Organic Complex Systems

A Comprehensive Theoretical Apparatus for Modeling the Organization and Dynamics of Living and Lifelike Systems

Part III: Considerations and Implications

Part III is a work-in-progress and not ready for distribution.

Revision 11

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Contents

Preface

Part III discusses considerations and implications of OCS and Organodynamics. It does this in the following three chapters.

The first of these summarizes the suggestions for further research that were mentioned throughout Part I and Part II.

The second and third chapters compare and contrast OCS and Organodynamics with existing theories. Chapter 2 contrasts Organodynamics with Nonlinear Dynamics and Chaos theories; while chapter three does the same for Algorithmic Information Theory.

These two chapters highlight the value provided by OCS and Organodynamics by describing its advantages and appropriate applications as compared with these other two contemporary disciplines.

Suggestions for Further Research

The bodies of both Part I and Part II of this treatise have occasionally identified areas of further research. The suggestions have been collected and placed in the table below.

The key phrase "further research" has been included near any of these suggestions within the body of Parts I and II. Therefore, searching for this phrase will find the instances of the suggestions that are itemized in this table.

	Topic	**Research Suggestion**	**Cross Reference**
1	Measure of degree of organization	Develop a measuring function for the degree of organization/disorganization of a system's *organization*.	Part I, p28, p87 Part II, p396, p426, p428
2	Measure of degree of persistence	Develop a measuring function for the degree of persistence of an organic system.	Part I, p76
3	Additional OCS frameworks	Develop other mathematical frameworks, in addition to Organodynamics, that also comply with the OCS organizing principles is left as further research.	Part II, p12
4	Nomenclature for representing system organizations	Organodynamics currently articulates a *organization* of a system as a set of duples (ordered pairs) of the components of the system's population. Develop other approaches to representing a system's organization.	Part II, p59, p62, p159
5	System Transforms	Organodynamics defines several categories of system transforms as well as certain properties of these categories. However, it defines no specific transforms as instances of these categories. The suggestion is to identify and define a number of system transform instances for each of these categories.	Part II, p74

	Topic	**Research Suggestion**	**Cross Reference**
6	Markov Chains	Extend the type of dependent stochastic processes used in the framework beyond that of Markov chains. In a sense, Markov chains are the mathematically simplest case. But they are not sufficiently general to model many, if not, most cases for dynamical organic systems, if only because organic systems are generally not "memoryless".	Part II, p92, p120, p162
7	Non-homogeneous Markov transition matrices	Develop more specificity to nonhomogeneous stochastic processes – especially population changes in Markov chains where in the transition matrix changes from one time step to another. In the Markov case, the issue is that the transition matrix for that time step generally will no longer be square, but will be rectangular.	Part II, p170
8	Stochastic networks	Investigate the theory of stochastic networks and its ability to represent the dynamics of circular networks in order to place the theory around autocogeneration on a stronger theoretical and practical foundation.	Part II, p226
9	Organodynamic Transforms	Organodynamics defines several categories of organodynamic transforms as well as certain properties of these categories. (Organodynamic transforms are "stochastic system transforms.) However, it defines no specific transforms as instances of these categories. The suggestion is to identify and define a number of system transform instances for each of these categories.	Part II, p235, p242, p249, p420
10	Loopback time steps in Simplex Organodynamic	The notion of loopback is introduced in the Simplex Organodynamic web construct. In order to do this properly, however,	Part II, p262

	Topic	**Research Suggestion**	**Cross Reference**
	Webs	the time step identity of a system state must be variable, so that the same state can participate repeatedly within the loop. The mechanism for enhancing system state to accommodate this should be investigated.	
11	Nested systems	In Organodynamics a simplifying assumption was made requiring that the components of a system either all be systems or all be non-systems. A hybrid nested system whose components are mixed in this regard is not supported – but needs to be. This should be a relatively simple extension.	Part II, p271
12	Conditional dependencies in nested systems	Organodynamics has examined the interdependencies between a composite system and its subsumed systems and described that they can both impose conditions on each other that, in fact, limit the possibilities of each other. It was also indicated that these dependencies and restriction can be richly described and implemented using conditional probability distributions – in addition to the conditional probability distribution already used in Markov chains to impose dynamical stochastic conditions. What needs further investigation is how these two sets of conditional probability distributions can work together to describe these interdependencies in composite and nested systems.	Part II, p271, p302
13	The entropy of an Organodynamic web, and other such structures	Investigate ways to represent the uncertainty of entire structures such as Organodynamic webs. Each such web represents a family of probability distributions, one at each node, time step, etc. Of course, each of these has its	Part II, p357

	Topic	Research Suggestion	Cross Reference
		own entropy. But, does it make sense to attempt to characterize an entropy of the entire Organodynamic web? One approach might be to "average them" – as was done with the definition of entropy itself. But to do this, one would have to be able to assign "visitation weights" to each distribution present within the web. It is recommended to look at the theory of stochastic networks to decide this. Also the concept of "entropy rate" may be useful here. It is also possible that characterizing an entire Organodynamic web with a single entropy value is misguided from the start.	
14	Moments of the Information Random Variable (IRV)	Not all discrete probability distributions have a natural way of being mapped to the real numbers. Thus, they do not have any domain-based random variables. But the entire field of statics depends upon the existence of random variables on probability distributions. But, Organodynamics has noticed something in common with all probability distributions – whether or not they have any domain random variables. That something is the notion of "uncertainty", which resides at the basis of probability. OCS has further shown that a random variable can be defined on uncertainty – to yield a "degree of uncertainty". This is called the Information Random Variable, or IRV. We showed that the first moment (the mean) of the IRV for any distribution is its entropy. However, we did not derive any of the central moments (variance, skewness, kurtosis, etc.). Deriving some of these – as well as	Part II, p371

	Topic	**Research Suggestion**	**Cross Reference**
		generating functions – is the subject of this suggestion.	
15	Fractal patterns and non-emergence	A systemic emergent property has been defined to mean a property of a system that none of its components exhibits. The opposite of this is a property that is shared by both a system and at least some of its components. Fractals happen to fit this description. Fractals could, then, be described as property-preserving function between a system and some of its components. Developing mathematics around this idea would bring fractals into the Organodynamic fold.	Part II, p385
16	Adaptation through memory	The notion of adaptation often used memory of past outcomes in the process of self-regulation. However, it is difficult to model this with Markov chains due to their limited memory (to the current time step). This, in order to model interesting degrees of adaptation, Organodynamics must be extended to utilize more general types of dependent stochastic processes that the limited and more simple Markov chains. Extending Organodynamics to do this has already been suggested. But supporting realistic adaptation is another.	Part II, p391

Novelty in OCS

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Organodynamics as an Alternative to Chaos Theory

It may have come to the attention of the reader that OCS has a lot in common with Nonlinear Dynamics and Chaos theories. Often, both Organodynamics and Nonlinear Dynamics can be applied to the same kinds of problems – problems in the area of complex dynamical systems.

Certainly, both theories make claims concerning their ability to model *complexity* and about their ability to model *uncertainty*, or *unpredictability*. Part II explains that Organodynamics has strong foundations in *information theory*, and therefore in *uncertainty*, since “The central idea of information theory is to measure the uncertainty associated with [probability distributions].” [Kleeman 2009].

The OCS foundation in information theory is readily seen in the way it uses uncertainty, probability and statistical entropy to introduce the spectrum that spans both randomness and determinism that is generated by the range of statistical entropy.

But, Chaos Theory also stakes its claim modeling a kind of unpredictability. Nonlinear Dynamics generally avoids the term *random*, and uses the term *chaotic* instead. (For example, there is no discussion of randomness in either of popular college textbooks on Chaos Theory - [Strogatz1994] or [Devaney 2003].)

In OCS, we use the term *random* to mean “producing different outcomes for each trial of the same experiment, all of which share the same initial conditions”.

But, Nonlinear Dynamics does not attribute the same meaning to *chaotic* that OCS does to *random*, as defined in the previous paragraph. Rather, as used in the above two texts and in other texts on nonlinear dynamics and chaos, *chaotic* means ”sensitive to initial conditions” (plus some other mathematical specifics) [Devaney 2003].

Nonlinear dynamics is very interested in the “surprisingness” that occurs whenever a nonlinear function is evaluated for two different parameter values that happen to be very close together, yet the evaluation produces two results that are “unexpectedly” far apart. This is precisely what is meant in nonlinear dynamics by “sensitivity to initial conditions”.

This author contends that it is this “surprisingness” that is meant by the term *unpredictable* in nonlinear dynamics.

Of course, this “surprisingness” is in the mind of the dynamicist who is evaluating the nonlinear function involved. It is not inherent in the mathematics.

If a computer were doing the evaluation, it is doubtful that the computer would be "surprised".

However, in nonlinear dynamics, the functions studied are *completely deterministic*. If any parameter is "fed into" the function 10,000 times, the answer will be exactly the same 10,000 times. Whenever two different parameters that are very close to each other are individually fed into the function 10,000 times, they will both produce the *exact same* two answers 10,000 times. If these two answers happen to be "surprisingly" far apart, then they will be the exact same "surprising difference" 10,000 times. There will be no variation in their difference for each of those times.

In other words, Nonlinear Dynamics and Chaos Theory are *completely deterministic*. There is nothing uncertain, random, stochastic or statistical at all about Nonlinear Dynamics. In the opinion of this author, the entire field of nonlinear dynamics is stretching the credulity of the term *unpredictable* by attributing it to their field.

Steven Strogatz addresses this issue in his well-known chaos theory book, entitled *Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry and Engineering* [Strogatz1994]. He describes *chaos* as "aperiodic long-term behavior in a deterministic system that exhibits sensitive dependence on initial conditions".

Strogatz goes on to explain that what is meant by "deterministic" is that "...the system has no noisy or random inputs or parameters. The irregular behavior arises from the system's non-linearity, rather than from noisy driving forces."

Thus, chaos theory is completely deterministic, and is nowhere random. As already stated, the use of the term *unpredictable* to describe nonlinear dynamics is highly questionable.

So, how is the reputation, and claim by [Devaney 2003], of Chaos Theory for modeling "unpredictability" justified? My interpretation and answer to this question follows:

As used by Chaos Theory, the term "unpredictable" does not mean *random*. Rather, it means "surprising to humans". Other words for this are *non-intuitive*, *unexpected,* or *obfuscatory*.

This fact can severely limit the applicability of nonlinear dynamics and chaos theories to science and engineering. Many if not most systems of interest to these investigators exhibit phenomena that are fundamentally stochastic. From the point of view of the investigator, these situations appear to embody random processes: ones that appear to produce alternative results under the same initial conditions.

The interest of these investigators is the variation in the results produced, even though the initial conditions remain the same. If the initial conditions have to be changed in order to obtain varied results, then the conditions of the investigation are not met.

This requirement is conspicuous in the world of modeling and simulation. There are entire classes of modeling technology that embodies this requirement for true randomness. This is referred to as *stochastic modeling*.

On the other hand, the modeling apparatus of Organodynamics is inherently probabilistic. A *probability functions* is one which produces different outcomes for each trial of the same experiment, where all the trials share the same initial conditions". Therefore, the processes themselves in OCS are actually non-deterministic and random.

But, OCS brings another dimension to the notion of unpredictability, because it allows the *degree of uncertainty* of any of its processes to vary continuously between *completely random* and *completely deterministic*. OCS inherits this capability from information theory through the idea of *statistical entropy* as formulated by Claude Shannon.

Admittedly, it is not surprising that Chaos Theory has a popular reputation as representing random behavior – even though it is completely deterministic. Some of this confusion is due to the choice of the term *chaos* to name the theory.

None of these observations in any way impugn the applicability of Chaos Theory to the modeling of complex dynamical systems. They are offered merely to deflect any misconceptions that Chaos Theory, in any way, embodies randomness.

Rather, it is anticipated that both OCS and Nonlinear Dynamics provide a pair of alternative, or companion, theories for modeling complex dynamical systems. There are applications, for example, that would benefit by the triangulation effect of using both approaches to model the same phenomena.

There is one advantage provided by OCS that I would like to point out. OCS provides a specific construct for modeling specific instances of organic systems. This construct is the *organic system*, which you will recall is a hierarchical structure of systems-within-systems…etc. Such a structure is designed to represent the entirety of a single organism, such as a multi-cellular biological organism. It can also model other biological entities such as organs, cells, and even ecological entities such as communities, etc. To my knowledge, Chaos Theory sports no such construct.

Of course, the domain of application of OCS and Nonlinear Dynamics are different. They overlap, but remain distinctive. OCS is focused on modeling "lifelike" systems. Nonlinear Dynamics has broader application.

But, all-in-all, the two theories are motivated by similar phenomena, and should be considered to be companions.

Subjectivity, Uncertainty and Information in OCS

[Note to Grant:

OCS and Organodynamics rely heavily on *information theory*. However, today there are two versions of information theory: the original, put for the by Claude Shannon in 1948, and a later alternative, called algorithmic information theory, attributed to Solomonoff, Kolmogorov, Chaitin and others.

Each of these two has its own idea of *randomness*. They diverge along several lines. Each also has its distinct application domains.

Organodynamics is an application of the original *information theory* put forth by Shannon, and virtually no application for algorithmic information theory. This section explains why.

<u>Information theory</u>

The information theory developed by Claude Shannon in 1948, and that has enjoyed continued development and application today in quantum theory, computer science, systems biology, and other disciplines, is a branch of probability theory.

Information theory is interested in defining a measure of the degree of information inherent in an *outcome of an experiment*. In colloquial terms, it is interested in how much information is inherent in *happenings*. In this sense, information theory is dynamical. Something is taking place over time.

The basic condition entertained by information theory is that there is an observer who is observing a *happening*. Prior to the happening, the observer has some degree of uncertainty regarding what its outcome will be. After the occurrence of the happening, the observer has some degree of surprise pertaining to the outcome [Khinchin 1957].

In information theory, there is a relationship between the *uncertainty of possible outcomes* before the occurrence of the happening and the *degree of surprise* afterwards. This relationship pertains to the degree of likelihood of an event that occurs. If an event has a very low likelihood (as measured by probability) then its degree of uncertainty before the occurrence is high. The converse is also true.

Moreover, the degree of uncertainty prior to the occurrence is directly related to the degree of information produced if the event actually does occur. That is, if an event is very unlikely prior to the performance of the experiment, then if that event actually occurs as the outcome it provides a large degree information. On the other hand, a highly likely event produces a relatively small amount of information if it occurs.

Thus, in information theory, the *degree of information of an event* is measured by its degree of uncertainty prior to occurrence, or realization.

Given this background, it is not surprising that information theory defines all of its measures in terms of probabilities. In fact, information theory is understood to be a branch of probability theory.

It's most basic measure, the *surprisal* of an event, is defined only in terms of probability and only probability (log(1/Pr(E))). The *surprisal* measures the degree of uncertainty inherent in an event.

Information theory's most celebrated measure, *entropy*, is defined as the expected value of the *surprisals* of all the sample points in the probability space. Thus, entropy too is defined only in terms of probabilities. Entropy is the measure of the degree of uncertainty embodied in an entire probability space – rather than merely one of its sample points.

Information theory, then, is based upon measuring the uncertainty that an observer has regarding an observed phenomenon. It is a measure, then, of a relationship between an observer and an observed.

Moreover, the probabilities, and therefore the degree of uncertainty, can change for a given observer whenever the observer obtains more, or less, information regarding the observed. In addition to that, two distinct observers can have distinct probability distributions that represent their respective uncertainties with respect to an observed.

Thus, Information theory is a measure of the subject (the observer) rather than of the object of observation. That is, Information theory is *subjective*. This, of course, is true also of the interpretation of probability theory used here.

<u>Algorithmic Information Theory</u>

However, Algorithmic Information Theory is also interested in developing a measure of the amount of information inherent in an object. Its approach is measure the size of a minimum algorithm required to compute the object. There is no reference to a subject observer. There is, however, reference to an algorithm – but it is not attributed to an observer.

Thus, the focus of AIT is strictly on the object. It is appropriate to say that AIT is *objective*.

Moreover, AIT is strictly deterministic. There is no mention of probabilities or probability spaces in the definition of its measure. Consequently, there is no notion of *uncertainty* in AIT.

What there is in AIT, however, is a notion of *complexity*. If complexity is conceived as a measure of the degree of internal interrelatedness of a system, then it is reasonable for AIT to claim that it is concerned with complexity.

End of Note to Grant]

OCS' views on information, uncertainty, randomness and probability are defined in terms of a relationship between an *object* and its *observer*. It is this relationship between the observer and an object that embodies uncertainty – not the object itself. This makes OCS a *subjective*, rather than *objective*, theory.

(Since we are dealing with dynamical systems then it is a *process* that is actually observed, rather than an object. However we shall not pick that nit here.)

This subjectivity is revealed by this: Two observers may observe the same process, but reasonably enjoy distinct uncertainty-information-probability views of it – owing to how much of the process has been realized to one observer as compared to the other.

Choosing either a subjective or an objective view of information and uncertainty is neither correct nor incorrect, but rather a conscious modeling decision based on modeling goals. If the modeler desires to model the dynamics between an observer and an object then a subjective model is appropriate. Otherwise, and objective model is appropriate.

Two Views of Information and Uncertainty

This OCS view of uncertainty and information is at odds with the views of several investigators, including [Kolmogorov 1956b], [Chaitin 1970, 1976, 1982], and [Holland 1995], who – if I may be so bold as to cramp them all into a category – intentionally conflate the two concepts of *uncertainty* and *organization*. It might be fair to say that this category is named "algorithmic information theory" (AIT).

Whereas, OCS attributes *uncertainty* to the relationship between an observer and an object, algorithmic information theory attributes *information* to an object independently of an observer. And, both theories go on to equate the notions of uncertainty, information and randomness.

In the algorithmic information theory view, a single object – standing alone in the universe with no observer in sight – has a "degree of information".

Whereas, in OCS, the degree of uncertainty is a measure of a relationship between an observer and an observed – which is why two observers can legitimately have distinct degrees of uncertainty regarding the same event. Moreover, in OCS – as in classical information theory, *information* is what results when uncertainty is *realized* through the conduct of a *trial*. Thus, *information* is the result of a dynamical process. It is not a static property of an object.

Both theories not only equate *information, uncertainty* and *randomness,* they also both proceed to develop *measuring functions* that they purport to measure both. As we shall shortly see, these two measuring functions are quite different from each other.

Again, there is nothing wrong with this algorithmic approach to uncertainty – or with the OCS subjective approach either. These are simply choices that are made so as to model with more fidelity certain aspects of the world that one sees and desires to reflect through an intellectual model. Nevertheless, it is important to understand the differences so as to minimize confusion.

Let me elucidate the distinction between these two views of information/uncertainty by an example from Kolmogorov. As reported by [Gleick 2011], Kolmogorov declared "a new conception of the notion 'random' corresponding to the natural assumption that randomness is the absence of regularity." Clearly, OCS finds considerable "regularity" in randomness, as evidenced by the mathematical equipment developed by the Organodynamic framework in Part II of this text for the sixth OCS organizing principle, *autocogeneration*.

Even more evidentiary of the distinction between these two views is the article by Kolmogorov and associates [Kolmogorov 1956b] entitled "Three approaches to the definition of the notion of amount of information." In this article, Kolmogorov lays out an alternative to Shannon's entropy as a measure of the "degree of information".

Kolmogorov's alternative posits that, for any object, there is an algorithm of minimal size that can generate, or compute, such object. The *size* of this algorithm, according to Kolmogorov, is the measure of the *degree of information* inherent in the object.

However, from the OCS perspective, any algorithm is by definition *deterministic*. Thus, if an algorithm exists to compute an object, then there is no *uncertainty* associated with that object on the part of any observer that is aware of the algorithm. The existence of the algorithm nullifies any claims to uncertainty!

Thus, I claim that Kolmogorov has "cleansed" Shannon's measure of information (entropy) by removing any scent of "uncertainty" from it. This is evident by the fact that he replaced all mention of *probability* with a deterministic *counting* – as we shall see. Owing to the fact that the mathematical way of representing uncertainty is with probability, then I believe that I am justified in describing Kolmogorov's act as "removing uncertainty" from his definition of the *measure of information*.

(Many students of the notion of *entropy* have always been uncomfortable with Shannon's conflation of *uncertainty* with *information*. One could say that Kolmogorov has given them a way out by providing a definition of *the amount of information* that is quite reasonable for the common usage of the word *information* – but that doesn't work very well as a definition of *uncertainty* – owing the reasons pertaining to determinism that I raised above.)

One could take this line of reasoning quite far by proposing that Shannon and Kolmogorov mean quite different things by the word *information*. For Shannon, it is the mathematical equivalent of *uncertainty*. His definition of "the amount of information" is defined in terms of probabilities – and only probabilities. Of course, *probabilities* are the very mathematicization of uncertainty.

But for Kolmogorov, information involves determinism, and therefore means something other than probabilities. This is made clear by the fact that he "cleansed" his definition of "the amount of information" of any references to probabilities, and replaced them with a simple deterministic count of the number of instructions in a Turing machine program articulation of the minimal algorithm required to compute the object whose "information" is being measured.

But, OCS is largely based upon the assumption that uncertainty operates within organic systems. And OCS uses probabilities to express this dynamic. Thus, the viewpoint of algorithmic information theory (Kolmogorov, Chaitin and others) is not useful to OCS; while that of Shannon (and Khinchin, etc.) is.

An advantage of the AIT approach is that any object can be attributed a *degree of information* in isolation from any observer. The disadvantage, however, is that probability has been removed from the conversation – along with any unpredictability aspect of uncertainty. It is fair to seriously question whether the notion of "uncertainty" is actually still present in an algorithmic definition of "information", since the probabilities in Shannon's entropy formula are replaced by deterministic cardinalities.

However, from the OCS perspective, uncertainty is fundamentally about the knowledge held by an observer regarding an object – rather than about the object itself. To OCS, an object standing alone with no observer cannot have any degree of uncertainty – either high or low.

The quantum mechanists found that they got into trouble if they attempted to ignore the observer from the process of doing science for elementary particles. And, they set out a number of guiding principles to include the observer - the use of probabilities being chief among them. OCS has elected to take the same approach regarding the study of living and lifelike systems.

OCS attributes degrees of uncertainty to observations made by an observer of an object. Thus, OCS needs a subjective definition of uncertainty – not the objective one from algorithmic information theory.

Information-based Modeling of Dynamical Systems

Another interesting point is that the OCS subjective view of uncertainty implies the possibility of the resolution of uncertainty by an event that reveals the *realization* or *manifestation* of a previously uncertain outcome. It is this manifestation event that transforms the uncertainty to certainty.

So, there is a distinction between 1) the condition that the observer has uncertainty and 2) the condition that the realization event has occurred (or the observer learns of its occurrence). Moreover, these two conditions happen at different points in time!

[Shannon 1968] elucidates the fact that uncertainty exists until the "outcome becomes known", but it was [Khinchin 1957] who explained it so well. Even Kolmogorov [Kolmogorov 1956a] makes reference to this fact. And, Organodynamics creates a modeling methodology that codifies it into practice.

The point being made is that *time* comes into play when an observer is involved and uncertainty/certainty is at issue. This is because there is a time differential between when the observer has uncertainty about the outcome and when the observer learns which outcome has been realized. This time differential enables this entire notion of uncertainty, and associated probability distributions, to be a model of change – a model that can be used in dynamical systems!

And, OCS exploits this time difference and these probabilities associated with them. If at time "t" the observer has uncertainty regarding the outcome at time t+1, then that uncertainty will be resolved at time t+1. And, at time "t", there is a probability distribution that describes the *choices* involved in that uncertainty, and that has an entropy value that measures the degree of that uncertainty.

This is "pure Shannon" and is precisely implemented by the Organodynamics modeling framework in this manner.

Organodynamics would not be able to use the algorithmic approach to model this uncertainty. This is largely because the AIT notion of *uncertainty* and *information* measure can occur within a single moment in time. It is a *static* attribute of an object. Objects, standing alone in the universe, with no observer, can posses "an amount of information" in AIT. This is not the case in OCS. Rather, an observer can have uncertainty about an object in the universe at time t concerning its realization at time t+1, and that uncertainty can be resolved at time t+1 by that observer.

Consequently, in OCS, using the Shannon model, a probability distribution and its degree of inherent uncertainty can be a model of a *time transition* – and therefore form the basis for modeling dynamical systems. The algorithmic approach to measuring "degree of information" cannot provide this mechanism.