Chapter 3

The Circle That Never Ends: Can Complexity Be Made Simple?

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3.1. Introduction: The Nature of the Problem and Why It Has No Clear Solution

There is no need to try to ease into the discussion because the issue being discussed here is too involved to waste words that way. It is important to get right to the point. The starting premise is that we seek to understand the world in which we live. This leads immediately to a whole set of related premises that define the problem as being the answer to the question "how we can obtain that which we seek." It is really the question "why is it so hard to understand the world around us" that should be asked, but that is the end of the story, not the beginning. The initial premise also leads to another, related, set of premises involving the existence of that world and our ability to ever know it completely, whatever "completely" might mean in this context. This is already a large problem. Here is why. As this is being written a number of things are happening. One possibility is that the author is merely stating the obvious. If that is true then no one should have reason to question what is being written. Another possibility is that the author is treading on at least some new ground. If that is true, then it is also possible that some of this new ground contributes to the body of knowledge we have already produced about the world we seek to understand. There is the problem. If the reader did not balk at the notion that the meaning of "completely" depends on a context of some kind then the problem should be clear. The context has to either be frozen at some state of history or it changes as we go along. One might argue that the changes are so slight as to be inconsequential for a discussion of this limited duration. That argument skirts around the issue. The issue is the circularity of context dependence. Classical science and its underlying philosophy have tried very hard to eliminate this context dependency, yet these very intensely focused efforts by the best minds we have had have merely made it clearer and clearer that the problem is here to stay and must be dealt with.

It would be very pretentious to claim that large insights into how to deal with this issue are going to be presented in a review of this duration. Rather, some glimpses at the nature of the situation as this author sees it are all that can be provided. Those glimpses have a history and the author has strong prejudices about where we are in our attempts to deal with this matter. In the spirit of Karl Popper's ideas (Popper[1], Dress[2)] about the necessary subjectivity of any scientist/scholar, those prejudices need to be made clear from the onset. For that reason, what follows will be based on one person's career and that person's attempts to understand the world, in keeping with the original premise. It is important to acknowledge the roles of a number of scientific leaders in the forming of this worldview. Julian Tobias, as a neurophysiologist and as a Ph. D. thesis mentor, asked many important questions that could not be answered. Aaron Katchalsky[3] presented an attitude and approach to solving the problem of how we can hope to understand the world that was powerful and unique. His death at the hands of terrorists in June of 1972 changed both scientific and world history, in the opinion of this author. Leonardo Peusner[4-12] as a graduate student in the Harvard Biophysics Lab helped by the work of Katchalsky and his students George Oster and Alan Perelson[13] showed an extended structure to our scientific model of the physical world. Later, Eric Schneider and James Kay[14] wove this together with even more to provide a picture of the ecosystems that are entwined as life on this planet. Then early on and again and again there were the ideas of Robert Rosen. (Rosen,[15-20] Mikulecky[21]). He died not that many years ago and his family was kind enough to allow me to have some copies of his unpublished work. His ideas made it clear that there has to be a new way of looking at the *process* of knowing. That is the approach to the problem to be briefly described here. One more thing needs to be dealt with before going any further. Is this science? Is it philosophy? In the world of knowledge that can be compartmentalized they each have their place. These are the kind of questions that can only be destructive in this context. The reason should be clear after the exposition has been ended. For now it will be necessary to accept another premise: *The nature of the world out there is such that the idea that much is lost by trying to reduce it to parts is paramount. The whole is always more than, and often different from, the sum of its parts.* This is true whether we are talking about the material world or our thoughts about that world. Anyone who has trouble accepting this premise will probably find what follows difficult to accept. Please give the entire development a chance before dismissing it. That is one distinct advantage of the brevity of the presentation.

3.1.1. The human mind and the external world

What is the connection between the thoughts going on in our minds at the moment and the existence of an "objective" and "physical" world in which that mind somehow has its existence? The nature of that connection is the key to everything that follows. There would not be a notion of an external world were it not for the constant input of sensory "signals" for lack of a better word. Sensory physiology is a fascinating subject. It deals with the way these signals are able to impinge on specialized "receptors" and undergo a transduction into nerve impulses that are "all or none". The all or none concept is the finding that nerves send signals of a given magnitude and they either fire or they don't. The intensity or strength of a stimulus is encoded by having the frequency of the nerve impulses change and by having more or fewer nerves become involved.

It is worth emphasizing that this is it as far as classical ideas about sensory physiology go. There is far more unexplained about how the conscious mind forms a concept of the world from this than there are things we can explain with any assurance. Yet there is a confidence that the things we do know provide a basis for constructing a reasonably "good" picture of the external world.

It is necessary to refer the reader to other works for details (Rosen,[15,17,18,20] Mikulecky[22-25]), but the picture alluded to is called a *model* of the world if certain things are true about it. It is necessary to recognize that the mind has some system it uses to represent the external world. That system, which is called a *formal system*, comes into being as a result of sensory input of the kind just described. That is a very long, involved story. Let us recognize some relationship between things we observe changing in the external world that we *believe* to result from some cause, *causality*, the sensory data the mind receives from it, and some form of *encoding* of those signals into the formal system. This has to be true for we try to evaluate the effectiveness of all this by making inferences about changes we experience in the external world by making *inferences*, that is to say, manipulations of the formal system by the mind, and then decoding the result of these inference in a way which allows some form of comparison with what was observed in the first place. There is a mathematical way of diagramming all this that involves mappings to represent the causal event we are attempting to explain, the encoding into the formal system, the inferential manipulation of the formal system, and the decoding to the external world. When the process being diagrammed works for us we say we have a model. In mathematical terms the diagram, called the modeling relation, commutes.

Now it is possible to deal with the myth of objectivity. The word myth is carefully chosen here because it is a belief that binds together so much in our way of looking at the world. It also is chosen to suggest that there are other ways of looking at the world. It is a myth because it ignores everything discussed here to describe how we form models. This is because only the formal system is subject to rigorous rules like those provided by logic. The formal system does not provide a way to accomplish the encoding, the decoding, the choice of formal system, nor the criteria for whether the modeling relation involving all these things really works as a description of the world or not.

3.1.2. Science and the myth of objectivity

Science has been our only real hope for an "objective" model of the real world. Unfortunately, it has had less than total success even thought its success has been monumental. The reason lies in the discussion of human perception very quickly summarized here. The inbuilt need for the brain to supply so much to the raw sensory data is not capable of being overcome. The best we have been able to do is to work within a set of rather rigid rules and avoid those questions that required more freedom to explore. The result has been an explosion in the technological side of scientific thought and a withering away of any recognition of the value of keeping the philosophy up with the technology. As a result, the model science developed lost touch with the fact that it necessarily had to be encoding, using implication in a formal system, and then decoding to try to make models that worked. The criteria for what worked and what didn't became more and more pragmatic until the success was the cause of an even larger failure. The scientific model works by suppressing the fact that there is and encoding and decoding from the real world by making the formal system a substitute for the real world. This job has never been completed, but that does not weaken the *belief* that it will. The scientific model, even if unfinished, is widely, almost universally, accepted as a "largest" model; one which all other models derive from or fit into. It is only because of this that very brilliant minds could be seduced into accepting the myth of objectivity. Once the inescapable need for the encoding and decoding were forgotten, the necessary subjectivity built into the process could be ignored and finally denied.

Yet as the brain functions it clearly does not deal with raw sensory data. It processes and chooses according to what it has already learned and come to believe. The very act of trying to make objective measurements, reducing reality to numbers, abstracting severely, is the result of a very deeply entrenched belief structure. The belief structure has an inbuilt irony connected with it because it can not accept any evidence that would result in its having to be changed. Thus the quest for knowledge shuts out certain kinds of information and knowledge because it does not fit the model that has been so universally adopted. A good case can be made for supporting this. If we relax these criteria for what constitutes "scientific" information about "objective reality" there are all sorts of other belief systems that now have room to attempt to supply alternative models. The writings of skeptics about "quack" science and snake oil salesmen give all the evidence we need to know this is so. Thus we have are in a really difficult situation, there are risks to be taken or we stagnate. Notions like the idea that we have reached the "end of science" (Horgan[26]) are among the most pessimistic of these. The situation is not so grim (Mikulecky[22-25]). There are ways to proceed that do not throw the baby away with the bath water. One such approach is what will be outlined here. The approach being offered is not a replacement for the attempted largest model of classical science. That is taken as impossible from the start. Nor does it discard any of the useful achievements of classical science. What it does do is to knowingly step outside of those bounds and try to incorporate what was accomplished into a different framework that retains the knowledge that science is one of many belief structures and necessarily involves the encoding and decoding mapping from and to the real world like all other belief structures. Once this is done, there a case can be made that human minds are open to such a range of belief structures. The most obvious examples have to do with scientists who were or are also spiritual or even religious people. The previous statement assumes that religion is usually a more severe and restrictive form of spirituality. The reason for assuming this should become clear later. Among the belief structures of importance are those that have their historical roots in cultures. This is a rich source of beliefs. It is most obvious in tradition directed cultures, but certainly not restricted to them.

3.1.3. Context dependence and self reference

Words generally do not have absolute meanings. The meaning depends on their context. This is the nature of semantics. It is the difference between semantics and syntax in language that serves as an analog model (a definition of what is meant by this will be forthcoming) for the problem we are dealing with. The formalists who sought for a truly objective way of understanding were seeking the analog of a language that had no ambiguity or context dependence. The idea that this argument is being written in English illustrates this issue very well. There is an old oral joke that asks how we spell the sound "fish". The answer is ghoti. The reader can ascertain that it works. "gh" as in "tough" and so on. This type of ambiguity appears to a greater or lesser extent in all languages, but is replete in English. A language of pure syntax is not possible. The notion of language has built into it the diversity of relationships between syntax, the structure and algorithms that encode that structure, and syntax, the so-called meaning of that syntax. The latter aspect cannot be safely encoded into syntax. There is always more needed, an important part of which must be supplied by the human mind. Subjectivity really is going to be everywhere we look. It cannot be wished away. The crux of the problem has always been clear in language, but Escher did some nice things to bring it home in art. Escher's art is worth a lot of discussion because it opens the Pandora's Box of the things we learn about all this from visual sensation, but there is no space for that now. It has been discussed in this context at some length elsewhere (Hoffman[27]).
In language we have the whole set of paradoxes like the old example: "All Corinthians are liars. I am a Corinthian." There are books full of related examples. There have been attempts to model these impredicatives, one of the latest being hyperset theory (Barwise and Moss[145]). It would be a distraction at this point to examine them further. Rather, the focus of this discussion will be an exercise carried out by Robert Rosen that began in the late 1950s and has been recently become a topic of discussion due to Rosen's last two books (Rosen[19,21]). In these books the issue of self- reference and context dependence is central. A key part to the story is a paper written in 1972 (Rosen[16]). From discussion with readers of Rosen's books much is missed if the earlier paper is not also read. For that reason, the main development will be summarized here. This summary will provide the tools needed for dealing with these issues and supply an answer to the question "Why is the whole more than the sum of its parts". This answer will define another aspect of complex systems that exists side by side with their atoms and molecules. Many other definitions of complexity exist (Horgan[29], Mikulecky[22-25].)

3.2. An Introduction to Relational Systems Theory

Relational systems theory is a topic growing out of Robert Rosen's critique of classical systems theory as a part of the largest model science has created. (Rosen[18-21]). The mathematical form of the theory is a particular version of category theory that Rosen developed for this purpose. The inspiration for this radical new approach came from the Relational Biology created by Rosen's mentor, Nicholas Rashevsky[30], who has been called the father of mathematical biology. Relational Systems Theory combines a familiar form of systems representation and analysis, the use of block diagrams, with some concepts about causality taken from Aristotle.

3.2.1 Relational block diagrams

A simple representation of components to a system is the input/output block diagram. In this representation, each block represents an agent that effects a change on something, namely its *input.* The result of this interaction is some *output*. The abstract way of representing this is

$$f: \quad A \to B \tag{1}$$

where *f* is the process that takes input A into output B. Clearly B can now become the input for some other process so that we can visualize a system as a *network* of these interactions. The relational system represents a very special kind of transition this way. Rather than break everything down in the usual reductionist manner, these transitions are selected for an important distinguishing property, namely their expression of process rather than material things directly. This is best explained with an example. The system Rosen uses for an example is the *Metabolism-Repair* or [M, R] system. The process, f, in this case stands for the entire metabolism going on in an organism. This is, indeed, quite an abstraction. Clearly, the use of such a representation is meant to suppress the myriad of detail that would only serve to distract us from the more simple argument put this way. It does more because it allows processes we know are going on to be divorced from the requirement that they be fragmentable or reducible to material parts alone. In this way the existence of context dependence and self-reference is no longer a problem. That is what is gained at the expense of the reductionist focus on material parts. The idea is that if the whole is more than the sum of the parts there must be a meaningful way of representing this whole.

The transition, f, which is being called metabolism, is a mapping taking some set of metabolites, A, into some set of products, B. What are the members of A? Really everything in the organism has to be included in A, and there has to be an implicit agreement that at least some of the members of A can enter the organism from its environment. What are the members of B? Many, if not all, of the members of A since the transitions in the reduced system are all strung together in the many intricate patterns or networks that make up the organism's metabolism. It also must be true that some members of B leave the organism as products of metabolism. The usefulness of this abstract representation becomes clearer if the causal nature of the events is made clear. To do this it is necessary to consider the nature of *information* in a complex system. The usual notions of information derived for communications theory will not help. Something very different is needed.

3.2.2. Information as an interrogative. The answer to "why?"

Aristotle developed a set of causal answers to the question "why?" that opens an entirely new realm of description in systems. This set has four causes, material, efficient, formal, and final. They can be illustrated as answers to the question of causes for the existence of a structure such as a house. The answers to the question "Why is that house standing there?" are:
Material cause: The things that the house is made of, bricks mortar, wood, metal, glass, etc.
Efficient cause: That which assembled the materials into the finished house, the builders, manufacturers, etc.
Formal cause: The plans, blueprints that allowed the builder to assemble the materials into a particular form.
Final cause: The reason the house was built: To be a dwelling place.

The reductionist/mechanistic approach to systems has no place for this kind of information. It is considered irrelevant. The question answered is "How does something work. A house is actually uninteresting from this perspective since it is not a mechanism, but a mere "thing". In the case of a living organism undergoing metabolism, both questions are interesting. The mechanisms of the organism constitute its *physiology*. Physiology combines anatomy and biochemistry with other information to answer how the organism does what it does. There is no interest in why these things happen because the question is not in the realm of classical science. What needs to be recognized is that the new information introduced by answering "why?" is of a very different kind and that the consideration of this information necessarily involves us in the knowing of what causes things to happen *independent* of the way they happen. Thus the two kinds of information will always be disjoint.
There is more. The relational statement that metabolism has the representation

$$f: \quad A \to B \tag{2}$$

is a causal statement in harmony with interrogative information. It can be diagrammed

$$f: \quad \to \quad A \quad \to \quad B \tag{3}$$

where the broken arrow represents efficient cause while the solid arrow represents material cause. This gives f, metabolism, the interpretation: that which takes A to B.

3.2.3. Functional components and their central role in complex systems

In the context developed so far, the mapping, f, has a very special nature. It is a *functional component* of the system we are developing. A functional component has many interesting attributes. First of all, it exists independent of the material parts that make it possible. This idea has been so frequently misunderstood that it requires a careful discussion. Reductionism has taught us that every thing in a real system can be expressed as a collection of material parts. This is not so in the case of functional components. We only know about them because they *do something.* Looking at the parts involved does not lead us to knowing about them if they are not doing that something.

Furthermore, they only exist in a given context. "Metabolism" as discussed here has no meaning in a machine. It also would have no meaning if we had all the chemical components of the organism in jars on a lab bench. Now we have a way of dealing with context dependence in a system theoretical manner. Not only are they only defined in their context, they also are constantly contributing to that context. This is as self-referential a situation as there is. What it means is that if the context, the particular system, is destroyed or even severely altered, the context defining the functional component will no longer exist and the functional component will also disappear.

3.2.4. The answer to "Why is the whole more than the sum of its parts?"

It is the functional components of a complex system that provide and answer to that question. The semantic parallel with language is in the concept of functional component. Pull things apart as reductionism asks us to do and something essential about the system is lost. Philosophically this has revolutionary consequences. The acceptance of this idea means that one recognizes ontological status for something other than mere atoms and molecules. It says that material reality is only a *part* of that real world we are so anxious to understand. In addition to material reality there are functional components that are also essential to our understanding of any complex reality. This is Rosen's most important breakthrough. It cannot be isolated from the other concepts used to formulate this argument. The context dependence, the self-reference, and the other ideas are all part of the conceptual framework. This conceptual framework *is not* modeled after the conceptual framework of reductionism. The two do not superimpose. They stand side by side as ways of understanding. Thus there can be no largest model of reality. It takes at least these two ways of seeing the world to understand it.

3.2.5. Reductionism and Relational systems theory compared

There is more to the difference between the two approaches than those points discussed so far. They can be summarized by comparison. The comparison can be presented as a difference between two types of system representation using the modeling relation already discussed. The system that is modeled using relational systems theory will be called *complex* and the system represented by the reductionist approach will be called *simple*. There is more to this distinction and the reader is referred to Rosen's books for details.

COMPLEX	**SIMPLE**
NO LARGEST MODEL	**LARGEST MODEL**
WHOLE MORE THAN SUM OF PARTS	**WHOLE IS SUM OF PARTS**
CAUSAL RELATIONS RICH AND INTERTWINED	**CAUSAL RELATIONS DISTINCT**
GENERIC	**N0N-GENERIC**
ANALYTIC ≠SYNTHETIC	**ANALYTIC = SYNTHETIC**
NON-FRAGMENTABLE	**FRAGMENTABLE**
NON-COMPUTABLE	**COMPUTABLE**

The differences leave little room for ambiguity. Each has a meaning that involves all the others. The largest model of the reductionist approach disappears as soon as the encoding and decoding between the real world and our mind's formal system are recognized. There is a more rigorous way of expressing this idea developed in detail in Rosen's books. The whole is more than the sum of its parts because each real thing has its own semantics, its own context. This is a labile thing and can be lost or destroyed by taking the system down to its parts. There are shadows of this idea in reductionist thought that will be discussed in more detail. The entwining of the causal relations will become clear as the [M, R] system discussion is completed. Genericity is a concept Rosen develops in detail in his last book.

The distinction between analytic and synthetic models is a very technical subject. It involves the mathematics of model representation in a space. The two kinds of models are different for any model that uses direct product spaces for one and direct sum spaces for others. This concept has been used to advantage in the discussion of quantum mechanical paradoxes among other things.

Fragmentability is the aspect of systems that can be reduced to their material parts leaving recognizable material entities as the result. A system is not fragmentable if reducing it to its parts destroys something essential about that system. Since the crux of understanding a complex system had to do with identifying context dependent functional components, they are by definition, not fragmentable.

3.2.6. The functional component is not computable.

In order for the computer to do its work, it must be programmed with algorithms. Algorithms are the syntax of computation. There are no semantics. Yes, every time this comes up someone points to attempts to get computers to deal with semantics using algorithms. That is not the problem. The problem is in the context dependence and self-reference. These things are inherently not reducible to the algorithmic, syntactic form computers need in order to function. This has been an idea much discussed and to my satisfaction, has been laid to rest. Again I refer the reader to Rosen's books for a more involved technical exposition of the failures of the Church-Turing thesis. In a nutshell it claims that anything in the "real" world must be computable and this just is not so.

3.2.7. An Example: The [M,R] system and the organism/machine distinction

The beginning of relational system theory was in the use of the [M, R] system to develop a model that made a firm distinction between the concept of organism and that of machine. The difference is manifest in the causal entwinement already identified as a characteristic of complex reality that is also missing in our mechanistic reductionist models.

The representation of metabolism as a functional component establishes the lack of any one to one correspondence between metabolism and any particular model made up of interconnected chemical reactions. The concept of metabolism cannot be reduced in that way. Surely, the interconnected reactions, the diffusion processes, the other more intricate transport processes, and so much more are included in this simple representation. The idea behind relational models is to forsake the detailed physics and chemistry to recover what is lost when that detail is preserved. Hence, for the sake of a representation metabolism formally looks like $f: A \rightarrow B$.

The next step is to recognize the other functions that must also be part of an organism. These functions are necessary for the organism to do so many things that a machine cannot do. The organism adapts and learns and adjusts and even heals. No machine-like thing has these abilities. Machines can mimic them, but in a context that is incapable of uniting them all into a complex whole. The key feature that makes the organism different is that within the function called metabolism is a subset of process usually called catabolism and anabolism. Very simply these refer to synthetic and break down processes. Any chemist knows that reactions take place by one direction in the reversible process being greater in its effect than the other. When the two directions are proceeding at equal rates nothing happens and an equilibrium state has been reached. In the organism, things are much more involved. Synthesis occurs along a pathway involving one or more reactions and breakdown by an entirely different pathway. There are also network structures so that blockage in one place does not necessarily stop a crucial chemical change from occurring. This feature of the system would be a severe liability in spite of all the unique functions it provides if it were not for another self-referential aspect of the system. The functional component f itself has a source in the system. Figure 1 illustrates the causal relations that are entailed by metabolism itself and the second function, repair, symbolized by φ. The solid arrow from φ to B depicts the efficient causation that φ entails. The dotted arrow from B to f depicts the material causation resulting from the use of products of metabolism to *repair* f. Now there is both metabolism and repair, hence the name Metabolism-Repair System or [M, R] system.

The diagram is not very involved in its syntax, but its meaning, its semantics, are at the heart of what complexity theory has brought to the discussion. The transition from products of metabolism to the causal agent for metabolism embodies the answer to the question "Why is the whole more than the sum of its parts" if what we mean by parts is the usual idea of atoms and molecules. In this abstract model of the system, the functional component f has an entirely different character from the material entities symbolized by A and B. The latter are physical, material collections while the former is not capable of being reduced to the same kind of material things. It is a context dependent functional component that actually disappears when the system is reduced to its material parts.

Its mathematical character is that of a mapping between sets. The model treats this mapping and others we will see as if they had the same character as the sets. Relational models are a breakthrough in modeling for just this reason.

A note on the word "entailment" as it is used with these causal representations. We speak about entailment as the causation we are referring to in answer to questions of "why?" with regard to the existence of the entities in the system. In Figure 1 everything is entailed except the functional component φ. In this respect, what we have so far is not different from a machine. The machine lacks sufficient causal entailment to be self-contained. In order to have the system in figure 1 something must entail φ from outside the system. This will always be the case with machines. The model of the organism, however, is not complete. There is, in fact, something in the organism that entails φ, its material cause is f and its efficient cause is β as is shown in the more elaborate model in figure 2.

The idea that this may be the beginning of an infinite regression may be coming to mind at this point. If we were describing a machine with this model, such would be the case. In the organism it can be demonstrated in mathematical terms that given certain properties of the mappings we have introduced, the replication function β and the products of metabolism B are the same entity. The proof for this requires only that some of the mappings be 1:1. The one gene one enzyme relation is but one way of fulfilling this mathematical requirement with real data from the organism as we know it. The proof then really identifies the mapping from β to f as having the same nature as that from B to f yet in one case it is an efficient causation and in the other case it is a material causation. The final model is shown in figure 3. The need for an infinite regression is now gone. The organism differs from a machine in being ***closed to efficient cause***. Notice that this is a necessary but not sufficient condition. The syntax of the diagram in figure 3 is *not* a definition of organism. It could never be. Without the accompanying semantics it could represent many other things. In the context of those semantics, the diagram indeed represents the organism as a [M, R] system that is closed to efficient cause. This closure gives a formal model for Maturana and Varela's[31] concept of an autopoietic unity.

3.2.8. Relational Models of Mechanisms

Traditional science has produced a large number of models of mechanistic systems using the reliable techniques it has generated for this purpose. The use of relational models for mechanisms can be instructive but the utility of the traditional model makes this more of an exercise than anything else. Before relational modeling came on the scene, there were modeling methods for mechanistic systems that have an interesting and somewhat peculiar history. It is worthwhile to review some of that history to establish that the principles applied in the very abstract relational modeling of complex systems has certain parallels in traditional scientific modeling. This involves some ideas that never have become widely recognized. This, however, says nothing about their utility and their ability to reveal more about systems than the mainstream approach. The mainstream approach ultimately involves a largest model, namely a dynamics that comes from Newton's laws and the use of sophisticated differential and partial differential equations as equations of motion to obtain trajectories for any system, no matter how large or complicated. In recent years the ultimate has been achieved through the development of techniques to handle the most elusive of these trajectories that exhibit chaotic dynamics.

3.2.9. Newtonian dynamics is not unique; there are alternatives that yield equivalent results

An example of the Newtonian approach and its use of dynamics is the development of the trajectory of a particle. This involves quite a few assumptions as the actual particle's motion is abstractly encoded into an equation of motion. The mass of the particle is centered at point called its center of gravity. All that matters about the identity of that particle is that mass. Its motion can be deduced from its mass and location no matter what else we may know about it. Any particle with the same mass will move in the same way. This is so fundamental and so well accepted that these ideas about encoding into a formal model, stripped of everything else about the particle's identity, is taken as a description of reality by most scientists. To call it an abstraction may seem obvious to a non-scientist, but it is a description of reality in science. This is because of the utility it has provided. This is a simple example, but the caveats apply far beyond the extent to which this example suggests.

There are three Newtonian Laws of motion and they can be stated simply here for the purpose of this discussion. First, The Law of Inertia simply establishes that particles remain at rest or in motion at a constant speed unless acted upon by some external force. The second, the relation between the mass of the particle, m, the external force, F, and the resultant change in the particle's motion, the acceleration of the particle, a is the equation of motion

$$F = ma \tag{4}$$

Much of physics is devoted to a host of very useful ways of using this equation. A simple one will serve to illustrate this use will be adequate.

The third law establishes the interaction between the force being applied and the particle by requiring that the exchange of force be reciprocal, the particle acts on the body supplying the force with an equal and opposite force.

The common force acting on all particles on our planet comes from the earth itself and is called gravity. Thus all particles fall towards the earth with the same acceleration (neglecting the friction of the air) as can be nearly perfectly established in a freshman physics lab. The acceleration due to gravity, g, is therefore a constant of the motion here on earth. The equation of motion is obtained by the use of two alternate ways of expressing the acceleration mass product

$$m\frac{d^2x}{dt^2} = mg \tag{5}$$

where x represents the position of the particle on a vertical line. This equation is easily solved by integration twice and by use of the initial conditions that the initial position is x_o and the initial velocity is v_o. The resulting trajectory of the particle is

$$x = x_o + v_0 t + \frac{1}{2} g t^2 \qquad (6)$$

A different way of obtaining the same result comes from reasoning involving energy. This is a very simple example of the type of thermodynamic reasoning that will be developed in some detail shortly. By using the exchange between the kinetic energy of the particle

$$KE = \frac{1}{2} m v^2 \qquad (7)$$

and its positional or potential energy

$$PE = mgx \qquad (8)$$

Looking at the initial state where

$$PE_o = mgx_o \qquad (9)$$

and

$$KE_0 = 0 \qquad (10)$$

And any other state, the Law of Energy Conservation requires that

$$PE - PE_0 = KE - KE_0 \qquad (11)$$

Proper substitution and solving for x results in the same trajectory obtained by integrating the equations of motion.

The existence of an alternate to classical Newtonian dynamics has been known for a long time. It has not been given much significance. Even with the myriad of versions of so-called "complexity theory" (Horgan[27], Mikulecky[24,26]) there has been little discussion of the relevance of this lack of uniqueness of the seemingly largest model. The significance is more than trivial and deserves some discussion.

3.2.10. Topology, Thermodynamics and Relational Modeling

Thermodynamics is usually a significant part of every physics textbook. It was Clifford Truesdell[32] who pointed out the formal difference between thermodynamics and all of the rest of physics. Thermodynamics is different for a very important reason that gets pointed out from time to time and then forgotten. The reason for the difference is that all of the rest of physics is the study of mechanism while thermodynamics is the study of system properties ***that are independent of mechanism***. The reason that this is not as obvious as it might be is that thermodynamics has always been molded and shaped to be compatible with the study of mechanism. This attempt to force thermodynamics into the reductionist scheme has had some rather bizarre results.

Relational systems theory is also free of mechanisms and is based on a different kind of mathematics than is the traditional mechanistic approach. Mechanistic theories are centered on dynamics and make extensive use of calculus and differential equations. Much progress resulted in the past two or three decades due to the related progress in non-linear dynamics as formalism. This includes the entire field of "chaotics".

Some important progress in the theory of chaotic systems is a result of Leon Chua's[33] work on chaotic electrical networks. This is one piece of evidence of the utility of network theory in the broader study of systems.

Relational theories have a complimentary focus to that of dynamics. Rather than focusing on the details of the dynamics of the system's parts, relations between parts are the center of attention. Often, these relations entail concepts that have little apparent connection with the dynamics of the parts. In a very real way, relational thinking is an extension of the thermodynamic reasoning described above. It says little or nothing about mechanism and particle motion. Instead it looks at the system's *function*. In relational theories this can be formulated in terms of *functional components* formulated independently from the material parts of the system.

Network Thermodynamics is a transition between these extremes and has properties of both. It can give us an example of the application of dynamic systems theory to the making of models with the idea that represents a broader class of alternatives within the largest model. Other modeling methods such as cellular automata could have been chosen, but there are some features to the Network Thermodynamic formalism that allow certain points to be made during this discussion. The material aspects of the system are still the focus, but the functional aspects arise out of the *particular* organization of the *particular* system. In other words, the formalism has two distinct aspects, one constituting a general theory for formulating the thermodynamic aspects of complicated systems: (e.g., Meixner[34,35], Oster, Perelson and Katchalsky[35,13], Oster and Desoer[36], Oster and Perelson[39,40], Oster and Auslander[38,39], Perelson[42], Perelson and Oster[43], Peusner[4-12], Mikulecky and Sauer[46], Mikulecky[47]) the other a technique for modeling very complicated particular physical systems: (e.g., Blackwell[48], Breedveldt[49], Gebben[50], Karnopp and Rosenburg[51,52], Koenig, Tokad, and Kesevan[53], MacFarlane[54], Rideout[55], Roe[56], Thoma[57]).

It is in this latter aspect that its role as a facilitator for computer applications arises: (e.g., Wyatt[58], Wyatt, Mikulecky and DeSimone[59], Mikulecky[60-65,47], Mikulecky, Huf and Thomas[66], Minz, Thomas, and Mikulecky[67,68], Peusner, Mikulecky, Caplan and Bunow[69], Oken, Thomas and Mikulecky[70], Seither, Trent, Mikulecky, Rape, and Goldman[71,72], Seither, Hearne, Trent, Mikulecky, and Goldman[73], Talley, Ornato and Clarke[74], Thakker, Wood, and Mikulecky[75], Thakker and Mikulecky[76], Walz[77], Walz, Caplan, Scriven, and Mikulecky[78], White[79,80], White and Mikulecky[81], Cable, Feher, and Briggs[82], Feher[83], Feher, Fullmer, and Wasserman[84], Fidelman and Mierson[85], Mierson and Fidelman[86], Fidelman and Mikulecky[87,88], Cruziat and Thomas[89], Goldstein and Rypins[90], Horno, Gonzalez-Fernandez, Hayas and Gonzalez-Caballero[91,92], Huf and Howell[93], Huf and Mikulecky[94,95], May and Mikulecky[96,97], Mikulecky and Thellier[98], Prideaux[99]). Both aspects of Network Thermodynamics bring in topology as a way of encoding the *organization* of the system along with its dynamics.

The application of Network Thermodynamics to chemistry has been mainly in the area of modeling chemical kinetics and the modeling of large chemical networks. This is because the problems that motivated its development were from biology. The modeling of chemical reaction networks is special because of the early onset of non-linearity in the equations. Recently, the usefulness of topological reasoning has become much more widely recognized in chemistry (Mikulecky[64]).

The second law of thermodynamics has been proved in a number of different ways, but the most elegant from a mathematical standpoint is the proof Caratheodry devised after Max Born lamented to him about the “roughness” of the Carnot Cycle proofs used before that. Caratheodry’s proof is a purely topological argument resting on one piece of experimental reality, namely the irreversibility of real processes (Mikulecky[47]).

Topology and mechanism free reasoning are paired in both Network Thermodynamics and in the kind of relational model devised to distinguish organism from mechanism. The idea that being closed to efficient cause is paramount is a completely mechanism free concept. The introduction of functional components allows us to even discuss process in a manner not dependent on the identification of the specific mechanisms entailed in those processes. If one considers how much scientific effort goes into trying to tie down illusive mechanisms, the impact of this should not be lost.

There is more to this comparison of the Newtonian Dynamics approach with other approaches. Modern non-linear dynamics started with topological reasoning as well. Poincare had the insight to realize that the requirement for complete solutions to nonlinear differential equations had to be sacrificed if any progress with real systems was to be made (Abraham and Shaw[100-104]). He introduced techniques that are now standard and have developed at a very significant pace in the area of chaotic dynamics. Phase plane diagrams, attractors, repellers, strange attractors, basins of attraction, etc. are part of a *qualitative* approach that is at the heart of this exciting field.

3.2.11. The mathematics of science or is all mathematics scientific?

The formal system into which real systems are encoded in the modeling relation is usually, as we have seen in this very brief discussion, some form of mathematics. Is all mathematics useful for this purpose? Once one understands that the candidate for largest model in the form of Newtonian dynamics has alternatives, the answer has to be in the affirmative. Yet most of the mathematical repertoire of the science curriculum has traditionally centered on the calculus and the solution of differential equations of motion to obtain trajectories. This is not the mathematics of science, but the mathematics of reductionist science. Even within reductionist science, topology and group theory have proven to be useful formal tools. Unfortunately, there has been much done using these and other mathematical tools that have not been universally understood or discussed because of the influence of reductionism on the curriculum used to prepare scientists mathematically. The usual practice of requiring calculus and differential equations clearly relates to the reason why these areas were developed in the first place. Newtonian dynamics and the calculus are all part of the same formal system and it is that formal system that obscured the fact that encoding was involved at all. The consequences of this are far from trivial. It is possible to become a highly respected and well- known contributor to the scientific literature without ever going outside the bounds of the traditional mathematical tools. The dominance of reductionism has more consequences than this, but in the context of this discussion the situation being described is as self-referential as it is disappointing to anyone trying to go beyond the bounds of the reductionist paradigm. It is not really possible to describe systems holistically in that context.

There are many possible applications of mathematics outside the Newtonian dynamic framework that can be very helpful in making the problems that seemed to be outside the realm of science more accessible to a disciplined, rigorous approach. Even areas of reductionist science have been explored using other areas of mathematics for formalisms into which the real world can be encoded. The mathematical approach Rosen adapted for his study of the [M, R] system is a version of category theory (Arbib and Manes[105]). Finally, topology and relational mathematics has been successful used to reformulate Newtonian dynamics (Abraham and Marsden[106] and a significant portion of the formal aspects of chemistry (Oster and Perelson[40], Perelson and Oster[43],).

3.2.12. The parallels between vector calculus and topology

In their development of Network Thermodynamics, Oster, Perelson and Katchalsky[13] pointed out the usefulness of a number of additional mathematical tools in scientific modeling. Their history is interesting, but two earlier works mentioned stand out in particular. First the work of Kron demonstrates that all the partial differential equations of mathematical physics could be arrived at using network representations (a list of his works is referenced in their paper). The second is the work of Branin (1966) who carefully established homology between the vector calculus and topology.

3.3. The Structure of Network Thermodynamics as Formalism

Network Thermodynamics combines topology with analytical mathematics to model large complicated systems in a way which demonstrates the role of organization in dynamic models.

Network thermodynamics as developed By Oster, Perelson and Katchalsky[13] also used a representation for systems called bond graphs (Karnopp, and Rosenburg[51,52]) which has become used by a number of scientists and engineers to deal with large complicated systems. Another version of Network Thermodynamics developed by Peusner[4-12] uses the representation well known in electrical circuit theory and is amenable to computer simulation using circuit simulation programs such as SPICE as general purpose simulators (Mikulecky[47,108]).

What Network Thermodynamics and physical systems theory have done is to demonstrate that the mathematical formalism that makes electrical circuit theory possible is applicable to all physical systems. The Newtonian approach can be replaced by energy conservation as shown in the simple example of a particle's trajectory. It is also possible to treat large complicated systems using network theory to obtain equations of motion and trajectories. The systems would be very cumbersome if treated as traditional boundary value problems even thought that is what they are. Here is where topology plays the key role. Instead of setting up a large number of differential equations and struggling to make sure they are a system by matching a large number of boundary conditions, the combination of constitutive equations for the circuit elements and topology for keeping their connections straight is a real savings in effort. It also supplies a lot of mathematical structure that would never have been seen to apply in the boundary value approach.

3.3.1. Network Thermodynamic Modeling is analogous to modeling electric circuits.

What makes the analog models possible is the recognition of two important ideas. The first is that in electrical circuit theory the circuit's topology or schematic is independent of what electrical circuit elements are used in the circuit. The two kinds of information can then be combined to arrive at a traditional systems description in terms of differential equations of motion and their resulting trajectories for the system. The second is that the circuit elements need not be electrical at all because of another key set of analogies. The pivotal topological unifier is in still another pair of mathematical relations the first of which has to do with conservation and the second with closure. These were introduced some time ago by Kirchhoff and are called Kirchhoff's laws. It is easy to show that even though these arise from conservation of charge and the closure of electrical potentials in closed loops, they apply to all physical systems because of the other conservation laws such as conservation of mass for mass flow and chemical reactions and conservation of volume in watery solutions and other fluid systems.

This section will be devoted to summarizing the basic formal aspects of Network Thermodynamics. First its detailed character as a modeling tool will be developed then the more general theoretical aspects will be outlined.

3.3.2. The Network Thermodynamic model of a system

The network thermodynamic model of a system has two complimentary but distinct contributions. Their explicit formal independence and strict complimentarity are one of the most striking aspects of the formalism. These two intertwined facets are the *constitutive laws for the network elements* and the *network topology*. The use of constitutive laws for the network elements is the way the physical character of each network element is represented abstractly. It is a common feature of the material world. The topology or connected pattern of these elements in a network is an independent reality about the system. The same topology can be realized for an infinite variety of collections of network elements. The same collection of network elements can be rearranged into a number of different topologies. The former fact is at the root of *Tellegen's Theorem* (Tellegen[109], Penfield, Spence and Duinker[41]), which is one of the major contributions of network theory to general systems theory.

3.3.3. Characterizing the networks using an abstraction of the network elements

The elements of any physical network can, with certain extensions for the non-linear systems, be classified from the relations between a simple set of observables, namely and *effort, e, across the element* and *flow, f, through the element* along with their time integrals called *momentum, p,* and *charge, q (*Oster, Perelson and Katchalsky[13,35]). These observables are associated with the networks elements in a manner that abstracts the effect of each of them as members of the system. The effort is some potential-like quantity's *difference across* the element while flow is movement of some entity *through* the element. The electrical manifestation of this general class of observables is the familiar voltage and current. These observables will be used to characterize the network elements uniquely. The analog between these observables and the electrical network allows the entire body of electrical network theory to be applied more generally.

One thing that has to be clear is the fact that since thermodynamics is, by its very nature, true for all mechanisms it alone can do nothing to help us distinguish between realizable mechanisms. It does, on the other hand, serve us very well in distinguishing between realizable mechanisms and unrealizable mechanisms such as perpetual motion machines.

A second import point is that even though it is independent of mechanism, it can be used to derive mechanistic models when used in the proper context. A primitive example of this is the use of energy conservation (The First Law of Thermodynamics) to derive the particle trajectory mentioned earlier.

Thermodynamic reasoning is complimentary to mechanistic reasoning and there is an asymmetry in their relationship. We can describe a mechanism thermodynamically and thereby determine its realizability, but we cannot discern mechanism from thermodynamic descriptions alone (Callen[110], Hatsapoulos and Keenan[111], Prigogine and Defay[112], Tisza[113], Truesdell[114]). The early application of thermodynamic reasoning to non-equilibrium systems was in non-equilibrium thermodynamics (deGroot and Mazur[115], Fitts[116], Prigogine[117]). This formalism was introduced into biology as a phenomenological approach to these complicated systems (Katchalsky and Curran[3], Caplan and Essig[118])

3.3.4. The nature of the analog models that constitute Network Thermodynamics

The generality of Network Thermodynamics as modeling tool and theoretical formalism for all of physical systems theory is well established through the modeling relation. (Rosen[18,19]) The modeling relation can be used to define *analog* models. If the same Formal System is able to form commuting models for two or more Natural Systems, these systems are said to be analogs of each other and each could serve as a formal system for all the others. This is the case among physical systems with electrical networks being the representative Natural System. The fact that electrical networks were the first to be formalized extensively has made electrical network theory the source of models for a broader class of physical systems. To exemplify this analogy it is instructive to look at the constitutive relations in more detail.

3.3.5. The constitutive laws for all physical systems are analogous to the constitutive laws for electrical networks or can be constructed as the models for electronic elements are

There are four possible binary relations among the network observables after the time integrals used to define charge and momentum are included (Oster, Perelson and Katchalsky[35], Peusner[12], Mikulecky[47]). Charge is the time integral of flow (or flow is a rate of change of charge) and the momentum is a time integral of effort. There are four distinct general network elements, each deriving their name from their electrical prototype.

RESISTANCE relates effort to flow.
CAPACITANCE relates charge to effort.
INDUCTANCE relates momentum to flow.
MEMRISTANCE relates charge to momentum.

Each of these network elements has its own unique interpretation with respect to how it handles energy. Foremost is the resistor, which is an idealization having the purpose to embody all the *dissipation* that goes on in a locality of the network element. Dissipation is the crux of irreversibility and the second law of thermodynamics. Systems in stationary states away from equilibrium are governed *totally* by resistance. Transient behavior comes from the time derivatives introduced by capacitance and inductance. In the Langrangian formulation of networks, it is the resistance that represents the non-conservative aspects of the system (Mikulecky, Weigand and Shiner[119]). Capacitance is a form of energy storage without dissipation and is, therefore, also an idealization. The capacitor is a good model of a reversible isolated system in its behavior as it approaches its equilibrium potential. Since there is always dissipation in real processes, reality requires that there also be a resistor somewhere in series with the capacitor in order for the mathematics to be a faithful description of the system's trajectory. It is the capacitors that provide the dynamics in most models. This is a bit counterintuitive, since it is in equilibrium thermodynamics that these reversible (dissipation-less) energy transfers arise. Inductors are the idealized inertial elements and occur mainly in mechanics. The isomorphism between the differential equations for harmonic oscillators and LRC circuits has often been made. In the case of a weight bobbing up and down on a spring fastened to a stationary object at its other end, the elastic spring is a capacitor, friction is the resistor, and the inertial force is the inductor. These seemingly simple analogical identifications link any physical system to the body of formal power resting in electrical network theory. This has been proven beyond a doubt to be a very significant formalism by its results, the myriad of achievements of modern electronics. This leaves the fourth element, the memristor. It also has analog physical realizations but they are rare (Chua[120]). So far, in all the applications encountered it has not been needed.

3.3.6. The resistance as a general systems element

Ohm's law is the binary relation between effort (voltage) and current (flow) in electrical networks. This *defining constitutive relation, $e = ir$* defines the resistance as a simple proportion between effort and flow in linear elements. The effort, e, is actually a *difference* between the two electrical potentials *across* the element, $e = v_1 - v_2$, where v_1 and v_2 are the electrical potentials at each end of the element. The current, i, is the flow of charge *through* the element.
Fick's law does the same for diffusion or mass transport in physical systems. The flow through the element, j, is, as in the resistor, proportional to the potential difference, Δc, across the element, which in this case is a concentration difference In this case the

element may represent a membrane between two solutions or any other two regions separated by a diffusion barrier. The concentration difference, Δc, is the *analog* of the voltage and is the specific manifestation of the effort in this case. The mass flow, j, analogs the current and is the manifestation of flow in this specific case. Fick's law is

$$j = D\,\Delta c \tag{12}$$

where D is the *diffusion coefficient* of the flowing substance in the media making up the membrane or whatever space the diffusion traverses. As an analog to Ohm's law, Fick's Law can be rearranged to the form

$$\Delta c = j\,(\frac{1}{D}) \tag{13}$$

showing that (1/D) is the analog of the resistance in the electrical case and is a specific manifestation of the generalized resistance. In other words, D is a *conductance* and if Ohm's law is rearranged,

$$f = le \tag{14}$$

where the electrical conductance, $l = (1/r)$, is an analog of D in Fick's Law.
Poiseulle's Law describes bulk hydraulic flow of volume through a pipe,

$$Q = L_p \Delta p \tag{15}$$

where Q is the flow of volume through the pipe, p is the hydrostatic pressure and its difference across the pipe analogs the effort, and L_p, is the *hydraulic conductivity*. A trivial analog also can me made for chemical reactions, but they, in general, present a special problem which must be developed with more care.

3.3.7. The capacitance as a general systems element

Electrical capacitance, C, has both a static and a dynamic manifestation. In the static case it is the following relation between charge on the capacitor, q, and voltage across it, v:

$$C = \frac{q}{v} \tag{16}$$

To convert this to the dynamic form, the equation is rewritten as

$$q = vC \tag{17}$$

and then differentiated with respect to time:

$$I = C\,\frac{dv}{dt} \tag{18}$$

Hence, in networks where the dynamics are relevant, the capacitor relates flow to rate of change of effort.

The analogies developed among the different physical systems with respect to resistance are, in fact, true for all of network theory so that electrical network theory can be used as the prototype for all physical systems. To demonstrate this, consider, for example, some compartment of volume V. In it are n moles of some substance. Then, by definition, the concentration, c, of that substance in that compartment is

$$c = \frac{n}{V} \tag{19}$$

This can be rewritten as

$$n = Vc \tag{20}$$

which is analogous to the static definition of electrical capacitance if the amount, n, is analogous to charge, the concentration, c, is analogous to voltage, v, and the volume, V, is analogous to capacitance C. Taking derivatives with respect to time yields,

$$j = V\,\frac{dc}{dt} \tag{21}$$

which is completely analogous to the dynamic equation for electrical capacitance. This "osmotic" capacitance is applicable to any situation where a process changes the concentration in a compartment such as diffusion or chemical reaction.

A similar set of analogies hold for the pressure driven bulk flow either due to configuration of the system such as in the case of a U-tube or due to the compliance of the liquid. Either will result in some relationship between the system's volume, V, and its hydrostatic pressure, p.

$$V = \gamma\ p \tag{22}$$

where γ is the analog of the electrical or the generalized capacitance. In dynamic form, after differentiation with respect to time,

$$Q = \gamma\,\frac{dp}{dt} \tag{23}$$

Similar analogies exist for the inductance and memristance, but since they have so far fewer occurrences in systems of interest, they will not be discussed here.

It is important to note that it is the capacitor that introduces a time derivative into a network's mathematical description and thereby introduces *dynamics*. Purely resistive networks have a totally algebraic mathematical description and thereby describe stationary states away from equilibrium. Another way of saying this is that capacitors only are necessary during the transient phase of any simulation. When the system reaches a stationary state, they can be taken out of the model without consequence.
The *voltage or effort source* may be seen as the limiting case of an capacitor with infinite (arbitrarily large) capacitance. In this case the effort approaches a constant value arbitrarily closely as its rate of change approaches zero.

3.3.8. The topology of a network

The collection of all the network elements cannot, by itself, constitute a network. There has to be something equally real to make it a functioning whole. The particular manner in which the elements are "wired together" must also be specified in some rigorous manner. This pattern of connections is the network's topology. Each element has two ends, which was the basis for speaking of flow and effort as being observed through and across the element. Every element has to either be connected at its ends to another element or to "ground". Ground is simply some reference potential, usually arbitrarily set to zero. These terms and concepts are obviously motivated by the structure of electrical networks and the analogy caries over to all physical systems. This is merely a way of saying that all physical systems can all be reticulated into a set of elements connected together. The basis for this statement has very deep roots in the structure of the underlying mathematics and has been though roughly established by Kron (Oster, Perelson and Katchalsky[19,35] and Branin[107]).

3.3.9. The formal description of a network.

In its most abstract form, a network consists of a set of nodes or verticies that are the connection points for the elements. This can be symbolized by the set of all vertices, *V*, such that any individual vertex, v_i , where i = 1, 2, …, k and k is the total number of nodes, is a member of that set.

$$v_i \in V \tag{24}$$

The *network* is then a *relation* on the Cartesian Product, N = V x V = {all pairs (v_r, v_s) | r,s = 1,2…k}. In other words, any given network is a subset of N, the largest possible network with k nodes. This is an extremely abstract and formal approach to a very practical subject, but it is done to motivate the connection between network theory and the important relational mathematics generated by category theory (Rosen[17-19]). The relation that defines the network as a subset of N is the association of the pairs of nodes with the ends of elements in the network of interest. Once this association is made, each surviving pair of nodes defines a *link* or *edge* of the network. If each branch were to be represented by a line, the resulting structure would be a *linear graph* and if the order of the nodes in each pair were to be taken into account, the lines would have arrows from the first node to the second or the reverse. This latter case constitutes a *directed graph* or *digraph*. The linear graph or the digraph corresponding to a network is an embodiment of that network's *topology* or *connectedness.*

For practical purposes, the constitutive relations describing the network elements and the topology of the network can be formalized independently and then combined to furnish a *solution* to the network. A network has a solution when all the observables in that network can be specified. The nature of the solution is a system trajectory. The formulation of the network is a set of coupled differential equations of motion.

Drawing the branches in the form of a connected set of lines or arrows with dots representing the nodes at the ends of the branches where the connections occur can diagram the formal representation of a network. This diagram is an application of graph theory, which is a part of topology.

By numbering the nodes and branches, another, equivalent representation is possible. This labeling system allows the construction of an *incidence matrix*, A. The incidence matrix has its columns numbered by the node numbers and its rows numbered by the branch numbers and the resulting matrix becomes an array of zeros and ones. In a linear (non-directed) graph only positive ones would appear and then only at the node/branch combinations where the node and branch were incident upon each other (the node is the end of that branch.) In a digraph a convention is adopted so that if the branch is incident on a node leaving the node it gets the opposite algebraic sign from the branch incident on a node entering that node. Using this definition, the linear graph representing the network's topology can be used to create the incidence matrix which is, in general a b x k array of zeros and plus or minus ones, where b is the number of branches and k the number of nodes. In turn, any incidence matrix has a unique realization in a linear graph. In other words they each can be used to generate the other.

The incidence matrix, by its nature, is a computational tool. This is easily demonstrated by the application of it as a representation of the networks topology to implement Kirchhoff's Laws[121]. These laws reflect two fundamental constraints on physical systems. They are consistent with the analogs developed among the different processes in that they apply equally well to all of them. The generalized version of the laws that had first been developed for electronic networks is:

Kirchhoff's Flow Law (KCL for Kirchoff's Current law) states that at any node in the network all flows sum to zero given that incoming flows have the opposite sign from outgoing flows. This is a simple statement of conservation for the flowing quantity (mass, charge, volume in an incompressible fluid, etc.). Using a vector of flows, $\mathbf{F} = (f_1, f_2, \ldots, f_b)$ which lists the flow through each branch *in the identical order as they were listed in the incidence matrix*, KCL can be written in the form

$$\mathbf{AF} = 0 \qquad (25)$$

This matrix-vector product produces a list if the algebraic sums of flows at each node and nulls it. Clearly this can be easily programmed as a constraint in any program designed for solving these networks.

Kirchhoff's Effort Law (KVL for Kirchhoff's Voltage Law) states that around any closed loop in the network the algebraic sum of all efforts must be zero. This follows trivially from the fact that efforts are differences in potentials at the nodes across the branches so that there is one positive and one negative contribution from each node in the sum. It is equivalent to saying that if one made a hiking loop in the mountains, and stopped a number of times, the differences in elevations between the starting-stopping point and the rest stops will sum to zero unless there has been an earthquake. This also has a convenient, practical representation in terms of a vector of efforts, **E** = (e_1, e_2, …, e_b), a vector of node potentials **v** = (v_1, v_2, …, v_b) and the transpose of the incidence matrix **A***,

$$(\mathbf{A}^*)\mathbf{v} = \mathbf{E} \tag{26}$$

This also is a useful representation of an important network property in a way that is readily utilized on the computer.

3.3.10. The formal solution of a linear resistive network

The real strength of network thermodynamics as a modeling tool is in its ability to simulate large, non-linear, difficult interacting physical systems. The following formal solution applies only to linear resistive networks and is here for mainly didactic purposes. Capacitors introduce network dynamics and lead to a set of state-space equations or equations of motion familiar to anyone who has studied linear dynamic systems. Non-linear systems require numerical work on a computer and are best handled by making the electrical analog and then simulating it on a strong circuit simulator such as SPICE. (Wyatt, Mikulecky and De Simone[59], Mikulecky[47], Mikulecky and Thomas[122], Tuinenga[123])

Using KCL,

$$\mathbf{AF} = 0 \tag{27}$$

And the defining constitutive law for **F** is

$$\mathbf{F} = \mathbf{L}(\mathbf{E} - \mathbf{X}) + \mathbf{J} \tag{28}$$

where L is a diagonal matrix with the branch conductances on its diagonal, **E** is a vector of efforts across the resistors (conductances) in each branch, **X** is a vector of the force sources in each branch (in series with the conductors) and **J** is the vector of flow sources in parallel with each branch.
Using KCL,

$$\mathbf{AF} = \mathbf{ALE} - \mathbf{ALX} + \mathbf{AJ} = 0 \tag{29}$$

or, using the relation between **v** and **E** above, rearranging,

$$(\mathbf{ALA}^*)\mathbf{v} = \mathbf{ALx} - \mathbf{AJ} \tag{30}$$

Defining an *admittance matrix*, **Λ = (ALA*),** which has an inverse, Λ^{-1}, yields the solution to the network in terms of the vector of node potentials, **v**

$$\mathbf{v} = \Lambda^{-1}\mathbf{ALx} - \Lambda^{-1}\mathbf{AJ} \tag{31}$$

When time derivatives are introduced by capacitances (or, more rarely, inductances which are inertial in character in mechanical systems) this becomes a version of the well-known *state vector* equations or equations of motion which are the substance of dynamics (DeRusso, Roy, and Close[124]). What is *special* about formulating the equations of motion in this manner is that the relationship between the constitutive relations describing the network elements and the topology of the network are explicitly identifiable via their mathematical encodings in the diagonal conductance matrix (and diagonal capacitance and inductance matrices in the more general case) and the incidence matrix respectively.
The formal solution for a non-linear network involves replacing the linear constitutive laws by non-linear versions, so that the generalization of Ohm's law relating effort to flow takes the form(s)

$$\mathbf{E} = \mathbf{R}(\mathbf{F}) \tag{32}$$

and

$$\mathbf{F} = \mathbf{L}(\mathbf{E}) \tag{33}$$

where the conductance function, **L**, and the resistance function, **R**, are now non-linear functions of the flow and effort respectively (Chua[125], Chua and Lin[126]). These non-linear constitutive relations still occur for each network element separately, but nevertheless they clearly complicate the mathematics significantly. The extreme case is the simple non-linear circuit containing one non-linear element (resistor) among a group of standard linear elements (resistors, capacitors and an inductor) that has been studied in detail because of its chaotic behavior it has been described using the *double scroll attractor* (Chua and Madan[32]). The study of large non-linear networks has been furthered most effectively in the electronics field and it should be no surprise that some of the most useful tools for dealing with these networks were developed in that field.

3.3.11. The use of multiports for coupled processes: the entry to biological applications

The multiport or n-port is a device which models coupled flows (Chua and Lam[127], Mikulecky[128]). Once again, for didactic purposes, the simpler linear case will be demonstrated. The more useful (and complicated) non-linear cases can easily be simulated on the computer, using SPICE as described later in this review.

Linear Multiports are based on non-equilibrium thermodynamics

The linear 2-port is simply a model of the phenomenological equations of linear non-equilibrium thermodynamics. Its general structure is shown in figure 4. If we replace symbol J for the flows with the symbol F and likewise identify the thermodynamic forces (Xs) with efforts (Es) in the conductance format it has its mathematical representation as

$$\mathbf{F}_1 = \mathbf{L}_{11}\mathbf{E}_1 + \mathbf{L}_{12}\mathbf{E}_2$$
$$\mathbf{F}_2 = \mathbf{L}_{21}\mathbf{E}_1 + \mathbf{L}_{22}\mathbf{E}_2 \qquad (34)$$

or in the resistance format as

$$\mathbf{E}_1 = \mathbf{R}_{11}\mathbf{F}_1 + \mathbf{R}_{12}\mathbf{F}_2$$
$$\mathbf{E}_2 = \mathbf{R}_{21}\mathbf{F}_1 + \mathbf{R}_{22}\mathbf{E}_2 \qquad (35)$$

This 2-port is easily generalized to an n-port device. Figure 4 shows a visualization of the 2-port as a network element. By rearranging the equations as follows

$$\mathbf{E}_1 = (\mathbf{R}_{11} - \mathbf{R}_{12}) + \mathbf{R}_{12}(\mathbf{F}_1 + \mathbf{F}_2)$$
$$\mathbf{E}_2 = \mathbf{R}_{21}\mathbf{F}_1 + (\mathbf{R}_{22} - \mathbf{R}_{21})\mathbf{F}_2 \qquad (36)$$

The network can be redrawn with the coupled flows "injected" into the resistors $\mathbf{R}_{12}$ **and** $\mathbf{R}_{21}$. This produces a purely resistive network, but it is disjoint. If we recognize the Onsager reciprocal relation[128,129],

$$\mathbf{R}_{12} = \mathbf{R}_{21} \qquad (37)$$

The network becomes connected as shown in figure5. *There is a unique relation between the Onsager reciprocity condition and the topological connectedness of the network representation!*

This ability to reticulate the linear 2-port into simple resitors does not exist for non-linear 2-ports. This is the heart of why the reductionist approach was so healthy while science had to rely mainly on linear models. The reduction ceases to be possible in non-linear systems. This is of importance in another, fundamental way in the network formulation of equilibrium thermodynamics as well.

For Biology, the n-port is the thermodynamic answer to the energetics of the biomass on the planet. It is the only way we have to model the marvelous processes that create structure and organization while the second law of thermodynamics collects it price – the continual production of entropy. In n-port coupled systems, any number of ports may be involved with the creation of negative entropy as long as the *overall net* entropy production is positive.

Because of the nature of physical systems, it is only the resistor elements that require multiport representation. Capacitances are modeled in the same manner when these devices are used. Linear multiport networks generate the same type of linear equations of motion as in the simpler case and present little further complication. It is easy to show that the algebraic structure of a network's solution remains invariant as the network is changed from a simple 1-port network to an n-port network. Furthermore, the steady state involves only resistive n-ports and sources.

A specific example of a 2-port network element would be the reaction-diffusion 2-port. In this case, substances A and B are diffusing across a region that also catalyzes their chemical interconversion. Diffusion is analoged by simple resistors while the first order reaction kinetics are analoged by controlled sources in the form of *unistors (*Mason and Zimmerman[132]). Unistors are special network elements that rectify flow completely and have a constitutive law that is of the form

$$\mathbf{F} = \mathbf{k}\mathbf{v}_1 \tag{38}$$

where $\mathbf{k}$, and $\mathbf{v_1}$ is the potential at one end of the unistor.
Another example is the *convection – diffusion* 2-port that is used to represent an aspect of biological membrane transport. Its constitutive equations are (Kedem and Katchalsky[133-135])

$$\mathbf{Q} = \mathbf{L_p}(\Delta\mathbf{P} - \sigma\,\Delta\,\Pi)$$

$$\mathbf{F} = \omega\mathbf{RT}\Delta\mathbf{c} + <\mathbf{c}> (1-\sigma)\mathbf{Q} \tag{39a,b}$$

where $\mathbf{Q}$ is the bulk flow , $\mathbf{F}$ is the diffusion flow, $\Delta\mathbf{P}$ is the hydrostatic pressure difference across the membrane, $\Delta\Pi$ is the osmotic pressure difference across the membrane, $\mathbf{L_p}$ is the hydraulic conductivity, $\omega\mathbf{RT}$ is the permeability of the membrane to the diffusing substance, Δc is the concentration difference of the diffusing substance across the membrane, $<\mathbf{c}>$ is the average of the concentrations in the baths bathing the membrane, and σ is the reflection coefficient for the diffusing substance in this membrane

3.4. Simulation of Non-Linear Networks On Spice

The mathematical difficulties encountered when the network elements are non-linear are most easily handled by computer simulation on SPICE. The simple examples given above should not be misinterpreted. They are demonstrations of a method that is more useful as the problem gets more difficult. The ultimate difficulty is not in the size of the network but in the presence of non-linearity in the constitutive relations of one or more elements. As in any other method for dealing with such difficulties, the computer and numerical analysis come to the fore. In the case of network thermodynamic models, there is a distinct advantage.
As the explosion in chip technology became a central theme in electronics, a method for the design and simulation of these elaborate, large non-linear networks had to be developed. The development of simulators is a saga worthy of review in its own right. For our purposes it is sufficient to relate that one outcome of this enormous effort has become well entrenched and almost a standard as such programs evolved. The circuit simulator *SPICE* (*S*imulation *P*rogram with *I*ntegrated *C*ircuit *E*mphasis) developed in the EE and Computer Sciences department at UC Berkeley is now used extensively in the industry (Chua and Lin[126], Tuinenga[123]). Its use as a general physical systems simulator

was developed by Thomas and Mikulecky[129] after they did some initial simulation work on the French program AZTEC. Over the years, a myriad of biochemical, physiological, and pharmacological systems were successfully simulated using this program.

The linear elements are analoged as resistors and capacitors as described above. The non-linear elements are represented by devices called *controlled sources* that allow the simulation of non-linear resistors and capacitors as well as the more complicated chemical reactions that are often very non-linear. In biochemistry, special kinds of non-linearity arise in enzyme-catalyzed reactions. This involves the Michaelis-Menten class of reaction mechanisms and the various forms of inhibition interactions they entail.

3.4.1. Simulation of chemical reaction networks

The simulation of chemical reaction networks on SPICE has had significant applications. The methodology is rather simple (Wyatt[58], Wyatt, Mikulecky and De Simone[59]). The most extensive of these applications is in the area of biochemical/pharmacological networks (Thakker, Wood, and Mikulecky[75], Thakker and Mikulecky[76], Walz, Caplan, Scriven, and Mikulecky[78]). Let's look at an example from biology. This particular system, folate metabolism, is an important one in the synthesis of nucleic acids on the way to making building blocks for DNA and RNA. For that reason it plays an important role in cancer chemotherapy. (Seither, Trent, Mikulecky, Rape, and Goldman[71,72], Seither, Hearne, Trent, Mikulecky, and Goldman[73], White[79,80], White and Mikulecky[81]). The particular biological flavor of this problem manifests itself in many ways, not the least of which is the nonlinearity of the kinetics for each reaction step and the many interactions between constituent chemical entities in the form of various types of inhibition (competitive, non-competitive, etc.)

Included in some of these studies is the parallel capacity to simulate the distribution and transfer of materials in compartmental systems, a specific application of reaction diffusion systems theory and/or batch processing theory.

3.4.2. Simulation of mass transport in compartamental systems and bulk flow

As demonstrated in the works cited in the previous section, simulations combining non-linear reaction networks with mass transport introduce no additional complication. The use of *multiports* enables the simultaneous simulation of different, interacting processes.

The use of multiports allows chemical reaction and mass transport to be coupled with bulk flow. In chemical operations this may be a very helpful feature.

3.4.3. Network thermodynamics contributions to theory: some fundamentals

As late as 1973 Callen[136] wrote:

"In short my thesis is that *thermodynamics is the study of those properties of macroscopic matter which follow from the symmetry properties of physical laws, mediated through the statistics of large systems.*

Two considerations contribute at least to the *a-priori* plausibility of this construction. Firstly, it rationalizes the peculiar nonmetrical quality of thermodynamics."

Since that time there have been successful attempts to rectify the situation. Among them is Network Thermodynamics and Thermostatics that have made this rationalization totally unnecessary. In particular, using this approach, the assumption Callen makes that these things must come about through statistics is shown to be totally uncalled for.

3.4.4. The Canonical Representation of linear non-equilibrium systems, the metric structure of thermodynamics, and the energetic analysis of coupled systems.

We now know that network thermodynamics is the canonical representation of linear non-equilibrium thermodynamic systems. The Onsager/Prigogine representation is a reductionist partial description. When the more holistic approach of Network Thermodynamics extends the non-equilibrium thermodynamic formalism, all steady state systems are complete circuits with resistors AND sources. The formalism Onsager and Prigogine developed only studies the resistors. That practice caused Tellegen's Theorem and the accompanying mathematical structure of the state space to be missed. This is profound! Onsager's formulation of non-equilibrium thermodynamics was found lacking by Callen, Tisza and others due to its affine coordinates. Peusner showed that *every* Onsager system has a unique embedding in an orthogonal, higher dimensional system and that those coordinates were precisely those dictated by the network representation! In other words, the simple 2-port networks representing the linear two-force/two-flow systems are more than just a convenient representation. The three resistors in this "T" network identify a set of orthogonal coordinates into which every affine Onsager system can be imbedded. This provides a *common metric* for measuring distance in entropy/energy spaces as far from equilibrium as we like (Mikulecky[47]).

The geometry and the energetics are tightly coupled here. Kedem and Caplan[137] showed that there was a transformation of variables in any Onsager system (linear phenomenological description) that yields an important geometric invariant, q, the *degree of coupling* (Caplan and Essig[118]). For any linear 2-port

$$q = \frac{L_{12}}{(L_{11}L_{22})^{1/2}} = -\frac{R_{12}}{(R_{11}R_{22})^{1/2}} \qquad (40)$$

The sign of q depends on whether the coupled process are effectively moving in the same (positive) or opposing (negative) directions. Using the constraint of positive definiteness on the coefficient matrix (the **L** matrix) imposed by the second law of thermodynamics, the value of q is also restricted

$$-1 \leq q \leq 1.$$

The maximum efficiency of any linear energy conversion device is a function of q alone:

$$Maxumum\,Efficiency = \frac{q^2}{(1-(1-q^2)^{1/2})^2} \tag{41}$$

In the embedding described above, q is the parameter that determines the angle of "tilt" in order for the affine Onsager coordinates to fall onto the orthogonal set of planes making up the canonical orthogonal coordinate system. Thus q is indeed an important invariant of the system in this way also.

3.4.5. Tellegen's Theorem and The Onsager Reciprocal Relations (ORR)

Lars Onsager[130,131] won the Nobel Prize a while back in part for his work on non-equilibrium thermodynamics and in particular, his proof of the "reciprocal relations". His proof used statistical physics in the domain of *fluctuations* around equilibrium. The decay of those fluctuations was described by the linear phenomenological laws and the use of statistical physics was thought necessary to obtain the proof. Peusner[11,12] was able to accomplish the proof much more simply, accurately and directly using Tellegen's Theorem which is a result at the most basic level in network thermodynamics. He systematically matched elements of his proof with that of Onsager to show that all the molecular statistics could have been ignored since the
necessary and sufficient elements of the proof are topological properties that Onsager had implicitly assumed and which were in no way dependent on molecular statistics.
Tellegen's theorem is, in its simplest form, a statement of power conservation in a complete network. To be complete, the network must have energizing sources or charged capacitors to make it work. The simplest possible example is the series circuit containing a single resistor and a constant source of current or voltage. Tellegen's Theorem is then

$$J_s X_s + J_r X_r = 0 \tag{42}$$

For any network the vector of flows and the vector of efforts (forces) are orthogonal:

$$\mathbf{JX} = 0 \tag{43}$$

In other words, the power dissipated by the resistor and the power supplied by the source are equal and by using the appropriate sign convention of opposite sign so they sum to zero. This looks trivial, but it has a very general form for any network that can be derived using Kirchhoff's laws and the network topology, *independent of the identity of the circuit elements.* For that reason, the *quasi power theorem* is easily proved as well.
In this version there are two different networks (starred and unstarred) with exactly the same topology. If we take a vector of flows from one and a vector of forces (efforts) from the other, these vectors will always be orthogonal!

$$\mathbf{J\,X^*} = \mathbf{J^*\,X} = 0 \tag{44}$$

These can either be two different networks or the same network at different times. Using this Onsager's reciprocity theorem can be proven without the use of statistical thermodynamics or near equilibrium assumptions other than that the system is still in the linear domain.

It had been know by experimentalists for about a century, that the reciprocal relations (in particular Saxen's relations (Miller[138,139]) held in non-equilibrium situations far enough from the domain of Onsager's proof (fluctuations around equilibrium) to make his proof seem odd, at best. Peusner's topological proof not only did not need or use statistical physics, but also was valid *everywhere* in the linear domain far beyond the domain of Onsager's attempt. Thus it was in complete harmony with the myriad of experimental results.

Furthermore there is an intimate link between the ORR and the ability to have a simple, topologically connected network element representing any linear non-equilibrium (Onsager) system. In fact this is the canonical representation that yields the metric in entropy or energy space. This is but one more demonstration that topological (non-mechanistic) considerations underlie many fundamental relations in these systems.

3.5. RELATIONAL NETWORKS AND BEYOND

3.5.1. A message from network theory

Network Thermodynamics is presented here as a transition between the classical mechanistic approach to systems theory and a more modern relational approach. It is used as a very special example of the class of modeling techniques that can be incorporated into the largest model of dynamic systems theory. Another approach might be cellular automata, for example. The Network Thermodynamic approach illustrates the way organization in the form of network topology plays a key role in the formalism that leads to a set of equations of motion and resulting trajectories. Network thermodynamics, as it has been applied in biology, has been intended to focus on the complexity of these systems. Yet it uses standard mechanistic observables and results from a reductionist approach to synthesize elaborate models of these complicated interacting systems. Complexity theory means many things to many people (Horgan[29], Mikulecky[24,26]), but one common thread is that it is a reaction to the effect of *reductionism* on modern scientific thinking and practice. Complexity theory uniformly deals with a statement that has become one of its central dogmas:

"The whole is more than the sum of its parts"

To use the approach to complexity put forth by Robert Rosen[18-21] (see also Mikulecky[24,26]), the question "Why is the whole greater than the sum of its parts?" needs to be answered. Its answer is deep and certainly not obvious. It has had partial answers from the growing number of scientists showing an interest in complexity research. Those partial answers all involve the idea that "emergent" properties arise in complex systems and that these properties somehow arise out of the system's material parts, but do not map to them in any clear way. Had these emergent properties been easily predicted from the parts of the whole, the notion of emergence would never have arisen. Instead, these emergent properties often either involve surprise or a suspicion of error or both. It is possible to illustrate a simple version of this with multi-port networks. One clear example is in network thermodynamic models of salt and water transport through epithelial membranes such as those that line the gut, kidney tubules, and gall bladder.

3.5.2. An "emergent" property of the 2-port current divider

Emergence is a central concept in complexity theory. There are at least two distinct kinds of emergence that can be identified and their difference is important. There is emergence in the real world whenever evolution or developmental processes occur. In the modeling of the real world, emergence is a phenomenon of the modeling process itself when unexpected results come from a model. The case considered here will deal with emergence as a model is changed from a simple set of 1-ports to 2-ports.

The model was created to show how sodium transporting epithelial membranes can transport large volumes of isotonic fluid across the wall of structures such as the gall bladder, the small intestines, and kidney tubules. This model involves a series/parallel combination of convection-diffusion 2-ports and a source representing the active transport pump across the basolateral cell membranes. The tissue as a whole is capable of transporting isotonic sodium chloride from the lumen to the blood across the tissue even if no gradients exist. The new, *emergent*, property involved is *the 2-port current divider principle*. In the case of simple 1-ports, a current source feeds into the node connecting a pair of resistors. The current splits up according to the resistances relative values. In the 2-port case, if the input is solute flow and the two 2-port elements are not identical, volume will flow across the system from zero potential to zero potential at the other end. This new property of the 2-port system is indeed an emergent property and tells us that the world of physical multi-port devices is as capable of producing interesting new phenomena, as was the case when the multi-port was introduced in electronics. Some variations on this theme involve a biological fuel cell and other interesting devices (Mikulecky[47]).

This emergent property was shown to both reinterpret established results and to predict new findings in the epithelial tissues that had been the motivation for the analysis (Fidelman and Mikulecky[88], Mikulecky[47,108,122,128]) of a network model for coupled solute and volume flow through an epithelium.

What these theoretical developments show, in a consistent way, is that even in physical systems that are derivable from the Newtonian Paradigm's "largest model" there is much of the overall system's properties that is lost unless a more holistic approach is used. Network Thermodynamics, by including the energizing sources along with the dissipators uses the entire system in its considerations. By so doing, the formalism reveals some of the most interesting properties a system may possess. In *every* case these properties arise *independent of* the basic physics in the constitutive relations. These properties are primitive *relational* properties and provide a basis for understanding the more abstract relational approaches in complex system theory.

This brief sketch of the network thermodynamic formalism should make clear the reason why scientists who believe that the study of the world can only be done by certain "safe" methods, namely the repertoire of methods included in classical dynamic systems theory.

The very mathematical training of most scientists speaks to the idea directly. Newton's calculus and its application to systems of differential equations has become the mainstay of scientific mathematics. Topology, Category Theory, and related "relational" mathematics are not familiar tools. This is causes a mind set and an unconscious belief in the scientific method as we know it that is strong enough to make us feel comfortable that the answers we seek will come from learning to use this mathematics and this method as well as we can. This limits the universe of discourse. Complexity science emerged because this universe of discourse was too small. Too many interesting questions fall outside of it.

Network Thermodynamics took a new approach to systems theory and demonstrated that we were missing some really important ideas. It is now time to incorporate Network Thermodynamics into systems theory as a way of dealing with mechanism within the broader scope of relational systems theory.

3.5.3. The use of relational systems theory in chemistry and biology: past, present, and future

When Kedem and Katchalsky[140,141] introduced non-equilibrium thermodynamics into biology in the late 1950's they were among a handful of others who saw the need for this formalism in the study of living systems. Prior to this, equilibrium thermodynamics had some usefulness in trying to understand the energetics of living systems, but since their homeostatic nature made them much more like stationary states away from equilibrium, the theories for equilibrium were not very helpful.

Linear non-equilibrium thermodynamics itself had more of an impact in the realm of rethinking the conceptual framework for asking and answering energetic questions about living systems. From the very beginning of this rethinking it was clear to people like Katchalsky and Prigogine that the real breakthroughs would come when the formalism could be extended to nonlinear systems. This may be part of the reason why the conceptual insights gained using linear non-equilibrium thermodynamics never became as widely understood as they needed to be. As a result much time and energy goes into our modern discussions of complex systems in order to fill in gaps in the overall picture.

What were some of the conceptual changes that resulted from the non-equilibrium formalism? First and foremost, the entire set of rich conclusions about the nature of coupled systems and the appropriateness of this model for understanding how life was a direct result of the requirements imposed by the second law of thermodynamics. The highly interactive nature of living systems arises because of circumstances that require a response to a steady input of solar energy. The way the system responded to this energy throughput was by organizing better and better ways to keep this energy from becoming accumulated heat. Through coupled processes, the heat flow was channeled through biomass and a cooling effect was achieved which was part of the stabilization of the atmosphere. That atmosphere in turn provided a milieu that could sustain life.

A second realm of advances came for more technical reasons. Kedem and Katchalsky chose the realm of membrane transport for their first round of applications and, in particular, began by showing that without modeling the osmotic transient with a set of coupled equations, there was no way to fit the experimental curve describing the swelling and shrinking back to normal volume of a cell exposed to a slightly hypotonic solution due to *permeable* solutes. The role of the coupling coefficient, the reflection coefficient, in explaining some of the more difficult osmotic effects in tissue then followed from that. Today, this information has become an integral part of every physiology text that deals with osmosis in a careful way.

A very useful result was in the application of *Curie's Principle* to the "relational" explanation for active transport. The simplest representation of active transport using the linear non-equilibrium formalism is as follows:

The linear domain of the system can be modeled phenomenologically by the equations,

$$J_r = L_{rr} A + \mathbf{L_{rs}} \bullet \Delta\boldsymbol{\mu}_\mathbf{s}$$
$$\mathbf{J_s} = \mathbf{L}_{sr} A + L_{ss} \Delta\boldsymbol{\mu}_\mathbf{s} \qquad (45)$$

where J_r is the flow (rate) of the ATPase reaction, A is the reaction affinity, $\Delta\boldsymbol{\mu}_\mathbf{s}$ is the chemical potential difference across the membrane for the solute being actively transported, $\mathbf{J_s}$ is the solute flow, and the L's are the coupling coefficients. The bold symbols are vectors having both magnitude and direction, while the others are scalars. The chemical reaction flow and force are scalars while the mass transport flow of solute through the membrane and its thermodynamic driving force, the chemical potential difference across the membrane, are vectors. In order for the equations to make mathematical and physical sense, the coupling coefficients must be vectors as well. The dot in $\mathbf{L_{rs}} \bullet \Delta\boldsymbol{\mu}_\mathbf{s}$ is the vector dot product that results in a scalar. These "vectorial" coupling coefficients represent something about the structure of the space in which all this is happening. Either that space is asymmetrical so the coupling coefficient may be non- zero or the space is symmetrical and there is no coupling between mass flow and reaction, or, in other words, no active transport.

Curie's original statement could be translated and paraphrased as "Without the breaking of symmetry, nothing happens." It has a rigorous physical manifestation in non-equilibrium thermodynamics in that flows and forces of different tensorial character do not couple in an isotropic space (deGroot and Mazur[115], p. 31-33). In this case we can apply it by stating that the necessary and sufficient condition for active transport is that a chemical reaction takes place in an asymmetric space. The link between the two versions of Curie's principle was solidified by DeSimone and Caplan[142,143] although it's meaning was understood by Kedem and Katchalsky in the late 1950's. To this day it has had little impact on biologists. Reductionism has dictated a need to see a molecular mechanism to "explain" the phenomenon before they believe that they understand it.

Let us consider a relatively simple man-made experimental system to see what one mechanistic realization of this general principle can look like. Consider two cases of the system consisting of an enzyme imbedded in a membrane separating two solutions. In case a the enzyme is evenly distributed throughout the membrane while in case b it is only in one half. If the enzyme catalyzes the reaction A → B and each of the two solutions contains equal concentrations of A and B such that the ratio of concentrations is not the equilibrium ratio, the membrane bound enzyme will catalyze the reaction as A diffuses to enzyme sites in the membrane and B diffuses away. In the symmetric case, the diffusion paths are equal from either bathing solution so that the concentrations of A and B on both sides remain equal to each other even as the concentration of A diminishes and that of B is increased.

In the asymmetric case, the diffusion path through the membrane is much greater on one side than it is on the other. In that case the conversion of A to B one side will lag that on the other side and a gradient of A in one direction and B in the other will be created. Hence a gradient can be created *iff the reaction is in an asymmetric space.* (The same effect could be achieved by distributing the enzyme evenly throughout the membrane and shrinking the pores on one side). A close examination of every known scheme for active transport, either in theoretical models or in experiments obeys this symmetry/asymmetry principle.

This example shows more than an application of the non-equilibrium thermodynamic formalism. It shows the alternative way of approaching modeling in systems. It demonstrates that this type model can lead to principles which determine the conditions for important processes like active transport to exist. Yet, due to its non-mechanistic, phenomenological character, it does not get the status of an "explanation" among biologists. The new relational biology (Rosen[15-19]) develops this line of thinking further and points the way to a way of understanding the complexity of living systems as distinct from the simple mechanisms that have given a shadow of their magnificent reality.

Complexity theory teaches that real systems have other descriptions that are equally valid along with the classical, reductionist analysis. Network thermodynamics allows us to see some concrete example of what this means. By unifying the non-mechanistic thinking characteristic of thermodynamic reasoning with specific mechanistic realizations of very complicated systems it allows us to make the necessary transition from formalisms centered on mechanism to the complimentary formalisms which forsake that mechanistic detail for a way of understanding self-referential context dependent relationships which are at the heart of the real system. Network thermodynamics along with all the other mechanistic tools used in complexity research can never go beyond the scope of the largest model of reductionism, the dynamic system.

This introduction to the formal aspects of Network Thermodynamics has given a few examples of ways in which understanding of systems can be enhanced using Network Thermodynamics as an example of combining some non-mechanistic ideas with specific mechanistic models. The use of Network Thermodynamics was deliberate, but other ways of combining these two distinct ways of looking at systems are now well known in complexity research. What is almost universally ignored is that all these mechanistic approaches do not really deal with system complexity, rather they are a way of handling complication.

3.5.4. Conclusion: There is no conclusion

Network Thermodynamics has been demonstrated to furnish a list of parts that can be combined using specific topologies to model the mechanistic aspects of the organism. There is no limit to the size or level of complication of the system that this formalism can handle at the level of this mechanistic modeling. This is not enough.

Parts plus topology are not an organism

Have the necessary parts and topological schemes been discovered to construct or fabricate a mechanistic model of the organism? The Network Thermodynamic modeling formalism provides one way of seeing the role of organization in determining specific functional mechanisms. The metabolism of the organism in the relational systems theory formalism contains the following processes:

Diffusion
Electrical events
Bulk flow
Chemical reactions

Included in chemical reactions are the code carrying reaction processes involving DNA and RNA leading to protein synthesis and, in particular, the synthesis of the very protein enzymes that allow the DNA and RNA to be of any use at all.

This should be all that is necessary. But each network type listed here has its own character. The network formalism provides a common mathematical formalism to solve the problem of turning the network into a dynamic system of the traditional kind. The analogy between this formalism and the particle dynamics example given earlier is striking.

The use of n-ports allows larger networks combing all four of these physical processes into a larger, more complete mechanistic model. Different topological arrangements of a myriad of parts assembled into n-ports yields the many functional mechanisms in the organism.

The topology of bulk flow networks corresponds to the network of duct, blood vessels, cell membranes, etc that act as pathways for this flow. Electrical events are associated with neural networks, cell membranes, etc. Diffusion is organized into intricate networks by the sophisticated compartmentalization due to cellular structure and the organelles in the cells.

The chemistry is a world of its own yet linked to these other networks via n-ports that reflect the need for reactants and products to diffuse or be carried by bulk flow as well as the electrochemistry associated with charged molecules. The chemical events themselves are organized into elaborate networks of reactions. It would seem that, in principle at least, there are enough tools and parts and organizational schemes in this mechanistic shadow of the real organism to put everything together and create a model of the organism.

This is *not* enough. The functional components are so abstract and also so basic to the need for the closure of efficient cause that the system does not lend itself to "reverse engineering". In other words, understand physiology is not adequate if what is desired is an understanding of how the organism can be fabricated.

This has been known for a long time and has been simply stated. The Cell Theory has observed that cells always come from other cells. More recent acknowledgements of this idea coined the term "autopoiesis" (Maturana and Varela[31]).

These concepts are difficult for science to deal with because the quest for knowledge drives investigation with a belief in the possibility of finding answers to all well posed questions. The issue then may be in the posing of the question (Mikulecky[24]). A study such as this one that suggests that the synthesis of a cell is beyond the scope of the reductionist's mechanistic formalism is certainly open to question at this point in history.

There is an interesting and completely linked parallel between this question and that of the computability of complex systems beyond their mechanistic shadows. In both cases last resort answers to the evidence that there are real limits revolve around a hope that someday a point will be reached where the apparent obstacles to understanding will be overcome by the advancement of our knowledge through investigation. One can speculate that the same attitude must have been present when perpetual motion machines were the objective of the scientific quest. Thermodynamics put that idea to rest once and for all. Relational systems theory has provided another, related non-mechanistic formalism to shed light on still one more aspect of complex reality. The context dependence and self-reference inherent in all real systems make the use of this formalism necessary if an understand of why the mechanistic approach has failed to go beyond its self imposed limits is to be understood in context. Only by moving to a level of abstraction that divorces the parts and their topology from the observed action of the context dependent functional components as was done using the [M, R] systems and the relational formalism can the question of why organisms are different from machines and why they can not be constructed from mechanistic models can be answered.

This does not parallel the situation that occurred with perpetual motion machines in every way. In that case the synthesis of the desired mechanism was proven to be impossible. In the case of the organism, the system exists in the real world, but the ability to fabricate it is demonstrated to be outside the realm of mechanistic models. This does not mean that organisms cannot be constructed. It directs attention to the need for a new paradigm for fabrication that is not based on reverse engineering and mechanistic models. The relational model having given the insight that the desired system must be closed to efficient cause also falls short of the mark when we ask how this can be synthesized. It was formulated to answer the question "why?" rather than "how?". The use of entailment in answering the why question does show another insight. The question becomes one of transferring entailment from the creator of the system to the system itself. This concept seems entirely outside the present body of our knowledge. More is needed. In fact, the key to the fabrication problem is missing.

The self –referential circle is endless it seems. Hundreds of years of successful scientific inquiry has produced a technological world worth the awe it engenders. Even though it has not been mentioned specifically here, this, of course, includes quantum mechanics. Our quest for understanding of the universe in the large and the sub-atomic world in the small grows by opening new questions rather than by bringing and end.

Finally, the acknowledgement of the subjective aspects of our perception and formation of the models we use to view the real world makes it possible to reach a new level of understanding about the quest for knowledge. It enables us to step outside of the bounds traditional science has constructed in its attempts to eliminate this subjectivity and to view reality in a fresh way that encompasses the old and the new. The modeling relation applies to science as a world model as it does to all models our minds construct. In particular, the kind of abstraction used in constructing the [M, R] systems model can be applied to the modeling relation itself. The making of models of the modeling process is certainly context dependent as well as self-referential.

Where does this all lead? Once science is seen as a world model or belief structure using the inbuilt subjectivity of the modeling relation, the practice of imposing limits on models of reality and conforming to its largest model is open to scrutiny just like any other belief structure. The comparison of science with other belief structures becomes an obvious next step (Kercel and Mikulecky[144]).

Is this not what complex reality demands for its understanding? The definition of "complex" that lies behind all the concepts discussed here is that complex reality demands that there can be no largest model. Instead there must be a multitude of models corresponding to the multitude of distinct ways for interacting with the system. "Distinct" as used in this context means that the models resulting from different ways of interacting with the system cannot be derived from each other. The number of ways of interacting with a system as intricate as the human mind and its interacting with other minds as well as with the material aspects of complex reality suggests that the number of models needed is indeed infinite.

The circle is indeed endless and the conclusion is the beginning. Each new understanding changes the context of the system in a self-referential way so that what was known is now different and this necessitates a new model to incorporate this. At this point it seems best to allow the cycle of knowing to go on without trying to elaborate further. This is the best that can be done from this perspective at the moment.

3.6. References

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Figure Captions

Figure 1: The primitive Metabolism-Repair system. Solid arrows depict efficient causation and dotted arrows depict material causation. The functional components f and φ effect the material changes from A to B and from B to f.
Figure 2: Repair is entailed by replication, another functional component.
Figure 3: The relational diagram that is part of the way an organism is distinguished from a machine. The entailment is complete from within. It is closed to efficient cause. The syntax of the diagram is only part of the model. Some very sophisticated syntax *must* accompany it to make the model complete. Thus the requirement of the modeling relation to have semantics supplied to a purely formal system has been met. In the context of that semantics, the diagram represents an organism.
Figure 4. A linear 2-port network element.
Figure 5: The linear resistive 2 port is a simple resistive circuit.

Figure 1

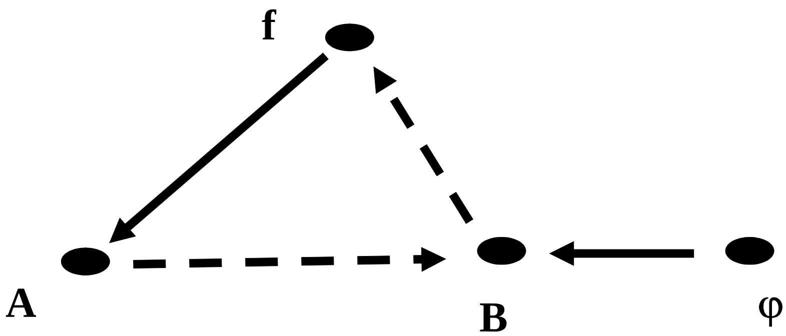

Figure 2

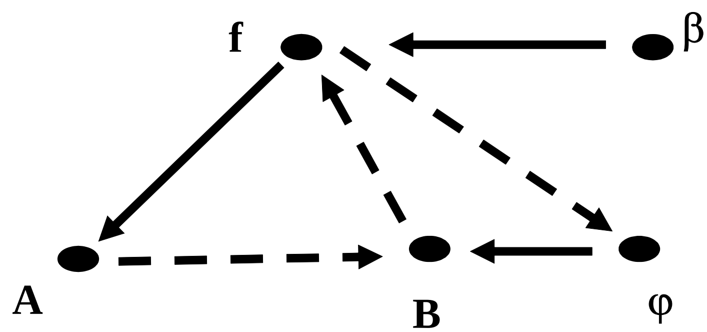

Figure 3

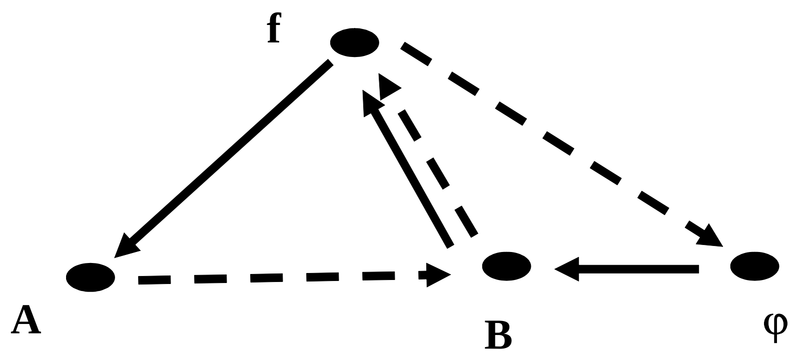

Figure 4

Figure 5