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SCIENTIFIC FOUNDATIONS FOR SYSTEMS ENGINEERING – CHALLENGES AND STRATEGIES

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ABSTRACT

There is an increasing realization of the need for fundamental research in the science of systems engineering. The International Council on Systems Engineering vision document calls for theoretical foundations for systems architecting, systems design and systems understanding. During a recent NSF workshop, a number of knowledge areas ranging from mathematics, information sciences, physical sciences, systems science to human and social sciences were identified as possible sources from which the scientific foundation of systems engineering can be enhanced. However, the primary challenge facing the community lies in orchestrating the breadth and diversity of the many knowledge areas into a cohesive foundation. This paper briefly surveys systems science-related efforts across multiple application domains. The specific objectives in this paper are to present a classification of initiatives for developing foundations for systems engineering, and to discuss the challenges, and potential strategies forward, associated with systems science research. The classification is discussed using two case examples - the Internet and the air transportation system. Through these examples, some of the key research challenges and strategies are exemplified.

Keywords: systems engineering, systems science, scientific foundations, complex systems, networks

1 INTRODUCTION: TOWARDS SCIENTIFIC FOUNDATIONS OF SYSTEMS ENGINEERING

Systems engineering is a rapidly growing discipline focused on large scale complex systems to ensure that different parts work together to achieve its overall objective effectively and efficiently. Systems engineering involves both the technical aspects of the system and the coordination of teams within organizations [1]. The fundamental concern in systems engineering is to manage the complexity in developing systems by partitioning the system, characterizing the relationships among them, identifying and eliminating unintended interactions, and verifying that the final design meets all requirements [2]. Although the discipline evolved out of aerospace and defense industries, it is gaining increasing adoption in a number of other industries such as consumer electronics, automotive, health-care, transportation and energy [3].

The increase in the complexity of large systems (e.g. aerospace vehicles, infrastructure systems) has resulted in many cases of schedule delays, cost overruns, and program cancellations [4, 5]. At the same time, the resulting number and scale of systems failures has also increased. Most of the failures occur at the interfaces of the elements in the system, where (for example) poor requirements tracking results in various integration issues. In order to address these challenges, many researchers have argued that there is a need to shift from heuristics-based processes to a science of systems engineering based on strong theoretical foundations [2, 3].

A recent document published by the International Council on Systems Engineering (INCOSE) [3] presents the future vision in the science of systems engineering. The key systems engineering imperatives include the need to expand theoretical foun-

dations for systems architecting, systems design and systems understanding, and expanding the application of systems engineering across industry domains, among others. A recent National Science Foundation (NSF) workshop, with co-sponsorship from INCOSE and the Office of the Secretary of Defense System Engineering Research Center, brought experts in systems engineering to address the issue of laying a theoretical foundation for the practice of systems engineering [6]. The workshop succeeded in listing some key issues that need to be addressed towards establishing such foundations, namely, (1) generating a list of knowledge areas on which theory may be built, (2) general measures of effectiveness (MOEs) of systems engineering methods, and (3) actions related to systems engineering that impact MOEs [6].

During the workshop, a number of knowledge areas ranging from mathematics, information sciences, physical sciences, systems science to human and social sciences were identified as possible sources from which the foundation of systems engineering can be developed. Collopy and Mesmer [6] highlight that the foundation for systems engineering does not only mean specifying knowledge areas, but also identifying specific elements within the knowledge areas, and how they can be integrated to answer questions specific to systems engineering.

While the INCOSE vision document, and the outcome of the NSF workshop, both have established a clear direction towards a theoretical SE foundation, we believe that *the primary challenge facing the community lies in tackling the breadth and diversity of knowledge areas*. Consequent challenges can be represented by a collection of key topics that relate to two specific systems communities, namely, the application domain specific communities (e.g., aerospace, energy, etc.), and domain independent communities (e.g., network science, organization science, etc.). In some cases, the research questions addressed by the two communities are identical, while in other cases, application-specific issues significantly hinder the application of theories to multiple domains. Hence, although current SE research transcends a large range of generalized and application specific methods with tremendous potential for cross domain research, there needs to be a systematic integration of these domains for lasting impact.

This paper focuses on a meta-analysis of systems science-related efforts across multiple application domains. The goal is to further the discussion on developing a cohesive scientific foundation for systems engineering and to suggest strategies that address the needs of systems science as identified by Triantis and Collopy [1] and Collopy [6]. The paper is structured as follows: In Section 2 we first present example application domains in the areas of air transportation and the Internet. In Section 3, we discuss classification of initiatives and a common framework for such initiatives towards developing the foundations for systems engineering. In Section 4, we discuss research challenges based on our two application domains. Some examples where these challenges have been successfully addressed are discussed as well. Finally, closing thoughts are presented in Section 5.

TABLE 1. Differences in research questions in the study of air transportation system (ATS)

Approaches	Research Questions
<i>Top-down</i> (Aggregate analysis)	What are the traffic forecasts? What are the fleet operating costs?
<i>Bottom-up</i> (Entity-level analysis)	What are the route characteristics? What are the aircraft characteristics?

2 EXAMPLE APPLICATION DOMAINS

2.1 Air Transportation System

The air transportation system (ATS) is a complex system with 40,000 commercial flights per day (US domestic), serving more than 1,800,000 passengers. The ATS annual growth has been accompanied by recurring problems of congestion and delays, which, in turn, have prompted agencies such as the Federal Aviation Administration (FAA) to make investments that attempt to reduce network-wide delays while ensuring safe operations. There have been bodies of research towards analyzing, understanding and solving foreseeable challenges faced by the ATS in the near future. Much of the research falls into two categories: 1) ‘top-down’ approaches that focus on aggregated system wide behavior, and 2) ‘bottom-up’ approaches that involve more detailed modeling based on characteristics of the constituent elements of the system. These approaches are developed by different communities, and are driven by different research questions, as shown in Table 1.

Top-down approaches: Top-down approaches include network-theoretic approaches for studying the global characteristics of the ATS (e.g., [7]). In these approaches, the air transportation system is abstracted as a complex network with flows, and aggregates individual decisions made by the different entities representing each node in the transportation network. For example, using data obtained from the Bureau of Transportation Statistics [8], DeLaurentis and Han [7] apply techniques from network science, including degree distribution analysis and centrality measures to model the importance of airports. The authors find a near-scale-free structure of the capacity network in the ATS. Song et al. [9] present a model that splits the air transportation network into two tiers. The model then uses available demand data with the result that it has to rely on future demand estimation for the prediction of network evolution. Kotegawa [10] uses machine learning algorithms to study network evolution using patterns derived from historical data. He compares algorithms based on logistic regression, random forests, and support vector machines to show high route addition and removal forecast accuracies. Collectively, these efforts provide aggregate information to support important planning decisions made by the airlines, viz. those of fleet planning, route selection, and schedule development.

Bottom-up approaches: Bottom-up approaches are typically used for airline logistics that involve matters such as fleet planning, schedule development and revenue management. Here, the approaches typically employ mathematical programming frame-

works that minimize (or maximize) some fleet level objective function while allocating resources (e.g., aircraft on routes) in the most efficient way possible. Much of the work done, however, does not directly consider the impact of externalities from network level effects. For example issues such as various environmental impacts (emissions, noise control) and effects of competition are not well studied in relation to route selection.

The top-down and bottom-up approaches model the ATS at two different levels of abstraction, which are appropriate for the corresponding questions addressed by each approach. However, these abstractions, do not have fruitful crossover, despite recognition of the impact that decisions made at one level of abstraction directly affects another (e.g. details on ‘bottom-up’ strategies related to how aircraft are allocated will affect the network dynamics being analyzed through ‘top-down’ analysis). Therefore, there needs to be a unifying framework that can better bridge the gap between abstractions through sound application of a unifying theory. In the absence of such a framework, decision-makers typically resort to use of top-down methodologies, due to simplicity, in making decisions [11].

2.2 The Internet

Another example of complex systems is the Internet, which consists of a multitude of devices and networking technologies operated by autonomous network operators, called autonomous system (AS). The Internet can be understood at three different levels, the internet protocol (IP) level, the router level and the AS level. Each AS has its own set of routers and routing policies [12]. Examples of ASes include Internet Service Providers (ISPs), corporate networks and universities. ASes are connected via dedicated links or public network access points based on certain routing protocols, such as Border Gateway Protocol (BGP). Therefore, the structure of the Internet can be viewed as an AS-level graph where each AS is a node, and the BGP peering between two ASes as links.

The AS-level Internet is dynamic in nature [13]. A new AS is added to the network when a new ISP or a large institution enters the network. New links are added when customer ASes purchase Internet access or when two ASes agree to share information between them. Links and nodes are removed from the network when the corresponding administrative domains cease to exist or merge with other ASes. The understanding of how node-level dynamics result in the observed topology of the Internet network is at the focal point of interest in the Internet study due to its importance in developing routing protocols, determining factors that affect its robustness, and understanding the interplay between technology, topology, and economic forces [12].

To model the evolutionary dynamics and topology of the Internet, there are mainly two research streams. Each stream focuses on a different aspect of the problem (see Table 2). The researchers in the first stream are mainly interested in understanding the underlying physical dynamics in the Internet by viewing it as complex network. The aim is to model the node-level behavior that results in synthetic Internet networks that explicitly

model certain characteristics of the real system. For example, one of the most well known characteristics of the Internet network is its power-law degree distribution discovered by Faloutsos et al. [14]. In order to generate the network topology with this special property, an example network evolution model is the Barabasi-Albert (BA) model [15] which explains the node-level behavior as a degree-based preferential attachment process. The model results in scale-free networks which exhibit power-law degree distribution. Other scale-free network generators include various BA variant models [16–18], BRITE generator [19], the Internet Topology Generator [20], and the decision-centric degree-based models developed by Sha et al. [21].

TABLE 2. Difference in research questions in the Internet study

Research Communities	Research Questions
<i>Network Science</i>	What are the underlying dynamics in the evolution of complex networked systems?
<i>Internet</i>	How to model the Internet evolution with domain-specific attributes?

The second stream of research is primarily driven by researchers from computer science and engineering, specifically from the field of computer networks technology. The models account for more domain-specific attributes and aim to show how the real Internet system evolves. The advantage of these models is that they do not only produce the prominent characteristics (e.g., power-law distribution), but also simulate the real status of Internet (e.g., geographic effect, routing traffic and transit cost) and intrinsic nature of ASes (e.g., behaving in selfish, optimizing trade-off and maximizing payoff). Consequently, the resulting models have better fidelity and predictability. In these models, different approaches such as optimization-based modeling, rules-based modeling, game-theoretic modeling and discrete choice modeling are adopted [22]. For example, Alderson et al. [23] propose a Highly Optimized Tolerance model and argue that the Internet topology can be understood in terms of trade-offs between network performance and the technological and economic factors constraining design. Later, Fabrikant et al. [24] show a similar phenomenon and suggest that the power laws tend to arise as a result of optimization by two objectives: “last mile” connection costs and transmission delays measured in hops. Lodhi and co-authors [25] develop an agent-based model, in which ASes behave selfishly and in decentralized manner with a cost-related criterion modeled as fitness function. Johari et al. [26] present a game-based model to form networks to study the routing traffic by considering the cost incurred in routing traffic. These approaches are analogous to the bottom-up approaches discussed in Section 2.1.

The research in the first stream is focused on an abstraction of the system, which only enables modeling the topology of the system. The theories do not include the domain-specific attributes, and hence, cannot account for the unique character-

istics of the Internet. On the other hand, in the second stream, the focus is on using application-specific knowledge. The resulting theories are highly specific to the Internet example, and cannot be applied to other complex networked systems. This again highlights the challenge of trade-off between generality and applicability of theories, as also indicated in the Air Transportation focused study.

3 Classification of Initiatives For Developing Foundations of Systems Engineering

3.1 Classes of Initiatives

In spite of different research streams in system studies, one of the key characteristics of research in systems science is that it draws upon, and contributes to a number of knowledge areas, as evidenced by the examples of the air transportation and internet case studies in the previous sections. As alluded to in Section 1, systems engineering is becoming an integral part of many application areas, and the vision is to develop application domain-independent foundations for systems engineering by building upon knowledge areas and integrating these areas in a cohesive and sensible manner. We believe that development of such foundations would involve four classes of initiatives. The first three initiatives are illustrated in Figure 1.

1. *Application* of foundational theories from different knowledge areas. Examples of the *application* of foundational theories are: i) application of utility theory to design decision making, ii) application of game theory to model interactions between different airlines in an air transportation system, and iii) application of social network theories to study interactions within an organization.
2. *Abstraction* of theories from specific domains to domain-independent knowledge. Abstraction involves generalizing a theory developed for a specific domain by relaxing assumptions that are valid strictly in a particular domain. For

example, the theory of social networks was initially developed to study interactions between people. However, it has been abstracted to general network science, which applies to many different types of networks beyond human networks, e.g., gene networks and computer networks.

3. *Translation* of theories from one domain to a different application domain. Translation involves understanding the differences between different application domains, and modifying the theory to make it suitable for the target domain. An example of translation is the adaptation of discrete choice analysis theory from transportation to include hierarchical choice in product design. We believe that all these transformations are necessary for developing the foundations for systems engineering.
4. *Integration* of different knowledge areas. Depending on the goals of a research activity, a system can be modeled at different levels of abstraction, and different knowledge areas can be used. In order to gain a holistic understanding of the system, it is important to integrate different levels of abstraction and different theories which may be developed with conflicting assumptions.

To understand these classes of initiatives, let us consider the two application areas discussed in the previous section. In each application, research is carried out either by fundamental scientific communities and by application-specific communities. There is a fundamental difference between the approach adopted by the two communities for abstracting the problems and then solving them. The fundamental research communities focus on generic problems at higher levels of abstractions that potentially have applications to a wide variety of problems. However, application of such techniques to real problems may be restricted to simplified problems. On the other hand, domain specific techniques provide greater insights into a specific domain by focusing on the nuances of their specific problems, but may be difficult to generalize to other domains. Therefore, within systems science there is a need to balance fundamental and application-specific investigations. There is a need for determining the levels of abstraction of problems such that fundamental research can be done while ensuring applicability across domains, i.e., the translate of theories. Understanding and bridging this gap is essential for transitioning from the current systems engineering to the future of systems engineering, as envisioned by the INCOSE vision document.

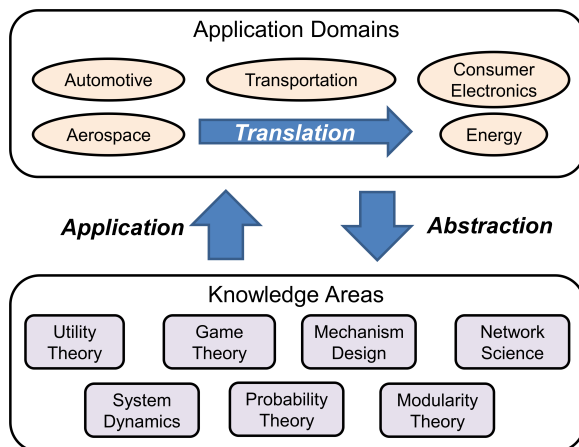


FIGURE 1. Abstraction, translation, and application of knowledge into different domains

3.2 Common Framework for Initiatives

In this paper, we take an initial step towards an archetypal description that bridges the interactions between the fundamental research and application-specific communities, as illustrated in Figure 2. The framework captures some common structure of complex systems applications. The common structure is highlighted using a multilevel framework shown in Figure 2, which decomposes the architecture of complex systems into five levels:

1. individual preferences,

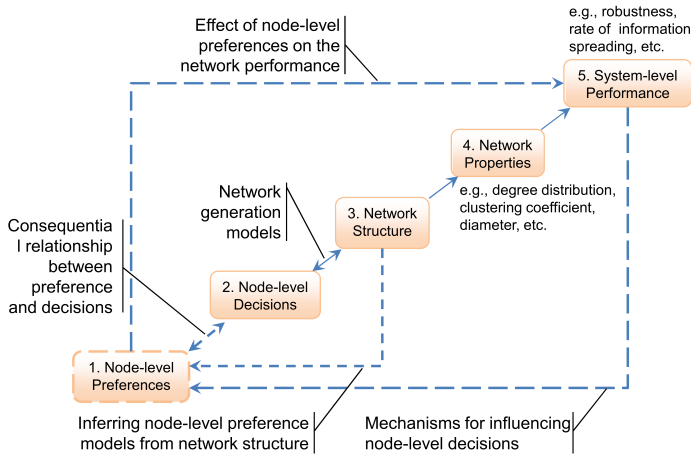


FIGURE 2. Overview of the decision-centric framework

2. micro-level behavior,
3. system structure,
4. system properties, and
5. system-level performance.

The framework places the systems analysis and design on a decision-centric foundation, and highlights the hierarchical interactions of nodes up to the system level.

The proposed framework is capable of capturing the decision-making nature of ASes in the Internet system. For example, two of the objectives of each AS are to minimize the cost of building links with other ASes and to minimize the sum of the distances to all other nodes (to minimize delay in sending and receiving packets) [27]. Since both these objectives are conflicting in nature, a trade-off is required. Each AS makes peering decisions to best route data based on commercial contractual relationships. The ASes' linking preferences (Level 1) and behaviors (Level 2) have significant impact on the global Internet structure and properties (Level 3 and 4). The global structure in turn affects the overall system-level structure and performance (Level 5), such as the system robustness, transit speed and routing efficiency. The same relationship between individual preferences and system-level performance is also observed in many other complex systems. Within this framework, the models developed by the network science community are at Levels 2 and 3, whereas the models developed by the computer science community are focused on Levels 3, 4 and 5. By utilizing this unified framework, the commonality and differences among systems across different domains can be identified. Table 3 lists the commonality between the air transportation system and the Internet.

The framework helps in identifying research gaps that occur at various levels of abstraction. System science has provided theoretical insights on modeling micro-level behaviors (Level 2) and analyzing their effects on system structure (Level 3), properties (Level 4) and performance (Level 5). For example, in the field of network studies, such as the Internet topology, the studies have been focused on developing nodes' linking probability models that generate scale-free degree distribution that ex-

hibits high clustering coefficient and low system robustness. In these studies, the micro-level behavior models are put forward directly without justifying *why* individual entity behaves in the way it is modeled. In other words, these decision-making studies place more attention on decision-making outcomes (micro-level behavior) instead of decision-making reasons (decision-making preferences). The relationship between individual preference (Level 1) and the micro-level behavior (Level 2) is not established. Thus the effect of individual preferences on the system structure, properties and performance is not clearly understood. This research gap impedes our understanding of system's evolutionary dynamics and ability to establish ways to direct the evolution of these systems.

In addition to establishing the research gap, the framework facilitates the incorporation and integration of theories from multiple knowledge areas, and enables the translation of theories. For example, the discrete choice random utility theory (RUT) can be adopted to model the ASes' decision-making behavior as the linking probabilistic to other ASes. The resulting discrete choice model is derived by assuming that each AS is trying to maximize its own utility (or payoff). For example, the utility, U , can be mathematically modeled as a linear combination of decision criteria $X = \{x_1, x_2, \dots, x_n\}$, weighted by $\beta = \{\beta_1, \beta_2, \dots, \beta_n\}$ which quantify the preferences for each criterion. Using probability theory, the utility-maximization assumption leads to a choice probability (i.e., behavior). By integrating theories from network science, the effects of preference (parameter β) on system-level performance can be analyzed. Further, if system structure data are available, the decision-making preferences can also be estimated by integrating estimation approaches such as maximum likelihood estimation.

In the context of ATS, using the decision-centric thinking, such integration of theories in random utility, complex networks and statistics also works. In ATS, the decision-makers are airline companies who try to maximize the payoff by determining whether to add (or delete) a route or not. With discrete choice analysis, the airline preferences on potential decision-factors, such as demand on a route, cost of running a route, etc, can be quantitatively modeled. By integrating complex network theories with the micro-dynamics of routes, we can gain a better understanding of how air transportation network evolves over time and forecast network evolution in the future [22, 28]. Therefore, the framework provides an appropriate level of abstraction which focuses the researchers' attention on attempting integration of theories to model the individual preferences and micro-level behavior. Such abstraction also ensures smooth translation from one application to another.

There are many challenges in implementing this framework in order to achieve better integration of theories across different applications. In the following section, we discuss some of the key research challenges and potential strategies towards achieving the vision of scientific foundations of systems engineering.

TABLE 3. Commonality and difference between air-transportation networks and autonomous system (AS) level Internet

	Air-transportation Networks	AS-level Internet
<i>Individual Objectives</i>	Maximize profit, connectivity, attractiveness for passengers	Shortest path to all other nodes, minimize cost of link creation
<i>Micro-level Decisions</i>	Route addition /deletion, Airport charges	Routing policies, link formation
<i>System Structure</i>	Airline connectivity among airports	Internet topology
<i>System Properties</i>	Clustering coefficient, network density, path length, etc.	Clustering coefficient, average path length
<i>System-level Performance</i>	Air traffic delay, robustness node service disruption, scalability	Robustness, overall (social) cost

4 RESEARCH CHALLENGES

There are numerous challenges in establishing a scientific foundation for systems engineering. Common to all areas are naturally the difficulties associated with funding incentives and in defining what combination of research areas would constitute systems engineering itself. In this section, we discuss four primary research challenges, that are prevalent across all areas of systems engineering, and potential avenues of addressing these challenges as well.

4.1 Challenges in Validation and Verification of Systems Science Research

Validation and verification (V&V) are critical aspects of ensuring sound development of any theoretical framework. Validation of theory-application pairing comes when the result produces a system solution (or decision) that is found to satisfy broader needs. Validation is naturally preceded by verification that ensures that none of the axioms or norms of a theory are violated in the course of its application to a system engineering problem. In the two case studies presented in this paper, validation is most often pursued via statistical correlation with historical data. For example, in the air transportation system case, a system-level solution can potentially be back-tested on prior data and conditions, to determine if the proposed solution will permit additional efficiencies, under statistical assumptions of the observed data. However, such validation is always imperfect, and the past results are no guarantee of future behavior. Further, as defined above, validation is most often thought of in the narrow (but important) sense of the specific application, and has large implications when real-world systems solutions are to be implemented based on such frameworks.

While measures are taken to ensure soundness of interacting frameworks of theories (verification), and, feasibility of proposed systems based solutions (validation), there is nevertheless an existing need for the development of further V&V methods, due to the large expanse of potential connections between various theories that exist across the system sciences. A recent example development is the emergence of V&V approaches for surrogate modeling in multidisciplinary and probabilistic design, especially in aerospace engineering. Here the diversity of methodological approaches, number of application examples from industry, and growth of commercial software has prompted much work in ensuring sound V&V practices for the area.

4.2 Challenges in Data-Driven Systems Science Research

One of the points that most panelists at the NSF workshop [6] agreed on is that the foundational theory of systems science should enable socio-technical studies on the interdependence between organizations and the systems that they develop. Such socio-technical studies are challenging due to the lack of availability of organizational data and temporal information about the system evolution. While some types of data are available (for example, BTS data on air transportation demand in the United States, or Internet data from our prior case study), they are nevertheless often times incomplete, or are difficult to obtain in general. Data from defense organizations are hard to acquire due to obvious security reasons. On the other hand, commercial organizations are unwilling to share such data due to competitive reasons. Few researchers are successful in getting access to the datasets, and those that do are under significant restrictions of sharing and publishing the results. Such lack of availability of data restricts reproducibility and also possibility of independent validation of results by other researchers. Therefore, it is difficult for the community to build on each others' work, which is a significant barrier in rapid development of the field of systems science.

Within the field of software systems, there has been significant progress in analyzing the development process from a socio-technical perspective. These studies represent multidisciplinary efforts integrating theories from organization science, social network analysis, and product development. Some of these studies have been enabled by comprehensive datasets such as the SourceForge Research Data Archive (SRDA) [29]. Researchers have carried out studies on the structure of software systems and its evolution [30, 31], and tested hypotheses about mirroring of the technical and organizational structures [32, 33], and socio-technical congruence [34, 35] for coordination of tasks. The development of such data repositories has been funded by federal agencies such as the National Science Foundation.

The repositories mentioned above are for open source software projects, where the information is available online. Such repositories are also being developed for proprietary data using the developments in the field of privacy-preserving data-mining [36]. Instead of directly providing access to the original data, a subset of anonymized or transformed data can be made available to the research community. Such transformed data preserves the global properties of the dataset while hiding the details

of individual records. Such techniques have been successfully demonstrated [37], and are currently in use for social media data analysis [38].

4.3 Challenges in Modeling Socio-Technical Systems

One of the challenges in engineering large scale complex systems is in developing valid models of both social and technical aspects, and their interactions. For example, in the air transportation system, models of decisions made by different stakeholders are essential for understanding the system performance. Majority of the decision-making models currently used for air transportation systems and the Internet are based on normative models of decision making with strong rationality assumptions. Similarly, the models of interactions between decision makers are based on game-theoretic concepts such as Nash equilibrium, which assume iterative reasoning by each stakeholder. However, it is well known that such assumptions of rationality and iterative reasoning are systematically violated by human decision makers. Due to the complexities and non-linearities in the systems, such violations can have drastic effects on the predicted performance of the system. Therefore, accounting for such descriptive behaviors of humans within socio-technical systems is essential for progress in the science of systems engineering.

During the past three decades, there has been significant progress on understanding human decision making. There is an enormous body of literature in the fields of psychology, behavioral economics and cognitive science that describes how decisions under risk and uncertainty are actually made by humans. In order to make progress in better modeling of socio-technical systems, we believe that the systems engineering community must leverage these developments.

4.4 Challenges due to Conflicting Assumptions between Knowledge Areas

Another major obstacle in the cross-domain research is the conflict in fundamental assumptions between different knowledge areas. For every theory, there are some basic assumptions (or axioms) that are made to simplify the real world scenario. When a theory from one domain is implemented in another domain, it is difficult to transfer the fundamental details of the theory to make the resulting application problem meaningful. For example, consider an aircraft wing design problem. It is a cross-disciplinary optimization problem consisting of fluid dynamics and structural dynamics. There are two approaches to deal with this problem: one to deal with one field at a time and transfer information to another domain and optimize the design after a large number of iterations. Another approach is to couple the governing equations in both fields and solve the single optimization problem. It can be shown that the latter approach is more efficient but the challenging part is to combine the equations from both domains. Similarly, for cross-domain research, the researchers need to have thorough understanding in both domains, which is difficult to find. Further difficulties are encountered across boundaries that involve more qualitative and/or data driven as-

sumptions in one area, against the backdrop of a more theoretical footing in another area. For example, assumptions about statistical modeling of observed phenomena drive the assumptions in the mathematical modeling of computational decision-framework in many areas such as finance, operations research and revenue management.

5 CLOSING THOUGHTS

Research within many knowledge areas in system science is being carried out, developing techniques and applying them to a wide variety of applications. At the same time, research focused in application domains experiment with system science methods, each domain emphasizing different needs (in consumer electronics, time to market; in aviation, safety and cost, etc.) [3]. Yet, if there were 20 projects that married a theory/method from system science to an application domain, would the community learn anything more than simply the sum of the individual project findings? Further, would this “sum” be a truly “integrative sum”? Our sense is no to both questions, and thus our motivation to write this paper. We see exciting opportunities in which each domain continues work on specific system challenges yet also embraces the need to articulate trade-offs between applicability and generality and the methodological constraints they discovered. The challenge in systems science is to balance these local and global knowledge needs, as already alluded to in the recent NSF Workshop. The need for integration of diverse communities is clear, but doing so in a realistic manner is an interesting design problem. For such integration to happen naturally but effectively, application specific researchers must formulate fundamental problems that can be solved by the “scientific” community, and result in new knowledge within the field. Similarly, the “scientific” community must be able to illustrate the application of the results and their limitations to the specific applications.

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