SANDIA REPORT

SAND2018-11859
Unlimited Release
Printed October 2018

Complexity and Simplicity: Putting Complexity Science in Perspective

Mark Ackermann, Nancy K. Hayden and Wendell Jones

Prepared by

Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Issued by Sandia National Laboratories, operated for the United States Department of Energy by National Technology and Engineering Solutions of Sandia, LLC.

Printed in the United States of America. This report has been reproduced directly from the best available copy.

Available to DOE and DOE contractors from
U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831

Telephone: (865) 576-8401
Facsimile: (865) 576-5728
E-Mail: reports@osti.gov
Online ordering: http://www.osti.gov/scitech

Available to the public from
U.S. Department of Commerce
National Technical Information Service
5301 Shawnee Rd
Alexandria, VA 22312

Telephone: (800) 553-6847
Facsimile: (703) 605-6900
E-Mail: orders@ntis.gov
Online order: https://classic.ntis.gov/help/order-methods/

SAND2018-11859
Printed October 2018
Unlimited Release

Complexity and Simplicity: Putting Complexity Science in Perspective

Mark Ackermann
Systems Analysis/Decisions Support Group

Nancy K. Hayden and Wendell Jones
Strategic Futures & Policy Analysis

Sandia National Laboratories
P. O. Box 5800
Albuquerque, New Mexico 87185-MS0150

Abstract

As technical systems and social problems in modern society become ever more complex, many organizations are turning to what is commonly termed *complexity science* to find solutions. The problem many organizations face is that they frequently have no clear idea what they are trying to accomplish, no in-depth understanding of the nature, size and dimension of their problem, and only a limited understanding of what theoretical approaches and off-the-shelf analysis tools exist or are applicable to their particular problem. This paper examines the larger topic of complexity science, providing insight, and helping to place its promises in perspective.

This page is intentionally left blank

TABLE OF CONTENTS

FIGURES

TABLES

EXECUTIVE SUMMARY

The topic of complexity science seems to be pervasive across academia, within government organizations and throughout much of corporate America. Complexity is not entirely new, having been studied, talked about, and in some cases, applied for many years. Once again, the topic has gained in popularity. It is not clear if this interest represents a true complexity renaissance, or is another example of the hype cycle [1]. While growing interest over the past three decades has helped to encourage the development of new models and tools, it has also driven sometimes unrealistic expectations for what complexity science can and cannot deliver.

Various organizations turn to complexity science hoping that the concept will hold something special for the challenges they face, often without being able to articulate precisely what they mean and what answers they hope to find. They have limited understanding of what complexity science is, what particular problem they are trying to solve, and what tools and theoretical frameworks might be applicable. Such endeavors have no viable path to a successful conclusion.

If applied properly—with a clear understanding of the problem at hand and realistic expectations regarding outcomes and solutions—the loose collection of topics collectively known as *complexity* s*cience*, can produce useful results. Examples of successful application of complexity science are available in the literature [2]. When used incorrectly or without a clear understanding of what one is trying to accomplish, attempts to apply some random technique from the complexity toolbox can lead to disaster, disappointment or confusion. The underlying problem is that complexity science is itself, complicated and ambiguous [3]. It is not a rigorous, well-developed scientific discipline and there are almost as many understandings of what complexity science is—and is not—as there are people trying to use it.

This paper attempts to take a systematic view of complexity science to put it into context and to give those—both experienced and inexperienced— useful insights and a place to start their exploration of a problem that has proven unyielding to traditional approaches. At its heart, one will see that complexity requires and results in simplicity, and that far from being the antithesis of reductionism, complexity actually *requires* reductionism, and the two approaches complement one another.

This page is intentionally left blank

NOMENCLATURE

EOLSS	Encyclopedia of Life Support Systems
GE	General Electric
IEEE	Institute of Electrical and Electronics Engineers
IISA	Information, Intelligence, Systems and Applications
LED	Light-emitting Diode
MIT	Massachusetts Institute of Technology
SCRM	Supply Chain Risk Management
Sunset technology	To be in the process of becoming obsolete
TSP	Traveling Salesman Problem
Wicked problem	A problem that is difficult or impossible to solve because of incomplete, contradictory, and changing requirements that are often difficult to recognize.

This page is intentionally left blank

1. BACKGROUND

Within some academic circles, complexity science is currently a very active area of research. What is known today as complexity science has emerged over the course of approximately 75 years, yet has theoretical roots that go back much further. The current interest in complexity science appears to have started in the mid-1990s with what some authors describe as, "the complexity turn" [4]. The most likely cause of the increased interest over the past quarter century, was the availability of low-cost, high-performance computers that made it possible for individual researchers to access and process large data sets, and to apply newer modeling and simulation techniques.

Traditional science has almost exclusively sought understanding through simplification of complex problems. This is often referred to as reductionism, or the reductionist approach [5]. The idea is to isolate key components of a system, reducing it to its most simple and basic elements. By understanding how each individual part of a system behaves, it is possible to understand relatively simple systems and physical processes. The key measures of any scientific endeavor are repeatability and the ability to predict outcomes from known input conditions [6-8]. If one cannot predict an outcome, then the underlying science is not well understood.

> "*…there is no big picture…just a lot of little pictures. Reduce everything to its most elemental form, molecules, and then, you know what it all means*."
>
> Quote from actor David Ogden Stiers, playing the character Dr. Sid Kullenbeck in the 1985 Universal Pictures movie, Creator [9].

Figure 1. David Ogden Stiers Playing the Character of Dr. Sid Kullenbeck

Complex problems are large and have many components that are highly interdependent and interconnected [10]. They exhibit significant nonlinearities and have what appear to be unexpected behaviors, all making it difficult to assess cause and effect relationships and to reliably predict outcomes. Complexity science attempts to address such problems by taking a holistic view, considering the specific problem and its environment as an interconnected system. The key thought is that it is not possible to understand all the workings of the world through a reductionist approach. One of the main benefits of the holistic view of a problem is that new behaviors are observed (or emerge) that were not evident when examining individual components in isolation. The classic example of emergent behavior is exhibited by a flock of birds in flight [11].

Complexity science is not a magic bullet. While it has a number of rather impressive success stories, existing tools and theories are not always the easiest approach to solving a complex problem. It deals with problems that are intermediate in scale between small systems where individual components can be completely modeled, and enormous problems, where an entire population is understood in statistical terms, but the behavior of individual components cannot be determined [12]. However, even when taking a holistic look at intermediate scale problems, one finds that the strategy employed is to simplify the system to the point where understanding of specific behaviors or trends can be achieved. Most real systems are too complex to model in detail, so new modeling approaches are pursued where many parameters are either held constant, or ignored, and only a few—thought to be the most important—are addressed in detail. This is an inherently reductionist simplification, but the new models and modeling approaches are still beyond the realm of what could be understood using strict, closed-form mathematical physics relying on linear dependencies. No matter how complex the problem, the ultimate goal is to simplify it sufficiently so that a human can understand the basic workings and use this knowledge to inform decisions and choices. To be successful, complexity science requires simplicity.

2. HISTORICAL DEVELOPMENT OF COMPLEXITY SCIENCE

A brief review of literature shows the use of the term *complexity,* becoming more prominent in the 1990s with significant numbers of publications from the year 2000 onward [13]. The existing body of work that most would consider to be the foundations of complexity science began to evolve in the 1940s with the introduction of General Systems Theory and Cybernetics [14]. This was followed in the 1950s with the development of Dynamics Systems Theory and the first attempt to pull together such work under the umbrella of Complexity Science. During the 1960s, Fractal Geometry was developed, along with an initial theory of Self-Organization and the introduction of Agent-based Modeling. The 1970s saw the introduction of modern Chaos Theory and the theory of Autopoietic and Adaptive social systems. During the 1980s, new research focused on the concept of Emergence and the tools of Multi-agent Modeling, while the 1990s saw modification of systems dynamics theories into an understanding of Dynamics in Systems.

While networked social systems were known—even if not well understood since antiquity—the rise of the modern internet furthered development of the New Science of Networks in the early 2000s. Some of these developments represent the introduction of new theoretical frameworks while others resulted from the development of new tools to understand existing problems, leading to new capabilities and eventually to new theories. The chronological development of some of the relevant theories is depicted in Figure 2.

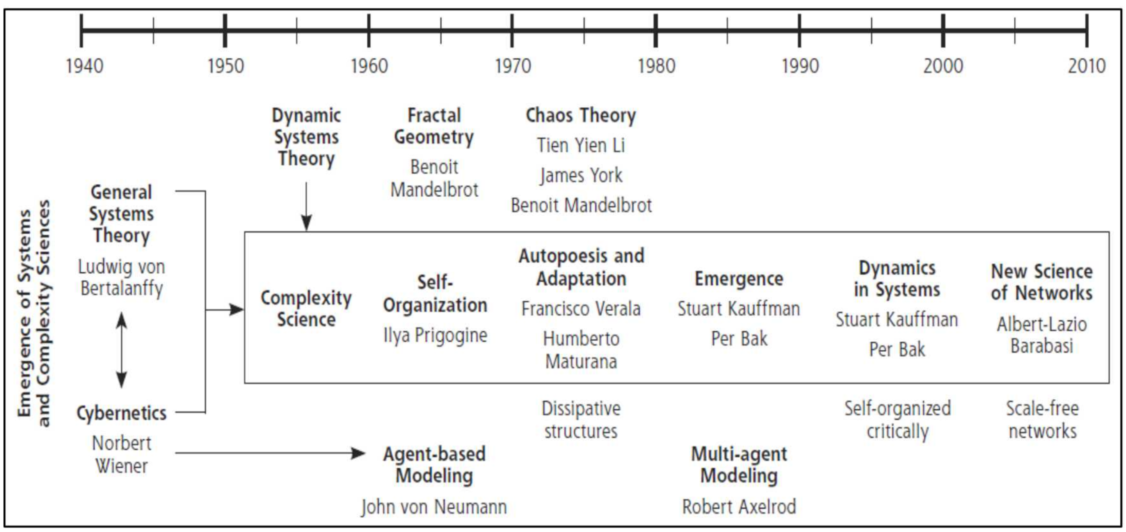

Figure 2. Chronological Development of Theories and Tools Contributing to Modern Complexity Science [14]

Extending back to the 1940s, one finds that parts of complexity science have their roots in the techniques and theories of thermodynamics and statistical physics. In 1738, Bernoulli published *Hydrodynamica* in which he laid out the kinetic theory of gasses [15]. The term *gas* actually dates to 1620 when Helmont described *air-like substances* as a gas, with *gas* being the Flemish word for chaos [16]. While Bernoulli provided an understanding of what a gas was and how it behaved, a gas was composed of billions of individual particles or bodies, and at the time, the mathematical tools based on Newtonian physics were limited to simple two-body problems.

Three-body systems proved to be mathematically difficult and the thought of mathematically describing billions of bodies was incomprehensible, at the time.

In 1822, Fourier [17] published his text on the <u>*Analytical Theory of Heat*</u>, in which he was able to describe the physical principles of heat transfer in mathematical terms. This work was based on the underlying concept that heat moved through solids because the energy of adjacent atoms was infinitesimally different, resulting in the flow of energy within the solid. Based on Fourier's work, Thompson [18], in 1849, published <u>*An Account of Carnot's Theory of the Motive Power of Heat*</u>, in which he introduced the term *thermo-dynamic*. Finally, beginning in 1859, Maxwell developed a mathematical formulation for the distribution of molecular velocities in matter, now known as the Maxwell-Boltzmann distribution [19]. This represented the first known statistical treatment of a many body system in physics and demonstrated how the average properties of matter can be understood without knowing the specific properties of each and every atom. This concept is somewhat different from complexity science, where the goal is often to gain insight into the behavior of a larger group, while maintaining some level of detail for the behaviors of the individual parts.

The concepts of statistical and aggregate behavior—combined with Anderson's 1972 explanation of how <u>*More is Different*</u> [20]—provide a key insight into what modern complexity science is and how it might be useful. Anderson clearly describes how in science, as one takes a larger look at systems embodying more and more components, different behaviors emerge with different laws required to describe what is observed. The underlying science is still based on what has been learned from the reductionist approach, but the assembled systems exhibit behaviors that appear to be more than simply the sum of their parts, which is the essence of emergent behavior.

Within the last 15-20 years, the emergence of very powerful desktop computers has enabled small companies and individual researchers to process and analyze very large data sets [21]. The use of such capabilities to support public policy decisions, political campaigns and commercial marketing practices has given rise to the technical disciplines sometimes referred to as *big data* or *data analytics*. [22-25] With microprocessors proliferating into every aspect of our lives, and the internet of things making sure they are all able to share their observations online, huge data sets are emerging. Their utility ranges from information only of interest to academics, to highly valuable purchasing patterns and preferences for select groups of consumers. Analytical techniques seem to be lagging the accumulation of data, but as the perceived value of such data sets increases, so too will the resources dedicated to improving analysis of these data [26-28].

The real utility of big data is that it provides the opportunity to see the patterns only obvious across a significant population, while maintaining the resolution to evaluate the behavior of individual agents. The overall study of bid data is in many ways similar to the study of complexity. It falls midway in between statistical ensembles where only aggregate behavior can be observed, and small data sets of individual actors in which larger population trends and preferences are not present. Due to the many similarities between problems of complexity and problems of big data, here the authors chose to include big data in the field of complexity science.

3. A BRIEF LOOK AT COMPLEXITY SCIENCE

With all the hype about complexity, it is difficult at times to separate fact from hyperbole. Anyone looking to complexity science for help with a difficult problem should first ask if it offers anything new, or if all the claims are just the gains in information resulting from faster processors working on larger data sets with greater access to online information resources. As with any branch of analysis, complexity science has utility—if properly applied, if the initial problem is well understood, and if the investigators are willing to accept the results with proper attention to their accuracy, variability and limitations.

As a generalization, complexity science is a loose collection of theoretical frameworks and tools intended to provide insight into problems that are described as complex, with the definition of *complex* varying from one framework to another. These are usually problems that have proven to be intractable for traditional theoretical approaches and are problems that often feature significant nonlinearities, interdependencies, size and non-deterministic components. Early attempts to explain complex systems required development of analytical and statistical models that were firmly grounded in mathematics, such as the statistical theory of gasses. In the more recent era, fast and highly affordable computers—able to store and process huge data sets—have allowed development of modeling and simulation techniques that provide insight into bewildering problems, even without a firm mathematical basis.

Models used to explore complex systems frequently rely on simplification of the problem by ignoring the classical dynamics of individual elements, and instead exploring statistical and nondeterministic approaches to explore the problem from a more generalized vantage point. At the same time, computer simulations add in details for individual actors that are difficult or impossible to account for with traditional mathematical formalisms. Many of the models currently in use cannot predict precise outcomes, but are useful for exploring large system behavior. A classic example comes from chaos theory, where the exact behavior of a system is highly dependent upon its initial state. This affects making predictions of exact behaviors impossible, while at the same time, easily being able to predict the range of potential behaviors that might be observed.

A key feature regarding the discussion thus far is the nature of the individual agents or elements of the systems described. These are atoms, molecules, or nano particles; they are not living creatures and do not exhibit random, illogical behavior. Reductionist approaches can explain and predict their behavior in simple systems, but cannot produce satisfactory answers for large interacting systems of such simple particles. The problems simply become too large. When biological agents are added to the system, analysis of the problem through reductionist approaches becomes essentially impossible. Most of the better known examples of success for complexity science include interacting biological agents, such as fish, birds and people.

Simplified models of biological systems have been used to provide insight into systems that appear to be nothing more than organized chaos, such as swarming birds and schooling fish. At the same time, complex models of physical systems provide some rather questionable insights into real-world systems such as weather and climate. Complexity science appears to have great potential for providing insight into otherwise intractable system problems. Yet at the same time, it fails when it is oversold, when the wrong tools are applied, and when policy is used to drive the models rather than having the modeling being used to inform policy decisions.

The weakest aspect of most models of complex systems results from a limited understanding of the underlying errors and limitations of the models by their developers—with no understanding and little regard for these errors by those who use the results of simulations to justify policy decisions. Analysis of error in complexity theories, models and simulation tools will be critical for relevance.

In addition to errors (known, uncharacterized, and unknown), there are other limitations that should be understood before attempting to apply complexity science to large problems that have proven difficult for more traditional approaches. One of the most common difficulties encountered is often termed, a *Grail Quest*. An organization becomes enamored with the elegance and novelty from successful examples of complex systems modeling and decides that they need to be applying complexity science to their own problem. Their decision is often made without a clear understanding of what their problem is, what they are trying to accomplish, why they believe that complexity science holds promise for their problem, and which parts of complexity science are relevant to their interests. Often, a small group is given the task of charging forward on a *Grail Quest*, and the overall effort results in limited accomplishment, thereby giving complexity science an undeserved negative reputation.

The pursuit of solutions using complexity science does not always result in useful answers. It is possible that existing models and tools will produce no clear insight into hidden dependencies and result in no clear path towards a solution. It is also possible that too many interdependencies will emerge causing the research team to get lost in the complexity of the modeling and simulation results. Worse than finding no clear answer is when a research team finds a bad answer, an incomplete answer, or an answer with significant limitations that are not well understood.

4. CHARACTERISTICS AND BEHAVIOR OF COMPLEX PROBLEMS

Up to this point in the report, complexity science has been freely discussed without clearly stating what constitutes a complex problem or system. This results partly from a multitude of definitions, and partly due to the necessity to lay some groundwork before attempting such a definition. While there are no general rules for what constitutes a complex system, the characteristics of such systems can be discussed, thereby allowing the reader to determine what qualifies as complex and what does not. From these characteristics certain behaviors arise that help to differentiate complex systems and problems from those that are large and complicated without actually being complex.

4.1. Characteristics

Complex problems are typically very large, easily exceeding the capability of traditional analytical techniques and often, the ability of humans to grasp all their parts. In addition to being large, they usually consist of a significant number of separate systems or components that are interconnected and interact both with one another, and with their environment. Because the systems can rarely be observed in isolation, they interact with their environment, forever evolving and changing as they are studied. This can be thought of as a temporal instability or a temporal evolution. Many complex systems are chaotic, or include chaotic components which makes them appear to exhibit random behaviors. Instead, the behaviors are well defined by physical processes, but poorly understood by humans where the specific evolution of the behavior depends strongly on the starting state or conditions. Complex problems frequently include a mixture of discrete and continuous variables, or worse yet, also include thinking biological systems capable of truly random acts. Finally, complex systems will frequently exhibit no clear cause and effect relationships, even if they actually exist within the system.

What constitutes a large problem is a matter of perspective. In physics, through reductionist techniques, it is possible to understand and predict the motion for all parts of a two body problem. When the problem is extended to just three bodies, analytical techniques are still useful, but closed-form mathematical equations become impossible without significant simplifying assumptions. When extending this to a many body problem—still with a small number of bodies—the basic physical processes are understood, but computer modeling becomes necessary to predict the motion of each component. For problems that include biological systems, even small numbers of components result in a complex problem.

One of the key characteristics of any complex system is that it is actually composed of a system of systems that interact with one another. This simple interaction results in nonlinear behaviors that are extremely difficult to address mathematically with traditional techniques. These problems are typically described by very large and highly nonlinear systems of differential equations that can only be addressed with numerical approximation techniques and fast computer algorithms.

Complex problems have a tendency to evolve with time. In some ways, attempts to solve complex problems results in the problem changing as the previous solution is applied. Some problems are described as never being the same twice, making specific solutions impossible.

Social issues and matters of public policy are excellent examples of problems that evolve by themselves and that tend to morph with efforts to fix the apparent underlying problem.

Many physical problems are repeatable and do not change while someone is attempting to correct them, but some systems that are purely physical in nature continuously change, and in seemingly random ways. Many of these problems are described as being chaotic. They might have well understood underlying physical processes, yet their temporal evolution appears to be at least partially random. These problems evolve in ways that are extremely dependent upon their initial state. Starting the problem from almost the same point results in a completely different answer. Classical examples of chaotic nonlinear physical systems include atmospheric turbulence and the double rod, or hinged pendulum.

One of the more difficult characteristics of complex systems is that they occasionally exhibit no clear relationship between cause and effect. They will at times exhibit positive feedback and at other times negative feedback—even when the cause and effect relationship for individual components or processes are well understood and not in question. An example comes from the world of economics and commerce. A small business owner might lower the price on a product and still see a loss of sales which appears to make no sense. The problem is that this small business exists in an environment of many businesses, small and large. Other economic conditions might be responsible for his loss of sales, even if competitors did not choose to compete and lower their prices.

4.2. Behaviors

Complex problems exhibit a number of behaviors and at times, it is difficult to determine what constitutes a characteristic and what should be characterized a behavior. One of the defining behaviors of a complex problem is that they exhibit emergence. When the problem is viewed in a holistic sense, new behaviors are observed that are not apparent for greatly reduced subsets of the problem. Complex problems often exhibit nonlinearity where responses to inputs are not proportional to the stimuli. Sudden transitions are behaviors often observed for complex systems. The system can exhibit a relatively stable range-bound behavior, then suddenly transitions to a new operating range. Many problems exhibit an adaptable behavior which is closely linked to the characteristic of evolving over time. Self-organization is seen in some systems, both biological and physical, where seemingly randomly acting components or agents adapt and organize themselves into functional systems or complex geometrical patterns. Finally, complex systems often have behaviors that are seemingly controlled by attractor states. They can be perturbed significantly, yet will quickly transition back to a previously seen range of behaviors.

Emergence is sometimes seen as the key behavior that differentiates a complex system from those that are merely large or complicated. Emergent behavior is seen when the flight of a single bird is compared with that of a flock of birds. The individual birds are no different when in a group or alone, yet large-scale group behavior is observed. This problem puzzled biologists for years, thinking that the birds were somehow communicating with one another, but in the end, agent-based modeling from complexity science demonstrated that behaviors very similar to a flock of birds, or a school of fish, could be created if each individual agent only followed a very small set of rules regarding collision avoidance while staying within the flock.

While emergence is an interesting behavior, it is unfortunate that it is viewed as a defining behavior of complex systems when viewed in a holistic sense. If one carefully considers emergence, it is clear that anytime the scale of a problem is changed, there are emergent behaviors. For example, when transitioning from classical to quantum mechanics, one suddenly finds quantized energy states, wave functions and tunneling. When going from small to large, one finds a grand ensemble of discrete wave functions overlapping and interfering, to form a macroscopic particle that obeys the laws of Newtonian mechanics. On the very large scale, the universe appears to exhibit behaviors not explained by Newtonian mechanics, thereby inspiring cosmologists to theorize the existence of dark energy and dark matter.

While emergence is an interesting and exciting behavior, nonlinearity is difficult and frustrating. Interconnected systems almost always exhibit nonlinear behaviors and the mathematical formalism to describe even small systems quickly becomes very difficult. Numerical approximation of these systems combined with high-speed computers, has made it possible to explore very complex nonlinear problems, but exact closed-form mathematical representations are essentially impossible.

Sudden transitions, phase transformations and tipping points are three ways in which a sudden, dramatic and highly nonlinear change in behavior is sometimes described. On a macroscopic level, the unexpected fracture of a mechanical support followed by the collapse of a structure can be viewed as a sudden transition—even though the process is well understood, yet still complex, on a microscopic scale. Phase transformations and tipping points are more frequently seen in social problems where the thought patterns for a group of agents suddenly change and new behaviors are observed. The new behaviors were previously possible, but not seen as productive or acceptable. Then, following some triggering event or tipping point, these behaviors suddenly become acceptable and common place, even if only for a short while.

Complex systems are highly adaptable. This is seen mostly in the biological world, where agents—some thinking and others reacting—can change their behavior to either their benefit or detriment. Although new behaviors that enhance individual and group survival tend to survive, they become instinctive while those that are detrimental die out over time.

Self-organization may be thought of as a form of adaptable behavior, but it is very specific whereas adaptability is more general. People tend to self-organize into groups. An interesting result of agent-based modeling showed that without the negative behaviors or influences of racism, neighborhoods would naturally tend towards cultural, if not racial, segregation on their own. People just tend to be more comfortable with others that exhibit similar behaviors to their own. Other biological systems self-organize in different ways. Coral reefs exhibit an amazing complexity of behaviors with highly diverse species both contributing and benefitting from the reef. They do not exist everywhere, but in certain places where conditions are right, coral reefs spontaneously emerge, grow and organize themselves as they develop and adapt.

This page is intentionally left blank

5. APPLYING COMPLEXITY SCIENCE

5.1. Theories, Tools and Approaches

To pursue a study of complex problems—whether one is trying to find solutions to known problems, or develop new theoretical frameworks for yet to be tamed problems—it is necessary to have an understanding for the whole of complexity science, the nature of complex problems and the strengths and limitations of individual theoretical frameworks. While many works describing elements of complexity science exist, only a few attempt to provide an overview of the topic.

An overarching study of complexity would need to start with an exploration of the types of problems that might be addressed with some of the tools from complexity science. This exploration would hopefully result in some understanding for the range of problems that are thought to be complex and possibly help establish some taxonomy for complex problems. In parallel with an exploration of the problem space, there should be an equally detailed exploration of the models used to understand complex problems. This effort should include an examination of the theoretical basis of each model, its mathematical underpinnings along with some understanding of inherent sources of error, strengths and limitations. Putting these two pieces together should allow someone new to complexity science to understand their particular problem and help them to identify the appropriate and inappropriate tools that might be used to approach the problem.

The task previously described is beyond the scope of this short white paper. Indeed, entire collections of books and countless journal articles are dedicated to each of these topics. Here, the authors can provide only a brief introduction to a small number of the major theories and tools behind complexity science. While Figure 2 presents a timeline for the major theories, it is a condensed version showing only the most well-known aspects of the field. A more complete mapping is seen in Figure 3. The creator of this representation has attempted to include most of the major parts of complexity science, along with a timeline for their development and some insight into how they are related to one another. A brief description of some of the better known theories and tools is presented in this figure.

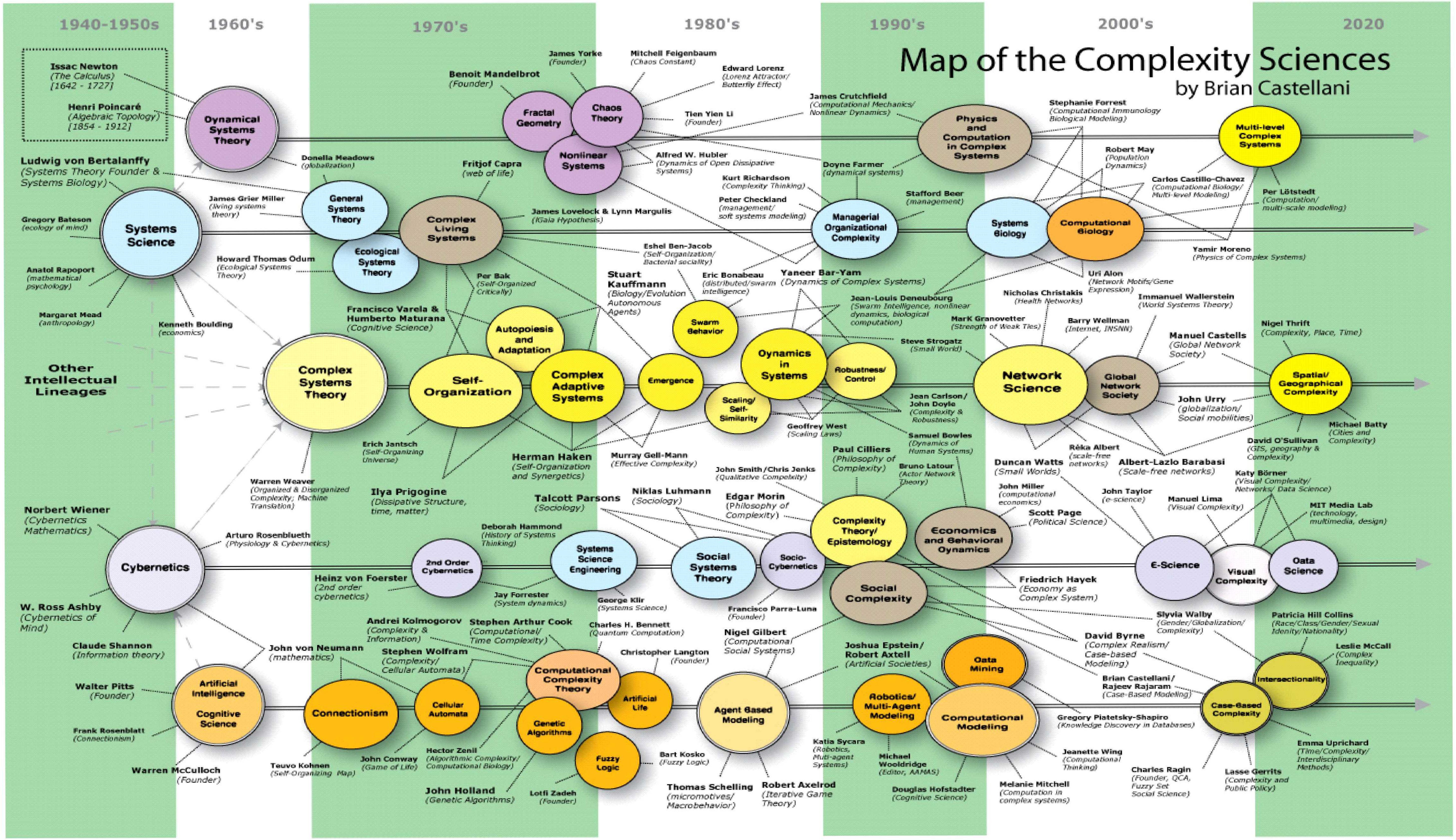

Figure 3. One Possible Taxonomy of Theoretical Approaches to Studying Complex Problems [29]

5.2. Statistical Mechanics

Statistical mechanics is a branch of theoretical physics that uses probability and statistical techniques to describe the average state of a system with a very large number of components, without having to know the state and dynamics of all the individual constituents [30]. It is included here with our discussion of complexity science as it represents the first real success at going beyond the simple two-body problem using Newtonian physics, providing aggregate solutions for systems with an extremely large number of bodies.

While statistical mechanics is technically an approach for dealing with any system consisting of a very large number of similar components, it was developed out of the kinetic theory of gasses and as a result, is almost always applied to the study of gaseous systems. When studying classical two body problems, concepts such as heat, temperature and entropy do not naturally arise and similarly, do not impact the problem [31]. In the study of thermodynamics, these properties can be measured and manipulated to predict the work that can be done by a gas, but the connection between the thermodynamic properties and the underlying physical processes are absent. Statistical mechanics connects classical physics with thermodynamics in a way that explains thermodynamic properties of a gas, with the classical Newtonian physics description of what each particle is doing, but in a statistical way that provides for distributions and randomness of particle positions and velocities.

While the concepts of statistical mechanics are well beyond this brief paper, and the study of the topic can take years to fully understand, there are a number of easy to comprehend examples that demonstrate the power of statistical mechanics. As an example, by starting with a few simple assumptions regarding the particles in a gas, through the techniques of statistical mechanics, one can calculate the scale height of the atmosphere as being approximately 8 km. With the scale height, one can calculate the reduction in barometric pressure, and hence, air density, with increasing altitude.

It should be noted that statistical mechanics is a well-developed physical theory with equally well-developed mathematical tools that can actually be used to calculate and predict properties of systems. Unlike pure theoretical constructs that can at best, provide a qualitative understanding of a system, statistical mechanics includes useful tools.

5.3. General Systems Theory

A fundamental concept of general systems theory is that all systems, be they physical, biological or social, share a number of underlying principles regarding their organization and how they operate. General systems theory began to emerge in the 1940s, resulting from the work of Ludwig von Bertalanffy [32]. He observed that systems in the real world are much more complex than can be explained by reductionist approaches, and that more importantly, real systems interact with their environment, and together, form an even more complex system. A second fundamental concept is that through careful analysis, one can identify isomorphisms between such diverse entities as the biological systems of an animal, and the functions of a modern digital control system. This can only be done by moving beyond the reductionist view of prevalent in each field of inquiry, and examining systems from a holistic point of view. The necessity of holism is a third fundamental concept of general systems theory.

Out of general systems theory grew a number of subfields of study that are more focused on understanding and solving problems in specific fields of inquiry. The more successful of these subfields include system dynamics, systems biology, systems ecology, systems psychology, systems engineering, and systems analysis [33]. What differentiates each of these subfields from their similar traditional field of study, is the holistic view where entities are examined as a whole functional unit system, existing within and exchanging information and resources with its environment. As an example, traditional biology might study the reproductive processes of a common frog, but systems biology would examine the reproductive behaviors and a frog species within its environment.

In the more quantitative technical fields of science and engineering, system dynamics, systems engineering and systems analysis are more commonly encountered. Each of these fields includes both theoretical frameworks and well-developed technical tools and approaches useful for solving real-world problems, predicting behavior and both understanding and correcting failures.

5.4. Cybernetics

Cybernetics traces its roots back to the 1940s, having developed nearly in parallel with general systems theory. It is a theory focused on understanding the similarities in control systems for goal-seeking systems that include sensing, feedback, stability and regulation [34]. These characteristics are sometimes described as causal circular chains where there is an action, followed by sensing and comparison with a desired goal, and finally a follow-on action to adjust the function of the system towards attainment of the designed goal. These systems include automated electro-mechanical devices, social entities, and individual biological units [35]. In a way, cybernetics can be thought of as a version of general systems theory for mechanical and biological control systems.

To those unfamiliar with the ancient Greek language, at first encounter, cybernetics sounds like some field of study that combines computer and information systems (the modern usage of the term cyber), with some form of genetics. While either of these thoughts can easily fit under the umbrella of cybernetics, the word *cybernetics* was first used by Plato to describe the governance of people within a society. Later, in 1834, Ampère used the word *cybernetique* to describe the functions of government [35]. Finally, in 1948, the modern usage appeared in the works of Wiener, where he used the name to identify the study of control and communication systems within biological and mechanical systems [36].

Cybernetics is a theoretical foundation for understanding control and feedback systems across many areas of science. It is not a tool or a set of tools. Similar to general systems theory, cybernetics encompasses almost all of the subfields that loosely make up complexity science. In many of these subfields, one will find tools and applications for applying cybernetics theory to understanding problems of a practical nature. The broad scope of cybernetics is almost bewildering as it has found application in the hard sciences, engineering, computer science, the biological sciences, the social sciences, mathematics, economics, law and even art.

5.5. System Dynamics

While system dynamics has strong theoretical roots, it is best viewed as a system of tools that allow one to study how the behavior of a highly nonlinear system with strong coupling between components evolves over time. The approach relies on the economic concepts of stocks and flows combined with feedback loops, both positive and negative, and time delays where appropriate [37]. While any system can, in theory, be understood through numerical simulation of nonlinear differential (and possibly integral) equations that describe its behavior—for many non-mechanical systems such as social organizations, economies, businesses and governments—the interrelations and dynamics are not understood well enough to allow description with closed-form equations. In such cases, the approaches of system dynamics are useful for understanding behavior and exploring *what if* scenarios.

System dynamics began in the 1956 when Massachusetts Institute of Technology (MIT) professor Jay Forrester took a position at the MIT Sloan School of management. He set out to see how his expertise in engineering could be applied to problems within the business world. Following this goal, he helped the General Electric (GE) Corporation understand why they had a manpower cycle that over three years, transitioned from famine to layoffs. Forrester determined that the GE corporate structure and their management and decision making times led to the cycle, independent of external economic forces [38]. The structure of the organization played a significant role in the dynamics of the system. This turns out to be a common finding for much of system dynamics, where the structure of the system largely determines the range of outcomes [39].

Following Forrester's work, other researchers began to develop computer models to allow for an easier application of the basic tools to problems of practical interest. Two of the first tools were SIMPLE (**S**imulation of **I**ndustrial **M**anagement **P**roblems with **L**ots of **E**quations) dating to 1958, and DYNAMO (**DYNA**mic **MO**dels) dating to 1959 [38]. Many subsequent versions and follow-on codes were developed based on the pioneering work of Forrester and these two tools.

System dynamics is generally not used to make exact predictions regarding the dynamics or end state of a system's behavior, but is more appropriately used to understand the dynamical impact of decisions, policy changes and indecision. It is an excellent tool for exploring *what if* scenarios in matters of policy impacting complex social, economic, managerial and government problems.

One of the key outputs from many system dynamics studies, as previously stated, is that the behavior of a system is often highly dependent upon the structure of the system. Changes in the underlying behavior normally require changes in the structure of the system [39]. Small changes in behavior can be affected by modification of the inputs and underlying assumptions. These are normally what is seen from policy decisions. Significant changes in behavior normally require a change to the system's structure.

5.6. Chaos Theory

Chaos theory is a branch of mathematics that attempts to address the behavior of deterministic systems that are not predictable. These are complex, highly nonlinear systems where their evolution over time is highly dependent upon their exact initial conditions. Very slight changes in initial conditions result in radically temporal evolution of their behavior [40]. This is at times, referred to as the butterfly effect. The thought is that in a highly chaotic system, a butterfly flapping its wings in West Africa can set in motion a chain of events that results in a hurricane striking the gulf coast of the United States.

Chaos theory has its roots in fundamental physics, beginning, *a priori*, with the axiom of causality. Every effect has a cause. Newton separated cause and effect, examining each independently in the form of initial conditions and motion. Laplace explored the concepts of determinism and predictability, arguing that only deterministic systems were truly predictable. Towards the end of the 19th century, Henri Poincare was exploring the phase space and deterministic evolution of an n-body mechanical problem [41]. He noticed that randomness and determinism were not entirely incompatible concepts as the system exhibited short-term predictability together with long-term unpredictability. A small, imperceptible cause can result in a considerable effect that is impossible to ignore. The effect can be attributed to randomness, but if one knew the exact state of the universe at the time of the cause, one could predict the effect. Since the phase space of the universe is far too complex to comprehend, or account for, one cannot accurately predict such seemingly random occurrences. Stated another way, the evolution of the system is highly sensitive to the initial conditions. Poincare could be considered the father of modern chaos theory, but the computational tools available in his time were insufficient to truly explore the concepts.

The father of modern chaos theory is Edward Lorenz from MIT. He created what was perhaps the first global circulation model to understand and predict weather. The model demonstrated a wide range of correct effects, but seemed to generate periodic cycles—a behavior not seen in nature. At one point, Lorenz used an intermediate state as the starting condition, hoping to get to a previously seen interesting effect more quickly. He was shocked to find that the results were completely different. Where the computer had tracked critical parameters to six significant digits, they were only displayed to three significant figures. When Lorenz attempted a mid-stream restart, he initialized the state with the three significant digits that he had. The very slight differences between the approximated digital state and the actual digital state were enough to cause a significant variation in the temporal evolution of the system. With this, modern chaos theory was born.

One interesting outcome of chaos theory is the concept of *strange attractors*. Many physical systems exist in states known as attractors. These are not exact repeatable states, but sort of an equilibrium state or a familiar range of states about some mean. The system is not precisely predictable, but it can be expected to exist somewhere within this equilibrium range. Chaotic systems exhibit attractor states, but also exhibit strange attractors. This is where the system is in continual change, but the dynamics of the changes take on a familiarity and exist within a range about some mean trajectory. The concepts quickly exceed the intent of this paper, but the authors close this section noting that atmospheric dynamics are chaotic. While the exact weather conditions cannot be predicted, they can often be predicted to be within some finite range about a familiar state, an attractor. There are also times when they transition from one attractor state to another and exhibit characteristics of a strange attractor along the way. To make matters truly complex, there are times where the system appears to be in some completely random state making the weather (and climate) unpredictable, even though the system is deterministic in theory.

5.7. Autopoiesis

Autopoiesis is the theory of self-reproducing systems, as developed by Maturana and Varela in the early 1970s [42]. The original theory was developed to understand what constitutes life and concerned itself with the biological structures and chemical processes that led to reproduction of biological units. This was Maturana's definition of life. A living system has structures and processes. Many of the processes are dedicated to reproducing the structures of the system and these structures in turn, define and limit the processes of the system.

Since its introduction, the concepts of autopoiesis have been adapted to describe reproductive processes in social systems, cognition and general systems theory. Luhmann extensively studied the theory of autopoiesis and applied it to social systems which he grouped into societies, organizations and interactions [43]. While organizations do not reproduce their components (or members), they tend to reproduce their organizational structures, or those things which make the organization unique. Autopoiesis is related to complexity in that organizations tend to produce and reproduce more complex structures than the surrounding social environment that originally produced the organization itself. Luhmann argued that the reproductive process in organizations is communication, including the message itself, the act of communication and an understanding of not only the message content, but the reasons (how and why) for the message to have been sent. It is through communication that the social unit will continue to reproduce its own structure and organization and it is this organizational structure that tends to cause the communication that ultimately contributes to the reproduction and sustainment of the social unit.

While autopoiesis describes one form of complexity, the reason for dedicating several paragraphs to the topic is that most policy decisions are highly complex, and many policy decisions impact organizations both in society and within government. As a general rule, government organizations tend to be autopoietic, and will strongly resist policy changes that threaten their existence. By understanding the reproductive process of such organizations, decision makers can craft policy to limit the destructive nature of bureaucracies, thereby enhancing the chances that a given policy change will be successful.

5.8. Cellular Automata

A cellular automata is an interesting time-dependent geometrical tool that can exhibit very complex behavior and as a result, has found wide-spread use in modeling and understanding certain complex systems. While a cellular automata is rarely used for exact quantitative results—with a few simple implementation rules—it provides qualitative insights that would prove difficult for traditional programming approaches.

In 1948, von Neumann was attempting to develop a reductionist model of biological evolution by developing an abstract set of primitive interactions required for evolution of complex life forms [44]. He constructed a two-dimensional lattice of cells with 29 discrete states per cell.

With the correct choice of rules for how cells transition from one state to another, he demonstrated the temporal evolution of a self-replicating automaton. In 1970, the Game of Life was demonstrated by Conway using a cellular automaton. The evolution of the game was such that it was almost impossible to predict possible future states from the one currently displayed. Then in the 1980s, Wolfram approached the topic with greater rigor and established a set of standard rules for how simple two-dimensional cells might evolve, and developed a classification for the behavior of the automaton over time. In many cases, the temporal evolution is rather uninteresting with the array progressing to one homogenous state or another. However, in a few cases the automaton will display some rather extraordinary and complex behaviors.

A cellular automaton is a geometric collection of cells, each with a fixed location. The array can be of any desired dimension, or can be more complicated, such as that necessary to describe an intricate road network. The most commonly encountered simple example is a two-dimensional array of square cells, similar to a checkerboard. Figure 4 shows the cellular array for traffic flow problem involving rotaries, or traffic circles [45]. The individual cells are clocked in parallel and all change state simultaneously with the clock. The cells can have any number of states, but require at least two. The future state of an individual cell is determined by some combination of the cells that surround it [46]. The specific rules are defined by the developer of the simulation. Most rules result in no special automaton behavior, but some rules result in rather interesting behaviors. Through a careful design of the cell array, selection of states and the rules that determine state changes, cellular automata can be used to simulate a variety of phenomena in fields ranging from art and music composition to traffic modeling and turbulence in gas flows [47].

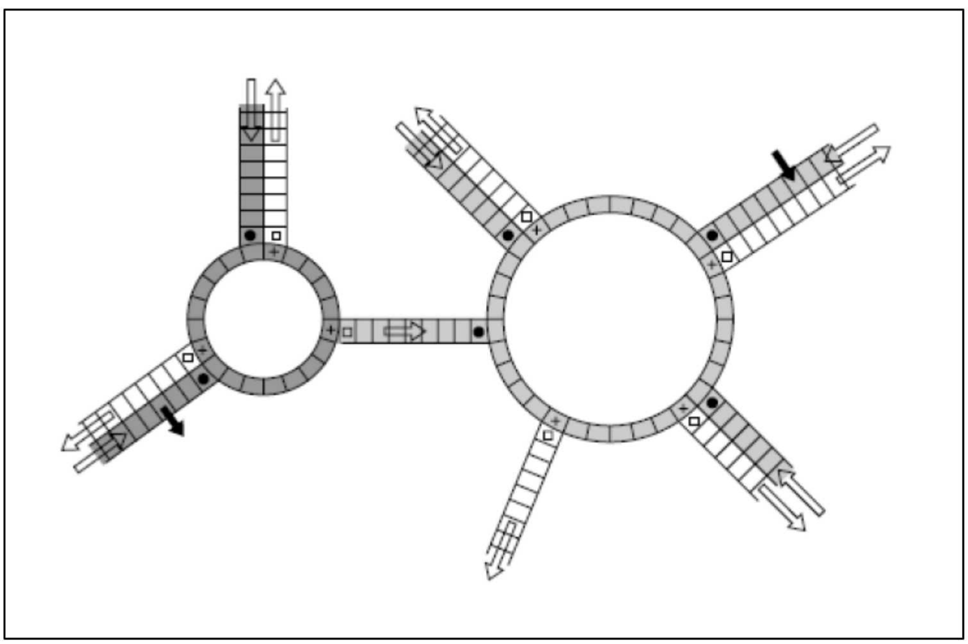

Figure 4. Cellular Array for a Traffic Flow Problem [45]

5.9. Network Theory

Network theory is a branch of mathematics, relying on graphical presentation and analysis tools to represent and assess networks in many branches of science and engineering [48]. A network is a collection of nodes that have some interconnection between various nodes. The number and complexity of the connections depends upon the specific problem being examined. For example, the network graph for a corporate email server would most likely represent a hub and spoke arrangement, with the server at the hub and individual clients at the end of each spoke. Other networks form more of a ring shape with distant nodes communicating through intervening nodes.

Network theory has its origins in the city of Konigsberg, now modern-day Kaliningrad in Russia [49]. At the time, the city consisted of two land masses separated by a river network and two islands. A total of seven bridges connected the various parts of the city. An 18th century mathematical model was to propose a path where an individual could cross each of the seven bridges only once. The 18th century mathematician, Euler, studied the problem and realized that the geography had no bearing on the problem. All that was important were the land masses and the bridges connecting them. These he could represent as nodes and connections and was thus able to show that no suitable path existed. Some argue that this example only required application of combinatorial analysis, but the graphical approach was more intuitive and made it easier to see the absence of any suitable solution. Since that time, graph theory has advanced as a rigorous mathematical discipline with formal theorems, proofs and tools that can be used to assess problems.

Network theory has found considerable use in modern society, being used to analyze social, economic and communication networks as well as supply chains, government and political organizations. While it is described as a theory, network theory includes a rich set of tools that can quickly be adapted to many complex problems.

Where cellular automata consisted of a fixed set of cells with their state transition only depending on the states of their immediate neighbors, networks feature nodes (basically cells) and connections with the connections being as important as the nodes themselves. The connections represent flows of information or resources.

Network theory is very useful for examining key players and key lines of communication in social networks. It is equally useful for identifying irrelevant and disconnected individuals as well as organizations that seemingly function only to further their own existence. In industrial applications, network theory helps to identify key steps in a manufacturing process, or can be used to identify critical supply chain deficiencies. Basically, network theory helps to expose the structure of a system. In many applications, the products of a system are significantly defined (or limited) by the structure of the system producing them. By understanding the structure, it becomes possible to more effectively impact the products and processes.

5.10. Agent-Based Modeling

Agent-based modeling is a powerful approach for exploring the dynamic evolution of systems that contain a large number of individual entities, called agents, each of which interacts with other entities and its environment through a set of rules [50]. Unlike cellular automata, agents can move if necessary, and can adapt and learn. They make decisions based on the predefined rules and whatever adaptation and learning that has occurred. The agents, through their actions, will form associations and networks and, depending upon the simulation, might demonstrate emergent behavior.

Agent-based modeling has demonstrated a number of important successful applications, such as birds in flight, schooling fish, and neighborhood segregation. When applied properly, it is a very powerful tool for understanding the simple causes for large-scale, seemingly complex behavior in large groupings of agents.

While there is a theoretical basis for agent-based modeling, it is primarily seen as a tool that can be used to explore complex systems and to understand why certain behaviors evolve as well as to explore *what if* scenarios. Well-developed tools, such as Repast (Java), Swarm, NetLogo, StarLogo, MASON and AnyLogic are available from either academic or commercial sources [51]. While agent-based modeling can be executed with simple tools such as spreadsheets and even by hand, the existence of well-developed tools will significantly aid those new to the field.

5.11. Genetic Algorithms

Genetic algorithms are a bio-inspired approach to finding high-quality solutions to difficult optimization problems. They are perhaps the best known member of a family of approaches known as evolutionary algorithms [52]. The concept is that successive evaluation of the given problem, various solutions of differing quality are found. The characteristics of these solutions are used to define the genetic sequence for that particular solution. Once a modest number of genetic sequences have been found, the approach is to try new solutions made from genetic combinations of these genes. As with biological evolution, those gene combinations that produce better solutions tend to remain in the population, while those gene combinations that result in poor solutions die off.

Genetic algorithms are quite attractive for finding solutions to complex problems that tend to be difficult for more traditional approaches. The traveling salesman problem (TSP) [53], is an excellent example of where genetic algorithms have proven highly effective for finding near optimal solutions. While there are a number of other techniques that are effective for the TSP example, genetic algorithms reliably provide high-quality solutions, even when the scale and complexity of the problem are significantly increased.

5.12. Neural Networks

Neural networks are interesting tools for providing partial solutions to problems of significantly algorithmic complexity. They consist of a number of layers of biologically-inspired, artificial neurons each consisting of a number of individual artificial neurons. Learning in the system is encoded as weighting factors representing the strength of the connection between neurons in different layers [54]. Neural networks can be implemented in electronic circuitry or can be simulated with traditional computer programming languages. Hard-wired neural networks can function with almost no time delay between input and output.

Neural networks have proven useful for computationally complex tasks such as sound recognition and image classification. These are problems where an algorithmic approach might be developed, but the computational and algorithmic complexity would quickly become overwhelming and the process of coding and debugging would be a daunting task. Neural networks require training, where algorithmic approaches require evaluation and refinement. For specific problems, neural networks provide a much faster and more effective solution than other approaches.

As with any technology, neural networks have their limitations and faults. One issue is that in spite of significant research, it is not always obvious how or why neural networks are able to function as they do. For problems of higher complexity, designing a network with the appropriate number of layers and neurons can be as much of an art as it is a science. An improperly designed neural network will provide unsatisfactory results. Also, neural networks require training. Once trained, they perform brilliantly on individual examples from their training set, but exhibit less than 100% performance for examples not previously seen. The more similar the new example is to one in the training set, the more accurate the classification. The trick is to design a network that has robust performance to properly classify new inputs.

5.13. Game Theory

Game theory is a branch of mathematics that examines situations where two or more agents (players) select strategies and make decisions to maximize their payoff according to the rules and structures of the game [55]. It is useful as a tool to understand how such decisions are made in view of one player's knowledge of another player's strategy and how strategies might change to maximize payoff. There are various types of games and numerous goals that might be sought. One common game has a zero-sum condition where one player only benefits at the expense of another [56].

Game theory has found significant application to the world of economics where individuals, corporations, nations and alliances seek to improve their position. On the world stage, there are ongoing interactions that are cooperative, non-cooperative, and even adversarial or counterproductive where one agent is willing to accept a loss if he can inflict a greater loss on a competitor or an enemy. As might be expected, game theory has also played a significant role in international relations and defense strategies for many nations.

Given the importance of game theory, some of the greatest mathematicians in modern times have devoted extensive effort towards furthering its theoretical basis, solving previously intractable problems and developing practical tools for its application. Names such as von Neumann, Nash [57] and Pareto [58] are commonplace in any study of game theory.

The most-simple games are for only two players, but they provide insight into strategies that might be employed to maximize an individual payoff, maximize the aggregate payoff for both players, and how to select a strategy given knowledge of the other player's strategy. Multi-player games then follow and quickly become more complicated. When considering application to real world problems, one finds hundreds to thousands of players with a mixture of knowledge regarding strategies of the other players and their goals. Not all players are rational, and what might seem irrational to one player is actually rational to another who has different, but undisclosed goals. Game theory, combined with other tools such as agent-based modeling, provides a very powerful set of tools and approaches for exploring highly complex problems. The outcomes of simulations and analyses are not useful to predict exact real-world behavior as the problems are too complex, but such simulations and analyses are extremely useful to understand patterns of behavior, to explore *what if* scenarios, and hopefully to identify courses of action that are likely to result in highly undesirable outcomes.

5.14. Data Mining

Data mining is a branch of computer science that has seen significant growth in recent years resulting from its direct application to business in the form of predictive analytics. It combines traditional data analytics and database systems with neural networks and other forms of machine learning to identify trends and patterns that are not evident in smaller datasets, and that cannot be identified through traditional statistical approaches [59]. Business can use the results of data mining for targeted marketing, informed strategic decisions and other forms of competitive advantage.

The utility of data mining is not limited to business applications. Because the tools and techniques are effective for finding subtle trends within highly complex and interrelated datasets, they are useful for exploring complexity in any system for which data exists. In addition to business, data mining is used to support and inform public policy decisions.

While the name *data mining* invokes images of attempting to dig for data, the actual purpose is to dig *through* mountains of data to extract knowledge [60]. While the mechanics involve data management, classifying, processing, visualization, modeling, fitness evaluation and model testing, the process of identifying the question, understanding what one is looking for and selecting the correct data sources is equally important. The datasets are too large and contain too much potential information for one to attempt to extract all possible knowledge. The most productive path to success is to first understand and correctly focus the question the data mining effort is intended to answer.

5.15. Time Series Analysis

Most data are collected over time. By applying the tools of time series analysis, one can determine if the data include a temporal component. By examining and comparing the temporal behavior of multiple parameters, one can quickly identify observations that are correlated and those that have no correlation. Beyond mere correlation lies the possibility of identifying cause and effect relationships [61].

Time series analysis has found widespread use in such diverse fields as the social sciences, physics, astronomy, engineering, the biological sciences and economics. Many processes exhibit behaviors that change over time, and time series analysis is very useful for identifying weak temporal signals immersed in a background of noise [62]. Physical parameters that are identified as being cyclic can be predicted more easily for some point in the future.

The tools of time series analysis include the mathematical Fourier transform (and its many related transforms) for the frequency domain, and autocorrelation and crosscorrelation techniques in the time domain.

6. UNDERSTANDING COMPLEX PROBLEMS

Beyond familiarity with the tools and theories of complexity science, it is necessary to have a deep understanding of the problem one is trying to solve and to clearly articulate the question that needs to be answered. These conditions are important in any field of analysis, but given the qualitative nature of results from the many tools of complexity science—understanding the problem, the question and the information sought—takes on a greater importance. The previous section presented a brief introduction to some of the major tools and theories of complexity science. This section examines the types of problems one might attempt to address and the nature of the information that might be sought for each type of problem when turning to complexity science.

Complex problems come in all sizes and shapes, yet if one believes the underlying principles of general systems theory, then most complex problems should have somewhat similar underlying characteristics. In 1948, Weaver proposed that only three types of problems really exist, those of simplicity, those of disorganized complexity and those of organized complexity [12]. Problems of simplicity are normally encountered in traditional reductionist approaches. The problem is reduced to its most simple form, and only the key elements of the problem are considered.

Disorganized complexity describes problems where the number of objects (such as components, etc.) is so large, that individual behavior cannot be analyzed. Only average properties, and possibly a distribution of properties for the system can be considered. An example of such a problem is seen in the kinetic theory of gasses where statistical mechanics is used to understand and predict properties of the system.

Organized complexity is something altogether different. The problem is not as large as those encountered with disorganized complexity, yet it is too large and too interconnected to be addressed with the tools and techniques from the realm of simplicity. One must examine the complex system together with its environment and employ techniques that provide insight into system behavior without sufficient detail to predict the behavior of individual components. The realm of organized complexity is what general systems theory and cybernetics started examining in the 1940s. This early examination is at the heart of what current-day complexity science aims to address.

Weaver provided some insight into why complexity science differs from traditional analysis techniques and why complex problems are different from traditional problems. Weaver's three categories of problems really provides no insight into the nature of the problems themselves. In 2003, Kurtz and Snowden at IBM developed a newer framework that has four major regions and a fifth smaller region [63]. Their construct is known as the Cynefin framework. While many representations are found in the literature, the basic framework is shown in Figure 5.

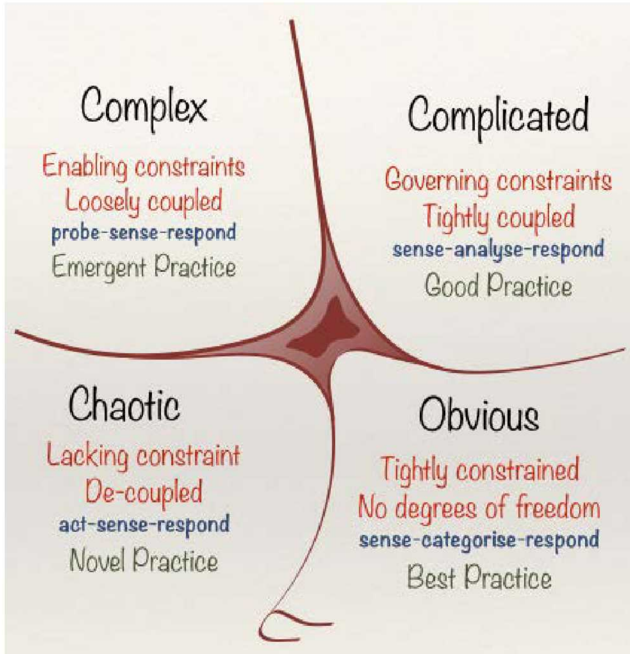

Figure 5. The Cynefin Framework for Complex Systems

The key feature of this framework is the presence of four distinct regions. On the right side, there are systems that are ordered while on the left are systems that are unordered, with unordered being similar to not ordered and distinctly different from disordered. The region in the center connecting the other four is the region of true disorder. Starting from the lower right in Figure 5, the regions are Obvious, Complicated, Complex and Chaotic. Another way of expressing these four regions are the Known, the Known Unknown, the Unknown Unknown, and the Truly Chaotic. Each region has its unique characteristics. This framework has some utility, but a full description is beyond the scope of this paper.

A problem seen with the Cynefin framework is that, like Weaver's model, it over simplifies the complex world and at the same time provides no real insight into the nature of complex problems. It tries to account for problems large and small all within these four regions and does not really address problems of scale, or levels of interconnection.

An important characteristic of complexity science is the peculiar relationship of complexity and simplicity. It is sometimes stated that if one cannot explain something in simple, easy to understand terms, they really do not understand what they are trying to explain. When dealing with complex systems, as the scale increases and the problem becomes more intractable, it is necessary to simplify the problem. In doing this, fidelity and accuracy are lost and it is no longer possible to describe the constituent parts of the system in sufficient detail to understand their individual behaviors. At the same time, aggregate behaviors and large scale effects begin to emerge. In looking at larger problems, new relationships are found and new behaviors emerge. This all requires new mathematical and physical descriptions often taking the form of new laws of behavior. Through this process of simplification, one again finds the complexity of behavior for the larger system.

An interesting and related problem to consider is how one goes about simplifying the problem. Many paths to simplification will result in unsatisfactory, if not useless, answers. It is important to know what insight one is hoping to gain before plunging into an effort to simplify a problem and look at larger scales. If the correct question is not asked, one might think they are solving a problem, but really only expending effort on a fruitless endeavor (a *Grail Quest*).

An alternate way to look at potentially complex problems is to classify them by their content. Some problems contain data, some contain systems and systems of systems, while others have some form of social or political content. These three categories of content are mostly unrelated to one another and help to describe three different types of problems. Such a framework would then naturally be three dimensional and lend itself to presentation on a common, three axis Cartesian-type graph. On the first axis, one would find Data Content. On another axis one would find Systems Content. On the third axis, one would find Social Content. This model is seen in Figure 6 with the key features of this framework presented in Table 1. With this information, an approximate mapping of the tools and theories onto the model axes is shown in Figure 7.

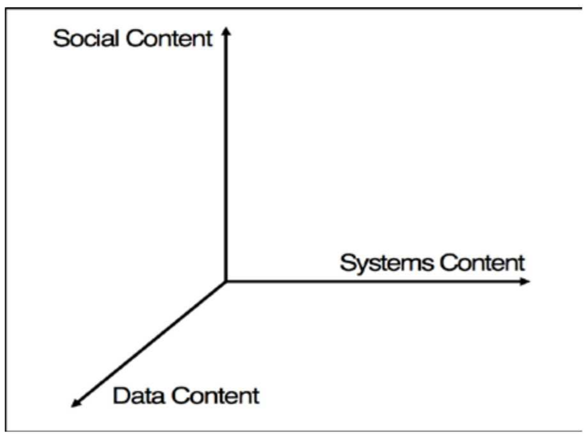

Figure 6. Three Dimensional Model for Complex Problems

Table 1. Characteristics of the Three Dimensional Model for Complex Problems

	Problem Type		
	Data	System	Social
Nature of Models and Tools	Analytical, Statistical	Coupled, Dynamic, Optimization	Agent-Based, Discrete Decisions
Nature of Solutions	Exact	Optimal, Best Possible	Nominal, Good Enough
Key Features	Information	Interdependent Systems	Winners and Losers
Lower Limit	Small	Simple	Manageable
Upper Limit	Very Large	Complex	Wicked
Issues	Big Data	System of Systems	Human Irrationality

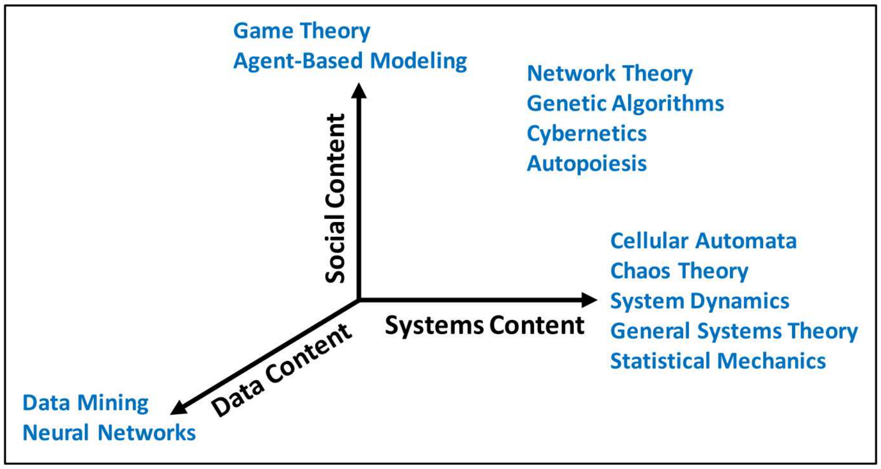

Figure 7. Mapping the Tools and Theories onto the Three Dimensional Framework

Data problems lend themselves to numerical and statistical analysis techniques. It is often possible to produce a mathematically exact solution to understanding the recorded behavior of parameters and values. When properly reduced, data problems produce information that can be acted upon by decision makers. They range in size from small to very large with the largest ones being thought of as *big data* problems. Modern data mining and machine learning techniques have proven useful for examining such large problems.

System problems usually consist of a large number of components that interact with one another in various complicated ways. They can consist of components with stochastic or deterministic behaviors. They might include mechanical, electrical, fluidic, biological, optical, chaotic, and possibly quantum mechanical components. The behavior of these systems is often approached with the tools of systems dynamics with the intent of understanding the limits of system behavior, predicting future states, or optimizing performance. Key features of such problems are interacting, interdependent systems and subsystems. The range in difficulty from simple to highly complex and are often thought of as being a system of systems.

Social and political problems include people or other decision-making biological entities for at least part of the system. These are often referred to as agents and individual agents are capable of independent goal seeking and decision making. Solutions to such systems are difficult and often unsatisfying. Often one must settle for solutions that appear to be *good enough*. A key feature of these problems is that no matter what the decision or solution, there will be both winners and losers. The problems range in size and complexity from those that are manageable to those that are considered to be wicked. The major issue associated with trying to solve such problems is that of human randomness.

One aspect of social problems that must be explored is the sudden appearance of wicked problems. These are problems that go well beyond the traditional difficult, complicated or complex. *Wicked problems* were first mentioned by Rittel in 1967 while discussing social problems that seem to defy solution [64]. Rather than being evil problems, wicked problems are difficult to even define as they keep changing while one is trying to address them. The requirements are often contradictory, difficult to nail down and frequently difficult to discover in the first place. Any attempt to solve such a problem causes it and the surrounding environment to change. Such problems frequently have no palatable solutions, but rather have options that range from unacceptable to those that are merely unappealing.

Social problems are particularly difficult due to the irrational tendencies found in most human behavior. While it is often argued that seemingly irrational decisions actually make sense to the individuals who made them, most such decisions are irrational and result from the interplay between the pattern-matching and contemplative portions of the human brain—the so-called *Thinking Fast and Slow* tendencies as described by Kahneman [65].

Assuming that one can identify where a given problem lies within the three-dimensional problem space, it is necessary to understand the epistemology of the solution sought. What type of learning outcome is hoped for from examining the complex problem? The knowledge sought can range from simply describing the complex system (empiricism), to being able to explain the system (phenomenology), and understanding potential future states (prognosticating). Table 2 presents the range of possible learning outcomes for each type of problem. The specific knowledge outcomes range from empiricism to prognostication. This range includes: Describe, Explain, Discover, Explore, Forecast and Predict as show in Table 2.

Table 2. Epistemology of Solutions Mapped against Complex Problem Type

		Problem Type		
	Relevant to	Data	System	Social
Describe	Past and Current	Past/Known Trends	Observed Performance	Observed Behaviors
Explain	Past and Current	Observed Trends	System Performance	Behaviors
Discover	Past and Current	Hidden Trends	Hidden Interdependencies	Hidden Agendas and Behaviors
Explore	Near to Far-Term	Hyopotheses	Possible Performance	Possible Events
Forecast	Near to Mid-Term	Range of Trends	Range of Likely Performance	Range of Likely Events
Predict	Near-Term	Specific Future Trend	Exact Performance	Specific Event

When one seeks to describe a complex problem, the knowledge gained is about past and possibly current states. Data problems are clearly about what has already occurred. For system problems, one might want to describe observed performance, while for social systems the past consists of observed behaviors.

To explain a complex system one requires more knowledge. Explanations are still about the past and present, but greater detail and insight are required than for mere description. For data problems, one would want to explain past trends. For system problems, the goal would be to explain past performance, while for social problems it would be necessary to explain past behaviors.

Discovering hidden features of a complex problem is the next level of understanding that one might seek. Discovery is again about the past and the present, but it is looking for hidden trends, interdependencies and human agendas rather than those that are obvious from a simple observation. Discovery requires a greater understanding of the problem than either explanation or description.

Finally, when one wants to understand possible futures for a complex problem, the choices are to explore the problem, forecast general futures or attempt to predict an exact future state. Exploration is the most general and can therefore extend the farthest into the future, covering near to possibly far-term outcomes. Forecasting requires greater accuracy and greater understanding of the complex problem, and therefore is not reliable as far into the future. As a general rule, forecasting over the near- to mid-term is the most that one can expect. Prediction requires exquisite knowledge of the systems past, present and dynamics. This is the most risky type of knowledge to seek and it should come with the greatest error bars, or ranges of uncertainty. It is really only useful in the near-term and should be pursued with significant caution.

For data problems, one can explore hypotheses about what might be captured in the data set, forecast a range of trends or try to predict a specific trend. For systems where the consequences of error are small (such as predicting the interests of a single, specific customer), predictions can be made more freely, but for systems where the consequences of erroneous prediction are large, more caution is required.

For system type problems, one can attempt to explore the range of possible future performance without providing judgements as to which futures are more or less likely. Forecasts regarding a range of likely future performance require greater knowledge and understanding than simple exploration. Finally prediction regarding exact performance requires the greatest care. In general, the dynamics of complex systems are sufficiently difficult to understand that no reliable predictions are possible. This fact, however, seems to have escaped those who profess the dangers of global warming and climate change. Atmospheric processes are extremely chaotic and highly unpredictable. The best that one can hope for would be to predict a range of futures and over time, such predictions have been made, ranging from significant global cooling to significant warming. Because of the immediate social component that enters the discussion, global warming and climate change is an example of a wicked problem that includes systems and social aspects.

When dealing with social problems, the future is mostly about future events. One can explore possible future events, forecast a range of likely events or attempt to predict specific future events.

The final aspect of the solution space for a complex problem is to understand the time available for study and the timeframe during which a solution is required. The problems are such that one could spend a great deal of time studying the system while never getting around to offering a solution. Politicians typically want solutions that can be implemented on timescales of 1-4 years, being driven by public opinion and election cycles. From Table 2, the authors note that accurate predictions are really only practical in the near-term, but they also require the greatest understanding of the complex problem.

With an understanding of the available theories and tools, an understanding of the types of complex problems—and a clear idea of the nature of the solution being sought—complexity science has the potential to provide useful insight into problems that have defied solution by traditional techniques. The issue that yet remains is that many real-world problems combine some elements from each of the three classes of problem types listed above. Such problems require some level of skill and patience to identify how best to attack them. Two such problems that will be discussed below are resilience and trust.

This page is intentionally left blank

7. RESILIENCE AND TRUST

Resilience and trust are two real-world examples of highly complex problems that governments, business, and private organizations attempt to address every day. The problems have amazing similarities and yet, in the end-game, are quite different. Resilience addresses how a system can recover from a sudden, unpredictable disruption in its environment. Trust examines the issue of some external agent clandestinely introducing defective materials, parts, software or supplies into a system to negatively impact products, services, or the functioning of the system. If discovered immediately, these defects are considered sabotage, but when undiscovered and activated at some later date, the defects are thought of as subversion. A trust example most anyone could identify with is that of cell phone security. Given that the phones are manufactured outside the USA, how can the user be sure that a malicious agent has not installed a backdoor access mechanism that bypasses the intended device security systems? One can look for the backdoor and have little chance of finding it, yet if it is there, it can be accessed at almost any time by some malicious actor.

The concept of trust will not be familiar to many readers. In the early days after World War II, the concepts of quality and reliability were gaining hold within government and industry. Quality was achieved by testing and removing substandard parts from the manufacturing process. Testing, however, was expensive. To reduce costs, the concept of a qualified suppler or qualified manufacturer evolved. The idea was to verify that a subcontractor was consistently producing a product within specifications resulting from a well refined, controlled and monitored manufacturing process. Once the process was qualified, the subcontractor could be *trusted* to produce components within specification without the need to screen each and every part. This concept of a trusted manufacturer is, however, different from the complex problem of trust as discussed in this report.

Trust, as used here, is the justified confidence that a system, product or process, will perform as intended, when intended, and without unintended behaviors, functions or features. Justified confidence requires positive steps to assess and assure the trust characteristics of a system.

On the surface, the concepts of trust and resilience are rather simple. Resilience requires a system to have excess capacity for immediately recover from an upset, and adaptive capacity for long-term adjustment to a *new normal* to address permanent changes in the operating environment. Trust simply requires measures to assure materials, parts, software and supplies meet the required specifications and do not introduce unwanted extra features. Beyond this naive view, the two problems have amazing similarities and both are extremely complex.

For either problem, one needs to understand their system and all its components, and examine how each component might fail and the consequences of that failure, including the potential for cascading consequences. However, this process must look beyond the system in isolation and consider it together with its environment. Critical failures in the environment can negatively impact the system in question resulting in a loss that is just as catastrophic as if the system itself had failed. When examining resilience, one must address both changes in the environment and random failures within the system. When addressing trust, one must watch for covert latent failure mechanisms introduced by an external agent. These failure mechanisms might be introduced into the system itself, or could be placed in the operating environment. They are not intended to cause failure immediately, but rather will be triggered or randomly occur at some later date, thereby making them more difficult to find and prevent.

For either problem, the supply chain is far too complex to examine in rigorous detail. Rather than a simple supply chain, one most likely finds a highly interconnected complex supply system of networked systems. There is also a product chain that extends out from the system in question to all the customers that are consuming that product or service. A random or intentional failure in the product chain can be just as damaging as a failure in the supply chain. Figure 8 provides only a hint of the potential complexity of the supply and product chain network.

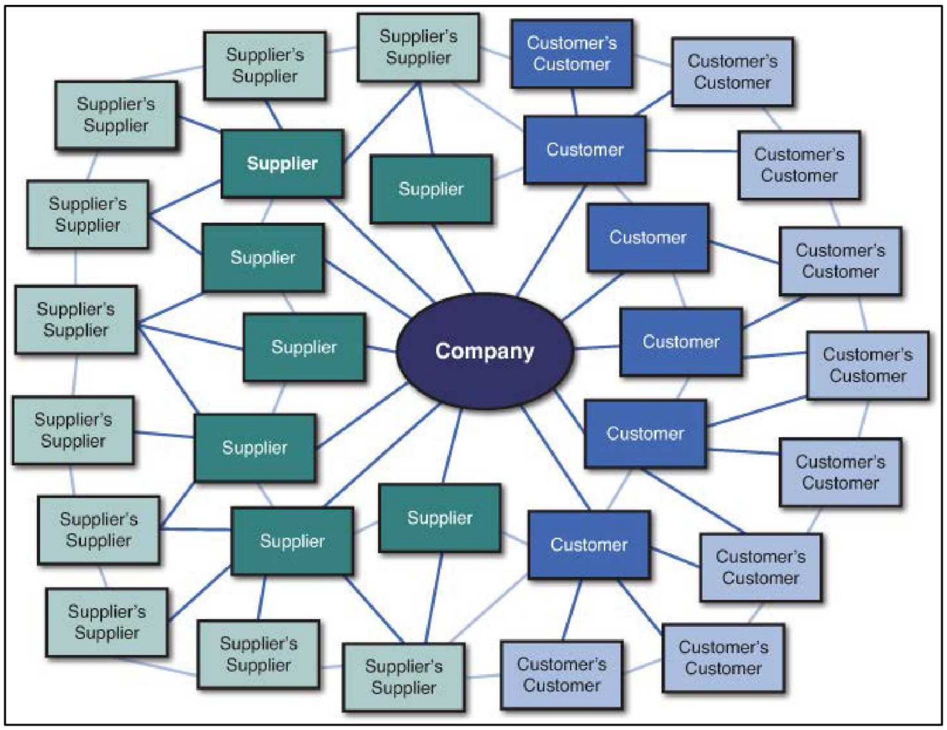

Figure 8. Depiction of Networked Supply and Product Chains [66]

Starting from the product and working down the supply chain, one normally finds that the network opens up in a fan or pyramidal shape. At the top sits the product, but that product is composed of systems. Each system is made up of multiple subsystems, which in turn are made from dozens of assemblies. Below these assemblies lie components, parts, and finally materials. A single part might be made from dozens of materials. A depiction typical of the upper portion of such a supply chain is seen in Figure 9.

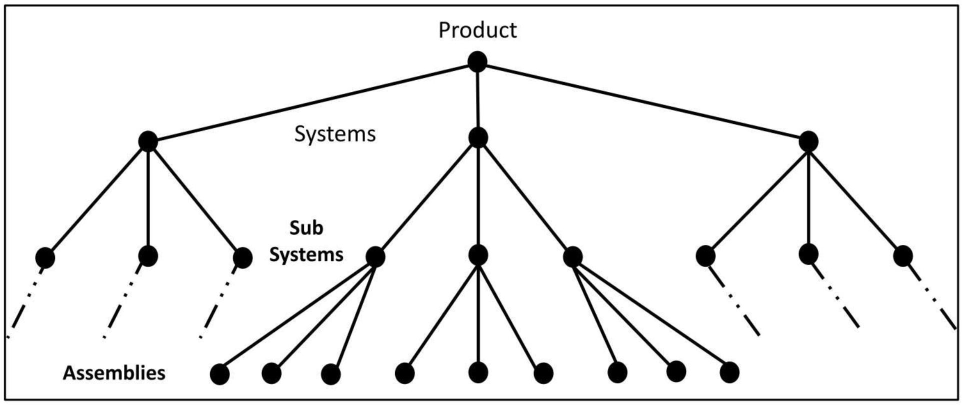

Figure 9. Depiction of Hierarchical Supply Chain

For a manufacturer, it is important to know if their supply chain converges to a single source for a critical material. Similarly for the producer of some highly specialized material, it would be useful to know if at the end of their product chain, there is a single manufacturer with a single product using that material. A notional product chain is shown in Figure 10. The likelihood of a single consumer for a product is significantly less than the possibility of a single supplier for a critical material, but both cases help to illustrate the importance of understanding the deep supply chain. For resilience, a deep understanding of the supply chain might reveal potential problems, such as situations where the available suppliers for a critical component all acquire that component from a single distributor.

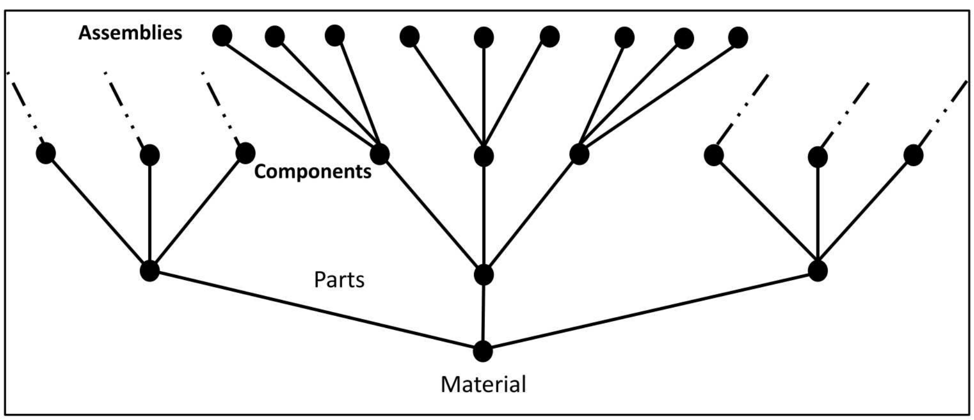

Figure 10. Depiction of Bottom to Top Product Chain

7.1. Resilience

When addressing problems of resilience, it is necessary to accept that all systems will eventually fail. If this is the system of interest—or the system of systems including the environment and supply chain—failures and disruptions will occur. Recovery from such upsets requires an understanding of the potential upsets and some level of planning for mitigating these disruptions. It is also necessary to accept that *it is all but impossible to achieve a deep understanding of one's supply chain*, especially with the added complication that supply chains are dynamic and any understanding will be transitory.

All systems require some combination of materials, utilities, services, equipment and people (or agents for the more general case), all of which have their own supply chains. How does one approach resilience if understanding the supply chain is extremely difficult, at best?

Resilience requires some combination of excess capacity and adaptive capacity. It is not practical or economically competitive to maintain a large inventory of all materials and supplies required for production of a product. Similarly, it is not practical to have multiple, independent sources for services and utilities, or an excess number of employees to staff a manufacturing process.

One approach to addressing resilience is to decompose the system under consideration into its constituent subsystems, assemblies, components, and so forth, to the desired level of granularity. Higher resolution requires more time and results in more cost, while lower resolution results in acceptance of greater risk. With the desired decomposition, each item can then be assessed as to how critical it is, and how unique it is. Critical items are those that cannot be changed without a major redesign of the system. Non-critical items require no modifications to the system, or very slight modifications to accommodate a change. Unique items are those where no suitable alternative with the same form, fit, and function exists. Common items are those for which multiple identical alternatives exist.

As an example, consider a small microprocessor controlled assembly that monitors the functions of an automobile engine and illuminates a yellow light-emitting diode (LED) to signify if the engine needs to be checked. The microprocessor is likely to be a critical item as any such change would require modifications to the circuit board and changes in the operating software or firmware. The yellow LED, however, is likely to be non-critical as even a very different LED could be substituted with no modification, or very minor modifications to the production circuit board. Uniqueness and commonality are another matter. While the microprocessor might be unusual—if it is available from multiple manufacturers—it would be considered common. On the other hand, if it were a sunset technology that only one manufacturer was still producing, then it would be unique.

Along with the concepts of criticality and uniqueness, it is useful to consider the actions of substitution and replacement. Substitution is a quick action where a similar item can immediately be used in place of the original. Replacement is a longer-term effort where a new item is permanently used in place of the original. For a replacement, one must find an entirely new component, whereas for substitution, one finds a new source for a form, fit and function equivalent item.

It is useful to plot the combination of criticality and uniqueness for each item on a Cartesian graph as shown in Figure 11. This graph includes the most likely actions required for each combination of these characteristics.

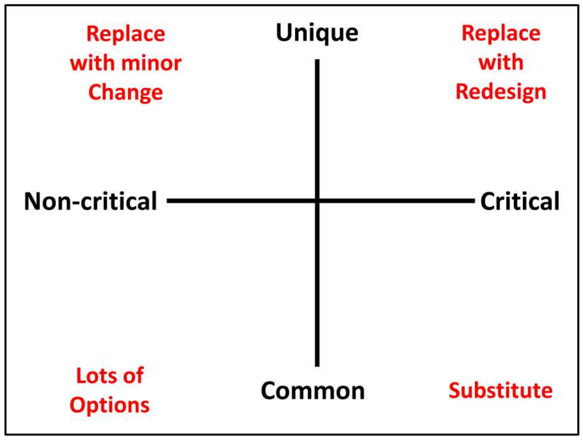

Figure 11. Assessing Criticality and Uniqueness of Any Item

Part of resilience planning is to develop a mitigation strategy. For all items, the long-term options are to replace or to substitute, but the viability of this approach in the short-term is highly dependent upon how quickly the system needs to recover and how long it will take to replace or to substitute items. Substitution is likely to be a rapid action provided the items really are common, while replacement is likely to take much longer. Either option represents some form of an adaptive response.

For true short-term recovery, the best option is to stockpile items that will pose more of a challenge to replace. Excess material stocks are a form of excess capacity. This is graphically shown in Figure 12. For items that are unique and critical, short-term resilience will come from excess capacity. For unique, non-critical items, or critical common items, some combination of excess capacity and adaptive capacity are required. For non-critical common items, resilience can most likely be realized through adaptation. This approach provides options for resilience where it is not necessary to have excess capacity everywhere, but only in targeted areas.

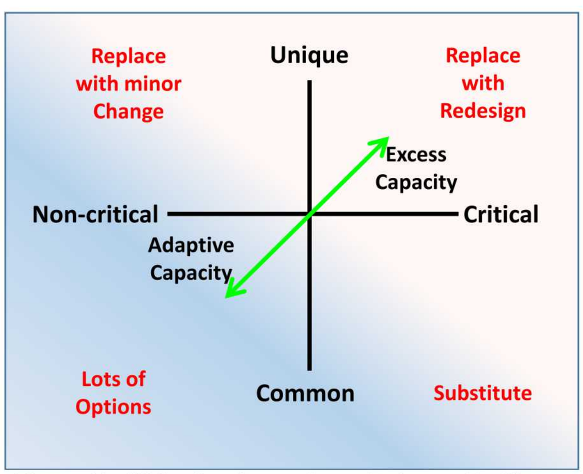

Figure 12. Mitigation Strategies to Enhance Resilience

While there are no simple answers for resilience, the proposed basic strategy provides the basis for planning to mitigate the negative impacts of failures in one's system, or changes in the operating environment. Stated more simply, the basic strategy consists of:

- Determine the required timescale for recovery
- Decompose system to desired level of granularity
- Ask which items can fail, and what happens if they fail
    - Note that failure can result from internal or external causes
- Determine which items are critical and which items are unique
    - How difficult is an item to substitute (short-term)
    - How difficult is an item to replace (long-term)
- Select appropriate combination of excess capacity and adaptive capacity for each item

7.2. Trust

Similar to resilience, trust requires a deep understanding of the system, the environment, the supply chain, how all the interrelated and interdependent systems and parts can fail, and what happens if concealed failure mechanisms are introduced in any part of the extended system. As discussed with resilience, *fully understanding this extended system of networked systems is all but impossible,* even for the most simple of situations. Making matters worse, when dealing with a skilled adversary, there is no such thing as a critical item and a non-critical item. An attacker with appropriate skill can find ways to introduce system failure through even the most mundane and uninteresting of components.

Experience suggests that it is often easier to hide intentional defects in nondescript components as they are frequently ignored and trusted outright, even without justification. As an example, the connectors on the ends of cables used in many systems ranging from aircraft to automobiles, normally have significant volume and could easily be modified to include active electronics that monitor and change signals on the cables. Yet the cables are simple pieces of insulated wires with somewhat bulky pieces of metal or plastic on their ends to connect to other assemblies. If the cable passes an electrical check for its intended connectivity, almost no one will question the cable and examine it further. On the other hand, an active component such as a microprocessor or memory chip might be subject to significant inspection and verification testing.

As discussed previously for resilience, any system will require some combination of materials, supplies, utilities, equipment and people to function. The difficulty of deep understanding of the supply chain has already been established. Similarly, *it is both impossible and cost-prohibitive to exhaustively examine and test all incoming items while at the same time, it is almost necessary to test everything*. These issues seem mutually incompatible, thereby making the problem of trust complex beyond imagination. While not necessarily including a social component, problems of trust are wickedly complex as the mitigation approaches involve both winners and losers in terms of where resources are applied and where they otherwise could have been applied.

One approach to trust is to closely examine the network of suppliers. Within the Department of Defense, this is known as Supply Chain Risk Management (SCRM [67]). Based on previous discussions in this report, this is not an effective approach.

A more reasonable approach is to accept that it is impossible to deeply understand the supply chain, even for simple systems. Also, it is necessary to accept that given sufficient time and resources, any adversary can attack almost any system. The key to trust in such circumstances is to put in place policies, practices and processes that will deter an adversary through preventive measures, detect subverted items through an inspection and testing protocol, and mitigate the effects of a successful subversion should it elude the first two measures [68]. The concepts of prevent, detect and mitigate are the trust principles for this approach.

Continuing with this approach, the first step is to decompose the system into items (or components) and assess each item to determine what parts can fail, how they can be made to fail, and the consequences that occur should they fail. Note that for trust, it is necessary to look at how something could be made to fail rather than only examining natural failure mechanisms. Following this, it is useful to develop a taxonomy for the constituent items. One possible approach is seen in Table 3. There are many other taxonomies that could be developed. Note that this example is only for an electronic system. A complete taxonomy must include categories for materials, supplies, utilities, equipment and manpower.

Table 3. Possible Taxonomy of Items Contained within a System

Item Taxonomy	
Mechanical	
	Inert
	Active
Electrical	
	High Voltage
	Low Voltage
Electronic	
	Analog
	Processors
	Memory
	Other Digital
Energy Storage	
	Chemical
	Electrical
Other	
	Gas/Vacuum
	Software
	Optical
	Magnetic
Special Components	
	Mission Specific

Next, based on a consideration of how items could fail or be made to fail, one develops a hierarchy of countermeasures than would help to prevent, detect and if necessary mitigate subverted items. One possible hierarchy of countermeasures is seen in Table 4.

Table 4. Hierarchy of Countermeasures

Identifier	Action	
A	Prevent access to information.	
	A1	All designs on isolated/classified networks.
	A2	Encrypt files.
	A3	Do not release parts list or bill of materials.
	A4	Rapid open buys.
	A5	Blind buys.
B	Prevent access to materials.	
	B1	Ship using multiple transport agents.
	B2	Ship to both Sandia and blind (sterile) addresses.
	B3	Bonded stores.
	B4	Secure internal movement of materials.
C	Minimize size where possible. Specify exact part when/where possible.	
D	Peer review, explain why component was selected, what it must do and what would result in case of failure.	
E	Independent review/assessment of component for inherent vulnerabilities.	
	E1	Red Team Assessment.
	E2	Cooperative Vulnerability Assessment (Black Team)
F	Assessment of changes in dielectric materials with long-term, low-dose radiation environment.	
G	Specify exact part from specific manufacturer.	
H	Minimize excess functionality. Use lowest capability part that meets requirements	
I	Assessment of changes in chemistry with long-term, low dose radiation environment.	
J	Software Security	
	J1	Peer review of software.
	J2	Minimize functionality.
	J3	Apply anti-software integrity techniques/tools.
K	Inspect upon receipt. Did you receive what you thought you were going to receive.	
L	Random sample mechanical inspection.	
M	Random sample radiographic inspection	
N	Random sample electrical function test.	
O	Random sample power spectral analysis where possible.	
P	100% sample mechanical inspection	
Q	100% sample radiographic inspection	
R	100% sample electrical function test	
S	100% power spectral analysis	
T	Statistical Sample Destructive Physical Analysis	
U	Specialized software verification inspection techniques.	
V	Test	
	V1	Test components, subassemblies, assemblies and systems in realistic environments.
	V2	Test in combined environments, such as radiation, vacuum and thermal, whenever possible.
	V3	Conduct parametric tests on a small number of components, subassemblies, assemblies and systems.
	V4	Test small number of components, subassemblies, assemblies and systems to failure.
	V5	Explain all failures (inadvertent, or when tested to failure).
W	Special attention required for mission-unique assemblies.	
X	Special attention required for mission-unique assemblies.	

Finally, the countermeasures are mapped against the taxonomy of item type based on the system decomposition. Depending on the level of risk that can be assumed, various countermeasures are proposed for different types of items or components. The proposed mapping seen in Tables 5-8 is notional, but based on significant insight and experience with the general concepts of trust and potential subversion mechanisms. Countermeasures grouped in green provide higher levels of trust. Those grouped in yellow provide lower levels of trust, while those in red result in almost no useful justified confidence in trust aspects of the item, component or system.

Table 5. Mapping of Countermeasures across System Decomposition Taxonomy

Applicable Trust Principle >>>			Prevent	Prevent	Prevent/Mitigate	Detect
			Limit Information	**Control Access**	**Reduce Inherent Susceptibilities**	**Test and Surveillance**
Mechanical	Inert	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C	K + (L or M) + (V1 + V5)
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	C	K + (V1 or V5)
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Active	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2	K + L + M + V1 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + L + V1 +V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
Electrical	High Voltage	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + F	K + M + N + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + N + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Low Voltage	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2	K + M + N + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + N + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow

Table 6. Mapping of Countermeasures across System Decomposition Taxonomy

Applicable Trust Principle >>>			Prevent	Prevent	Prevent/Mitigate	Detect
			Limit Information	Control Access	Reduce Inherent Susceptibilities	Test and Surveillance
Electronic	Analog	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + G	K + M + N + O + T + V1 + V2 + V3 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + N + O + T + V1 + V3 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Processors	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + G + H	K + O + R + T + V1 + V3 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2 + H	K + N + O + T + V1 + V3 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Memory	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + G + H	K + P+ Q + R + S + T + V1 + V2 + V3 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2 + H	K + N + O + T + V1 + V3 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Other Digital	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + G	K + M + N + O + T + V1 + V2 + V3 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + N + O + T + V1 + V3 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow

Table 7. Mapping of Countermeasures across System Decomposition Taxonomy

Applicable Trust Principle >>>			Prevent	Prevent	Prevent/Mitigate	Detect
			Limit Information	Control Access	Reduce Inherent Susceptibilities	Test and Surveillance
Energy Storage	Chemical	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2 + I	K + L + M + T + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	C + D + E2	K + M + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Electrical	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2 + F	K + L + M + T + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	C + D + E2	K + M + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
Special Components	Mission Specific	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2 + W	K + L + M + N + T + V1 + V2 + V4 + V5 + X
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	C + D + E2 + W	K + M + N + V1 + V5 + X
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
RF Components	MMIC	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + F + G + H	K + P + Q + R + S + T + V1 + V2 + V3 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + O + R + T + V1 + V3 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Other RF	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	D + E1 + E2 + F	K + M + N + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + N +V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow

Table 8. Mapping of Countermeasures across System Decomposition Taxonomy

Applicable Trust Principle >>>			Prevent	Prevent	Prevent/Mitigate	Detect
			Limit Information	Control Access	Reduce Inherent Susceptibilities	Test and Surveillance
Other	Gas / Vacuum	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2	K + L + M + T + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + M + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Software	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	J1 + J2 + J3	K + U
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	(J1 or J2) + J3	U
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Optical	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2	K + L + M + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + M + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow
	Magnetic	Green	2 of {A1, A2, A3} + (A4 + A5)	(B1 or B2) + (B3 + B4)	C + D + E1 + E2	K + L + M + V1 + V2 + V4 + V5
		Yellow	(A1 or A2) + (A4 or A5)	(B1 or B2) + (B3 or B4)	D + E2	K + M + V1 + V5
		Red	Less than yellow	Less than yellow	Less than yellow	Less than yellow

While there are many possible approaches to trust, the one presented above results from significant insight and research into the topic. To summarize this approach, one might consider pursuing the following steps:

- Define a virtual perimeter around the system
    - Anything crossing this perimeter is a supply
- Decompose system into subsystems and components to desired granularity
- Create a taxonomy of item types
- Consider how each item could fail or be induced to fail
    - What are the consequences of each failure?
- Create a list of countermeasures to prevent, detect and mitigate each failure
- Map countermeasures across item taxonomy
- Decide upon acceptable level of risk

8. SUMMARY

Complexity science is a rich, emerging field of analysis. While not a formal science at this time, future developments that address the fundamental underpinnings of the greater topic area will eventually help to transform complexity into a true scientific discipline. At present, it consists of a variety of theories and some well-developed tools that help to provide significant insight into problems that are very large, highly interconnected, and that might include a social component. The quantitative behavior of complex systems is extraordinarily difficult to predict, but with proper analysis, future behavior can be bounded and such techniques are useful to help examine *what if* scenarios and avoid strongly negative outcomes.

The problems of resiliency and trust are of high practical interest to industry and government organizations alike. Both are extremely complex and defy attempts to analyze using traditional techniques. Through a combination of complexity science and a practical approach to dealing with the topics, useful insight can be gained and progress made towards developing both resilient and trusted systems.

This page is intentionally left blank

REFERENCES

[1] O. Dedehayir, The hype cycle model: A review and future directions, Technological Forecasting & Social Change 108 (2016).

[2] E. Regis, The Info Mesa: Science, Business, and New Age Alchemy on the Santa Fe Plateau, ISBN-13: 978-0393341577, W. W. Norton & Company, (May 17, 2003).

[3] S.E. Phelan, What Is Complexity Science, Really?, Emergence, 3(1) (2001).

[4] J. Urry, The complexity turn, Theory, Culture and Society, Special Issue on Complexity 22(1): 3 (2005).

[5] A. Rosenberg, Reductionism in a Historical Science, Philosophy of Science, Vol. 68, No. 2 (Jun., 2001).

[6] M. Courtney, Epistemological Distinctions Between Science and History, https://arxiv.org/ftp/arxiv/papers/0803/0803.4245.pdf, ArXiv.org (2008), accessed November 2017.

[7] C.J. Wenning, Scientific epistemology: How scientists know what they know, J. Phys. Tchr. Educ. Online, 5(2), autumn 2009.

[8] A. Guillan, Epistemological Limits to Scientific Prediction: The Problem of Uncertainty, Open Journal of Philosophy, Vol. 4 (2014).

[9] Creator, Universal Studios, 1985.

[10] J.P. Strumberg, Systems and Complexity Thinking in the General Practice Literature: An Integrative, Historical Narrative Review, Annals of Family Medicine, Vol. 12, No. 1, January / February 2014.

[11] Example Emergent Phenomena, http://www.evolutionofcomputing.org/Multicellular/Emergence.html, accessed October 2017.

[12] W. Weaver, Science and Complexity, American Scientist, 36: 536 (1948).

[13] B. Castellani, Brian Castellani on the Complexity Sciences Theory, Culture & Society, http://www.theoryculturesociety.org/briancastellanionthecomplexitysciences/, accessed October 2017.

[14] J.P. Strumberg, Systems and Complexity Thinking in the General Practice Literature: An Integrative, Historical Narrative Review, Annals of Family Medicine, Vol. 12, No. 1, January / February 2014.

[15] D. Bernoulli, Hydrodynamica, 1738.

[16] A. Martini, The Renaissance of Science: The Story of the Cell and Biology, ISBN: 978-0-692-48512-5, Abbott Communications Group, Maitland, FL (2015).

[17] J. Fourier, The Analytical Theory of Heat, translation, Cambridge University Press (1878).

[18] W. Thompson (1st Baron Kelvin), An Account of Carnot's Theory of the Motive Power of Heat - with Numerical Results Deduced from Regnault's Experiments on Steam, Transactions of the Edinburgh Royal Society, XVI. January 2, (1849).

[19] J.C. Maxwell, Theory of Heat, Longmans, Green & Co., London (1872).

[20] P.W. Anderson, More is Different, Science, New Series, Vol. 177, No. 4047 (Aug. 4, 1972).

[21] H. Ekbia, Big data, bigger dilemmas: A critical review, Journal of the Association for Information Science and Technology. 66 (2015).

[22] S. Lohr, The Age of Big Data, The New York Times, February 11, 2012.

[23] A. McAfee, Big Data: The Management Revolution, Harvard Business Review, October 2012.

[24] H. Chen, Business Intelligence and Analytics from Big Data to Big Impact, MIS Quarterly Vol. 36 No. 4, December 2012.

[25] M. Conti, TRAP: using TaRgeted Ads to unveil Google personal Profiles, IEEE International Workshop on Information Forensics and Security (WIFS) (2015), also available at arXiv:1510.04031v1 [cs.SI] 14 Oct 2015.

[26] U. Sivarajah, Critical analysis of Big Data challenges and analytical methods, Journal of Business Research 70 (2017).

[27] D. Boyd, Critical Questions for Big Data, Information, Communication & Society, 15:5 (2012).

[28] F. Provost, Data Science and its Relationship to Big Data and Data-Driven Decision Making, Mary Ann Liebert, Inc., Vol. 1 No. 1 March 2013.

[29] B. Castellani, Sociology and Complexity Science: A New Field of Inquiry, ISBN: 978-3-540-88461-3, Springer-Verlag, Berlin, Heidelberg (2009).

[30] D. Flamm, History and outlook of statistical physics, arXiv.org, https://arxiv.org/pdf/physics/9803005.pdf (1998).

[31] Wikipedia, Statistical Mechanics, https://en.wikipedia.org/wiki/Statistical_mechanics, accessed September 2017.

[32] L. von Bertalanffy, General System Theory: Foundations, Development, Applications, revised edition, ISBN: 978-0807604533, Penguin University Books, George Braziller Inc. (1969).

[33] Wikipedia, https://en.wikipedia.org/wiki/Systems_theory#Examples_of_applications, accessed October 2017.

[34] N. Wiener, Cybernetics, Scientific American, Vol. 179, No. 5 (1948).

[35] Wikipedia, Cybernetics, https://en.wikipedia.org/wiki/Cybernetics, accessed August 2017.

[36] N. Wiener, Cybernetics: Or Control and Communication in the Animal and the Machine, ISBN 978-0-262-73009-9, Paris (1961).

[37] Wikipedia, System Dynamics, https://en.wikipedia.org/wiki/System_dynamics#History, accessed July 2017.

[38] J.W. Forrester, On the History, the Present, and the Future of System Dynamics, SYSTEM DYNAMICS – Vol. I - On the History, the Present, and the Future of System Dynamics - Jay W. Forrester, Encyclopedia of Life Support Systems (EOLSS).

[39] System Dynamics Society, Introduction to System Dynamics, http://www.systemdynamics.org/what-is-s/, accessed July 2017.

[40] Wikipedia, Chaos Theory, https://en.wikipedia.org/wiki/Chaos_theory#Introduction, accessed September 2017.

[41] C. Oestreicher, A history of chaos theory, Dialogues in Clinical Neuroscience 9(3) (2007).

[42] Wikipedia, Autopoiesis, https://en.wikipedia.org/wiki/Autopoiesis#Relation_to_complexity, accessed October 2017.

[43] D. Seidl, Luhmann's theory of autopoietic social systems, Ludwig-Maximilians-Universität München, Munich School of Management (2004).

[44] B. Mavric, Physical Applications of Cellular Automata, University of Ljubljana Faculty of mathematics and physics, Ljubljana, July 23, 2013.

[45] A. Yuen, Applications of Cellular Automata, University of Birmingham, Edgbaston Birmingham, United Kingdom.

[46] Wikipedia, Cellular Automaton, https://en.wikipedia.org/wiki/Cellular_automaton, accessed July 2017.

[47] G. Andrews, Cellular Automata and Applications, Whitman College, Walla Walla, WA.

[48] Wikipedia, Network Theory, https://en.wikipedia.org/wiki/Network_theory, accessed September 2017.

[49] G.L. Alexanderson, About the Cover: Euler and Konigsberg's Bridges: A Historical View, Bulletin of the American Mathematical Society, 43(4) (2006).

[50] Wikipedia, Agent-based Model, https://en.wikipedia.org/wiki/Agent-based_model, accessed November 2017.

[51] C.M. Macal, Introduction to Agent-based Modeling and Simulation, Argonne National Laboratory, MCS LANS Informal Seminar, November 29, 2006.

[52] T. Back, Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms, ISBN: 978-0195099713, Oxford University Press (1996).

[53] D.L. Applegate, et al., The Traveling Salesman Problem: A Computational Study, ISBN-13: 978-0691129938, Princeton University Press (2007).

[54] R. Rojas, Neural Networks, A Systematic Introduction, Springer-Verlag, Berlin, 1996.

[55] J.A. Paravantis, From Game Theory to Complexity Science and Agent-Based Modeling in World Politics, IEEE, 6th International Conference on Information, Intelligence, Systems and Applications (IISA). 2015.

[56] Wikipedia, Game Theory, https://en.wikipedia.org/wiki/Game_theory, accessed November 2017.

[57] Wikipedia, Nash Equilibrium, https://en.wikipedia.org/wiki/Nash_equilibrium#Applications, accessed November 2017.

[58] Wikipedia, Pareto Efficiency, https://en.wikipedia.org/wiki/Pareto_efficiency, accessed November 2017.

[59] D.J. Hand, Data Mining: Statistics and More?, The American Statistician, Vol. 52, No. 2, May 1998.

[60] Wikipedia, Data Mining, https://en.wikipedia.org/wiki/Data_mining, accessed November 2017.

[61] R.H. Shumway, Time Series Analysis Using the R Statistical Package, Free Dog Publishing (2017).

[62] Wikipedia, Time Series, https://en.wikipedia.org/wiki/Time_series#Methods_for_analysis, accessed November 2017.

[63] C.F. Kurtz, The new dynamics of strategy: Sense-making in a complex and complicated world, IBM Systems Journal, Vol. 42, No 3 (2003).

[64] C.W. Churchman, Wicked problems, Management Science, 14(4), 1967.

[65] D. Kahneman, Thinking, Fast and Slow, ISBN: 978-0374533557, Farrar, Straus and Giroux (2013).

[66] H. Chen, Defining the Supply Chain, Pearson, informit, January 10, 2014, http://ptgmedia.pearsoncmg.com/images/chap1_9780133453928/elementLinks/01fig02_alt.jpg, accessed December 2017.

[67] Defense Acquisition University, Supply Chain Risk Management, https://www.dau.mil/acquipedia/Pages/ArticleDetails.aspx?aid=58c41410-8bdc-4232-bc7a-d29cc62113e8, accessed December 2017.

[68] M.R. Ackermann, Implementing Trust Across the Nuclear Weapons Complex, SAND2015-4716, June 2015.

This page is intentionally left blank

DISTRIBUTION

1	MS0899	Technical Library	9536 (electronic copy)

This page is intentionally left blank

Sandia National Laboratories