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Modeling and Managing Interdependent Complex Systems of Systems: Fundamentals, Theory and Methodology

PART I: AN OVERVIEW

1.I.1 INTRODUCTION

What does it mean to label systems as interdependent and interconnected complex systems of systems (Complex SoS)? Do we measure their complexity in terms of their subsystems' multiple attributes and perspectives, their functionalities and resources, the number of shared states and decisions, resources, decision makers, and stakeholders, or in terms of their culture and organizational structure, etc.? Modeling is an amalgamation or symbiosis of the arts and the sciences. As the artist reconstructs images and ideas, scenes, people, and structures, so do the modelers of Complex SoS when they decompose and restructure the subsystems "from the inside out and from the outside in" and relate the components to each other through their natural, physical, organizational, and functional attributes, recreating the interdependent and interconnected entity. Using the building blocks of mathematical models (to be discussed in subsequent sections) and ultimately by exploiting the shared states and other essential entities among the subsystems, the modeler and other users are able to better understand Complex SoS. The term other common/shared essential entities includes shared decisions, decisionmakers, stakeholders, resources, organizational behavior and norms, policies and procedures, management, culture, and others. We adopt the premise that models are built to answer specific questions; they must be as simple as possible and as complex as required. Thus, modeling the natural environment and the constructed environment such as organizations, or a combination thereof, represents a similar challenge. Namely, how many perspectives of a single system must be considered by modelers to achieve close-to-a-holistic model(s) in response to the required needs? And are we able to conceive of and discover all the essential attributes, characteristics, and perspectives of Complex SoS? Such open-ended questions reinforce the notion that the modeling process is a journey of discovery, imagination, and creativity. When we think we have succeeded, we are likely to be proven wrong. This assertion ought to be interpreted constructively and philosophically, but never fatalistically. In other words, the modeling

Modeling and Managing Interdependent Complex Systems of Systems, First Edition. Yacov Y. Haimes.

process is an open-ended continuous journey of learning and exploration that is characterized by successes and failures through which progress is made and, eventually, models are declared representative and valuable.

What does it mean to characterize systems as Complex SoS? Indeed, the emergence of the complexity characterizing Complex SoS requires a reevaluation of their modeling, management, and communication. The evolution of the terms complexity and complex systems, their differing connotations during the last 50 years, and the ways in which they have led us to model and manage complexity are the subject of this book. Current models for Complex SoS are insufficient because too often they rely on the same modeling schema used for single systems. These models commonly fail to incorporate the complexity derived from the networks of interdependencies and interconnectedness (I-I) characterizing Complex SoS.

In their essence, most cyber–physical, organizational, and governmental enterprises, now and in the future, belong to Complex SoS. Understanding their complexity and being able to characterize them can lead us to reevaluate our theory and methodologies as applied to single systems; more specifically being cognizant of and responsive to the emergent nature of Complex SoS, given the *Evolving Base*. The *Evolving Base*, discussed in Chapter 9, is represented by the following dynamic shifting rules and realities for each subsystem and for the entire Complex SoS: (i) goals and objectives; (ii) stakeholders, decision makers, and interest groups; (iii) organizational, political, and budgetary baselines; (iv) reorganization and reallocation of key personnel; (v) emergent technology and its deployment; and (vi) requirements, specifications, delivery, users, and clients (Haimes, 2012b).

In modeling Complex SoS, holism must be equally applied to natural and constructed environments, as well as to human and community activities and behaviors. The challenge is how to model the interface and the interplay among these activities that are not independent; rather, their I-I are one manifestation of Complex SoS.

The above discussion is harmonious with the philosopher Jacob Bronowski's (1978) seminal statements:

> The world is totally connected. Whatever explanation we invent at any moment is a partial connection, and its richness derives from the richness of such connections as we are able to make. (p. 96)

> There is no nerve without the muscle and no muscle without the nerve in the total animal. This is the same statement as the one I made about the total connection of the world…. (p. 99)

Of the human senses, Bronowski argues that arts mediated by the sense of light, like sculpture and painting, and arts that mediated by speech and sound, like the novel, drama, and music, dominate our outlook. Most of the time we use vision to give us information about the world and sound to give us information about other people in the world. How do we translate and build on Bronowski's "vision" and "sound" in our modeling of Complex SoS? What kind of "instruments" do we need to model Complex SoS? In modeling, we commonly build on (i) domain knowledge, (ii) human and organizational behavior, (iii) the role of cyber–physical infrastructure in today's quality of life of communities and individuals, (iv) systems engineering theory and methodology, (v) databases, and (vi) modeling experience, among others. What is the role of inference and perception in translating a system and its environment from reality into an abstract vision that is built on Bronowski's and on other philosophers' ideas in support of the fundamentals of state-space theory (Bellman and Dreyfus, 1962, Nise, 2014)? The art and science of modeling is but an interpretation of the common multiple perspectives of Complex SoS used by modelers, namely, natural, physical, structural, organizational, or human behavior.

Fundamentally, this construable process represents a mental translation that implies a subjective cognitive understanding of each of the multiple perspectives of each system and their integration as a Complex SoS. Conceivably, two different modelers would interpret and perceive systems, subsystems, and, ultimately, the integrated Complex SoS, differently, given the amalgamation of the arts and sciences on which the modeling process is built. It is here where state-space theory contributes to harmonizing the modeling process of Complex SoS. In particular, given the large number of states (variables) required to model and represent the multiple subsystems and their multitude of perspectives, as well as the necessity for brevity yet representativeness, modelers from different disciplines, and thus different perspectives, will naturally tend to be influenced by their unique personalities and backgrounds.

Furthermore, the large number of states that might be generated through the iterative, learn-as-you-go modeling process necessitates the selection of a representative subset of shared states and other essential entities. Recall that we define essential entities to connote shared/common decisions, decision makers, stakeholders, resources, organizational setups, and history, among others. *This selection of a minimum number of shared states and other essential entities with which to identify critical I-I is the first step in identifying invaluable precursors to future impending failures*. Note that the I-I within Complex SoS constitute the essence of the sources of risk thereto. This step converts systems that heretofore were marginally connected in parallel to becoming connected in series. This process is pivotal for discovering one of the major sources of risk facing Complex SoS and the most important result of modeling the I-I within and among systems and subsystems. Working together collaboratively, modelers can develop better models by augmenting the ingenuity of other modelers and scholars, as they collectively focus on and interpret the genesis of the I-I characterizing the subsystems and, eventually, the entire Complex SoS. Alternatively, it is possible to envision separate modeling efforts by multiple modelers with a subsequent attempt to integrate the models to yield a better and more representative set of attributes of the overall Complex SoS. We ought to not overlook the modelers' inherent ingenuity, background, talent, experiences, and innovativeness, contributing to the iterative modeling process that is characterized by a trial-and-error and a learn-as-you-go process. In other words, the multipath exploration process that characterizes the modeling effort necessarily implies and even requires the intellectual creativity and energy of modelers of Complex SoS – a process that commonly yields to a better representation of the modeling efforts.

In his book *Ageless Body Timeless Mind*, the physician, philosopher, and author Deepak Chopra (1994) suggests the following three "models" of humans: *physiology*, *mental capacity*, and *spirituality*. No one would negate the notion that the human body is an interdependent and interconnected Complex SoS. Indeed, each organ is by itself a system of systems composed of multiple subsystems. The basic question is, can we model or represent a complete understanding of a person when we ignore one of the above three attributes identified by Chopra? The same principle of completeness/representativeness must apply to the natural and constructed Complex SoS. From several perspectives, Complex SoS are opaque. Our observations, studying and reading documents, consulting with knowledgeable experts, and exploring and exploiting all sources of information relevant to Complex SoS are important and invaluable. Nevertheless, this tedious and essential modeling process does not reduce the inherent intricacy characterizing Complex SoS. Moreover, the above solicited and collected information ought not lead us to the illusion that what we have observed and learned constitute the entire reality. *Rather, we ought to augment our acquired knowledge with an endless learn-as-you-go modeling process*. Thus, our notion in this book is that the modeling of Complex SoS is an intricate amalgamation of the arts, sciences, and engineering, guided by the ingenuity of systems modelers. This amalgamation of the visible and invisible, and the interplay between the arts and the sciences in the modeling of Complex SoS, is in many ways analogous to the architectural design of high-rise buildings and the ultimate translation of the design into the reality of a physical structure. Indeed, architects and systems modelers share some similarity in building on the arts and sciences in their specialties, although each discipline uses different crafts in its work. Modelers of systems and Complex SoS use the building blocks of mathematical and simulation models, among others, while architects use in their crafts of drawing and scale models to reflect weight, force, and balance as well as aesthetics, among other things. Both address the essential sequence of translating their conceptual, analytical, or other models into their ultimate realization.

Furthermore, the fact that all single systems and Complex SoS – natural or the constructed environment – are dynamically changing and evolving necessarily requires consideration of the time frame in modeling, implicitly or explicitly. Modeling such changing systems requires the use of dynamic models. This requirement adds an enormous challenge to modelers, who often revert, when possible, to steady-state models, taking cover under the adage that "models must be as simple as possible, but as complex as required." In other words, since the essence of modeling is an amalgamation of art and science, imagination, judgment, and experience, then "assumptions" become an essential instrument that modelers use to navigate between the grace of static simplicity and the harshness of dynamic complexity, with the required and challenging balance between the two. Of course, the choice between static and dynamic models is only one of the challenges facing modelers of Complex SoS. Not all submodels of subsystems necessarily require the same inherent characterization, e.g. linear vs. nonlinear, static vs. dynamic, deterministic vs. stochastic–probabilistic, lumped parameter vs. distributed parameter, or discrete vs. continuous. Here again, modelers necessarily resort to the essential guidance provided by the arts and sciences, namely, the creativity and imagination that constitute the foundation of the modeling process. This never-ending process of tradeoffs is necessarily resolved with justified assumptions by the modelers and by their ultimate users.

1.I.2 CAPTURING THE ESSENCE OF A SYSTEM VIA MODELING

There is an unfortunate imbalance in the curricula of most undergraduate and graduate programs in systems engineering and in industrial engineering and operations research that is driven by a focus on *system optimization* versus *systems modeling*. Such imbalance in education and subsequent experiences could lead to optimizing a system with a poorly constructed or misrepresentative model. In system optimization, we assume knowledge of the systems model under specific assumptions, where for each set of inputs we can generate, or probabilistically estimate, the outputs. For example, in the context of risk management, no effective risk management policy options can be developed, nor can the associated tradeoffs among all critical costs, benefits, and risks be evaluated, without having constructed a model, or a set of interdependent models, that represents the essence of the system, or of the Complex SoS.

Students and other professionals often ask: "What is systems engineering?" Indeed, systems engineering is distinguished by a practical philosophy that advocates holism in modeling and cognition in decision making. This philosophy is grounded in the arts, natural and behavioral sciences, and engineering. Hence, the systems engineering discipline is supported by a complement of modeling methodologies, tradeoffs among multiple noncommensurate, competing, and conflicting objectives, optimization and simulation techniques, data management procedures, and decision-making approaches. The ultimate purpose of systems engineering is to (i) build an understanding of the nature of systems and Complex SoS, their functional behavior, and interaction with their environment; (ii) improve the decision-making process in planning, design, development, operation, and management; (iii) collect appropriate databases with which to populate the systems models; and (iv) identify, quantify, and evaluate risks, uncertainties, and variability within the decision-making process.

One way to gain a better understanding of systems engineering is to consider the well-publicized ideas of Stephen R. Covey in his best-selling book, *The Seven Habits of Highly Effective People* (Covey, 1989), and to relate these seven habits to various steps that constitute systems thinking, or the systems approach to problem solving. Covey's journey for personal development, as detailed in his book, has much in common with the holistic systems concept that constitutes the foundation of the field of systems engineering. Viewed in parallel, the two philosophies – Covey's and the systems approach – have a lot in common. Analyzing a system cannot be a selective process, subject to the single perspective of the analyst who is responsible for deciphering the maze of disparate databases and knowledge. Rather, a holistic approach is one that encompasses the multiple visions and perspectives at play, supported by vast pools of data and other information. Such a systemic process is imperative to successfully understand and address the natural and the constructed environment, including organizational systems, which at their core are composed of interconnected, interactive, and interdependent Complex SoS – the theme of this book.

Systems engineering cannot be practiced effectively, if at all, without models – analytical, conceptual, or simulation. Models, experiments, and simulations are conceived and built to answer specific questions. A mathematical model is a set of equations that describes and represents the *essence* of the real system. The *Merriam-Webster Dictionary* defines *essence* as "The most significant element, quality, or aspect of a thing" (2017). The equations describe the various aspects of the problem; they identify the functional relationships among all of the system's components, elements, and its environment; they establish measures of effectiveness and constraints and, thus, indicate what data should be collected to deal with the problem quantitatively. These equations could be algebraic, differential, linear, or nonlinear or take other forms depending on the nature of the system being modeled.

In general, models can help us assess the consequences of a course of action, given what we know, or what we think we know, what we need to know, or what and where additional knowledge is needed to build a more effective model for decision making. Furthermore, mathematical models are the imperative mechanisms with which to perform quantitative systems engineering. They are built and used to help systems engineers, managers, and decision makers better understand and manage a system using its relevant and/or critical interdependent and interconnected subsystems; namely, a Complex SoS. In the medical sciences, for example, there are mathematical models that use various states of the patient, e.g. temperature and blood pressure, to help in a diagnosis. Such models are important to correctly understand the human body as a Complex SoS.

Modeling has a strong element of art because successful models must build on the artistic traits of experimentation, imagination, creativity, independent thinking, vision, and entrepreneurship. Systems modelers must possess and merge values and traits offered by both the arts and the sciences. However, in contrast to scientific knowledge, whose validity can and must be proven, mathematical models cannot always be successfully subjected to such metrics. In fact, the more complex the system to be modeled, the lower the modeler's ability to verify or validate emerging models. Some scholars even argue that no complex model can be verified or validated, which is due, in part, to the dynamic and probabilistic characteristics of all natural and constructed Complex SoS. Heisenberg's (1930) uncertainty principle is at work here as well, namely, once the system's model is deployed, the essence of the system will change.

Models can help answer limited questions about the behavior of systems under both steady-state conditions and dynamic forced changes. The multiple perspectives that characterize each system, and the entire Complex SoS, require developing models that represent the essence of the multiplicity of perspectives, attributes, functions, and dimensions of the system. Physical, chemical, biological, and other natural laws serve as the first principles and the foundation for such models. Although mostly necessary, these natural laws are not sufficient for model construction because of the intricacy of systems and of Complex SoS. Furthermore, the influence of organizational and other emergent forced changes (EFCs) from within or outside the Complex SoS affects it positively or negatively. The term EFCs connotes internal or external changes that may positively or negatively affect one system, or the entire Complex SoS. The multiple perspectives of any system, whether it is the human body, the environment, a bridge, a building, or an airplane, cannot be adequately modeled using a single model – a fact that presents a challenge to modelers. Thus, what is needed is a mechanism or a systemic framework, with which to augment natural and physical laws with human and organizational behavior, imagination, inventions, innovation, entrepreneurship, out-of-the-box thinking, and boundless experimentation.

Natural and constructed environments and organizational systems are, at their core, composed of interdependent and interconnected Complex SoS. A wildlife refuge in Alaska and a large suspension bridge over the Bosporus in Istanbul connecting Europe with Asia are two examples of such Complex SoS. The wildlife refuge may support ample species with diverse life cycles; their interdependency constitutes a complex ecosystem. The bridge over the Bosporus may be perceived merely as an infrastructure that is constructed of steel, asphalt, cement, and light fixtures. Nothing could be further from the truth. The suspended cables in the bridge are 60 cm in diameter and contain countless numbers of bundled steel wires. Similarly, the hanging cables, the towers, the bridge itself, and the myriad supporting invisible physical infrastructures all constitute an interdependent and interconnected Complex SoS. Clearly, there is a need to understand the science and engineering that ultimately determine the reliability, sustainability, and safety of Complex SoS, including bridges. Such understanding may employ expertise in civil and structural engineering and systems engineering, the arts and sciences, and organizational and behavioral sciences, among other fields of study. Systems engineers are commonly the integrators of contributions made by experts in these diverse disciplines. Indeed, systems integration, where Humpty Dumpty is put together so that the system can function as intended, cannot be successfully performed in earnest without a heavy reliance on systems modeling.

1.I.3 A BRIEF HISTORY OF MODERN SYSTEMS ENGINEERING

Systems engineering has many parents. During his distinguished career, Albert Einstein attempted to develop a unified theory that embraced all forces of nature as a system. Feynman et al. (1963) described a hierarchy or continuum of physical laws as distinct systems or disciplines that are cooperating and interdependent. Modern systems foundations are attributed to various scholars. Among them is Norbert Wiener, who in 1948 published his seminal book *Cybernetics*. Wiener's work was an outgrowth or response to the development of computer technology, information theory, self-regulating machines, and feedback control. In the second edition of *Cybernetics* (Wiener, 1961), Wiener commented on the work of Leibniz:

> At this point there enters an element which occurs repeatedly in the history of cybernetics – the influence of mathematical logic. If I were to choose a patron saint for cybernetics out of the history of science, I should have to choose Leibniz. The philosophy of Leibniz centers about two closely related concepts – that of a universal symbolism and that of a calculus of reasoning. From these are descended the mathematical notation and the symbolic logic of the present day.

Ludwig von Bertalanffy (1968) coined the term *general systems theory* around 1950, which is documented in his seminal book *General System Theory: Foundations, Development, Applications* (Bertalanffy, 1976). Of particular interest (pp. 9–11):

> In the last two decades we have witnessed the emergence of the "system" as a key concept in scientific research. Systems, of course, have been studied for centuries, but something new has been added…. The tendency to study systems as an entity rather than as a conglomeration of parts is consistent with the tendency in contemporary science no longer to isolate phenomena in narrowly confined contexts, but rather to open interactions for examination and to examine larger and larger slices of nature. Under the banner of systems research (and its many synonyms) we have witnessed a convergence of many more specialized contemporary scientific developments. So far as can be ascertained, the idea of a "general system theory" was first introduced by the present author prior to cybernetics, systems engineering and the emergence of related fields …. Although the term "system" itself was not emphasized, the history of this concept includes many illustrious names. As "natural philosophy", we may trace it back to Leibniz; to Nicholas of Cusa with his coincidence of opposites; to the mystic medicine of Paracelsus; to Vico's and ibn-Kaldun's vision of history as a sequence of cultural entities or "systems"; to the dialectic of Marx and Hegel, to mention but a few names from a rich panoply of thinkers.

Kenneth Boulding, an economist, published his 1953 work *General Empirical Theory* (Boulding, 1953) and claimed that it was the same as the general systems theory advocated by Bertalanffy. The Society for General Systems Research was organized in 1954 by the American Association for the Advancement of Science. The society's mission was to develop theoretical systems applicable to more than one traditional department of knowledge.

Several modeling philosophies and methods have been developed over the years to address the complexity of modeling large-scale systems and to offer various modeling schema. In his book *Methodology for Large-Scale Systems*, Sage (1977) addressed the need for value systems that are structurally repeatable and capable of articulation across interdisciplinary fields that can be used to model the multiple dimensions of societal problems. Blauberg et al. (1977) pointed out that, for the understanding and analysis of a large-scale system, the fundamental principles of *wholeness* (representing the integrity of the system) and *hierarchy* (representing the internal structure of the system) must be supplemented by the principle of "the multiplicity of description for any system." To capture the multiple dimensions and perspectives of a system, Haimes (1981) introduced Hierarchical Holographic Modeling (HHM), which is the subject of Chapter 3 and is applied throughout this book. Recognizing that a system may be subject to a multiplicity of management, control, and design objectives. Zeigler (1984) addressed such modeling complexity in his book *Multifaceted Modelling and Discrete Event Simulation*. Zeigler introduced the term *multifaceted* "to denote an approach to modeling that recognizes the existence of multiplicities of objectives and models as a fact of life" (p. 8). In his book *Synectics, the Development of Creative Capacity*, Gordon (1968) introduced an approach that uses metaphoric thinking as a means to solve complex problems. Hall (1989) developed a theoretical framework, which he termed *metasystems methodology*, to capture the multiple dimensions and perspectives of a system. Other early seminal works in this area include *Social Systems – Planning and Complexity* on societal systems and complexity by Warfield (1976) and *Systems Engineering* (Sage, 1992). Sage identified several phases of the systems engineering life cycle. His analyses embraced multiple perspectives including the structural definition, the functional definition, and the purposeful definition. The multiple volumes of the *Systems and Control Encyclopedia: Theory, Technology, Applications* (Singh, 1987) offer a plethora of theories and methodologies for modeling large-scale and complex systems. Thus, multifaceted modeling, meta-systems, HHM, and other contributions in the field of large-scale systems constitute the fundamental philosophy upon which systems engineering is built.

Indeed, several modeling philosophies and methods have been developed over the last seven decades to address the complexity of modeling large-scale systems and to offer various modeling schema. They are included in the following volumes: *Views on General Systems Theory* (Mesarović, 1964), *General Systems Theory* (Macko, 1967), *Systems Theory and Biology* (Mesarović, 1968), *Advances in Control Systems* (Leondes, 1969), *Theory of Hierarchical, Multilevel Systems* (Mesarović et al., 1970), *Methodology for Large-Scale Systems* (Sage, 1977), *Systems Theory: Philosophical and Methodological Problems* (Blauberg et al., 1977), *Hierarchical Analyses of Water Resources Systems: Modeling and Optimization of Large-Scale Systems* (Haimes, 1977), and *Multifaceted Modelling and Discrete Event Simulation* (Zeigler, 1984). Haimes (1981) developed Hierarchical Holographic Modeling (HHM) for Complex SoS; Gheorghe (1982) presented the philosophy of systems engineering as it is applied to real-world systems. Haimes and Macko (1973), Hall (1989), Macko and Haimes (1978), Haimes et al. (1990), and Haimes (2007, 2008, 2012a) developed a theoretical framework to capture the multiple dimensions and perspectives of a system and (Lasdon, 1991) published a seminal book on optimization theory for large systems; indeed, Lasdon is among the pioneers who contributed to decomposition and hierarchical coordination of large-scale systems. Other works include those by Sage (1977, 1992, 1995), Shenhar (1994), and Sage and Rouse (1999). Eisner (1993), Maier (1998), and Sage and Cuppan (2001) together provide valuable insights into SoS and definitions of emergent behavior of complex systems in the context of SoS.

Most of the works on systems of systems have been devoted to their organizational, functional, and structural nature. There has been comparatively little inquiry into the problem of modeling Complex SoS, and most of the contributions within the last two decades have focused on their description, classification, and characterization. For example, Ottino (2003) reviewed three major tools for quantitative modeling and studying complex systems: nonlinear dynamics, agent-based models, and network theory. Shalizi (2006) reviewed the main methods and techniques of complex systems, which include tools for analyzing data, constructing and evaluating models, and measuring complexity. Chang and Harrington (2005) provided a comprehensive description of agent-based models of organizations. Amaral and Ottino (2004) described network theory and its importance in augmenting the framework for the quantitative study of complex systems. Lloyd and Lloyd (2003) presented a general method for modeling complex systems in terms of flows of information. Page (1999) discussed robust computational models. In an analysis of the challenges associated with complex systems engineering, Johnson (2006) provided a comprehensive review of emergent properties and how they affect the engineering of complex systems. Bar-Yam (2003a) reviewed past lessons learned from problems with systems engineering historically and suggested adopting an evolutionary paradigm for complex systems engineering. Within the application of complex systems theory to a multiscale analysis of military littoral warfare, Bar-Yam (2003b) suggested the necessity of considering the specific organizational and technological requirements needed to perform effectively in a highly complex environment. In health care, Funderburk (2004) presented a brief survey of several formal dynamic and/or network-based models that are relevant for health-care policy development and evaluation. Tivnan et al. (2007) described the formulation, successful replication, and critical analysis of Levinthal's model of emergent order for economic firms. Jamshidi (2009a, b) edited two volumes on systems of systems engineering. In the preface to the first volume (2009a), he wrote: "The SoS [Systems of Systems] concept presents a high-level viewpoint and explains the interactions between each of the independent systems. However, when it comes to engineering and engineering tools of SoS, we have a long way to go. This is the main goal of this volume" (p. *ix*). Indeed, Jamshidi confirmed the need for concerted efforts in modeling Complex SoS.

Sage and Biemer (2007) argued that no universally accepted definition of SoS is currently available. Sage and Cuppan (2001) built their analyses on five properties of SoS suggested by Maier (1998). During the past decade, several disciplines have recognized the importance of addressing the management, and thus the modeling, of their SoS including finance, health care, defense, and physical–cyber infrastructure systems. De Laurentis (2008), Lewe et al. (2004), Parker (2010), and Dahmann and Baldwin (2008) all suggest that SoS problems require a new modeling paradigm that can account for the multiplicity of stakeholders, objectives, interdependencies, and emergent outcomes. Fisher (2006) argued that emergent behavior is inherent in SoS and traditional software and systems engineering methods are inadequate for interpretation of SoS. De Laurentis and Callaway (2004) discussed the need to focus the modeling effort on SoS interdependencies, and they suggested that the evaluation of an individual entity at its own level is of less importance than how it affects the higher levels of the organization of which it is a member. Similarly, Thissen and Herder (2003) claimed that efforts to increase understanding at the overall SoS level are much needed. Aktan and Faust (2003) called for the need for SoS modeling approaches for civil engineering researchers and practitioners. They maintain that an integrated modeling of large-scale infrastructure SoS encompassing engineered, human, and natural elements has been unsuccessful thus far.

The emerging roles of systems engineering in the design, implementation, and management of Complex SoS have resulted in increased interest in engineering systems as SoS and as an emerging multidiscipline. Sousa-Poza et al. (2009) and Keating (2005) articulated several of the critical research challenges that SoS must address and identified a preliminary set of critical research areas for a more integrated research agenda. Maier and Rechtin (2009) indicated that SoS pose specific challenges for design and development, which are distinct from those of conventional systems. The principal challenges include designing for social and technical equilibrium, promoting sequential decision making for technology, and creating system roadmaps with large uncertainty.

Gorod, Sauser, and Boardman (2008) identified distinguishing characteristics as a foundation on which to build an effective SoS management framework. Dahmann et al. (2011) proposed a time-sequenced, incremental development "wave" modeling approach using an implementers' view of systems engineering for SoS. In order to achieve a common purpose, an SoS approach is essential in resolving issues involving heterogeneous, independently operable systems. Successful operation of SoS requires communication, coordination, and negotiation among appropriate individuals and groups across enterprises using an effective protocol (De Laurentis et al., 2007). Multiple criteria decision analysis and conflict resolution using graph models were discussed extensively in Hipel et al. (1993), Li et al. (2004), and Kilgour and Hipel (2005). An application of Extensible Markup Language (XML) to represent data communicated among systems was proposed by Sahin et al. (2007).

The mathematical methods used in the studies of Complex SoS include nonlinear dynamics, graph and network theories, and agent-based modeling and simulation (ABMS) (Barabási and Albert, 1999; Ottino, 2003; Baldwin et al., 2017). Bifurcation and catastrophe theory (Arnold, 1994) have also been used to describe the behaviors of nonlinear systems. These theories focus on and classify phenomena characterized by sudden shifts in behavior arising from small changes in circumstances, analyzing how the qualitative nature of equation-based solutions depends on the parameters that appear in the equation. Various methods and techniques used in complex systems science can also be found in Shalizi (2006), Lloyd and Lloyd (2003), and Page (1999).

The essential characteristics of Complex SoS present serious difficulties for traditional hazard analysis techniques (Alexander et al., 2004). Bristow et al. (2012) argued that risk analysis of extreme events affecting SoS should address the complex, ambiguous, and uncertain aspects of extreme risk and the strategic interactions among multiple participants. Investigations of several accidents of complex systems, such as the Three Mile Island accident (Perrow, 1999), showed that the causes of complex system failure usually include multiple component failures and their unexpected interactions. Perrow pointed out that the root causes of system accidents reside in the properties of complex systems themselves, rather than in the errors that owners and operators make in running them. It is the system's characteristics that make it inherently vulnerable to such accidents. Eusgeld et al. (2011) also discussed the potential failure propagation among infrastructures leading to cascade failures, and they analyzed two modeling alternatives, comparing integrated with coupled models.

1.I.4 BUILDING BLOCKS OF MATHEMATICAL MODELS AND THE CENTRALITY OF STATE VARIABLES IN SYSTEMS MODELING

The systems modeling process relies on the fundamental building blocks of mathematical models: input, output, state variables, decision (control) variables, exogenous variables, uncertain and random variables, and time frame. These are commonly augmented to yield multiple, noncommensurate, and commonly competing objective functions and constraints. Note that these building blocks are not necessarily distinct and they may overlap. For example, input and output may be random. All good managers desire to change the states of the systems they control in order to support better, more effective, and more efficient attainment of the system objectives. At the same time, these managers demand acceptable tradeoffs among the many competing objectives but within an acceptable time frame and cost structure. The objectives and motivations of the stakeholders and decision makers are to determine the desired levels of the states of the system within an acceptable time frame and acceptable tradeoffs. As noted earlier, a large number of states, sub-states, and sub-sub-states characterize Complex SoS. For example, the state of blood might be characterized by white cells and red cells; however, the states of each category can be further subdivided. Thus, we use the term *vital states* to connote selected fundamental and indispensable states that are central to the essence of the Complex SoS as a whole and the associated goals, objectives, and major decisions. As another example, to control the production of steel requires an understanding of the states of the steel at any instant – its temperature, viscosity, and other physical and chemical properties that characterize its quality. Similarly, to know when to irrigate and fertilize a field, a farmer must assess the states of soil moisture and the nutrients in the soil. And, to treat a patient, a physician must first know the temperature, blood pressure, and other states of the patient's physical health. Finally, the body and its systems are continuously bombarded by a variety of bacteria, viruses, and other pathogens. A more detailed characterization and discussion of the vulnerability of a system as a manifestation of its states will be introduced in Part II of this chapter in the context of the resilience and vulnerability of Complex SoS.

Consider the following diverse examples:

- Engineers are asked to determine the safety of a municipality's drinking water. Can they perform this task without determining the state of acidity of the water and the states of turbidity, dissolved oxygen, bacteria, and other pathogens?
- Teachers are required to nominate the top five students in their classes for awards based on their performance. Can they make such a selection without having assessed the states of the prospective candidates' knowledge, talent, competence, aptitude, performance, and learning capabilities?
- Bus drivers are commissioned to transport musicians to a tightly scheduled concert and must guarantee that their busses are mechanically

and otherwise reliable to ensure timely arrival at the concert site. Can they ascertain the reliability and functionality of their buses without knowing the states of the latter's fuel, oil, tire pressure, and other mechanical and electrical components?

The above examples, and almost all other real-world problems, share the following systems-based fact – all are characterized at any moment by their respective *essential* state variables. (The term essential states connotes the minimum number of state variables with which to effectively model a system or Complex SoS.) In reality, all states are under continuous change and natural, EFCs – positive and negative. We earlier defined EFCs as *external or internal forces that may negatively or positively affect specific states of a system*. The fact that the states of a system are functions of the time frame and that most, if not all, systems are dynamic and evolve over time, necessarily implies that representative models ought to be dynamic as well. Complying with this premise means ideal models must be dynamic, which could be a more elaborate task for modelers. At the same time, despite the fact that in reality, real systems may vary over time, not every model will require time-dependent state variables. This is where the artistry, creativity, good judgment, and experience of the modeler come into play. Recall that models are built to answer specific questions and to represent the essence of the system under consideration. Thus, if over time, small or insignificant changes in a state of the system have no important effect on the answers sought from the model, then that state variable may be assumed to be static or time independent. The decision as to whether a state variable should be modeled as static (constant) or dynamic (time dependent) depends on the modeler's ability to select the best representative model topology (structure and form).

In fact, the art and science of systems modeling is characterized by a never-ending tradeoff process by modelers faced with various levels of complexity and detail. However, since models should also be as simple as possible yet as complex as required to answer specific questions, tasks may also include (i) selecting a minimum number of *vital* state variables from each building block of the model to adequately represent the essence of the system, (ii) determining the required complexity of the model (e.g. topology and parameters), and (iii) developing the required database (as appropriate) to populate the model in order to provide meaningful and specific answers. All these and many more specific details, which will be further explored in subsequent sections and chapters of this book, represent real challenges in terms of the model's required complexity, cost, and time of completion, its users and stakeholders, its required databases, the needed level of testing, and, not the least, the scope and specificity of the assumptions made in its construction.

1.I.5 THE CENTRALITY OF THE STATES IN MODELING COMPLEX SYSTEMS OF SYSTEMS

Recall Chen's (2012) succinct definition of *state variable*: "The state $x(t_o)$ of a system at time t_o is the information at time t_o that, together with the input $u(t)$, for $t \geq t_o$, determines uniquely the output $y(t)$ for all $t \geq t_o$." The states of a system, commonly a multidimensional vector, characterize the system as a whole and play a major role in estimating its future behavior for any given input. Thus, the behavior of the states of the system, as a function of time, enables modelers to determine, under certain conditions, its future behavior for any given *input* or *initiating event*. In other words, all systems are characterized at any moment by their respective state (variables) and the conditions thereof, and these conditions are subject to a continuous change. In addition a modeler, who is determined to select only those state variables that represent the critical elements of a system (i.e. essential states), must decide whether those state variables should be modeled as static (constant) or dynamic (time dependent), deterministic or stochastic, etc.

Given that all systems, large and small, can be characterized by their states, we must also recognize the inherent hierarchy of states, sub-states, and sub-sub-states – a crucial attribute in systems modeling. For example, a representative water resources system that supplies water to a large community can be characterized by the states of the water distribution (groundwater and surface water) storage, purification, and sewer systems. The data for each of the states can be further presented by sub-states. As another example, the states of the water distribution system may be represented by the status of the main carriers, local pipes, pumps, and storage tanks. With any Complex SoS, the most critical fact to note is the relationships that exist within and among the states of the system, which necessarily overlap the multiple perspectives of the system represented by the multiple models. In other words, a central role of modeling Complex SoS is to understand the essence of the I-I of the shared states and other essential entities (defined earlier) of the Complex SoS under consideration; namely, to comprehend, or "make a whole," of the various attributes that characterize the multiple systems that constitute Complex SoS. This important task cannot be achieved without domain knowledge of the systems and carefully discovering and identifying those states that characterize the most important aspects of each system and of the Complex SoS as a whole. Furthermore, the fact that all state variables are functions of random and uncertain initiating events requires that our modeling efforts take into account both epistemic and aleatory uncertainties (Paté-Cornell, 1990, 1996; Apostolakis, 1999; Haimes, 2016).

Consider the following definitions of the vulnerability and resilience of a system Haimes (2016):

> *Vulnerability is the manifestation of the inherent states of the system* (e.g., *physical, technical, organizational, and cultural) that can be subjected to a natural hazard or be exploited to adversely affect (cause harm or damage to) that system*. The vulnerability of a system is multidimensional, a *vector* in mathematical terms. (p. 56)
>
> The resilience of a system is also *a manifestation of the states of the system and it is a vector that is time- and threat (initiating event)-dependent*. More specifically, *resilience* represents *the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable cost and time*. In other words, resilience is a vector state of the system that is neither abstract nor static, nor deterministic. Moreover, resilience is similar to vulnerability in that it cannot simply be measured in a single unit metric; its importance lies in the ultimate multidimensional outputs of the system (the consequences) for any specific inputs (threats). (p. 57)

The question "What is the resilience of the University of Virginia?" is unanswerable without specifying the specific threat, considering the specific likely vulnerable or affected states of the University of Virginia, and of the timing of the threat. Likewise, questions on the vulnerability and resilience of a system can be answered only when the threat (initiating event) scenario (or a set of scenarios) is identified or the vital states of the system and of Complex SoS are specified. Resilience is not merely an abstract concept; it is a state of the system (composed of a vector of substates) that may have different responses to different inputs (threat scenarios).

This discussion of the centrality of states of the system in modeling will be further explored in Part II of this chapter and throughout this book and will be related to (i) intrinsic meta-modeling coordination, (ii) integration of the multiperspective models, and (iii) the necessity of relying on the states of the system. This is in contrast to relying solely on the extrinsic output-to-input model coordination and integration, which does not build explicitly on the shared (common) states and other essential entities, and the overlapping states among the systems and subsystems that constitute Complex SoS.

1.I.6 THE CENTRALITY OF TIME IN MODELING MULTIDIMENSIONAL RISK AND UNCERTAINTY

Time is central to all decisions, whether connected implicitly or explicitly, and thus to systems modeling. For a pilot, the time frame may be measured in mere seconds; for a planner, it may be years or decades. Indeed, all real-world Complex SoS are characterized by dynamic multiple objectives, often noncommensurate, competing, and in conflict with each other. Chapter 5 is devoted in its entirety to the subject of multiple objectives. A Pareto-optimal policy (solution) is such that improving one objective can be achieved only at the expense of degrading another objective. Pareto-optimal policies associated with such systems models are achieved through the manipulation of the appropriate states of the system, and since the latter are functions of time, the time frame becomes critical to systems modeling. Models that are built to answer specific questions must also be constructed to address the question: What is the impact of current decisions on future options, given the inevitable EFCs? (Recall that the term *emergent forced change was* defined earlier in this chapter.) Uncertainty, commonly viewed as *the inability to determine the true* *states of a system*, can be caused by *incomplete knowledge* and/or by *stochastic variability*. Two major sources of uncertainty in modeling affect risk analysis (Paté-Cornell, 1990, 1996; Apostolakis, 1999; Haimes, 2016). *Knowledge (epistemic) uncertainty* manifests itself in the selection of appropriate model topology (structure) and model parameters, which can be sources of ignorance (e.g. when modelers lack knowledge of important interdependencies within the states of the system and among other systems). *Variability (aleatory) uncertainty* applies to all relevant and important random processes and other random events. Uncertainty dominates most decision-making processes and is the Achilles' heel for all deterministic, and most probabilistic, models. Uncertainty on the part of the modeler often results in the selection of an incorrect model topology (structure) – for example, selecting a linear model for a highly nonlinear system, thereby inaccurately rendering its parameters, data collection, and processing techniques. Model uncertainties will often be introduced through human errors of both commission and omission. Uncertainty analysis becomes even more imperative in risk analysis of the I-I of emergent Complex SoS. Sources of uncertainty and lack of understanding of the complexity associated with the subsystems of Complex SoS would likely result in (i) adherence to unrealistic assumptions, (ii) a lack of awareness of and accountability to the critical I-I of the Complex SoS under consideration, (iii) poorly selected representative model topology and comprehensiveness, (iv) a dated or insufficient database to populate and calibrate the multiple subsystems models, and (v) essential risk scenarios being poorly represented or structured for all interdependent and interconnected systems. In sum, uncertainty analysis associated with Complex SoS is probably one of the most difficult, albeit important, tasks in the broader risk analysis process.

An adverse initiating event is likely to yield multidimensional probabilistic consequences to each system and to the Complex SoS. These consequences are represented by a complex multidimensional risk function, the modeling and quantification of which present considerable challenges. The selection of appropriate models to represent the essence of a system's multiple perspectives also determines the effectiveness of the entire risk assessment, management, and ultimately the communication processes. In particular, the scope and effectiveness of strategic risk management options are implicitly and explicitly dependent on the system perspectives that are included (or excluded) in the ultimate modeling efforts. In particular, a probable initiating event would necessarily affect only sub-states of a subsystem but not necessarily the entire Complex SoS. Thus, one must model the different probability distribution functions of consequences affecting each subsystem resulting from the same initiating event. Each perspective of a system – manifested through its structure, functionality, the services it provides, the customers it supports, and the other systems on which it depends – will experience specific, and likely, unique consequences resulting from the same initiating event.

Recall that the complexity of SoS stems primarily from the I-I within and among its number of systems and subsystems. Consider, for example, the I-I among three common cyber–physical infrastructures: electricity, communications, and water (and of course the communities they serve). A major initiating event that may cause the failure of the electricity system would result in adverse consequences to the other two cyber–physical infrastructures because of their dependency on electricity; neither one can operate without electricity. *Clearly, there is a need to understand and thus model the pathways through which the failure of one system propagates to other interconnected systems*. For example, an effective risk analysis of a Complex SoS requires a clear understanding of its configurations to enable the identification of specific critical failure modes. This enables the development and deployment of effective risk mitigation and other management strategies. Current risk models of systems that do not consider the inherent interdependencies among systems are likely to be inferior to those models that do. We emphasize throughout this book that the I-I are best understood and modeled through the *shared states* and other essential entities of the Complex SoS as a whole. Recall that the states of Complex SoS represent the smallest set of linearly independent system's outputs, such that the values of the members of the set at time t_o, along with known forcing functions, completely determine the value of all system variables for all $t \geq t_o$. Thus, the behavior of the states of the system, as a function of time and other inputs, enables modelers and risk analysts to determine, under certain conditions, its future behavior for any given *input* or *initiating event*. Indeed, in industrial production and management, the feedback control process is predicated on the fact that the smooth operation of the multiple interconnected subsystems is built on the knowledge of the operational states of each subsystem at each instant.

Systems modelers face nontrivial challenges when selecting the minimum number of states to adequately and effectively represent (model) the subsystems under consideration. Consider, for example, the challenges in selecting the states in the risk modeling process for sustained years of drought, including (i) availability and quantity (states) of groundwater and surface water, (ii) quality (states) of groundwater and surface water, and (iii) human, livestock population, and industrial needs for water. The above states of water quality and quantity have direct impact on the (i) rural or urban populations and on livestock, (ii) agriculture and industry, and (iii) future recovery of the states of water quality and quantity for the entire River Basin.

From the perspective of the *reliability of* Complex SoS, shared states and other essential entities within and among the subsystems represent the essence of the I-I that characterize Complex SoS. Initiating events affecting one or more of the interdependent and interconnected subsystems would necessarily increase the probability of failure of the entire SoS (Haberlin and Haimes, 2018; Lewis and Haimes, 2018). This fundamental fact can be viewed in the parlance of fault-tree analysis (NUREG, 1981) as converting subsystems from being "marginally connected," or in parallel, to becoming "directly connected," or in series. The subject of fault trees will be introduced and elaborated upon throughout this book; also, consult the Appendix in this book. (Chapter 13 of the fourth edition of the book *Risk Modeling, Assessment, and Management* (Haimes, 2016) is devoted to fault-tree analysis.) Also, Chapter 10 of this book presents four case studies with a reliance on fault trees. Nuclear reactors, which epitomize Complex SoS, have always relied on fault-tree analysis to ensure their safety. Thus, from that perspective, subsystems that share states and other essential entities *are most likely to* be affected by adverse initiating events. For example, this phenomenon is most evident in the growing use of cloud-computing technology, where numerous hardware–software subsystems are shared among multiple users (Haimes et al., 2015). Similar results have been demonstrated with I-I among cyber–physical infrastructures. An initiating event may not affect all shared states and other essential entities of different subsystems of a Complex SoS in the same way. This fact necessarily implies the following scenarios when analyzing risk to Complex SoS: (i) When each subsystem has different decision makers, then decisions made to control subsystem A may affect positively or negatively subsystem B that shares subsystem A's states and other essential entities. (ii) When decision makers collaborate among themselves and coordinate their decisions, this can have a positive effect on Complex SoS and improves their overall effectiveness and management. (iii) When different initiating events affect one or more subsystems, the level of shared states and other essential entities among them can positively or negatively affect the risk management process of the entire Complex SoS. Therefore, modelers should recognize and exploit the shared states and other essential entities among subsystems. As a natural example of interdependent subsystems, the states of the Earth and its moon relative to each other and to the sun are known at any instant due to shared gravitational forces. In their case, without any initiating events affecting any of them, the states of their celestial coordinates in space and time can be determined.

Guiding principles for modeling Complex SoS are presented in Chapter 9. The following *Evolving Base* is a sample of emergent components of Complex SoS: (i) goals and objectives; (ii) stakeholders, decision makers, and interest groups; (iii) organizational, political, and budgetary baselines; (iv) reorganization and reallocation of key personnel; and (v) requirements, specifications, delivery, users, and clients. Changes to these components are common to most complex systems, but most notably of the interdependent and interconnected Complex SoS, where they have a more dominant impact. In particular, modelers ought not overlook the likely multiple impacts of the *Evolving Base* on the shared/common states and other essential entities within and among the systems that constitute Complex SoS.

The organizational infrastructure at all levels of the subsystems and the systems of systems necessarily affects the corresponding states and substates. This fundamental fact constitutes a major driver in both the modeling and the management of the I-I of Complex SoS. Decision-making processes of most, if not all, organizations are characterized by a state of flux, given the mobility of executives within the organization and of incoming leadership replacing departing personnel at all levels. New leaders and executives to the organization are commonly hired to infuse new ideas and energy into the organization. A by-product of this process can lead to a recalibration of the goals and objectives of the subsystems, if not of the entire organization Complex SoS.

1.I.7 SYSTEMS MODELING AND INTEGRATION

Consider the laptop computer as Complex SoS; it has become an indispensable enabler for students, laypersons, and professionals alike including the writing of this book. The average laptop is assembled from about 2000 components (subsystems), each of which is designed and manufactured to perform certain critical functions on which the reliability and functionality of the laptop depend. The battery alone (as one subsystem) is assembled from multiple components and subcomponents. The nontrivial task of integrating and connecting the laptop's "2000 subsystems" requires understanding not only the functionality and role of each subsystem but also its effect on the performance of other subsystems. Without relying on systems modeling, such systems integration of multiple subsystems of hardware along with its software could neither be successfully accomplished, nor would the overall computer system's performance be realized.

Effective systems integration of Complex SoS requires accounting for all the system's functions, aspects, and components. For example, software-intensive systems not only require the integration of components but also understanding the functionality that emerges from that integration. Indeed, when two or more components are integrated, they often deliver more than the sum of what each was intended to deliver. Invariably, the integration adds synergy and enhances functionality. Also, the process of risk assessment and management is a requirement for successful systems integration; this is especially true for software-intensive systems.

1.I.8 STRUCTURE, STATES, AND FUNCTIONS OF COMPLEX SYSTEMS OF SYSTEMS

Consider the "translation" of the intricate relationships among *structure*, *states*, and *functions* of a system as suggested by Bronowski (1978). The states of a manufacturing system are directly influenced and affected by an intricate mix of machines, robots, materials, humans, organizational structures, and users of the final product, among others. And all of the above affect the system's functionality and thus the products of the manufacturing Complex SoS. Conversely, the conditions of the states of the manufacturing Complex SoS directly affect the integrity of the structure and its functionality. Furthermore, the I-I within and among the different components/subsystems that characterize Complex SoS may take many forms and levels, each of which defines the structure and functionality of the resulting subsystems and ultimately the entire Complex SoS.

The fact that, by their definition, Complex SoS are composed of interdependent and interconnected systems and subsystems implies that their modeling provides a more holistic vision and representation than when modeled as separate subsystems. In many ways, once a subsystem becomes a part of Complex SoS, it is likely to lose some or much of its autonomy and unique attributes and characteristics. Such change may be manifested via subsystem functionally, its role in the organization, or in the decision-making process. In modeling a single system of Complex SoS, each system thereof must be viewed holistically, especially when considering the natural and constructed environment and systems involving humans and community behavior. Holism represents a challenge in how to model the interface and the interplay between the *structure* of systems and the *nature* of systems.

How much perception and an ability to infer do good modelers need in order to build effective models? This includes the need to translate the reality of Complex SoS and their environments into an abstract vision that draws on modeling experience and expertise, and to use and build on the fundamentals of state-space theory and methodology.

In many ways, modeling can be viewed as an interpretation by the modelers of the multiple perspectives of Complex SoS – natural, physical, structural, organizational, and the influence of human behavior.

1.I.9 THE MULTIFARIOUS PERSPECTIVES AND DIMENSIONS OF COMPLEX SYSTEMS OF SYSTEMS

The complexity resulting from the I-I among the systems and subsystems that characterize Complex SoS can neither be well-understood nor modeled by a single individual. To be effective, the learn-as-you-go dynamic modeling process must be performed by a cross-disciplinary team: one that includes systems modelers and other individuals who possess domain knowledge of the historical, technical, and organizational complexity as well as other characteristics and orientations of the Complex SoS under consideration. In the book *The Wisdom of Teams*, Katzenbach and Smith (2015) identify four major attributes of an effective team: (i) a small number of members; (ii) with complementary experiences, perspectives, and skills; (iii) who are committed to a common purpose and performance goals; and (iv) where all members are mutually accountable. There are no specific norms that guide the composition of modeling teams for a given Complex SoS. Rather, the team is built with core resident modelers selected for their expertise and ability to contribute to the modeling process. The team is often augmented with additional expertise as needs arise over time.

Organizational dynamics and perspectives contributing to, and part of, the flow of EFCs, are likely to affect the states of many subsystems or the entire Complex SoS. (*Recall that the term EFC was defined earlier as emergent forces originating from within or outside one system, or from the entire Complex SoS*, that would affect the Complex SoS *positively or negatively*.) Slow or fast emergent internal and external EFCs, to which all systems and entire Complex SoS are commonly subjected, must continuously be accounted for in the modeling process. In particular, the criticality of slow creeping changes that affect the shared and other essential entities characterizing Complex SoS may not receive the serious consideration required by the modelers, stakeholders, and other principals engaged in the process. The I-I characterizing Complex SoS necessarily require appropriate knowledge and awareness of the emergent nature of the Complex SoS reality. *In other words, subsystem A that is affected by a specific EFC would also affect other subsystems that share states and other essential entities with it*. This concept of interdependence and interconnectedness has basic ramifications on the theory and methodologies that we deploy in modeling and managing Complex SoS in this book.

1.I.10 WHAT HAVE WE LEARNED FROM OTHER CONTRIBUTORS

Reflecting on the history of modern systems theory, and its close ties to the Gestalt psychology first introduced in 1912, we can underestimate neither the intellectual power of the multidisciplinary talent required for modeling Complex SoS, nor the holistic philosophy that has sustained it; thus forcing it to transcend the arts, the humanities, and the natural, social, and physical sciences, as well as engineering, medicine, and law. The fact that systems engineering and systems analysis have continued to grow over the years and contribute to other fields of study can be attributed to the fundamental premise that Complex SoS can be understood only if all the I-I among its systems and within its environment are also understood and accounted for. For more than a century, particular mathematical models, upon which systems-based theory and methodologies were developed, have been deployed in myriad large-scale projects in the natural and constructed environments. Moreover, if we were to identify a single concept that has dominated systems thinking and modeling, it would be *state-space theory* and the Gestalt–holistic philosophy. It can be argued that the art and science of systems modeling have served, in many ways, as the medium through which the holistic systems philosophy has informed and guided not only the practice of engineering but of a broad range of other fields. As the discipline of systems engineering continues to develop and expand into new domains, the need has emerged for new organizational and modeling paradigms to represent Complex SoS.

1.I.11 CONCLUSIONS

No single book on complexity and Complex SoS can do justice to, nor adequately represent, the plethora of perspectives and the multifarious nature of Complex SoS. And this book is of no exception. However, not attempting to try would constitute a fatalistic foresight that would be an enigma to scholarship and to the essential quest for discovery and learning. The vision and challenges that inspired the conception and guided the writing of this book stem from the following: *the need to not only define and represent but also to analytically quantify at least one fundamental characteristic of Complex SoS*, *namely*, *their interconnectedness and interdependencies*. This quest was enabled and augmented by the vast literature on modeling and optimizing (as well as in the sense of Pareto optimality associated with multiple noncommensurate, competing, and conflicting objectives), to which this author has contributed several books and copious technical articles since the 1960s.

1.I.12 MODELING AND MANAGING INTERDEPENDENT COMPLEX SYSTEMS OF SYSTEMS: BOOK OVERVIEW

As we present various methods for modeling and managing Complex SoS, it is important to map the course through which these theories, methodologies, case studies, and example problems are presented in the 15 chapters of this book, along with the Appendix.

Chapter 1: Modeling and Managing Interdependent Complex Systems of Systems: Fundamentals, Theory, and Methodology

This chapter is of two parts. Part I provides an overview of the entire 15 chapters of the book. Part II provides a comprehensive discussion on the resilience and vulnerability of Complex SoS. The Appendix, which follows Chapter 15, augments the textbook with systems engineering fundamentals that support basic theory and methodology on Complex SoS. [The book begins with a Foreword titled "Philosophical and Historical Perspectives on Understanding Commonalities Characterizing Complexity"]. The following sections present a general overview of the entire book and 15 chapters highlighting each of the succeeding 14 chapters and the Appendix.

The theme of the book advances the notion that current models for Complex SoS are insufficient, because too often they rely on the same modeling schema used for single systems. These models commonly fail to incorporate the complexity of the networks of I-I characterizing Complex SoS, and consequently the risk analysis and management based on such models suffer. For completeness, we redefine I-I to connote interdependencies and interconnectedness. Revised theoretical and methodological foundations for understanding, modeling, and managing risk to accommodate the unique attributes of Complex SoS are provided by research and case studies. The 15 chapters of this book underscore that effective modeling of Complex SoS lies in adequately understanding and modeling the I-I of systems manifested through shared/common states and other *essential entities* within and among the systems that constitute SoS. The term essential entities connotes shared/common, decisions, decision makers, stakeholder, resources, organizational behavior and norms, policies and procedures, management, culture, and others.A history of the discipline of systems engineering and the development of systems of systems with their unique complexities provide the base upon which to build new methods of modeling and managing interdependent and interconnected Complex SoS.

Chapter 2: Modeling, Decomposition, and Multilevel Coordination of Complex Systems of Systems

This chapter is of two parts. In studying Complex SoS including their technological, societal, and environmental aspects, the efforts in their modeling, as well as in their management, are magnified and often overwhelm the analysis. This is due to the (i) high dimensionality (very large number of variables), (ii) complexity (nonlinearity in the coupling and interactions among the variables), and (iii) dynamic changes and emergent behavior of the resulting models. In modeling the I-I of Complex SoS, one of the major impediments faced by modelers from the natural and behavioral sciences, engineering, and other professions stems from the dynamic and evolving nondeterministic processes that govern the interactions among the system's components. Whenever decentralization of a complex system is needed, the system is further decomposed to enable its effective modeling and ultimate coordination among the subsystems, as well as with the corresponding decision makers and the associated stakeholders. Part I of this chapter expands the concept of the hierarchical-multilevel approach, based on the decomposition of Complex SoS, and the subsequent modeling of the subsystems as independent at the lower levels of the hierarchy. This innovative decentralization utilizes the concepts of strata, layers, and echelons to enable systems modelers to analyze and comprehend the behavior of the subsystems at a lower level of the hierarchy and to transmit the information obtained to fewer subsystems at a higher level. Part II provides a primer on the theory and practice of incorporating probability distribution and uncertainty analysis in modeling Complex SoS. We address Bayesian methods for risk and uncertainty analysis.

Chapter 3: Hierarchical Holographic Modeling of Complex Systems of Systems

Hierarchical Holographic Modeling (HHM) is a holistic philosophy and proven methodology aimed at capturing and representing the essence of the inherent diverse characteristics and attributes of a system – its multiple aspects, perspectives, facets, views, dimensions, and hierarchies. The HHM (Haimes, 1981), which forms the basis for this chapter, emerged from a generalization of a Hierarchical Overlapping Coordination method and is capable of representing fundamental attributes of Complex SoS, which have commonly escaped multiperspective modeling representation.

The fundamental attribute of interdependent and interconnected Complex SoS is their inescapably multifarious nature: hierarchical noncommensurable objectives, multiple decision makers, multiple transcending aspects, and elements of risk and uncertainty. In part, this may be a natural consequence of the fact that most Complex SoS respond to a variety of needs that are basically noncommensurable and may under some circumstances openly conflict.

The HHM reflects a difference in kind from previous modeling schemas and contributes to the theory and methodology of modeling Complex SoS. There is a useful analogy between HHM and the capture of images. Conventional photography captures only two-dimensional planar representations of scenes and is analogous to conventional mathematical modeling techniques that yield "planar" models. Three-dimensional cinematography, however, is similar to the multidimensional schema needed to model the multifarious attributes of interdependent and interconnected Complex SoS. This chapter demonstrates the impracticality of representing, within a single model, all the aspects of an interdependent and interconnected Complex SoS, which may be of interest at any given time to its management, government regulators, students, or any other stakeholder.

Chapter 4: Modeling Complex Systems of Systems with Phantom Systems Models

In this chapter we introduce phantom systems modeling (PSM), a modeling paradigm that is congruent with and responsive to the uncertain and ever-evolving world of emergent systems. The PSM methodology/philosophy serves as an adaptive process, a learn-as-you-go modeling laboratory, where different scenarios of need and stages of development for emergent SoS can be explored and tested. These scenarios build on and extend the basic theory and philosophy of HHM by offering operational guidelines and principles on which to model interdependent and interconnected Complex SoS. In PSM, methodology and technology match, and emergent systems are studied through PSM similar to the way other appropriate models are constructed for systems with different characteristics. Equally agile and adaptive, PSM can be continually manipulated and reconfigured in the attempt to answer difficult emergent challenges. Examples of PSM include difference equations and differential equations for dynamic systems, algebraic equations for static systems, and probabilities for systems that are driven by random events and processes.

Chapter 5: Complex Systems of Systems with Multiple Goals and Objectives

For sound and informative decision-making processes, it is imperative that decision makers also be provided with the tradeoff values associated with the respective objectives. An "optimum" solution may exist for a model; however, for a real-life problem such an "optimum" depends on myriad factors, which include the (i) specificity of each subsystem; (ii) extent of shared states and other essential entities within and among the subsystems; (iii) identity, perspectives, and biases of the modelers, decision makers, and stakeholders; (iv) credibility of the database; and (v) time frame. Therefore, a mathematical optimum for a model does not necessarily correspond to the "optimum" for the real subsystems, nor for the Complex SoS, because multiple decision makers, and thus perspectives and needs, with varied authority are associated with each subsystem and with the Complex SoS as a whole. Each subsystem commonly represents different constituencies, preferences, and perspectives; as elected, appointed, or commissioned; or as public servants, professionals, proprietors, or associates; and connected with a specific level of the various hierarchies of objectives within the subsystems and the Complex SoS as a whole. This chapter outlines methods for achieving resolution to the multiobjective decision making associated with Complex SoS. Note that Complex SoS commonly involve multiple decision makers and decisions or "compromised" solutions are often reached through negotiation, either through the use of group techniques of multiple-criteria decision making (MCDM) or on an ad hoc basis.

Chapter 6: Hierarchical Coordinated Bayesian Modeling of Complex Systems of Systems

In this chapter we incorporate multiple decompositions from multiple perspectives, supported and populated with Bayesian data analysis. This modeling theory, philosophy, and methodology integrate all the direct and indirect relevant information from different levels of the hierarchies while placing more emphasis on relevant direct data. Indeed, by modeling the systems and data from different perspectives (such as via HHM), we can fully extract and exploit information from different dimensions via Bayesian modeling. In sum, we coordinate the results from different decompositions and perform quantitative modeling of Complex SoS supported with and enriched by multiple databases.

Chapter 7: Hierarchical-Multiobjective Modeling and Decision Making of Complex Systems of Systems

Many of the world's cyber–physical critical infrastructure systems fall within the category of Complex SoS. They are commonly composed of interdependent and interconnected subsystems, which in their essence constitute Complex SoS with multiple functions, operations, and stakeholders. Emergent, large-scale engineering systems profiled in this book such as aviation, supply chain, the power grid, and cyber–infrastructure systems, all pose significant challenges to risk modeling and management. The complexity of cyber–physical SoS is characterized by the highly interdependent and interconnected physical, economic, and social components that constitute a major source of EFCs to infrastructure systems. This means identifying relationships among different system components and understanding their impact on the systems so that efficient risk management strategies, including preparedness and response planning, can be deployed. Risk assessment, management, and communications are indispensable tools within which to evaluate the states of the system, reduce its vulnerability, and increase its resilience to EFCs. The development and application of risk analysis theories and methodologies for these cyber–physical infrastructure Complex SoS presented in Chapter 10 are key to their effective and efficient management.

Chapter 8: Modeling Economic Interdependencies Among Three Sectors: Supply Chain, Electricity, and Communications

This chapter introduces the inoperability input–output model (IIM) (Haimes and Jiang, 2001; Haimes, 2016), which is based on the input–output model developed by Leontief (1951a, b) for modeling the impact of the disruption of specified sectors of the global economy. For example, supply chain, electricity, and communications are three safety-critical sectors of every country's economy and key to its population's well-being. They literarily constitute the lifeline of every modern community and transcend cultural, societal, and political borders. Together, they comprise interdependent and interconnected emergent Complex SoS. Furthermore, their I-I represent significant universal sources of risk to the population they serve and to the economy of every country in the world. To model the impact of their disruption on the regional and national levels, we select the supply chain, to which Chapter 11 is devoted to in its entirety. Furthermore, we present (via four case studies in Chapter 10) the I-I that exist among the electricity, communications, and water systems. We quantify the consequences resulting from the I-I that characterize these three safety-critical sectors (supply chain, electricity, and communications) with the IIM. Note, however, that in Chapter 10 we quantify, via fault-tree analyses, the I-I among the Complex SoS by building on OR Gates (systems connected in series) and on AND Gates (systems connected in parallel).

Chapter 9: Guiding Principles for Modeling and Managing Complex Systems of Systems

This chapter presents and updates guiding principles for effective risk modeling, assessment, management, and communication associated with interdependent and interconnected Complex SoS. Risk analysis has become a dominant interest and a requisite area of expertise in almost every discipline as well as in government, public, and private organizations. By its nature, risk analysis is an intricate, dynamic process – an amalgamation of the arts and sciences – tailored to the specific sources of risk to Complex SoS. It follows then that for any system, especially for interdependent and interconnected Complex SoS, the balance between quantitative and qualitative risk analysis will be problem-and domain-specific. The 10 principles set forth in this chapter are intended to guide both quantitative- and qualitative-centered risk analyses. Meeting the challenges associated with defining, modeling, and quantifying the multidimensional risk function of a single system, and even more importantly for interdependent and interconnected Complex SoS, will likely be guided by the specific discipline performing such tasks, and influenced by the specific experiences and expertise of its risk modelers and decision makers. While the disciplines of systems engineering and risk analysis share the wide common denominators of philosophy, theory, methodology, and practice, each discipline has historically evolved along separate pathways, and thus has distinctive followers and protocols.

Chapter 10: Modeling Cyber–Physical Complex Systems of Systems: Four Case Studies

This chapter presents four cyber–physical case studies following the theory and methodology developed for Complex SoS in the previous chapters. The research protocol in each case shares the following common denominators, namely, that it builds on and exploits (i) state-space theory and methodology, (ii) modeling interdependencies and interconnectedness (I-I) via shared states and other essential entities (decisions, decision makers, stakeholders, resources, organizational setup, goals, and objectives, among others), (iii) analytically quantifying via fault-tree analysis (without the reliance on reliability) the I-I within and among the subsystems that compose Complex SoS, (iv) outlining the detailed methodological process, and (v) drawing lessons learned.

Chapter 11: Global Supply Chain as Complex Systems of Systems

The supply chain is the backbone of the global economy of every country, and its success is paramount to the success of individual economies as well as individual businesses with which we interact daily. Declaring the supply chain a safety-critical Complex SoS requires an understanding of its myriad basic intertwined systems and subsystems, which permeate through every country's economy, starting with raw and scarce material and heavy metals to abundant processed and manufactured commodities.

Chapter 12: Understanding and Managing the Organizational Dimension of Complex Systems of Systems

This chapter addresses the impact of organizational culture, vision, and the quality of leadership as critical drivers to effective and successful performance of interdependent and interconnected Complex SoS. The organizational structures vary so widely, especially among the private and public sectors, that they may be branded from their modeling perspectives as unbounded sets. A hierarchy of multiple conflicting, noncommensurate, and competing objectives characterizes both the private and public sector organizations. Moreover, the hierarchy of objectives is associated with the decision makers and stakeholders responsible for different levels of the organization's history, mandate, vision, and structure. Each organizational structure has specific characteristics that require customized modeling efforts. This chapter also demonstrates common denominators among them to enable modelers to exploit the essential attributes that most, if not all, organizational groups share.

Chapter 13: Software Engineering: The Driver of Cyber–Physical Complex Systems of Systems

This chapter illustrates the challenges and associated difficulties in understanding and modeling cyber–physical Complex SoS. The historical, cultural, organizational, and cognitive differences associated with the conception, design, development, and integration of cyber (software) and physical (hardware) systems comprise the ultimate cyber–physical Complex SoS. We often neither understand nor appreciate the two distinctive worlds in which both *software* and *hardware* are conceived, developed, and ultimately integrated. When the design, development, and ultimate integration of cyber and physical systems are executed separately, and without a strict adherence to compatibility between the two components of the cyber–physical Complex SoS, the results are likely to contain myriad predictable and invisible sources of risk.

Chapter 14: Community Preparedness for Risk to Infrastructure Complex Systems of Systems

Protection of Complex SoS may include a variety of risk-related countermeasures, such as detection, prevention, hardening, and containment. These all important risk management policy options are aimed at increasing security. To appreciate the limitations of these security measures when they are not balanced with resiliency, it is important to understand the epistemology of infrastructure risks in terms of threats to Complex SoS and of their vulnerability. In this chapter, we understand the composite of humans, organizations, and human–cyber–physical infrastructures to constitute, in their essence, interdependent and interconnected Complex SoS. These include human stakeholders as well as the multiple functions and operations of the physical infrastructures, such as roads and bridges, telecommunications networks, electric power generation, oil and gas pipelines and installations, and water treatment and supply utilities, to cite a few. Each of these individual entities constitutes a *subsystem*, and their integration with the other subsystems makes up interdependent and interconnected Complex SoS. The subsystems may function autonomously despite their I-I; however, each is susceptible to experiencing unique adverse consequences resulting from an initiating event that affects a subset or all of them. In turn, such consequences may propagate and inflict other disastrous results. This chapter also addresses the challenges in establishing a national preparedness system for terrorism and natural disasters.

Chapter 15: Modeling Safety of Highway Complex Systems of Systems via Fault Trees

Transportation is an emergent safety-critical interdependent and interconnected sector of the economy, which in its essence constitutes Complex SoS. Almost uncounted factors and sources of risk characterize and determine the ultimate safety of transportation on the highways. As a starting point, we investigate the modeling of automobile safety as a function of its design (assuming an average uniform level of safety characterizing all drivers). We focus primarily on how automobile accidents occur and address the broader challenge of quantifying and managing the risk inherent in particular automobile designs. The highway safety of the transportation Complex SoS draws on fault trees for assessing the risk thereto. The modeling process of improving highway safety can be used as a prototype for modeling other associated emergent Complex SoS. For example, there were about 222 million registered drivers in the United States in 2016, and there were over 32 000 fatal motor vehicle crashes in the United States in that year. The frequency and severity of motor vehicle accidents is of such consequence that they comprise the sixth leading cause of death in the United States and the number one cause of death due to injury. Current studies reveal that researchers have made an effective use of accident databases, simulations, and crash testing to examine narrowly defined factors that contribute to automobile safety. An evaluation of the contributions of poor driver judgment, vehicle failure, poor weather conditions, and other causative factors can offer insight into steering and other failures. This can guide the development of technologies to mitigate both the likelihood and the consequences of the associated failures.

Epilogue

Complexity and interdependent and interconnected emergent complex systems of systems, the theme of this book, have mesmerized all of us for decades: students and philosophers, practitioners and modelers, systems engineers and risk analysts, and other professionals engaged in this ever-growing and expanding enterprise. Among the many drivers that continuously redefine Complex SoS are the emergence of new technologies, notably the seemingly seamless integration of the physical infrastructure world with the more amorphous cyber world. Indeed, the new world in which we live, and on which we are becoming increasingly dependent, is the genesis of a new era: the era of the Internet of Things, the era of smart cities, and the era of robotics and automation that result in displacing workers and drivers of vehicles.

This book focuses on emergent Complex SoS and on the myriad associated theories, methodologies, and practices that transcend all 15 chapters.

We expect that the readers of this book will not only benefit from its content but also, most importantly, will build and expand on both the theory and methodologies advanced in this book.

PART II: ON THE RESILIENCE AND VULNERABILITY OF COMPLEX SYSTEMS OF SYSTEMS

1.II.1 INTRODUCTION

Why do farmers irrigate their crops in nonrainy seasons? And why do farmers add fertilizer to the soil? The genesis of both questions stems from the condition of the *states* of soil moisture and nutrients.

Our premise is that the vulnerability and the resilience are a manifestation of the states of a system, and that a threat to a vulnerable system would necessarily lead to risk. And the resulting risk is a function of the (i) specific threat, (ii) specific state of vulnerability of the system to the threat and (iii) specific time frame. In other words, while one may speak generically about risk, and define risk in terms of a probable threat and consequences to a vulnerable system, its quantification calls for a more careful consideration that goes back to Lowrance's definition of "Risk as a measure of the probability and severity of adverse effect" (Lowrance, 1976). Furthermore, a specific threat to a system that affects more than one state of that system would likely yield multiple adverse consequences – each is associated with a specific vulnerable subsystem of the Complex SoS. This statement does not exclude additional risks that may result from cascading effects of the multiple vulnerabilities of Complex SoS. Referring to the above farmer's dilemma consider moisture and acidity as two states that represent the soil's condition. Depriving the crops of irrigation when soil moisture is below the required level would impair the growth of the crops in specific ways. Similarly, depriving the soil of lime to neutralize high soil acidity (threat) would damage the growth of the crops. In other words, in each case, a specific threat to a vulnerable system would yield specific probable consequence (risk). (We define risk as "a measure of the probability and severity of adverse effects" (Lowrance, 1976).) In addition, there may be cascading effects resulting from the impact of one threat (either lack of irrigation in non-rainy season, or lack of adding lime) to other states of the soil. Factoring in soil nutrients, which constitute multiple states (e.g. one state for each critical nutrient), would further complicate the quantification of the multiple risks to which the crops might be subjected. In sum, a farm's soil with appropriate levels of moisture and nutrients can be sufficiently resilient and to safely withstand a short period of vulnerability to drought and a delay in adding fertilizers.

Systems engineering fundamentals are the building blocks of mathematical models and, especially, the notion of state variables (other building blocks are inputs and outputs, objective functions, and random, decision, and exogenous variables). The ultimate goal of all decision makers is to make appropriate decisions with which to manipulate the states of the system to achieve (i) specific goals and objectives, (ii) at acceptable tradeoffs (e.g. cost, assurance, quality, etc.), and (iii) within an acceptable time frame. For example, the farmer would also wish to control the states of soil moisture, acidity, and nutrients of the farm at an acceptable cost and within an appropriate time frame.

The terms "system vulnerability" and "system resilience" have become common in the parlance of risk analysis and systems engineering. This evolution has become more prevalent due to acts of terrorism, frequent natural disasters commonly attributed to climate change, and other acts with adverse effects on communities and on the natural and constructed environment. Sadly, a significant number of archival publications continue to "dance around" the essence of the resilience and vulnerability of a system by ignoring the fundamental tenet that both are manifestations of the states of the system. That is, a system's resilience and vulnerability are functions of the state of the system, the time frame, and the initiating event (threat). We offered the following definitions: *Vulnerability* refers to the inherent states of a given system (e.g. physical, technical, organizational, and cultural) that can be exploited by an adversary to adversely affect (cause harm or damage to) that system. *Intent* is the desire or motivation of an adversary to attack a target and to cause adverse effects. *Capability* is the ability and capacity to attack a target and to cause adverse effects. *Threat* denotes the *intent* and *capability* to adversely affect (cause harm or damage to) the system by *adversely changing its states*. A threat with adverse effects to a vulnerable system may lead to risk (Haimes, 2006). Throughout the rest of this book, the term *threat* will connote a threat with adverse effects. *Resilience*, however, has been more characterized than adequately defined in the literature.

Consider, for example, the following parochial "definitions," none of which refers to resilience as a manifestation (or a function) of the states of the system: (i) Resilience is the ability of a system to absorb external stresses, or a system's capability to create foresight, to recognize, to anticipate, and to defend against the changing shape of risk before adverse consequences occur. (ii) Resilience refers to the inherent ability and adaptive responses of systems that enable them to avoid potential losses, and capability of a system to minimize adverse consequences, and (iii) to recover quickly from adverse consequences.

In this book, and throughout our several earlier publications, we have defined resilience of a system as a manifestation of the states of the system. Most critically, it is a state vector that is threat and time dependent. Thus, resilience, in this book, also connotes the ability of the system to withstand a disruption within acceptable degradation parameters and to recover within an acceptable composite cost and time (Haimes, 2008, 2009, 2016). Moreover, neither vulnerability nor resilience can be measured in a single metric unit because the states of the system form a multidimensional vector, and so are the multidimensional consequences (the outputs) of the system for any specific inputs (threats). Note that the consequence (that is considered as part of the risk metric) is in fact the output of the systems model, and that the input to the system's model is commensurate with the concept of a threat. For example, the risk associated with a cyber attack on a cyber–physical Complex SoS depends on both the resilience of the system to the specific cyber attack and its sophistication. This is because resilience, as a function of the states of a system, can be measured only in terms of the specific threat (input), the system's recovery time, and the associated composite consequences. Thus, different attacks would generate different consequence (output) trajectories for the same resilient system.

Consider the immunization of a population against a major strain of flu virus termed Type B. Assume that the population develops resilience for multiple strains of viruses of Type B, except for an evolving strain of Type A. In this case, even though the population might have resilience (immunity) for Type B, the appearance of strain A into this population would likely be infectious. Here again the risk to the population from a threat is dependent on the specific type of threat, the time frame, and the states of the system; namely, the risk from a threat is dependent on the resilience of the system to the specific threat, and the ability of the (states of the) system to withstand that specific threat.

Likewise, consider any physical infrastructure, such as electric power, transportation, or telecommunication. In any such Complex SoS, the question "What is the resilience of infrastructure x?" is unanswerable because the *answer* implicitly depends upon knowing the specific threat, and the states of the system, and whether infrastructure x would recover following any attack y within an acceptable time and composite costs and risks. Thus, the only way such a question can be answerable is when the threat (or a set of threats) is specifically identified. Indeed, the system's resilience is not merely an abstract attribute of the system; rather, it is a state of the system (composed of a vector of sub-states) for which any specific sub-state may respond differently to different inputs (threats). For example, a water distribution system may have redundancy in its electric power subsystem, and thus it may be resilient to a major storm that would shut down one of the power lines to the water distribution system, leaving the other redundant line intact. On the other hand, suppose the water distribution system is dependent on only one main pipe to supply water to its customers, and it is located in a region susceptible to earthquakes. The system is resilient only to the extent that the main pipe is functioning and it can withstand an earthquake up to level 4 on the Richter scale. However, the system would likely fail during an earthquake of level 5 or 6. Here again, measuring the resilience of the water system is actually measuring the responses of the states of the system to the specific threat (input) and in this case the scale of the earthquake. *We will revisit the resilience and vulnerability of interdependent and interconnected Complex SoS in subsequent chapters*.

One may associate a vector of resilience with each subsystem, given no direct interdependencies exist among the subsystems of a Complex SoS with respect to the specific input/threat. Thus, there is a hierarchy of resilience attributes for any natural or the constructed environment. For example, the human body as a Complex SoS is made up of many subsystems (e.g. the digestive, pulmonary, and auditory systems, among others), each with a set of resilient organs and sub-organs, where the latter depends on the states of each organ and on the inputs (e.g. physical or biological threats). The duration of the output (e.g. a temporary or long-term impaired, or a loss of, functionality of specific organs or sub-organs) is a function of the corresponding affected states. This example reinforces the thesis that system resilience can be measured in terms of the outputs/(responses) given inputs/(threats) to the system. (Note that the inputs to the system, the states of the system, and the outputs are commonly time variant and probabilistic, as will be discussed subsequently.) To further appreciate the centrality of the system's input–output relationship to its resilience (states of the system), consider the fact that despite the resilience of the human body to various physical and biological attacks on it, its ultimate resilience depends upon the states of the body at the time, as well as the type and strength of such attacks.

A system may also be characterized by its specific redundancy and robustness. *Redundancy* refers to the ability of certain subsystems of a system (or of a Complex SoS) to assume the functions of failed subsystems without adversely affecting the performance of the Complex SoS itself. Of course, redundancies constitute an integral part of all safety-critical systems. *Robustness* refers to the degree of insensitivity of a system to perturbations, or to errors in the estimates of those parameters affecting the design choice.

1.II.2 RELATING THE CENTRALITY OF STATE VARIABLES TO THE DEFINITIONS OF RISK, VULNERABILITY, AND RESILIENCE

During the last several decades, the terms vulnerability, resilience, and risk have received multiple diverse definitions and interpretations. The fact is that all three are related, interdependent, and interconnected via the (i) states of the system under consideration; (ii) initiating event, e.g. a threat, or what we generally have called in this book *EFCs to connote internal or external forces that affect the states of the system positively or negatively*; and (iii) time frame. The fundamental difference between the impact of EFCs on a single system and their impact on an interdependent and interconnected emergent Complex SoS stems from the intrinsic characteristics of EFCs, introduced in Part I of this chapter.

Current risk analysis of a single system must be fundamentally extended when applied to Complex SoS. As noted in Part I of this chapter, this complexity stems primarily from the interdependencies and interconnectedness (I-I) within and among the systems and subsystems of SoS. Consider, for example, the I-I among three common cyber–physical infrastructures: electricity, communications, and water (and of course the communities they serve). A major initiating event that may cause the failure of the electricity system would result in adverse consequences to the other two cyber–physical infrastructures because of their dependency on electricity; neither one can operate without electricity. In the parlance of risk analysis, the states of each of the three infrastructures – electricity, communications, and water – could be at (i) different *states* of viable performance and security, (ii) *vulnerable* to different EFCs, and (iii) operating in different *time frames* (duration, day/night, season, etc.). Clearly, there is a need to understand and model the pathway through which the failure of one system propagates to other interdependent and interconnected systems of a Complex SoS. Indeed, an effective risk analysis of Complex SoS requires a clear understanding of the configurations of (i) the interdependencies and interconnections of the states of the systems that compose Complex SoS, (ii) the vulnerabilities and resilience of each system and the Complex SoS as a whole to specific (scenarios) of probable EFCs, and (iii) the time frame of the risk scenarios. Such analyses of risk scenarios would enable the identification of specific critical failure modes and the development and deployment of effective risk mitigation and other risk management strategies. Sadly, current risk models of systems do not consider the inherent I-I among the many systems that comprise Complex SoS; thus, the corresponding risk analysis is likely to be inferior to those models that do.

Recall our premise from Part I of this chapter that the above interdependencies and interconnections of Complex SoS are best understood, and thus modeled, via the *shared states* and other essential entities within the Complex SoS. And, that the term "essential entities" connotes shared/common decisions, decision makers, stakeholders, resources, organizational behavior and norms, policies and procedures, management, culture, and others. Also recall that the states of each system, and of the Complex SoS as a whole, play a significant role in estimating the future behavior of the systems for any given input. We requote here Chen's (2012) conceptual definition of state variables that posits that the "state $x(t_o)$ of a system at time t_o is the information at time t_o that, together with the input $u(t)$, for $t \geq t_o$, determines uniquely the output $y(t)$ for all $t \geq t_o$."

The genesis of the I-I can be traced to the shared/common *states* and to other shared *essential entities that characterize SoS*. Similarly, Nise (2014) emphasizes that state variables represent the smallest set of linearly independent system variables such that the values of the members of the set at time t_o along with known forcing functions completely determine the value of all system variables for all $t \geq t_o$. Thus, the behavior of the states of the system, as a function of time and other inputs, enables modelers and risk analysts to determine, under certain conditions, its future behavior for any given *input* or *initiating event*. Indeed, in industrial production and management, the feedback control process (as an integral part of risk management and quality control) is predicated on the fact that the smooth operations of the multiple interconnected subsystems are built on the knowledge of the operational states of each subsystem at each instant. As a simple example, to determine the reliability and functionality of a car, one must know the *states* of the fuel, oil, tire pressure, and the states of other mechanical and electrical components (due to the dynamic nature of all states).

Systems modelers face nontrivial challenges when selecting the minimum number of states to adequately and effectively represent (model) the subsystems under consideration and, thus, the risk thereto. Challenges in selecting the states in the risk modeling process for sustained years of drought include (i) availability and quantity (states) of groundwater and surface water in storage, (ii) quality (states) of groundwater and surface water in storage, and (iii) human and livestock population and industrial needs for water. The above states have a direct impact on rural or urban populations and on livestock, as well as on agriculture and industry. These states also adversely impact future recovery of the states of water quality and quantity for the entire River Basin.

From the perspective of the reliability of Complex SoS, shared states and other essential entities within and among the subsystems represent the essence of the I-I that characterize Complex SoS. *Initiating events affecting one or more of the interdependent and interconnected subsystems would necessarily increase the probability of failure of the entire SoS* (Haimes, 2018). This fundamental fact could be viewed in the parlance of fault-tree analysis (NUREG, 1981) as converting subsystems from being "marginally connected," or in parallel, to becoming "directly connected," or in series. Nuclear reactors, which epitomize Complex SoS, have always relied on fault-tree analysis to ensure their safety. From the perspective of fault-tree analysis, subsystems that share states and other essential entities *are most likely to* be affected by adverse initiating events. For example, this phenomenon is most evident in the emergent extensive use of cloud-computing technology, where numerous hardware–software subsystems are shared among multiple users (Haimes et al., 2015). Similar results have been demonstrated with the I-I among cyber–physical infrastructures. An initiating event may affect shared states of different subsystems differently. This fact necessarily implies the following three scenarios when analyzing risk to Complex SoS: (i) When each subsystem has different decision makers, then decisions made to control subsystem A may affect positively or negatively subsystem B that shares subsystem A's states and other essential entities. (ii) When decision makers collaborate among themselves and coordinate their decisions, this can have a positive effect on Complex SoS and improve their overall effectiveness and management. (iii) When different initiating events affect one or more subsystems, the level of shared states and other essential entities among them can positively or negatively affect the risk management process of the entire Complex SoS. Therefore, modelers and risk analysts should recognize and exploit these attributes of shared states and other essential entities among subsystems. As a natural example of interdependent subsystems, the states of the Earth and its moon relative to each other and to the sun are known at any instant due to shared gravitational forces. In this case, without any initiating events affecting any of them, the states of their celestial coordinates in space and time can be determined.

Uncertainty analysis becomes even more imperative in risk analysis of emergent Complex SoS. Two major sources of uncertainty in modeling affect risk analysis (Pate-Cornell, 1990, 1996; Apostolakis, 1999). *Knowledge* (*epistemic*) *uncertainty* may manifest itself in faulty selection of appropriate model topology (structure) and model parameters, due to ignorance of the system or of the SoS under consideration. *Variability* (*aleatory*) *uncertainty* applies to all relevant and important events and must not be overlooked. Sources of uncertainty dominate most decision-making processes, especially Complex SoS, and are the Achilles' heel for all deterministic and probabilistic models. Sources of uncertainty and lack of understanding of the complexity associated with one subsystem of SoS would likely result in (i) adherence to unrealistic assumptions, (ii) a lack of awareness of and accountability to the critical I-I of the SoS under consideration, (iii) a poorly selected representative model topology and model comprehensiveness, (iv) a dated or insufficient database to populate and calibrate the multiple models, and (v) risk scenarios essential to any risk assessment, management, and communication process being poorly represented or structured for all interdependent and interconnected systems. In addition, model uncertainties are often introduced through human errors of both commission and omission. In sum, uncertainty analysis associated with SoS is probably one of the most difficult, albeit important, tasks in the broader risk analysis process.

1.II.3 SYSTEMS ENGINEERING AND RELATING VULNERABILITY AND RESILIENCE TO THE RISK FUNCTION

Risk analysis and systems engineering/analysis share a common philosophical approach to problem solving, but they differ in their historical evolution and technical maturity. Both aspire to the *Gestalt*–holistic philosophy in their problem-solving methodologies. Systems modeling frameworks build on a plethora of theories, methods, tools, techniques, and practice to provide, to the extent possible, the instruments with which problems are studied, assessed, understood, managed, and solved (Haimes, 1989, 2009). Risk analysis is similar to systems engineering/systems analysis, which is predicated on the centrality of the *state-space theory and practice and of* their role in determining the resulting outputs (consequences) for each input (initiating event). Note that (i) the *performance capabilities* of a system are a function of its state vector; (ii) a system's *vulnerability* and *resilience vectors* are each a function of the input, its time of occurrence, and (the vector of) the states of the system and of the Complex SoS; (iii) the *consequences* are functions of the time of the event, the states vector of, the vulnerability, and the resilience of the system and of the Complex SoS; (iv) the *states* of a system are time dependent and commonly fraught with variability uncertainties and knowledge uncertainties; and (v) *risk* is a measure of the probability and severity of adverse effects (i.e. consequences). These five premises, among others, imply that *risk is a vector of the same units (dimensions) as the consequences and is a function of (i) time; (ii) the probability of the threat (initiating event) and its specificity (input); (iii) the probability of the consequences, given the threat; (iv) the states of the system (including its performance capability, vulnerability, and resilience); and (v) the vector of the resulting consequences*.

Based on the above discussion, it is appropriate to make the time domain explicit in the questions of the risk assessment process (developed by Kaplan and Garrick (1981)), and to the three original questions, namely, "What can go wrong? What is the likelihood? What are the consequences?," we add a fourth question: "Over what time frame?" (Haimes, 1991).

Consider a sample of the multidimensional vector of consequences from hurricanes *Harvey* and *Irma* that hit the southern part of the United States in 2017: loss of lives; displaced population; destruction of major infrastructure Complex SoS, e.g. electrical grid, transportation, and water supply; and major flooding of homes, roads, and myriad facilities. Other consequences are loss of jobs and erosion of confidence in government and technology, among others. If we were to develop risk scenarios for future hurricanes with an unusually high surge of water, a similar vector of risk components would necessarily emerge from the risk assessment process. Since consequences are measured through a natural vector of noncommensurate attributes, the units of each element of the risk vector ought to correspond respectively to the same units of the vector of consequences for each system that constitute a Complex SoS. Identifying and modeling the I-I among the myriad infrastructures, within and among the affected populations and communities, become a challenging risk modeling and management task.

The above discussion on risk analysis implies that significant modeling efforts are required to first evaluate the vector of consequences for each threat scenario (as functions of the threat (initiating event), the vulnerability and resilience of the Complex SoS and their subsystems, and the time of the event). Then each element of this vector must be paired with the (i) probability of the scenario's occurrence or (ii) probability of the severity of the consequences. This fundamentally complex modeling and analysis process cannot be performed correctly and effectively without relying on the states of the system being studied.

The multifaceted composition of risk to Complex SoS includes the levels of uncertainty and intensity of the initiating events or threats, the time frame, and the dynamic, probabilistic, and often nonlinear natures of the states of all natural and constructed environments on which the system's vulnerability and resilience depend. This intricacy cannot be modeled and understood on an ad hoc basis. In other words, *we must understand, model, and define the complexity of risk, vulnerability, and resilience in a systemic way and through a methodical, theoretically based systems approach, where the states of the system constitute the essence of the analysis*.

In sum, by projecting Heisenberg's uncertainty principle and Einstein's advice on the complexity of theories to the field of risk analysis, we assert, by paraphrasing, that (i) to the extent that quantifying the vulnerability to and the resilience and risk analysis of Complex SoS is precise, it is not real and (ii) to the extent that quantifying the vulnerability to and the resilience and risk analysis of Complex SoS is real, it is not precise.

1.II.4 MODELING AND QUANTIFYING THE CONSEQUENCES AND RISKS TO THREATENED COMPLEX SYSTEMS OF SYSTEMS AND THEIR VULNERABILITY AND RESILIENCE

This section builds on the premise introduced earlier that both vulnerability and system resilience are manifestations of the states of the system. In the following modeling effort, we use an existing discrete, linear, time-invariant, dynamic, and normally distributed stochastic model to formulate the dynamics of the vulnerability and resilience of a system (Guo and Haimes, 2017). The intention is to motivate researchers and practitioners to develop causal relationship models with which to relate the vulnerability and resilience of a system, and of Complex SoS, to policies and actions made for reducing their vulnerability and enhancing their resilience for specific threats.

The literature in systems engineering, operations research, system dynamics, decision analysis, process control, and risk analysis, among others, is replete with tools and assumptions to enable analysts and practitioners to model Complex SoS with simplified models. The most relevant example is control theory, or simply process control. The characterization and quantification of the states of a threatened system analyzed through its high vulnerability and low resilience, and the ultimate quantification of the associated risk function – fall into this modeling paradigm. As noted earlier, fundamental tradeoffs exist between model complexity and solution feasibility or simplicity. Indeed, since models ought to be as simple as possible and as complex as required, then the ultimate choice depends on myriad factors. For example, most graduate curricula in systems engineering, electrical engineering, and process control focus primarily on multidimensional, continuous and discrete dynamic, linear – with time-invariant coefficients – and normally distributed stochastic models. The reason is that relatively simple closed-form solutions for such models exist and are widely used. What follows is a representation of the vulnerability and resilience of a system adopted from a simplified modeling approach.

Let the state vectors of the vulnerability and resilience of the system at time k be represented, respectively, by Eq. (1.1):

$$\mathbf{v}(k) = [v_1(k), v_2(k)], \quad \text{and} \quad \mathbf{r}(k) = [r_1(k), r_2(k)] \tag{1.1}$$

We consider that the dynamical changes of $\mathbf{v}(k)$ and $\mathbf{r}(k)$ are independent of each other. This assumption will enable us to use a linear dynamic model. (It is also possible to define and add to the system of state equations a new state variable that relates the associated interdependency.) We represent the dynamics of the vulnerability and resilience of the system in the following discrete linear, time-invariant, dynamic, and normally distributed stochastic model.

For time (stage) $k = 0, \ldots, T-1$, system's vulnerability and resilience are expressed with the set of Eq. (1.2):

$$\begin{aligned} v_1(k+1) &= a_1 v_1(k) + b_{11} u_1(k) + b_{12} u_2(k) + w_1(k) \\ v_2(k+1) &= a_2 v_2(k) + b_{21} u_1(k) + b_{22} u_2(k) + w_2(k) \\ r_1(k+1) &= a_3 r_1(k) + b_{31} u_1(k) + b_{32} u_2(k) + w_3(k) \\ r_2(k+1) &= a_4 r_2(k) + b_{41} u_1(k) + b_{42} u_2(k) + w_4(k) \end{aligned} \tag{1.2}$$

where $u_1(k)$ represents the threat (adverse disturbance), $u_2(k)$ represents risk management actions, and $w_i(k)$ for $I = 1, 2, 3, 4$ are independent and normally distributed random variables that represent random variability in the states introduced into the model. The initial conditions are represented in Eq. (1.3):

$$\mathbf{v}(0) = \mathbf{v}_0, \mathbf{r}(0) = \mathbf{r}_0, \tag{1.3}$$

Model coefficients a_j and b_{ij} ($i = 1, 2, 3, 4$; $j = 1, 2$) describe the contributions from the previous system states and system inputs to the current system states. These coefficients can be derived from historical data or system simulation. The time horizon is T stages ($k = 0, \ldots, T-1$).

Let the vector of consequences $\mathbf{y}(k)$ of the assumed threat to the system at time k be represented by $\mathbf{y}(k) = [y_1(k), y_2(k)]$; it can be described by the following set of equations:

$$\begin{aligned} y_1(k) &= c_1 v_1(k) + d_1 r_1(k) + \upsilon_1(k) \\ y_2(k) &= c_2 v_2(k) + d_2 r_2(k) + \upsilon_2(k) \end{aligned} \tag{1.4}$$

The coefficient vectors are defined as $\mathbf{c} = [c_1, c_2]^T$ and $\mathbf{d} = [d_1, d_2]^T$, where $\mathbf{c}$ and $\mathbf{d}$ are model coefficients and the variables $\upsilon_1(k)$ and $\upsilon_2(k)$ are independent and normally distributed random variables that represent the element of randomness introduced into the model. The coefficients a_i and b_{ij} ($i = 1, 2, 3, 4$; $j = 1, 2$) describe the "contributions" from the previous system states and system inputs to the current system states. These coefficients can be derived from historical data or from system simulation. In short, Eqs. (1.1)–(1.4) represent vectors of vulnerability, resilience, and consequences.

1.II.5 ON THE RELATIONSHIP AMONG VULNERABILITY, RESILIENCE, AND PREPAREDNESS

Vulnerability, resilience, and preparedness are considered integral to addressing risks associated with Complex SoS. We noted how a natural and/or human (e.g. a terrorist) threat at a specific time to a given system (i) can adversely affect one or more states of a system, or a Complex SoS; (ii) an initiating event is commonly multidimensional with its probability and time frame; and (iii) where the states of a system, or Complex SoS, are commonly represented by vulnerability and resilience and the probabilistic multidimensional consequences. Moreover, the level and magnitude of the vulnerability and resilience of each system and of the Complex SoS as a whole and consequently the level and magnitude of the associated consequences all are functions of the states of the systems and of the Complex SoS.

The mathematics and engineering literatures on what is commonly termed *state-space theory* quantify the states of a system as functions of time, inputs, and random decision and exogenous variables, and where the outputs (consequences) are functions of the states of the system. Given that both the vulnerability and resilience of a system are manifestations of the respective states of the system, it is logical to quantify the consequences resulting from a threat through the states of the system.

Determining the impacts of current decisions on future options requires a continuous quantification of the dynamically evolving risk function. Intelligence collection and analysis associated with the tracking of EFCs to a targeted physical infrastructure, or cyber–physical infrastructure Complex SoS, constitute an ongoing process of a commonly adaptive, incremental risk modeling, assessment, management, and communication. Bayesian analysis (discussed extensively in Chapters 2 and 6) constitutes a critically important mechanism with which to update the probabilities of specific threats with newly gathered intelligence. Through the theory of scenario structuring, a large number of conceivable scenarios are developed and ultimately reduced to a group of significant and critical ones (Haimes, 2016). Without this last step, the resources required to invest in preparedness for a large number of scenarios would be prohibitive. The often incoherent and inconclusive sources of information and other intelligence on a tracked scenario require continued reassessing and reevaluating their evolution (along with all other tracked scenarios) at each stage of the analysis. As more intelligence and information become available, incremental investment in risk management can be an effective policy through which to minimize potential disasters within the budgeted resources.

In his classic book *Normal Accidents*, Perrow (1999) presents a comprehensive discussion of accidents. Appreciating the interplay among terrorism, natural hazards, and accidents is fundamental to understanding and benefiting from the synergistic results derived from investing for either purpose. A well-planned and well-executed preparedness plan can make threatened systems more resilient against both types of events. Also, it is imperative to understand the difference in the public perception and the psychological response to economic impacts and other devastation resulting from *acts of terrorism* versus *natural hazards and accidents*. Thus, it is constructive to distinguish between the two from sociopolitical perspectives. Indeed, although the consequences from the two events might be similar, the nature of the initiating events in the case of terrorism is critical in terms of public perception and acceptance, economic impacts (e.g. demand reduction), and impact on public policy and overall national security. In other words, it can be viewed as an unacceptable risk to be unprepared for certain types of terrorist attacks, as compared with certain types of natural disasters, because the sentiment of public acceptance can be entirely different depending on the event.

One approach to measuring the resilience of an infrastructure is to predict the trajectory of recovery time following a catastrophic event. Namely, how long would it take to achieve recovery from 10% to 90% of full capability, and at what level of resources? In some sense, cost and recovery time become synonymous with the resilience of Complex SoS and their interdependent and interconnected systems (infrastructures). Consider, for example, the possibility of developing a nationally shared, very secure information infrastructure dedicated to supporting critical Complex SoS. Such a system could add resilience to the country's critical infrastructures, particularly utilities and financial institutions that rely heavily on secure cyberspace to conduct their business. Furthermore, it could potentially be a cost-effective vehicle for reducing risks to critical interdependent infrastructures when compared with the alternative of hardening each of the individual infrastructures separately. Some of the ways that such a system could be used to enhance resilience are to support automation, distributed decision making, information sharing, remote human monitoring and control, automated sensing and control, machine-to-machine communication, and real-time network reconfiguration.

In the next section, we address the prevailing policies of executives of privately owned critical infrastructure, which lead to the tragedy of the commons syndrome.

1.II.6 INFRASTRUCTURE INTERDEPENDENCIES AND THE TRAGEDY OF THE COMMONS

The I-I among infrastructure Complex SoS, such as energy, telecommunications, banking and finance, transportation, and human services, have been widely acknowledged in the literature. Often recognized, but not proactively acted upon, is the central role that the resilience of one infrastructure plays in determining the resilience of other interdependent infrastructures as Complex SoS. This notion, akin to the tragedy of the commons, highlights the role of I-I in the resilience, and ultimate security, of Complex SoS.

Consider, for example, the importance of a resilient water supply system. To varying degrees, the failure of a water supply system (similar to any other interconnected and interdependent system) would affect the performance of other infrastructures. In particular, the operation of wastewater facilities as a Complex SoS may be hampered due to a shortage of finished (fresh)water, emergency services may be strained, and the generation and distribution of electrical power may be disrupted. Furthermore, this Complex SoS is managed by multiple government agencies at the federal, state, regional, and local levels with multiple stake holders, decision makers, and conflicting and often competing objectives. Also, these agencies have different missions, resources, agendas, and timetables. Finally, organizational and human errors and failures are common and may result in dire consequences. Thus, making a water supply infrastructure more resilient would affect the performance of other interdependent systems. Here is where the tragedy of the commons must be understood in the broad infrastructure resilience context.

1.II.7 EPILOGUE

Part II of this chapter highlights the centrality of the relationships among the vulnerability and resilience of, and the risk to, Complex SoS. Note that all three terms/attributes – vulnerability, resilience, and risk, while representing different characteristics of the Complex SoS under consideration, share the following common denominator: All are functions of the (i) states of the Complex SoS, (ii) initiating event/threat, and (iii) time frame.

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