HollandJG-III 2011; HollandJGa 2012]; [HollandJG 2013].

### *3.c. The Modeling Paradigm*

The mathematics of the formal theory is rich and flexible, but researchers who desire to develop simulations of organic systems will often find it too complex to work with directly. Fortunately the "join and split" algebra on Markov chains mentioned above suggests that we are working with network concepts. And this fact enables the construction of a higher-level network analogy that serves as a toolkit of building blocks for constructing models of organic complex systems. This network analogy hides the mathematical complexities of Organodynamics – and, with the help of an associated software package – can make Organodynamic modeling accessible to practitioners who want to ignore the mathematics. Indeed, the purpose of the OCS modeling paradigm is to "wrap", or hide, the mathematical abstractions of Organodynamics inside a higher-level network analogy[9] involving the "arcs," "nodes" and "loopbacks" discussed earlier, and thus largely avoid the mathematical complexities of the OCS formal theory.[10] See Appendix 1 for an example of an OCS model featuring an oxidation-reduction reaction.

In addition, the mathematics of these constructs is defined in a manner that permits them to be implemented in modeling software where they can be manipulated as though they are unitary network elements. The paradigm thus encourages an incremental approach to modeling via a sequence of "nested" approximations that build from the simplest elements to the final description.

[9] A precedent for this kind of abstraction level wrapping is seen in queuing network modeling, particularly in applications to computer systems performance analysis and modeling [Bolch, *et al*. 2006].

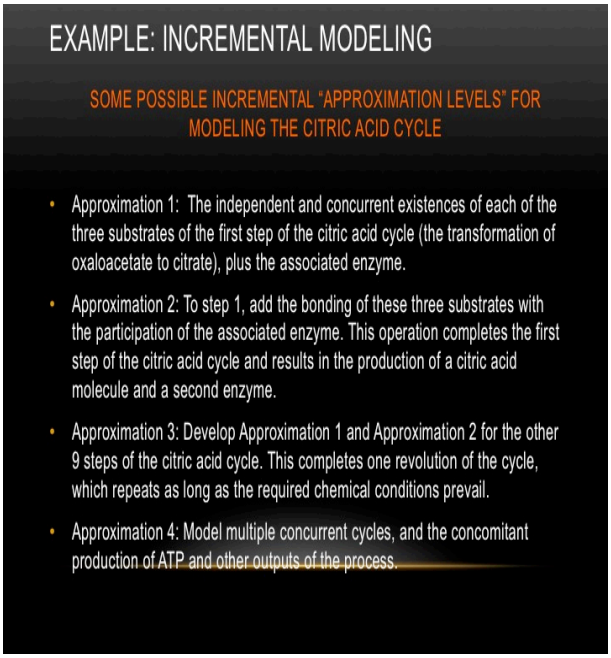
[10] This "abstraction level wrapping" is similar in concept to what occurs in computer science when machine language is "hidden" inside of higher-level programming languages. However, while this trick is ubiquitous in compiler technology, its application to mathematical modeling paradigms does not enjoy the same level of ubiquity. This "wrapping" usually occurs only when there is some division of labor between mathematicians who invent the modeling paradigm and engineers who ultimately apply it to application domains.

## OCS Applied to a Real-World Example

Suppose that we want to represent cellular respiration [Watson 1970, pp.32-70] with an Organodynamic model. Such a model, even though it represents "merely" a subset of the biochemical processes of a cell, could nevertheless be enormously complex. To make the modeling process more manageable, we approach the problem incrementally as a sequence of approximations, each of increasing organizational complexity, until we have reached the desired stopping point. This can continue to any desired level of organization.

The initial approximation could model the first step of the citric acid (Krebs) cycle, the transformation of oxaloacetate to citrate. This step alone involves the concurrent coexistence of four distinct molecules: three substrates (oxaloacetate, acetyl co-enzyme A, and $H_2O$) and an enzyme (citrate synthase). Each of these must first be represented – at least for a few clicks of time – as a single process that exists concurrently with the other three. We model each of these as a Markov chain whose states are their possible atomic/molecular configurations. These four Markov chains form the first level of approximation.

Then, at some particular time step, an "encounter" probabilistically occurs wherein these four input molecules chemically react and produce two outputs: a citric acid molecule as well as another co-enzyme (CoA-SH). This reaction is represented in Organodynamics as an "algebraic operation" on Markov chains that is performed on these three substrates and one enzyme. Because it has four input molecules and two output molecules, this operation is both a "split" and a "join" simultaneously. This operation is a second-level approximation that represents the transformation of the citric acid cycle from step one of the cycle (oxaloacetate) to step two (citrate).




The third approximation could consist of repeating these same two levels of approximation nine more times to produce the remaining nine steps of the cycle. One revolution of the entire cycle produces one energy-carrying molecule adenosine triphosphate (ATP), three electron-transfer molecules (Nicotinamide Dehydrogenase - NADH) and some carbon dioxide. A third approximation could then develop multiple concurrent instances of this citric acid cycle, all of which produce ATP, NADH and carbon dioxide.

The next major stage of cellular respiration after the citric acid cycle is the *electron transfer chain*. This stage could be modeled by performing the same three approximation levels we applied to the citric acid cycle. The electron transfer chain utilizes the outputs of the citric acid cycle (ATP, NADH and carbon dioxide) to produce many more energy-carrying molecules (ATP, etc.).

Of course, the citric acid cycle is a well-established biochemical process so there may not be much utility in developing an OCS model of it except perhaps as a classroom demonstration, or to compare modeling paradigms. This example was presented here to suggest the viability of OCS modeling to biochemistry. A more practical application of OCS modeling in a laboratory environment could be to test the viability of a novel biochemical theory prior to subjecting the theory to laboratory trials. A computer model may be more efficient and could rule out certain hypotheses before proceeding to laboratory trials. In a commercial environment, where a computer often generates thousands of hypotheses, OCS modeling could be used to rule out all but a few, which could then go to laboratory trials. These are all traditional uses of mathematical modeling in both academic and commercial environments.

This example has hopefully demonstrated the value of an incremental approach to modeling organic complex systems. The OCS modeling paradigm establishes repeatable guidelines for this type of incremental approach to the development of complex Organodynamic models, which can then be designed and implemented *in silico* using the OCS simulation software package.

### *3.d. The Software Package*

In order to provide a platform for modeling organic complex systems, a simulation software package is in development that implements the formal theory and the modeling paradigm. It is designed to operate in a distributed high-performance computing network. The package does not require external or third party software libraries. This is desirable for licensing reasons and also because the package will operate unencumbered in a distributed computing environment.

It is clear that the size and complexity of OCS models will generally require their distribution across multiple cores in central processors and in multiple computers in a network ("horizontal scalability"). These computers may be a heterogeneous set which may involve multiple hardware and operating systems. In order to accommodate the level of network interaction involved, as well as the heterogeneous nature of the hardware and operating system mix, the use of the enterprise-class Java platform is indicated. Enterprise Java was engineered from the start to support heterogeneous hardware and software mixes as well as high levels of network interaction among the parts of the application, as well as high degrees of concurrency. It is expected that the horizontal scalability of the platform to multiple computers in a network will overcome any performance loss incurred due to the virtual machine architecture of the enterprise Java platform.

## 4. Summary

This article outlines a new systems theory named *Organic Complex Systems* (OCS): a theory of lifelike systems that lies beyond traditional biological understanding. Such systems may include artificially engineered lifelike systems, non-carbon-based extra-terrestrial organisms, synthetic biological systems and autonomic software systems.

OCS is based on seven concepts that define a class of dynamical systems that is considered to be *lifelike*. It includes, but is not limited to, biological organisms. The concepts (*organization, emergence, compositeness, reorganization,* autocoorganization*,*

*uncertainty* and *persistence*) are intended as organizing principles of living and lifelike systems. OCS presents a new system-oriented perspective of what it means to be "alive."

As a conceptual theory, OCS requires a mathematical underpinning through which it can formally articulate its principles. It would be ideal if an existing mathematical systems theory could perform this task. Nonlinear dynamics seems an obvious candidate for this role, since it formally articulates some of the seven concepts of OCS. However, as a deterministic system, nonlinear dynamics cannot account for the crucial role that uncertainty plays in OCS. Consequently, we have developed the theory of Organodynamics – a complex adaptive systems theory – to fill this void.

The most significant distinction between *Organodynamics* and *nonlinear dynamics* is in their respective mathematical foundations. Nonlinear dynamics achieves complexity through the use of nonlinear functions and equations – algebraic, differential and integral. This being so, its mathematics are strictly deterministic (contrary to the expectations of many). But Organodynamics achieves complexity through a mathematical foundation that integrates certainty and uncertainty, or randomness and determinism, based on probability theory, stochastic processes and information theory.

The mathematical foundation that uncertainty provides in Organodynamics is not without precedent. Such a probability-based perspective began with statistical mechanics in the 19th century and was carried on by quantum mechanics and information theory in the 20th.

Information theory, introduced by Shannon in 1948, provides the essential mathematical foundations of Organodynamics. Shannon codified information theory when he extended probability theory with a single functional that measures the uncertainty inherent in a probability distribution. This functional takes the probabilities of a distribution as its only parameters and calculates the degree of uncertainty of the distribution as the result. Because of the equivalence of Shannon's definition of this functional to another measuring function of the same name introduced by Gibbs in 1902, Shannon named his measure *entropy*.

The application of other ideas from probability theory to Shannon's concept of entropy, such as stochastic processes, has enabled information theory to ascertain the conditions under which randomness asymptotically approaches regularity – and even certainty. This has enabled information theory to provide a foundation for describing a disparate variety of complex phenomena. It is these features of information theory that make it such an appropriate mathematical foundation for Organodynamics, and in turn, for OCS.

In the 19th century the notion of entropy was initially introduced in classical physics as a measure of energy spread or dissipation in thermodynamics. But later Maxwell, Boltzmann and especially Gibbs expanded this physical notion of entropy to a statistical one in their articulation of statistical mechanics.

Subsequently, the concepts of probability and uncertainty as measured by the statistical entropy function – introduced by Gibbs, canonized by Shannon, elaborated by Khinchin and championed by Jaynes – have provided the essential foundation of modern information theory. This expanded understanding of entropy – though perhaps not yet broadly held by the general scientific population – has promoted information theory to

one of the most promising advances in mathematics, science and engineering in the past century.

As a complex adaptive systems theory, Organodynamics is distinguished from nonlinear dynamics in several ways. Organodynamics shows how and under what conditions random processes can achieve regularity by asymptotically approaching stationarity; while nonlinear dynamics depicts relatively stable initial conditions transforming into chaotic ones. Organodynamics drives system regularity with mechanisms from information theory such as stochastic dependence, mutual information and entropy rate; while nonlinear dynamics uses constructs such as various forms of attractors. Finally, Organodynamics focuses on developing the mathematical foundations of a general theory of the living; while nonlinear dynamics has a broader purview than the lifelike.

It is thus reasonable to characterize Organodynamics as a complex adaptive systems theory that provides an alternative to nonlinear dynamics. Furthermore, Organodynamics provides the mathematical foundations of OCS, which ponders the dynamical organization of living and lifelike systems that include but also go beyond traditional biology.

Both theories bring important perspectives to the investigation of complex adaptive systems. However, currently there is no broadly adopted contemporary systems theory that provides the alternatives and capabilities that Organodynamics brings.

OCS research provides four interrelated activities: developing the conceptual theory, formalizing these concepts into a complex adaptive systems theory (*Organodynamics*), creating an accessible modeling paradigm and developing the associated simulation software package. These activities cover both theory and practice and support the mathematical modeling and simulation of living and lifelike organisms, whether they are biological or extra-biological. Preliminary versions of all four OCS research activities have been developed in the form of working documents and software.

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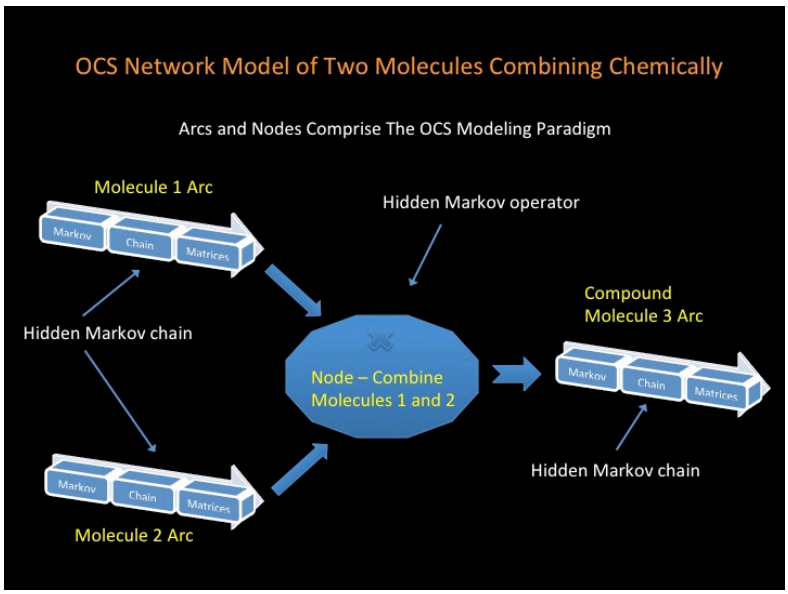
# Appendix 1. OCS Network Model of Two Molecules Combining

This appendix provides an example biochemical process – an oxidation-reduction reaction, and shows how OCS can be used to construct a dynamical model of it.

Like any other network model, a "directed graph" consists of "arcs" – which are line segments that represent processes. As well, these arcs can join at certain points in time into intersections called "nodes." "Nodes" in the toolset represent "join" and "split" operations in Organodynamics. And "arcs" in the toolset represent stochastic processes in Organodynamics. In the same way that "arcs" connect "nodes" in a directed graph, stochastic processes connect split and join operations in Organodynamics.

For example, suppose we want to model an oxidation-reduction reaction involving two molecules as a discrete sequence of time steps. Each of these two molecules would coexist concurrently for some number (*n)* of time steps before they interact and bond chemically. During this time, each molecule is individually an n-step process that changes its state (rotation, location, etc.) throughout these time steps. Their change of state is also uncertain, because each changes position, orientation, etc., continuously. These two processes are concurrent over the *n* steps. In the directed graph analogy of the modeling paradigm, an "arc" represents each of these two processes. So the model of these three molecules as they change in time consists of two concurrent "arcs."




However, it can happen that, at some time step, the states of these two are such that they can bond chemically. At that time, we can represent this bond as a coming together, or intersection, of these two arcs. This intersection is represented in the graph theory analogy as a "node." In Organodynamics, such a coming together is a "join operation" – which is mathematically an algebraic operation on multiple stochastic processes ("arcs" in the modeling paradigm).

Thus, the history of two molecules that coexist independently for awhile and then bond chemically can be represented in the modeling paradigm as two separate "arcs" which then join at a "node," which represents the chemical bonding of the two molecules at some point in time. In Organodynamics the "arcs" actually represent two concurrent stochastic processes, and the nodes represent algebraic operation on these two stochastic processes. However, the biochemist does not need to know the details of Organodynamic mathematics since it is fully incorporated in the OCS software. Instead,

one only deals with the actual molecules and directed graphs in the modeling paradigm. Once the model of the molecules as arcs and nodes has been prepared it is then run on a computer using OCS software.

## Appendix 2. Applying Information Theory to Science

E. T. Jaynes has outlined a procedure by which information theory can be applied to any domain of application – specifically to a scientific investigation. This appendix makes an interpretation of this procedure that is in line with what we have established in the present article.

### *Jaynes' Procedure*

Accordingly, this procedure can be reduced to these four steps:

1. We identify how *system state* is defined for the system being studied. From this, the system's *state space* is known.
2. We empirically or theoretically identify the probabilities of each state occurring at the system's next change of state. At this point, we will have a probability distribution whose sample points are the states of the space. In other words, we have adopted some state space of a system of interest as its sample space by assigning probabilities to those states.
3. Next, we observe how the probabilities of that distribution may change over time – creating a sequence of probability distributions, one for each time step, and each having the same state space. This sequence is a stochastic process.
4. The entropies of the probability distributions in this stochastic process form a sequence of numbers that may or may not converge to a limit, be periodic or aperiodic or exhibit other mathematical behaviors.

This sequence of entropy values in step (4), then, can characterize the nature of the ongoing uncertainty of the system's state change behavior. For any specific application domain, the interpretation of this uncertainty behavior depends very much on the choice of system state (step 1) by the observer. Because any system may exhibit many kinds of properties, it generally permits a choice of system state according to the interests of the observer/experimenter. This interpretation also depends on the nature of the change represented in the sequence over time: is it periodic, asymptotic, unbounded, etc.? Depending on choice of state space and the mathematical behavior of the stochastic process, various interpretations are reasonable. They may depend on the experimentation domain, and are left to the observer. For example, unbounded behavior in step (4) may represent instability in a mechanical system or unpredictability in the stock market, depending upon the application domain and the choice of system state. In any event, entropy behavior over time in stochastic processes has many applications and interpretations.

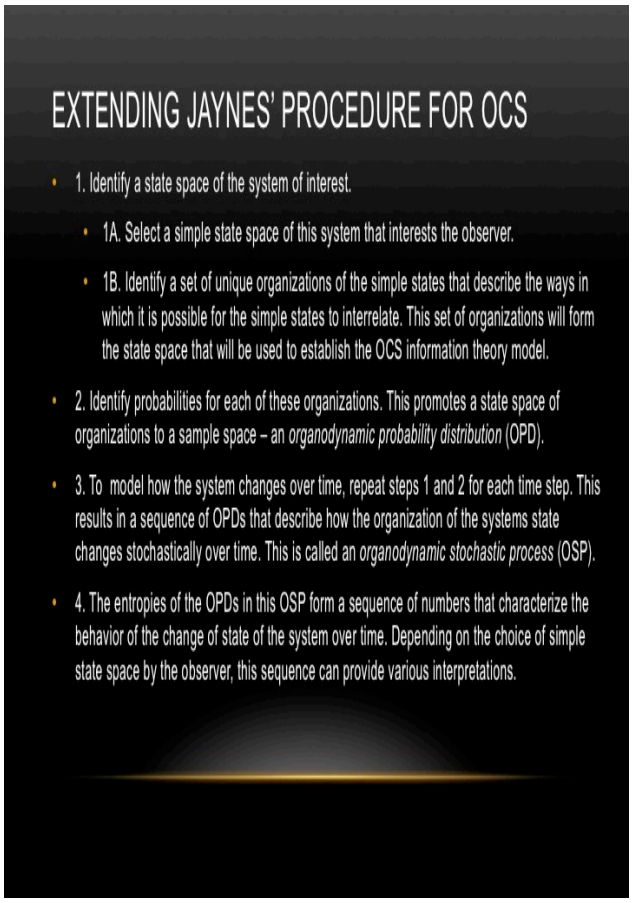
### *Organodynamics from Information Theory*

The act of applying Jaynes' procedure to inject information theory into OCS results in creating Organodynamics as a formal mathematical theory. Subsequently, researchers apply this framework to specific organic systems domains by ascertaining which specific probability distributions apply to the organic systems domain of interest.

### *Biochemical Example*

Let us examine the usefulness of this procedure via an example from biochemistry that is widely studied in biology courses – keeping in mind, however, that Jaynes' procedure also applies to higher levels of biological organization (e.g. population biology and ecology contain endless applications). Indeed, Jaynes' procedure can be applied to any organic complex system.

Our example features a eukaryotic cell —a cell that is advanced enough so that its molecules are organized into subsystems called *organelles* (and other macromolecules) that have specialized functions.[11] However, we shall view the cell in a slightly different way. If you were to take a "snapshot" of the cell at any moment, its components would be arranged ("interrelated") in a particular way, which OCS calls an *organization* of its components. At some other moment, taking a snapshot would capture a slightly different arrangement of the same components – another distinct *organization* of the same cell. Now, imagine the collection of all possible "snapshots" of that cell. This collection of snapshots, or *organizations*, is a new system in which each of these organizations is a component.




This new system is a different representation of the cell as compared to our initial view. The new representation is a way of looking at the cell that emphasizes its structure or organization and enables a discussion of its reorganizations over time. It does this by defining these components of the new system to be *organizations* of macromolecules rather than *individual macromolecules*. Another way of saying this is that the new system has a new state space – one whose states are organizations. It also happens that Organodynamics defines this new system structure in a manner that nests the simpler original system of macromolecules inside of it as components, thus preserving both views within its mathematical constructs.[12]

The second step in Jaynes' procedure is to assign probabilities to each of these possible *organizations* in the state space of this new system. These probabilities represent the likelihood that each specific organization will be the one that the system reorganizes to

[11] An example of an organelle in eukaryotic cells is the cell nucleus. Other examples are ribosomes, the mitochondria, the Golgi apparatus, the endoplasmic reticulum and the cell membrane.

[12] We refer the reader to the Organodynamics working document [HollandJG-II 2011] for details.

the next time it changes its organization. The resulting distribution is called an *Organodynamic probability distribution* (OPD)[13].

The third step in Jaynes' procedure is to form a stochastic process by observing how these OPDs change over time (*e.g*. in our eukaryotic cell example, due to changing chemical conditions in the cell), and to represent each of these different conditions with its own distinct OPD. For example, for any stretch of time in which no molecules enter or leave our eukaryotic cell, the molecular constitution of the cell will be changing among a specific set of possible configurations – limited by the possible oxidation-reduction reactions among the existing atoms in this (temporarily closed) system. Each one of these configurations, or *organizations*, has a distinct probability of appearing.

However, once one or more molecules enters or leaves the cell through its semi-permeable membrane, then the underlying collection of molecules (the system's population) will have (slightly) changed, and a new sample space of molecular arrangements (configurations or *organizations*) now exists with its own set of probabilities – one for each possible organization of molecular arrangements for the new population of macromolecules. In this way, as time passes and molecules enter and leave the cell, new molecular populations with new sets of possible molecular arrangements, or organizations, with new sets of probabilities will come into being at each change. Thus, each time there is a change in molecular constitution, there will be a new OPD with a new entropy value.

This results in a sequence of OPDs over time, one for each change of molecular constitution when molecules leave or enter the cell. Such a sequence of OPDs is called an *Organodynamic stochastic process* (OSP). Each OPD in an OSP has an entropy value. These values form a sequence of numbers that may or may not converge to some limit – or may be periodic or aperiodic, etc. These mathematical behaviors can be characterizations of various types of behavior by the organic system, including stability/instability, predictability/unpredictability, self-regulation, etc., depending on the choice of state space in the first step [Prigogine 1996, pp. 4, 81]. These characterizations obviously may pertain to the ability of the cell to *persist* for varying lengths of time.

We have now extended our initial model of the eukaryotic cell to a more complex system that represents the *uncertainty regarding which organization will next obtain*. In addition, we have also introduced the notion of *persistence* by characterizing the long-run behavior of the entropies of the time steps of these stochastic processes. Thus, we have embodied all three of the themes that run through the seven organizing principles mentioned earlier: *organization*, *uncertainty* and *persistence*. Clearly, this same approach can be applied to other levels of organization: organelles, tissues, organs, organisms, ecologies, extraterrestrial entities or human-engineered artificial systems.

[13] All of this may sound familiar to students of statistical mechanics, where the set of *structured organizations* just described is suggestive of a Gibbs *ensemble* of systems, each describing the states of their particles (positions and momenta) – each of which is assigned a probability [Tolman 1938, pp. 45-48]. Indeed, both OCS and statistical mechanics represent a set of *alternative configurations* or *organizations* of a state space, and each becomes a probability space. However, the definitions by OCS and statistical mechanics of *system state* are different, owing to a difference in focus of the two disciplines. As noted above, statistical mechanics is focused on changes in conjugate variables (e.g. *position and momentum*) of its systems-of-interest. On the other hand, Organodynamics is focused on changes in the *system organizations* of its systems-of-interest. In addition, statistical mechanics mostly assumes the uniform distribution and statistical equilibrium, whereas Organodynamics does not.