# ABOUT THE COMPLEXITY
# OF LIVING SYSTEMS MODELS

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***Abstract***
*In this paper we attempt an overview of the philosophical implications of complex systems thought, and investigate how this alternative viewpoint affects our attempts to design and utilise models for living systems. We classify the types of complex system that relate to self-organisation. The overall requirements for self-organising modeling are considered and some alternative ways of looking at some specific problems that may arise are explored. As a novelty, the paper proposes various ways of moving forward in the area of practical model design.*

## 1. Introduction

Living systems are open thermodynamic systems which are self-organizing. A living system, for the purposes of this paper, is taken to consist of components, each of which are chemical factories enclosed in a semi-permeable membrane through which energy and material is exchanged with their environment. The molecules which enter the components are transformed by chemical reactions into molecules of a different form. The *function* of a component is defined by the mass-energy transformation process it performs. The components are interconnected by the flow of mass and energy (usually in the form of macromolecules) between themselves. The interconnections of components by such flows is referred to as the *production-consumption structure* of the system. Some of the flow is used to regulate the functioning of the components. This is referred to as the controL structure of the system, that can be a part of, or completely independent from the production-consumption structure.

A *system environment* consists of the set of elements which are not part of the system but which affect the system. For living systems the environment consists of abiotic and biotic elements. The *abiotic elements* make up the *physical environment*, i.e. the source of energy and material for living systems. The physical environment can be heterogeneous and unpredictable both spatially and temporally. The *biotic environment* consists of other living systems which interact with the studied system. These interactions take many forms. Some systems can supply food from some *resources*, or can modify the physical environment in such a way as to make it more adequate.

When identifying a system and its biotic environment one runs into a difficult conceptual problem. Any system being studied is a component of another system (called the supersystem). All living systems are part of a *hierarchical* or more precisely *heterarchical structure* (see later). The problem is to choose correctly the level of a given system in the hierarchy and to differentiate between systems at the same level in hierarchical structure. The problem is not difficult when dealing at a species level in the hierarchy but it becomes quite difficult when dealing with micro or macroscopic systems (i.e. cells or ecosystems).

When an analyst decides to draw the system boundary, he must first decide which level in the hierarchy will contain his system as well as the levels which will contain the supersystem, components and subsystems. This is in effect a problem of vertical separation. Where the system boundary is drawn, depends on the degree of horizontal separation between the elements of the system compatible with the issues addressed by the analyst.

## 2. Types of complexity

Previous work has identified four classes of complexity [1], of which only the last is directly relevant to our focus here. In this more general treatment we will extend these concepts to cover high-dimensional complexity, where in the limit the system is assumed to possess infinite components. These four nested complexity types (the later including the former) are:

**Type 1: Static Complexity** - Fixed structures, frozen in time

For example the visual complexity of a computer chip or a picture. This form of complexity is studied by such techniques as Algorithmic Information Theory [2] and is also common in physics.

**Type 2: Dynamic Complexity** - Systems with time regularities

This includes such states as planetary orbits, heartbeats, seasons. They have cyclic attractors. Multiple cycles may be superimposed in highly complex systems (decomposable by such techniques as Fourier analysis). These closed systems are those conventionally studied in the sciences, where the time regularity gives the repeatability necessary for prediction, and again are equilibrium systems where initial transients have been discarded.

**Type 3: Evolving Complexity** - Open ended mutation, innovation

This mainly relates to the process of evolution in nature where a single cell gave rise to an extraordinary diversity of forms and functions. Also related are diffusion aggregration and similar branching tree structures. These are historically constrained and form ergodic or strange attractor systems. They involve searches of state space, but more importantly the creation of new areas of state space and new possibilities by the production of new components. These are open, non-equilibrium systems and can be regarded as existing on a permanent non-repeatable transient. The high-dimensionality here is embodied in the large populations typically encountered which taken together ensure evolutionary uniqueness.

**Type 4: Self-Organising Complexity** - Self-maintaining systems, aware

Operating at the edge of chaos, these systems loop back on themselves in nonlinear ways and generate the rich structure and complex mix of the above attractors. This is the advent of autopoiesis, the creation of adaptive self-stabilising organic systems that can swap between the available attractors depending upon external influences and also modify and create the attractors coevolutionarily (by learning). They differ from the purely evolving category in that state space is canalized by the self-organising nature (downward causation) of their internal emergent processes, thus possible functions are self-limiting. These systems occupy dissipative, semi-stable, far-from-equilibrium positions exhibiting the typical power law distribution of events familiar from critical systems at the phase transition, they are structurally and organisationally both open and closed, with semi-permeable material and informational membranes allowing the passage of operational triggers driving their attractor modes.

## 3. Self-organisation, complexity and order

Self-organisation imposes a set of axioms that prove different in many ways to those usually adopted in scientific work. These assumptions are common to most of the complexity specialisms, and relate to system properties that are uncontrolled, nonlinear, coevolutionary, emergent and attractor rich, as well as being heterarchical, non-equilibrium, non-standard and non-uniform. Additionally, behaviours showing unpredictability, chaotic instability, mutability and phase changes, along with inherently undefined values, self-modification, self-reproduction and fuzzy functionality. But according to other paradigm, life is a solution to the problem of maximizing energy degradation in a changing and sometimes unpredictable environment.. This goal is reflected in the species organizational goals, which are to maximize their offspring, subject to the constraint that they preserve the microenvironments of other species. Indeed, no single goal is predominant. The self-organization process optimizes between the goals of the various levels. This optimization process leads to many different solutions, hence the richness of the variety of life. *Organization* can be defined as the process by which the system reaches and maintains its optimum operating point. The term *self-organization* indicates that the changes in the system are generated from within the system.

Each solution to the problem of life can be characterized by an optimum operating point. The optimum operating point for any level in the hierarchy (that is ecosystem, species, individual) is dependant not only on environmental conditions but on conditions at other levels in the hierarchy. Thus any determination of the optimum operating point must take into account events from the perspective of all three hierarchical levels. Any attempt to discover the optimum operating point of a self-organizing system will require not only the ability to determine all of the trade-offs involved and the optimization between them, but will also require the ability to model the interaction of the system with its environment. This modeling must take into account the interactions of the supersystem and components with their environments as well.

Let now consider a system, made up of components which are interconnected by flows of mass and energy. These flows define the structure of the system. *Structural complexity* is defined as the number of interconnections between components in the system. *Functional complexity* is defined by the number of distinct functions carried out by the system. The notion of complexity is a relative one, relative to the observer who defines the system. How the observer chooses the components can radically affect the observer's perception of the complexity of the system.

*Randomness* and *order* are the antithesis of each other. If it requires much information to describe a systems structure or function, then it is said to be random. If little information is required then it is said to be ordered. Thus a system may have a complex structure (i.e. many interconnections) which is describable by a simple algorithm and hence ordered (for example a highly periodic lattice structure in a crystal would be easy to describe and at the same time complex). At one extreme a system's structure may be completely described, given one connection, and thus is ordered. In the other extreme every connection may have to be given in order to describe the structure. This latter case is that of a random structure.

One source of confusion is that the capacity of system's structure to be random increases with the number of possible interconnections and hence with the number of system components. This observation has led many people to associate increases in complexity with increases in randomness. This association is a misconception. It is the *capacity for randomness* which increases with complexity, not necessarily the actual randomness. When comparing two systems the observer must be careful to distinguish between the information needed to describe the system, which is an *absolute* (in the sense of being independent of the system's size) measure of order or randomness, and the *relative* degree to which the system has reached its maximum possible randomness. The later is a function of both the information required to describe the system and its complexity.

## 4. A holistic framework for complex self-organizing structures

The following properties are specific for most of complex systems. Not all these features need be present in all systems, but the most complex cases (self-organizing too, of course) should include them.

- **Uncontrolled** - Autonomous agents, no executive or directing node (power symmetry).
- **Nonlinear -** Outputs are not proportional to input (superposition does not hold)
- **Emergence** - Properties are not describable in part terms (meta-system transitions [3])
- **Coevolution -** Part structure correlates to an external environment (contextual fitness)
- **Attractors -** Each occupies a small area of state space (concurrent options)
- **Non-Equilibrium -** System operates far from equilibrium (dissipative).Energy flows drive the system away from equilibrium and establish semi-stable modes as dynamic attractors. This relates to metabolic self-sustaining activity which in living systems is usually called autopoiesis.

**Non-Standard** - System contains structures in space and time (heterogeneous); initially homogenous systems will develop self-organising structures dynamically.

- **Non-Uniform -** Parts are non-equivalent (different rules or local laws)
- **Phase Changes -** Edge of chaos states maintained (power law distributions of properties occurs in both space and time) .
- **Unpredictability** - Sensitivity to initial conditions (chaos)
- **Instability -** Stepped evolution or catastrophes exist (punctuated equilibria)
- **Mutability** - Random internal changes or innovations occur (dynamic state space); new configurations are possible due to part creation, destruction or modification. This relates to changes to the

structure of state space, which must be regarded as dynamic, not static and does not conserve world lines which may bifurcate and merge over time.

- **Self-Reproduction -** Ability to clone identical or edited copies (growth)
- **Self-Modification -** Ability to change connectivity at will (redesign)
- **Undefined Values -** No pre-established categorisation (constructivist semantics)
- **Fuzzy Functions -** No designed or clear functionality (probabilistic correlation)

We can summarise the structure of complex systems in an overall heterarchical view (Figure 1) where successively higher levels show a many to many (N:M) structure, as does the overall metasystem.

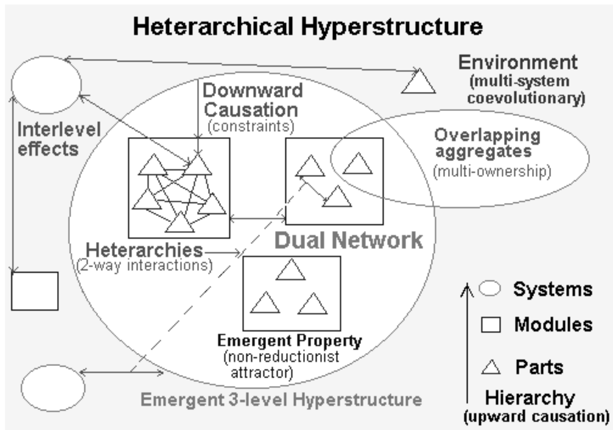


Fig. 1. A typical hyperstructure for self-organizing systems

Part interactions create emergent modules with new properties. These modules themselves interact as parts at an higher level and this process leads to the creation of an emergent *Hierarchical system* (the upward causation). The components at each level connect horizontally to form an *Heterarchy* - an evolving web like network of associations. This combination of hierarchy and heterarchy within a system is called a Dual Network by Goertzel [4]. Additionally systems can have overlapping members at each level (e.g. individuals can belong to many social groups, molecules to many substances, a situation to many models and a model to many situations). These large scale interacting emergent systems are called Hyperstructures, groups of interlaced dual networks constrained by downward causality [5]. Here we extend these ideas slightly by allowing explicit cross level interference between systems (e.g. an individual affecting another country overall, a cell affecting an external part). This extended design we call here an *Heterarchical Hyperstructure*. Given that a metasystem has such a set of structures, then the overall fitness will relate to the interdependent properties at all levels, in other words to the full contextual environment.

Now, putting some of the main points together we can arrive at a definition of what sort of theory we are proposing by using complexity thinking.

*Definition. Critically interacting components self-organize to form potentially evolving structures exhibiting a hierarchy of emergent system properties.*

The elements of this definition relate to the following:

- Critically Interacting - System is information rich, neither static nor chaotic
- Components - Modularity and autonomy of part behavior implied
- Self-Organize - Attractor structure is generated by local contextual interactions
- Potentially Evolving - Environmental variation selects and mutates attractors
- Hierarchy - Multiple levels of structure and responses appear (hyperstructure)
- Emergent System Properties - New features are evident which require a new vocabulary

**5. Self-organizing modeling requirements and solutions**

Let us look now at some goals for modeling complex structures with self-organisation:

- **Functionality**. This aspect sets the scope of our systems and should identify those features that conventional techniques cannot supply but without neglecting those currently available facilities than may so easily be lost in the change of methodology.
- **Evolution Ability.** This is the systems ability to cope with long term slow environmental change, with novel but persistent situations. Organically it implies multiple instances (or populations) of program variants. Modular crossover may be required to preserve and build up function (by parallel schema searches).
- **Development.** This implies a self-organising phenotype, with internal self-generated attractors. Based upon an internal (cellular) modular population this will be coevolutionary self-organising (similar to the brain or an ecosystem) and this relates also to contextual requirements, the ability to select appropriate forms for the local needs by using local information.
- **Learning.** Knowledge relates to dynamic memories. Operating in an environment implies a two way correlation or structural coupling, a tracking of non-stationary system perturbations in real time from both points of view. This requires evolving values or associations - an open ended, initially undirected, and self-modifiable categorisation technique (neural network style). For complex environments we also have multiple conflicting values, thus multioptimisation techniques of some kind will be required to implement choice.
- **Usability.** If the techniques developed are to become widespread, we require ease of programming, the usability of the techniques by non-specialists. This seems to require libraries of standard modules (like neurons and nuclei) together with frameworks for supplying variation and evaluation.

Anyway, if we compare the complexity of even a massive simulation to just a simple cell, which alone contains tens of thousands of varieties of molecules interacting at around a trillion reactions a second., it probably more raw computational power in the organisms inhabiting a spoonful of soil than in all of the world's computers added together. Thus we should scale our expectations accordingly and not expect our often trivial simplifications to achieve major results. But although the achievement of the above goals in a computer program context (simulation model) generates many problems, we can suggest some approaches for suitable solutions.

- **Environmental Robustness.** Robustness relates to avoiding the system disintegrating over time, and to the necessary compromises between its ability to correlate with the immediate environment yet maintain its structure as a system. If the environmental coupling is too tight the system will become unpredictable (trying to respond to too many perturbations), yet conversely if too loose the system will become unresponsive, settled into a single attractor. We thus need to either explicitly define the dimensionality of our interfaces or provide methods for this to evolve.
- **Predictability**. Humans need to be able to have confidence in a system and this concerns being able to understand and relate to the system behavior. Systems that do unpredictable things can only be allowed in situations where that is acceptable to the users, and this excludes very many social situations where conformance to norms is expected.
- **Real World.** Many real world tasks are fuzzy problems, ill-defined scenarios that relate badly to typical academic research simplifications. If we are to generate genuinely useful adaptive programs then these will need to perform in noisy and sub-optimal environments which abound in conflicting and emotional goals.
- **Performance.** The time taken to adjust to new situations will be crucial to the satisfactory performance of new organic technologies. To obtain good performance we may need to use transient (short lived) attractors due to coevolution time restraints.
- **Evaluation Function.** We need a better evaluation technique for multidimensional systems, one more in tune with how we ourselves do this in, as yet, poorly understood intuitive ways - a fast holistic mode. This evaluation needs to include multiple levels and not just the single level optimisation (internal

genetic or phenotypic) often seen, and should both take into account the contextual (associative search) nature of solutions and the multidimensional nature of rewards or needs.

- **Multiple Matching.** Parallel operation implies that more than one rule may be simultaneously active, thus a prioritisation scheme may be necessary.
- **Unknown Function.** The evolutionary stable states available to the system cannot be known in advance for unpredictable environments. We need techniques with which to constrain system functions to just those desired, to encourage appropriate emergence, and this implies that performance measures or rewards must still be specified by humans.
- **Fault Tolerance**. Provision for self-repair or redundancy may be necessary and this seems to be better included early in the design.
- **Computation.** Unlike natural systems, we need to compute self-organization (evaluating transition rules for example) and not just let it happen physically. This will have major performance implications unless we can find another way to add parallel processing power.

## 6. Conclusions

This overview has highlighted many differences between conventional modeling approaches and those derived from an life system viewpoint. Most of these differences have been poorly addressed so far, especially in combinations where epistatic interactions are important. Many current models are employed, but in general these each abstract only a few limited properties for evaluation and none come very close to natural self-organising and self-maintaining systems. We need to understand and make use of self-organisational shortcuts and especially to consider the metabolic contextual implications of situated self-organisation, concentrating less on the genetic building blocks and more on their internal interactions. The connectivity approach used in this paper is appropriate to this view. Some work has started in trying to take these issues into account [6] but a great deal still needs to be done before we are able to grow adequate and resilient adaptive programs for real-world application in unrestricted domains.

## 7. References


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