Engineering systems. The processes of engineering analysis and design can be systematically performed within a systems framework. Generally, an engineering project can be modeled to include a segment of its environment that interacts significantly with it to define an engineering system. The boundaries of the system are drawn based on the goals and characteristics of the project, the class of performances (including failures) under consideration, and the objectives of the analysis. A generalized systems formulation allows researchers and engineers to develop a complete and comprehensive understanding of engineering products, processes, and activities. In a system formulation, an image or a model of an object which emphasizes certain important and critical properties is defined. Systems are usually identified based on the level of knowledge and/or information that they contain. Based on their knowledge levels, systems can be classified into consecutive hierarchical levels. The higher levels include all the information and knowledge introduced in the lower ones in addition to more specific information. System definition is usually the first step in an overall methodology formulated for achieving a set of objectives.

The first step in engineering problem-solving is to define the architecture of a system. The definition can be based on observations at different system levels that are established based on the goals of the project. The observations can be about the different elements (or components) of the system, interactions among these elements, and the expected behavior of the system. Each level of knowledge that is obtained about an engineering problem defines a system to represent the project. As additional levels of knowledge are added to previous ones, higher epistemological levels of system definition and description are possible which, taken together, form a hierarchy of the system descriptions.

Informally, what is an engineering system? According to Webster's dictionary, a system is defined as "a regularly interacting or interdependent group of items forming a unified whole." For engineers, the definition can be stated as "a regularly interacting or interdependent group of items forming a unified whole that has some attributes of interest." Alternately, a system can be defined as a group of interacting, interrelated, or interdependent elements that together form a complex whole that can be a physical structure, process, or procedure of some attributes of interest. All the parts of a system are related to the same overall process, procedure, or structure, yet they are most likely all different from one another and often perform completely different functions.

Systems engineering can be defined as a discipline that establishes the configuration and size of system hardware, software, facilities, and personnel through an interactive process of analysis and design, satisfying an operational mission need in the most cost-effective manner. A system engineering process identifies mission requirements and translates them into design requirements at succeeding lower levels to insure operational and performance satisfaction. Control of the evolving development process is maintained through a continuing series of reviews and audits of technical documentation produced by systems engineering and other engineering organizations.

Objectives in the framework of decision-based design. The primary objective of this paper is to utilize expert-opinion elicitation to provide a plan for adapting and developing quantitative models and measures of various ignorance and uncertainty types that are suitable for prediction and decision-based design of complex engineering systems. This objective can be achieved by performing the following tasks as shown in Figure 1:

1. Define a hierarchical taxonomy of ignorance.
2. Associate ignorance taxonomy with phases of modeling and analytically simulate engineering systems.
3. Identify and develop quantitative methods for modeling various uncertainty types. Probabilistic and non-probabilistic methods should be considered in this task to cover ignorance types discussed in subsequent sections. Verify developed methods.
4. Identify and develop quantitative methods for measuring various uncertainty types, such as the Hartley-like measures, Shannon-like entropies, fuzziness measures, etc. Probabilistic and non-probabilistic methods such as theory of evidence, generalized fuzzy measures, and imprecise probabilities, among others, should be considered in this task. Verify developed methods.
5. Identify and develop quantitative methods for modeling joint uncertainty types and combining uncertainty measures. Verify developed methods.
6. Assess suitability and practicality of using the methods and measures that are the products of Tasks 3, 4, and 5 for prediction and decision-based design (DBD) of engineering systems.
7. Develop illustrative examples and a case study. Validate case study using, for example, expert-opinion elicitation and uncertainty analysis.

In subsequent sections, background materials for performing these tasks are provided.

Ignorance and Knowledge

Modeling and analytically simulating engineering systems, as a process, involves several phases that typically consist of (1) conceptual modeling of a real system, (2) mathematical modeling of the conceptual models, (3) discretization and algorithm selection, (4) computer programming, (5) numerical solution, and (6) representation of the numerical solution [Oberkampf et al. 1999]. This process can be enhanced by assessing the state of knowledge and ignorance at the various phases. Knowledge regarding some domain of interest may be broadly understood as the body of justified true beliefs pertaining to the domain. It is always defined in the context of human experiences, from which it cannot be removed. As a result, knowledge would always reflect the imperfect human nature that can be attributed to our reliance on the senses for knowledge acquisition, and on the mind for extrapolation, creativity, imagination, bias, and application. An important aspect in dealing with knowledge is non-knowledge, or ignorance, that needs to be examined, modeled, and measured at the various phases.

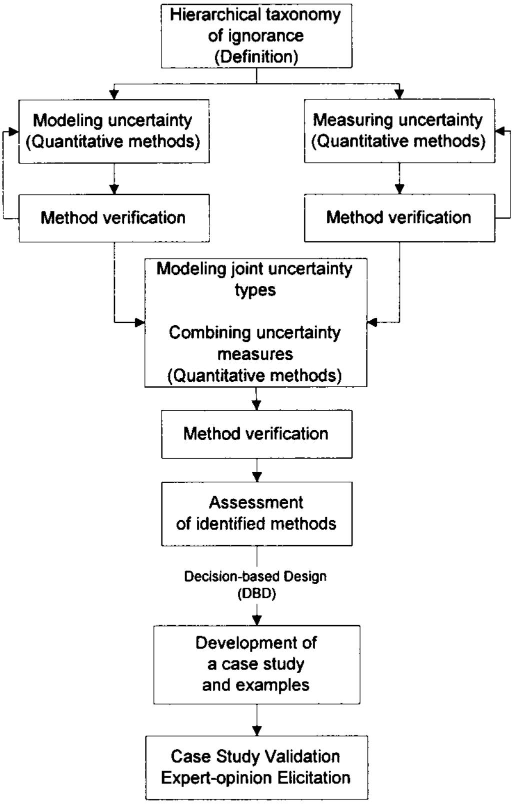

Figure 1. Decision-based design, verification, and validation of engineering systems.

Time and its asymmetry are crucial in defining knowledge and ignorance [Horwich 1987]. Time asymmetry describes the inability of humans to go back in time. Horwich [1987] described how the philosopher Kurt Gödel speculated in a theory which is consistent with the General Theory of Relativity that time flows from the past to the future, passing through the present, and allowing for "time travel" to the past. However, based on our current technology and knowledge, we can safely state that time as a phenomenon has a unidirectional flow. Time is, therefore, a one-dimensional continuum of instants with temporally occurring events. The present (or now) is a gliding index that moves in a unidirectional form from the past to the future. As Plato put it, "It is as if we were floating on a river, carried by the current past the manifold of events which is spread out timelessly on the bank" [Honderich 1995].

Engineering is a practice that often tries to make statements about the future, especially in designing new systems. However, Aristotle asserted that

[Honderich 1995] contingent statements about the future have no truth value, unlike statements about the past and present which are determinably either true or false. Events of interest can be viewed to progress in time tree-like, with fixed branches of the past, and forming branches of the present. However, the future contains branching manifolds of undetermined possibilities. Decision-based design (DBD) would attempt to explore these possibilities in the context of their benefits, costs, uncertainties, and risks. Ayyub [1998 and 2001] provided a classification of ignorance as shown in Figure 2. Klir and Folger [1988] developed and used various mathematical models and uncertainty measures to analyze and quantify uncertainty. These models are based not only on probability theory, but also on various combinations of fuzzy-set and rough-set theories with evidence theory, possibility theory, imprecise probabilities, and various other theories formulated in terms of non-additive measures. The theories for modeling uncertainty have attributes and bases that make them each uniquely suitable for modeling specific types of ignorance depicted in Figure 2. Consistent methods of uncertainty-measuring and modeling are needed to allow combining the results from the models.

Knowledge is primarily the product of the past, as we know more about the past than the future. For example, we can precisely describe past daily temperatures, but cannot accurately forecast future temperatures. Time asymmetry of knowledge can be attributed to several factors, of which the significant ones are:

1. our limited capacity to free ourselves from the past in order to forecast the future;
2. our inability to go back in time and verify historical claims gives us overconfidence in the superiority of our present knowledge; and
3. the unidirectional nature of causation to the past but not the future. We tend to explain phenomena based on antecedents rather than consequences. Therefore, we assume that causes precede effects, although the order can be switched for some systems in order to create the effects needed for some causes. Thus, the unidirectional temporal nature of explanation might not be true all the time and sometimes can be non-verifiable.

Engineers tend to be preoccupied more with what will happen than what has happened. This preoccupation might result in bias and time asymmetry. Engineering systems can be characterized by their goals as well as by their causes, thereby removing some of this asymmetry.

Generally, engineers, like most people, tend to focus on what is known and not on the unknowns. Even the English language lends itself to this emphasis. For example, we can easily state that Expert A *informed* Expert B, whereas we can only state the contrary indirectly by using the negation of the earlier statement, "Expert A *did not inform* Expert B." Statements such as "Expert A *misinformed* Expert B," or "Expert A *ignored* Expert B" do not convey the same (intended) meaning. Another example is "John knows David," for which a meaningful direct contrary statement does not exist.

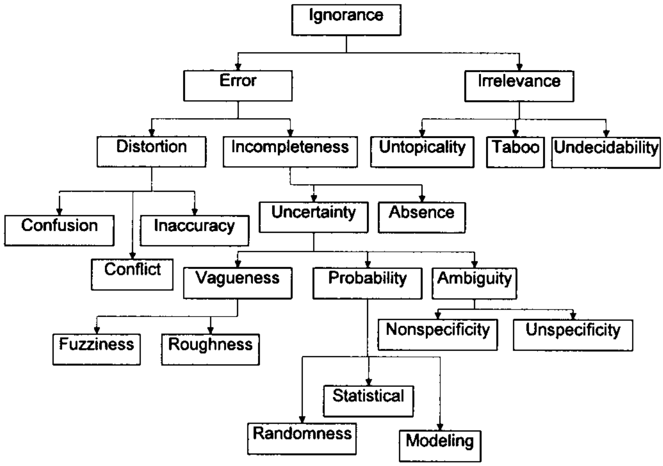

Figure 2. Classification of ignorance [Ayyub 2001].

Classification of ignorance. Knowledge and ignorance cannot be defined in absolute terms. It can be rightfully argued that they are not absolute, and are socially constructed and negotiated. A non-absolute working definition of ignorance can be taken as "Expert A is ignorant from B's viewpoint if A fails to agree with or show awareness of ideas which B defines as actually or potentially valid" [Smithson 1988]. This definition allows for self-attributed ignorance, and either Expert A or B can be attributer or perpetrator of ignorance. Ignorance can be classified into two types, error and irrelevance. The taxonomy of ignorance shown in Table 1 defines these types and their various aspects shown in Figure 2.

Knowledge categories. Human knowledge is acquired by various means that were categorized by the Greek philosopher Plato (427-347 BCE) [Honderich 1995] into four categories as shown in Figure 3. The most basic category is called cognitive knowledge *(episteme)* that can be acquired, for example, by human senses. The next level is based on correct reasoning from hypotheses such as mathematics *(dianoi)*. The third category *(pistis)* is based on appearances and deception and is followed by conjecture *(eikasia)*, where knowledge is based on inference, theorization, or prediction based on incomplete evidence. These four categories define knowledge. They constitute the human cognition that might be different from evolutionary knowledge. The *pistis* and *eikasia* categories are based on expert judgment regarding system issues of interest. Although these two knowledge categories might by marred by uncertainty, they are sought after in many engineering disciplines by decision and policy makers.

Table 1. Taxonomy of ignorance [Ayyub 2001].

Term	Meaning
Error	Being ignorant of something.
Distortion	Refers to bias, inaccuracy, or confusion.
Confusion	Wrongful substitutions.
Conflict	Conflicting assignments or substitutions.
Inaccuracy	Bias and distortion in degree.
Incompleteness	Defined by its components of uncertainty and absence.
Uncertainty	Incompleteness in degree.
Vagueness	Defined by its components of fuzziness and roughness.
Fuzziness	Non-crisp membership to sets.
Roughness	Non-crisp boundaries of sets.
Ambiguity	Multioutcomes of a process.
Unspecificity	Outcomes or assignments that are not completely defined.
Nonspecificity	Outcomes or assignments that are improperly defined.
Probability	Defined by its components of randomness, statistics, and modeling.
Randomness	Fundamental non-predictability of outcomes.
Statistical	Samples versus populations.
Modeling	Use of simplifying prediction models.
Absence	Incompleteness in kind.
Irrelevance	To ignore something due to its perceived inapplicability.
Untopicality	Intuitions of experts that are negotiated with others in terms of cognitive relevance.
Taboo	Socially reinforced irrelevance. Issues that people must not know, deal with, inquire about, or investigate.
Undecidability	Issues that are considered insoluble, or solutions that are not verifiable.

Various Classifications of Uncertainty Types

Systems engineering provides a general framework for engineering analysis and design. The systems definition can be based on observations at different system levels in the form of a hierarchy. An epistemological hierarchy of systems suited to the representation of engineering problems with a generalized treatment of uncertainty can provide realistic assessments of systems [Klir and Folger 1988]. Uncertainty modeling and analysis in engineering started with the employment of safety factors using deterministic analysis, then was followed by probabilistic analysis with reliability-based safety factors. Uncertainty in engineering was also classified into objective and subjective types. The objective types included the physical, statistical, and modeling sources of uncertainty. The subjective types were based on lack of knowledge and on expert-based assessment of engineering variables and parameters. Similar classifications are utilized in quantitative risk analysis for policy-related areas [Morgan and Henrion 1992]. Uncertainties in engineering systems can mainly be attributed to ambiguity and vagueness in

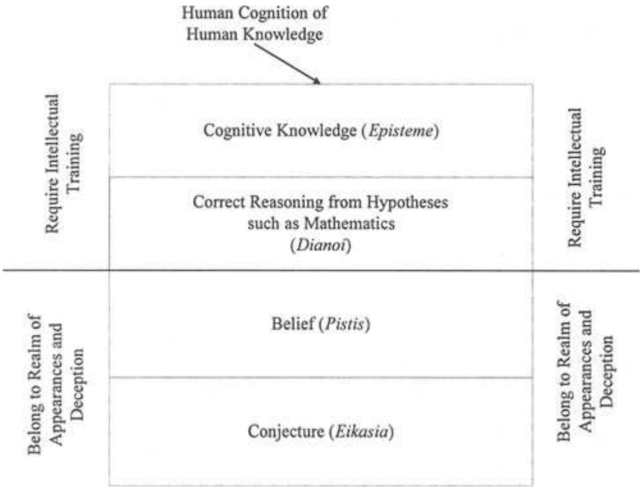

Figure 3. Knowledge categories [Ayyub 2001].

defining the architecture, parameters, and governing prediction models. Stochastic modeling and analysis is needed in cases of probabilistic, ambiguous, or aleatory uncertainty. Cognitive, vague, or epistemic uncertainty can be handled using fuzzy sets and logic in other modeling scenarios [Pate-Cornell 1996]. The ambiguity component is generally due to non-cognitive sources. These sources include (1) physical randomness, (2) statistical uncertainty due to the use of sampled information to estimate the characteristics of these parameters, (3) lack of knowledge, and (4) modeling uncertainty. This last is due to simplifying assumptions in analytical and prediction models, simplified methods, and idealized representations of real performances. The vagueness-related uncertainty is due to cognitive sources that include (1) the definition of certain parameters, (e.g., structural performance—failure or survival—quality, deterioration, skill and experience of construction workers and engineers, environmental impact of projects, conditions of existing structures); (2) other human factors; and (3) defining the inter-relationships among the parameters of the problems, especially for complex systems. Other sources of uncertainty can include conflicting information, and human and organizational errors.

Analysis of engineering systems commonly starts with a definition of a system that can be viewed as an abstraction of the real system. The abstraction is performed at different epistemological levels. The resulting model can depend largely on an analyst or engineer; hence the subjective nature of this process. During the process of abstraction, the engineer needs to make decisions regarding what aspects should or should not be included in the model. These aspects include the previously identified uncertainty types. In addition, there can be other aspects of the system which are more difficult to deal with because of their unknown natures, sources, extents, and impact on the system.

Uncertainty modeling and analysis for the abstracted aspects of the system need to be performed with proper consideration of the non-abstracted aspects of a system. The division between abstracted and non-abstracted aspects can be a division of convenience that is driven by the objectives of the modeling system or simplification. However, the unknown aspects of the system are due to ignorance and lack of knowledge. These aspects will depend on the knowledge of an analyst and the state of knowledge about the system in general. The effects of the unknown aspects on the ability of the system model to predict the behavior of the real system can range from none to significant.

Uncertainty in abstracted aspects of a system. Engineers and researchers deal with the ambiguous types of uncertainty in predicting the behavior and designing systems using the theories of probability and statistics. Probability distributions are used to model system parameters that are uncertain. Probabilistic methods developed and used for this purpose include, for example, reliability methods, probabilistic engineering mechanics, stochastic finite element methods, reliability-based design formats, random vibration, and other methods. These treatments, however, realized the presence of a cognitive type of uncertainty. Subjective probabilities used to deal with it have been based on mathematics used for the frequency type of probability. Uniform and triangular probability distributions have been used to model this type of uncertainty for some parameters. Bayesian techniques were also used, for example, to deal with gaining information about uncertain parameters. Therefore, the underlying distributions and probabilities were updated. However, regardless of the nature of the gained information, whether cognitive or non-cognitive, the same mathematical assumptions and tools have been used.

The cognitive types of uncertainty arise from mind-based abstractions of reality. These abstractions are therefore subjective, and lack crispness. This vagueness is distinct from ambiguity in source and natural properties. The axioms of probability and statistics are limiting for the proper modeling and analysis of this uncertainty type and are not completely relevant nor completely applicable. The vagueness type of uncertainty in civil engineering systems was previously discussed elsewhere along with selected applications of fuzzy set theory to such systems.

Fuzzy-set theory has been developed by Zadeh [e.g., 1965] and used by scientists, researchers, and engineers in many fields. Example applications are provided elsewhere [Kaufmann and Gupta 1985]. In engineering, the theory was used to solve problems that involve the vagueness type of uncertainty. For example, civil engineers and researchers started using fuzzy sets and systems in the early 1970s [Brown 1979]. The theory has been successfully used in, for example, (1) strength assessment of existing structures and other structural engineering applications; (2) risk analysis and assessment in engineering; (3) analysis of construction failures, scheduling and safety assessment of construction activities, decisions during construction and tender evaluation; (4) impact assessment of engineering projects on the quality of wildlife habitat; (5) planning of river basins; (6) control of engineering systems; (7) computer vision; and (8) optimization based on soft constraints.

Uncertainty in non-abstracted aspects of a system. At the different levels of developing a model, an analyst or engineer needs to decide upon the aspects of the system that need and do not need to be abstracted. The division between abstracted and non-abstracted aspects can be for convenience or to simplify the model. The resulting division is highly affected by the knowledge and background of the analyst or engineer, as well as by the general state of knowledge about the system.

The abstracted aspects of a system and their uncertainty models can be developed to account for the non-abstracted aspects to some extent. Generally, this accounting process is incomplete. Therefore, a source of uncertainty exists due to the non-abstracted aspects of the system. The uncertainty types in this case include physical randomness, vagueness, human and organizational errors, and conflict and confusion in information.

The uncertainty types due to the non-abstracted aspects of a system are more difficult to deal with than those due to the abstracted aspects. The difficulty can stem from a lack of knowledge or understanding of the effects of the non-abstracted aspects on the resulting model in terms of its ability to mimic the real system. Poor judgment or human errors about the importance of the non-abstracted aspects of the system can partly contribute to these uncertainty types, in addition to contributing to the next category, uncertainty due to the unknown aspects of a system.

Uncertainty due to unknown aspects of a system. Some engineering failures have occurred because of failure modes that were not accounted for in the design stages of these systems. This can be due to (1) ignorance, negligence, human, or organizational errors; or (2) a general state of incomplete knowledge about a system. These unknown aspects depend on the nature of the system under consideration, the knowledge of the analyst, and the state of knowledge about the system in general. The non-accounting of these aspects in the models can result in varying levels of their ability to mimic the behavior of the system. The effects on the models can range from none to significant. In this case, the uncertainty types can include physical randomness, human and organizational errors, and lack of knowledge.

Engineers have dealt with non-abstracted and unknown aspects of a system by assessing modeling uncertainty, which is defined as the ratio of a model's predicted variable or parameter to the value of the variable or parameter of the real system. This ratio, which is called bias, is commonly treated as a random variable that can consist of objective and subjective components. This approach is based on two implied assumptions: (1) the value of the variable or parameter for the real system is known or can be accurately assessed from historical information or expert judgment, and (2) the state of knowledge about the real system is absolutely complete and reliable. For some systems, the first assumption can be approximately examined for its validity. The second assumption cannot be validated because of its absolute strictness.

Potential Areas of Application: Verification and Validation

To better understand the verification and validation (V&V) process (see Figure 4), a formal treatment of uncertainty and error is necessary. An error can be due to distortion, which is a recognizable deficiency in any phase of modeling that is not due to lack of knowledge or to incompleteness. Uncertainty, however, is a type of error that represents a potential modeling deficiency due to lack of knowledge. Uncertainty can be mainly attributed to ambiguity and vagueness in defining the architecture, parameters, and governing prediction models for the system. Modeling uncertainty arises from using analytical models to predict system behavior. Statistical uncertainty arises from using samples to characterize populations. In this paper, expert-opinion elicitation is presented as a way to deal with uncertainty in selected technical issues related to a system of interest.

Verification. The verification process deals with the distortion type of error that can be modeled using numerical methods. Verification consists of three stages: conceptual model verification, design verification, and code verification. The verification can be done by comparison, tests of agreement between the computational model and solution, and benchmark results (analytical or very accurate numerical solutions) of simplified model problems, as shown in Figure 5.

Validation. The validation process (see Figure 6) deals with the uncertainty type of error. Validation consists of two stages: conceptual model validation, and results validation that can be done by expert-opinion solicitation. To perform the validation of a design, the uncertainty for that system needs to be modeled. The uncertainty can be modeled using fuzzy sets, probability, statistics, and numerical methods. The system can be divided into its abstracted aspects, non-abstracted aspects, and unknown aspects. Probability distributions are used to model parameters that are uncertain in the abstracted aspects of the system. The vagueness is dealt with by fuzzy sets. The non-abstracted and unknown aspects of the system are treated by assessing modeling uncertainty or bias, which is treated as a random variable. The next section describes expert-opinion elicitation, a proposed method for results validation.