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MODELING AND INFORMATION IN THE DESIGN PROCESS

Daniel A. McAdams*
Department of Mechanical Engineering
University of Missouri – Rolla
Rolla, MO 65409–0050

Clive L. Dym
Department of Engineering
Harvey Mudd College
Claremont, CA 91711–5990

ABSTRACT

This paper examines how models and information are used in engineering, and especially in the engineering design process. Model use and information content are both important and strongly coupled, if only because models are used to develop information upon which basis engineering decisions are made and outcomes achieved. Classical decision theory suggests that the quality of a decision-making process is independent of the outcome, and yet models are used to obtain the best information possible in order to achieve the best outcome. This paper considers definitions of models, the implications of the information content of engineering models, and the role(s) models play in design decision making. It is suggested that a taxonomy of design models may be useful to the extent that it connects to both the type and quality of information it imparts, and to the quality of the outcome desired. The type of model is important for self-evident reasons; the quality of information is also important because design models must be predictive in ways that enable design. The quality of the outcome is important since that is the underlying point of a design process.

Keywords: model, information, model taxonomy

INTRODUCTION: MODELING IN ENGINEERING AND IN ENGINEERING DESIGN

There have been many, many definitions of (engineering) design that emphasize different aspects of the design endeavor. For example, Simon [1] points to the designed artifact as the interface between its “inner” content and the “outer” environment in which it operates. Dym [2] characterizes the synthesis process as a thoughtful one intended to achieve given objectives without violating specified constraints. Notwithstanding these definitions and many more, Blumrich’s [3] definition seems most insightful for the present purpose because of its focus on problem structure and implicit recognition of the critical role of synthesis in engineering design: “Design establishes and defines solutions to pertinent structures for problems not solved before, or new solutions to problems which have previously been solved in a different way.”

Myron Tribus has applied decision theory to the engineering design process to create a “Theory of Engineering Design” [4]. The importance of decision making in design has fostered a framing of engineering design as almost entirely a decision-making process [5], and it has resulted in a Decision-Based Design (DBD) research community. Extensive effort has been exerted to apply these ideas to aspects of engineering design, particularly concept selection and other key decisions generally made early in the design process [6-12]. Concepts from decision theory have also been used to develop an axiomatic framework for design [13].

The synthesis of solution alternatives and decision making are without question critical to engineering design. In fact, the synthesis of solution alternatives and decision making are also critical to disciplines and pursuits outside of engineering design. Politicians, military officers, businessmen, doctors, and many others are faced with the problem of determining solutions to non-trivial problems and selecting a “best” solution or solution approach. A key distinguishing element of solution synthesis and decision making in engineering design lies in the type of models used—and the roles they play—in the design process. While other disciplines also use models and other theoretical constructs, the use of physically appreciable and mathematically approximate models from engineering science is more closely associated with engineering design than other pursuits. Further, the ways in which both the abstract and poorly understood nature of design synthesis interacts with the mathematically clean, reductionist nature of decision making make engineering design uniquely challenging and rewarding.

The goal of this article is to develop the case that a formal taxonomy of models used in engineering design would be a beneficial step toward a larger goal of developing a deeper and richer understanding of modeling from the perspective of the engineering designer. Through a better classification of models

*corresponding author

and the concomitant understanding, designers can appropriately select and use models for design tasks with less error and less iteration.

In addition, a deeper understanding of engineering design models will improve the ability to teach design. Engineers are taught a vast array of models in four or more years of higher education, including simple mathematical descriptions of Newtonian mechanics, elaborate computer-based analysis techniques, and laboratory and other physical experimental procedures. Covering these models represents a tremendous effort on the part of students and educators, these models embody a deep and powerful—yet often poorly utilized—body of knowledge. It is generally assumed that engineering students will be able to apply the models learned as they design new products and processes. Thus, most engineering courses are taught extant models from a "science" perspective: they are not taught how to create or make models. Still worse, all too often students are not brought to appreciate that the equations, programs, and ideas they use to formulate and solve problems are themselves only models, that is, they are only representations of how we perceive and describe reality. Consequently, we cannot assume that students can or will intuitively construct relevant and appropriate design models. In fact, far too few students make the connection between engineering analysis and engineering design [14]. A better classification and understanding of models as used in engineering design will better allow students to select and construct useful design models, rather than simply recall and exercise some model in the hope that it is relevant.

Over the last 30 years, computers have dramatically changed the way that engineering models are used to solve problems. Although computers have prompted significant changes in the way models are solved, the formulation of engineering models is still very human process. Decisions about which factors must be considered—and which ignored—require judgment and experience. Abstracting the causal nature and form among different relevant factors is also very much a human process. In fact, identifying what interests (or not!) a designer may always be an innately human activity. Nevertheless, model formulation and use are principled activities. The principles are over-arching or meta-principles phrased as questions about the intentions and purposes of constructing a model [15]:

- ***Why?*** What are we looking for? Identify the need for the model.
- ***Find?*** What do we want to know? List the information we are seeking.
- ***Given?*** What do we know? Identify the available relevant information.
- ***Assume?*** What can we assume? Identify the circumstances that apply.
- ***How?*** How should we look at this model? Perhaps identify the governing physical principles.
- ***Predict?*** What will our model predict? Identify the causal relations between what I know and what I want to know.
- ***Valid?*** Are the predictions valid? Identify tests that can be made to validate the model, i.e., is it consistent with its principles and assumptions?
- ***Verified?*** Are the predictions good? Identify tests that can be made to verify the model, i.e., is it useful in terms of the initial reason it was done?
- ***Improve?*** Can we improve the model? Identify information that is not adequately known, information and causal relations that should have been included, and/or assumptions/restricted that could be lifted. Implement the iterative loop that we can call "model-validate-verify-improve-predict."
- ***Use?*** How will we exercise the model? What will we do with the model?

Though this list of principled questions is not an algorithm for constructing a good model, if models are organized and represented in a useful fashion, perhaps these principles can be applied to make the use of models more thoughtful and more systematic. Thus, computers may be able to assist designers in constructing models, as well as for solving them. In terms of quickly reviewing a knowledge base for potentially useful design models, a human designer will always be limited by his own memory, expertise, and "computational" search speed. With a taxonomical model representation that is design relevant, the memory and speed of computers can be used to search for a set of models likely to be of use to the designer. In cases where a computer's knowledgebase exceeds that of the designers, the computer can suggest models that the designer might not have developed.

WHAT IS A MODEL?

In the context of engineering design, the construction of models and interpretation of results obtained with them is particularly challenging as the models are *predictive*: the models do not describe an existing system, they are used to predict how some nonexistent system will work. This lack of reliable or more complete information about the product or system being designed compounds the challenges of model construction. Thus, this section clarifies the meaning of "models" and how they are used in engineering design.

The noun model means different things to different people, and even different things to the same people at different times or in different contexts. Rather than propose (another) idiosyncratic definition, the present discussion begins with a dictionary definition [16]:

model *(n)*: a miniature representation of something; a pattern of something to be made; an example for imitation or emulation; a description or analogy used to help visualize something (e.g., an atom) that cannot be directly observed; a system of postulates, data and inferences presented as a mathematical description of an entity or state of affairs

All of these definitions in some way are appropriate for some aspect of engineering design though the last two seem the most appropriate (and, relevant to the discussion in the previous section, the last of these seems to exemplify how engineering has been taught in the decades since 1957's Sputnik launch). However, the fourth definition may be most relevant if a different exemplar is chosen (with emphases added):

model *(n)*: a description or analogy used to help visualize something (e.g., *an artifact that has not yet been realized*) that cannot be directly observed (*because it does not yet exist*)

It is also important to note that the modeling and design activities are done in several languages, often simultaneously [17]. These modeling or design languages include text, drawings or sketches, physical models, computer programs, and mathematical formulas.

Another definition, general yet meaningful, states that a model is "an abstraction constructed to represent a specific subset of a specific reality" [18, 19]. Though broad enough for many discussions, including the present one, this definition still leaves ample room for confusion. For example, the letters that construct the words of this text are in this context also a model: the letters represent a particular audible sound. The words of this text read as a combination of letters are also a model: the combinations each represent a particular concept. Continuing along this line of reasoning may provide for some interesting discussions, but it does not move us in the direction of understanding and classifying models.

Developing a perfect definition of a model in the context of engineering design is no less an elusive task than developing a general definition. Yet, a perfect definition of a model, while hard to develop, is almost certainly unnecessary. For example, what is the definition of "m"? Among others, in the word model, "m" is the 13th letter of the alphabet that is pronounced in a defined and accepted way. In the equation $F = ma$, "m" is used as a symbol that, in this context, has been defined to stand for the concept of mass. Both definitions are equally correct in how they are used in their contexts. Similarly, our present interest in models is in how they are used in the context of engineering design. Though other dictionaries will have different model definitions, we elect to use the dictionary definition of model given as the one needed, and we move on to exploring how models are used.

HOW ARE MODELS USED IN ENGINEERING DESIGN?

Models are used for many reasons, including the simple experience and joy of formulating and solving a mathematical problem. However, we will here focus on some of the more practical reasons that models are used in engineering. We note parallels between how models are used in the scientific method and engineering modeling, and we will use these similarities to discuss model use in engineering design.

In the elementary picture of the scientific method shown in Figure 1, we identify a "real world" and a "conceptual world." The "real world" is the external one in which we observe various phenomena and behaviors, whether natural in origin or produced by artifacts. The "conceptual world" is that of the mind—where we live when we try to understand what is going on in that external, real world. The development of the conceptual world can be viewed as having three stages: observation, modeling, and prediction:

- During the *observation* part of the scientific method, we measure what is happening in the real world. Here we gather empirical evidence and "facts on the ground." Observations may be direct, as when we use our senses, or indirect, in which measurements are taken to indicate through some other reading that an event has taken place. For example, we often know a chemical reaction has taken place only by measuring the product of that reaction.

- In this elementary view of how science is done, the *modeling* part is concerned with analyzing the above observations for one of (at least) three reasons. These rationales are about developing: models that *describe* the behavior or results observed; models that *explain why* that behavior and results occurred as they did; or models that *allow us to predict future behaviors* or results that are as yet unseen or unmeasured.

- In the *prediction* part of the scientific method, we exercise our models to tell us what will happen in a yet-to-be-conducted experiment or in an anticipated set of events in the real world. These predictions are then followed by observations that serve either to validate the model or to suggest reasons that the model is inadequate.

The last stage clearly points to the looping, iterative structure apparent in Figure 1. It also suggests that modeling is central to all of the conceptual phases in the elementary model of the scientific method. We build models and use them to predict events that can confirm or deny the models. In addition, we can also improve our gathering of empirical data when we use a model to obtain guidance about where to look.

Engineers are interested in designing devices and processes and systems. That is, beyond observing how the world works, engineers are interested in creating artifacts that have not yet come to life. As noted by Simon [1], "Design is the distinguishing activity of engineering." Thus, engineers must be able to describe and analyze objects and devices into order to predict their behavior to see if that behavior is what the engineers want. In short, engineers need to model devices and processes if they are going to design those devices and processes.

While the scientific method and engineering design have much in common, there are differences in motivation and approach that are worth mentioning. In the practices of science and of engineering design, models are often applied to predict what will happen in a future situation. In engineering design, however, the predictions are used in ways that have far different consequences than simply anticipating the outcome of an experiment. Every new building or airplane, for example, represents a model-based prediction that a building will stand or an airplane will fly without dire, unanticipated consequences. Thus, beyond simply validating a model, prediction in engineering design assumes that resources of time, imagination, and money can be invested with confidence because the *predicted outcome will be a good one*.

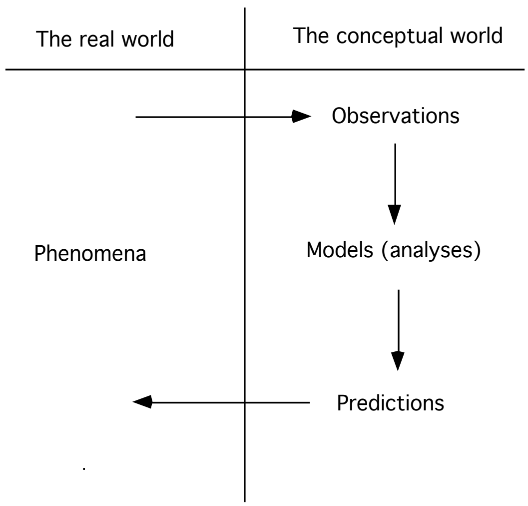

Figure 1. An elementary depiction of the *scientific method* that shows how our conceptual models of the world are related to observations made within that real world [15].

Inasmuch as the modern engineering curriculum is very much science-based, one further difference between scientific and engineering models is worth noting. Students are taught a large volume of scientific material on the premise that it will improve their ability to do engineering. This premise is in turn based on the fact that in many cases, engineering relies on science to produce scientific models, or descriptions of systems or artifacts that exist, that are then used to product how some new system or artifact will work. In many cases these models are based on "natural laws." Natural laws are not viewed as models by some [20], as if these natural laws are superior and to be more trusted than models not based on natural laws.

It may, in fact, be true in nature that Newton's 2nd law of motion or the conservation of energy or any other natural laws are absolutely true in the universe—and there may be good reason to treat them differently. However, our perceptions, descriptions and predictions are predicated on behavior models that we construct to try to explain the universe. Some of these models have become so deeply entrenched, so empirically well-supported that we want to elevate them to some super-model status, and thus we call them "laws." (It is also well to remember that, for example, notwithstanding his laws of motion, many of Newton's predictions about the world were simply wrong.) There may well some underlying law(s), but as we attempt to express these laws, whether in a natural human language or in a mathematical formula or in any other abstraction, we are constructing and expressing and using a *model*. Thus, from an engineer's point of view, the only practical difference between models based on natural laws and those that are not is our degree of confidence in the model. Designers construct such models to produce information that will enable a better design of an artifact.

We might also say that in engineering design we construct models to obtain or predict information about the future. The information thus produced may be used to assess feasibility, specify a part or a material, show the assembly of parts, or for any of a huge number of other purposes. The critical characteristic of a model in the design context is the type of information it produces. If we already had the information, or didn't need that information, we would not produce the model. Thus, *design models operate on information to produce information*. If we then classify models for design, the classifications should be tied to the information needed as input to the model and as information produced by the model.

The information produced by a design model may be a number, a graphical result, or represented in any of the other languages used in engineering design. For example, a number from a lift model may be used to assess whether or not a plane will fly—and if that number is significantly wrong, the plane will not fly! For example, a drawing of a wing assembly may be used to assess whether or the wing can be made—and if the graphic is unclear, we may incorrectly predict the wing's assembly. The error, or uncertainty, in the model-produced information certainly affects our ability to make correct predictions. Thus, if we classify models, the classification must be closely tied to the error or uncertainty in the information produced by the model.

It would seem that our understanding of modeling in design could benefit from exploring the role of information in design modeling. We will attempt to address information properly below. First, however, we will review some definitions for information and review their motivation and suitability for engineering design. Then we will review useful classifications of information.

INFORMATION IN ENGINEERING DESIGN

The management and transformation of information is central to the design process [17]. As with the word model, the word information means different things to different people and different things to the same people, and even different things to the same people at different times or in different contexts. Again we resort to the dictionary [16] rather than propose an idiosyncratic definition:

information*(n)*: the communication or reception of knowledge or intelligence; knowledge obtained from investigation, study, or instruction; intelligence, news; facts, data; a signal or a character (as in a communication system or a computer); something (as a message, experimental data, or a picture) which justifies change in a construct (as a plan or theory); and a quantitative measure of the content of information, specifically a numerical quantity that measures the uncertainty in the outcome of an experiment to be performed.

In effort to improve our understanding of information and its use in engineering design, more focused definitions have been proposed. Shannon [21] proposed a mathematical definition useful for communication theory. Suh [22] proposed a mathematical definition (similar to Shannon's) in an effort to develop a theory of engineering design based on a set of fundamental axioms The dictionary definition encompasses both these definitions.

Hazelrigg [13] defines information as "the basis upon which good decisions are made." This definition has a strong analogy to one of the dictionary definitions presented earlier: "something as a message, experimental data, or a picture, which justifies change in a plan or a theory." Note that here the information is coming from a picture or experimental data. Thus, the information is extracted from a model. More recently Hazelrigg [20] expanded his definition of information: "Information relates to a specific decision. It is what the decision is based on. Quantitatively, it can be measured as the probability that the preferred choice in a specific decision with specific alternatives will lead to the outcome most desired from among the outcomes actually achievable from the available alternatives."

Hazelrigg's definitions of information are based on viewing or *modeling* engineering design as a decision-making process. This is a model that describes how a process works, or perhaps what the process ought to be. There are many decisions that get made during any design. Thus, approaching these decisions rationally and rigorously is important. Nevertheless, just as the same artifact is modeled in different ways to produce different information and understanding, engineering design can be modeled in different ways. Care should be taken in modeling engineering design solely as a decision-making process and in using that model alone as a basis for making recommendations for action and drawing conclusions about the design activity.

In decision theory, the quality of a decision is independent of and unrelated to the outcome. That is, the mathematics of decision theory enables decisions that lead to some highest expected value (interpreted in the probabilistic sense) of some outcomes, but it does not allow the designer to set the value of the expected outcome. In a decision problem, there are alternatives, outcomes, and information. The information is used to predict the outcomes of the different alternatives. For example, a bike designer wishes to design a bike frame that weights less than four pounds. Three different frame design are proposed: *A*, *B*, and *C*. Models of these frames are constructed to include geometry and density as input information and to produce weight as part of their output information. Based on the information produced by the models, the designer may estimate that the probability that *A* weighs less than four pounds is 20%, the probability that *B* weighs less than four pounds is 15%, and the probability that *C* weighs less than four pounds is 10%.

The designer could then choose frame *A*. But, at this point it seems clear that there are more than these three possible alternatives. Perhaps the models used by the engineer are very crude and don't consider local variations in frame tubing wall thickness or other methods that might reduce bike weight. One additional action would be to construct a model that produces more accurate information about frame weight. Perhaps with this information, the designer would estimate the probability that *A* weighs less than 4 pounds at 99%. Including the production of more data in the decision making process can be addressed by the decision-making process to some extent [23, 24]. Another, and perhaps more likely action would be to synthesize an additional concept in the hope that it would weigh less than four pounds. A premise in the decision theory is that the alternative courses of action have been identified. It is unclear if formally including the synthesis of new alternatives as an alternative in the decision-making process is possible.

It could be argued that the designer is modeling the wrong thing. A decision support model should not model frame weight; rather, it should model the potential of that frame to make money for the company. If the frame loses money for the company, it is a poor design from one important perspective. Nevertheless, part of the ability of the frame to make money for the company resides in its weight, so the designer is still faced with making models that account for weight as a design objective. Additionally, during the construction of the frame (weight) model, the designer's understanding of unnecessary sources of weight in the frame increases. In this example, the designer is able to use this new understanding to synthesize a new frame concept that weighs less than four pounds and so achieve the desired outcome.

In this example, where the designer is interested in an outcome that includes a frame weighing less than four pounds, modeling the design process as a decision-making process could have led to an irrational outcome: the rational course of action would be to generate more frame designs. Viewing engineering design as a whole, therefore, shows that there are many aspects of design that are poorly modeled only as decisions; concept synthesis is perhaps the clearest example. Different types of models are used in design and different models of design are needed. In this simple example, modeling design as a decision-making process produced the information that none of the frame alternatives is particularly attractive. The weight model produced information that enabled the engineer to design a frame that weighed less than four pounds. Together, the models produced information that enabled the desired outcome.

Though the probability of getting what a designer wants is certainly information, it seems perhaps too narrow a definition. In estimating the probability of achieving a specific outcome, it is likely that information will again be extracted from models. The information input to and output from these models is unlikely to be expressed in probabilities of desired outcomes. In general, to produce information on the probability of achieving some desired outcome, we need other types of information.

As with the term model, a perfect and unambiguous definition of information is elusive, and unlikely to bring us a better understanding of its use in engineering design. Greater understanding is likely achieved by identifying the different types of information used in engineering. Thus, we continue with some observations on information in design and briefly address organizing design information.

FOUNDATIONS OF AN INFORMATION-BASED TAXONOMY OF *DESIGN*

Having decided that a simple and complete definition for information is elusive and unnecessary, we now tackle the integration of our ideas about how design is done into an information-based organization or taxonomy of design. Again, we argue that the endeavor is worthwhile to the extent that such an organization helps us to understand and articulate that part of design that can be modeled as a set of thought or cognitive processes, which could bring us closer to a coherent theory of design; it could also help us learn (and then teach) what it is that designers do. Further, an organizing principle could help us classify computer experiments in design modeling, which in turn helps us externalize our thinking about design and aids in the development of computer-aided design tools that could have significant practical application. We start by summarizing the most salient ideas about characterizing design in an orderly but non-tabular form [17]. In addition, bearing in mind that words are used by different authors to mean different things, we will try to (1) conform to the dictionary definitions of the essential or critical terms, and (2) characterize the design process in an explicit ordering of decreasing abstraction (or increasing refinement):

- design *task*,
- design *strategy*,
- design *method*, and
- design *mechanism.*

A design *task* is viewed as a *transformation* of an initial information or knowledge state to a final knowledge or information state [25, 26]. Thus, both the initial and final states must be articulated, as must the transformation(s) by which we proceed from one state to the other. Since the initial and final states are actually representations of the artifact being designed that are expressed at different levels of abstraction, our state descriptions must be complete and unambiguous at their respective levels of abstraction. Thus, at the start of the design process, we need a sufficiently clear description of the intended end point of the process and the constraints within which the designed device must operate. For the resulting design to be accepted as complete, we must have a set of fabrication specifications that allow the artifact to be built exactly as intended by the designer.

In general, the design activity is one of refinement, wherein the initial state is more abstract than the final state. Notwithstanding local variations within a complex design process (e.g., to achieve a specific subgoal, it might be useful to backtrack to a higher level of abstraction to search for other possibilities in terms of physical principles, embodiments, components, and so on), the general direction of design transformation is toward increasing detail or refinement. Further, recognizing that the six kinds of states are themselves ordered—to some extent, and not altogether accidentally—according to the degree of refinement, we can perhaps assert that the degree of difficulty of a design problem is roughly proportional to the number of different layers between the initial and final states. Thus, we posit that the initial and final states of knowledge are characterized as each being within one of the following six knowledge-state layers [26]:

- *Layer 1 — perceived need*
- *Layer 2 — function*
- *Layer 3 — physical phenomenon*
- *Layer 4 — embodiment*
- *Layer 5 — artifact type*
- *Layer 6 — artifact instance*

The next step is the detailing of the information- or knowledge-state layers, while retaining the foregoing structure proposed [25, 26]. Dym [17] suggested that refinement of the values that can be inserted into the representation slots when numerical representations are identified. It may be useful to distinguish between discrete and continuous representations because choices of methods and mechanisms clearly hinge on the nature of the numerical representation. For continuous variables, some parametric or algorithmic approach might be appropriate, whereas discrete variables might indicate that approaches based on selection are more relevant. Thus, five representation languages would be identified here [17]:

- *textual*
- *numerical–discrete*
- *numerical–continuous*
- *graphical*
- *physical*

The information-state layers and their representations are not likely to be entirely independent because the more abstract the layer, the more likely that it is rather vague knowledge expressed in text. Conversely, artifact types and artifact instances are increasingly specific descriptors.

If the design problem is formulated in terms of the differences between the (given) initial information-state and a (sought) final information-state, the design process might be viewed as means–ends problem solving, and the design task is the elimination of the gap between the two problem states by transforming the initial information-state into the final information-state. The ends are thus the elimination of the differences between the initial and final states, while the means of achieving that end is an aggregated set of subtasks that make use of domain knowledge, including both generative and control knowledge, strategies, problem-solving methods, and various specific mechanisms. In all of these efforts, designers rely on models to transform information.

FOUNDATIONS OF A TAXONOMY OF *DESIGN MODELS*

Though not generally considered formal taxonomies, classifications of models do exist. Hazelrigg has classified models as being *iconic*, *symbolic*, or *analog* [27]. The dictionary definition of models presented earlier is to some extent a taxonomy: the different definitions and examples of models serve as a classification. Classifying models according to their mathematical form is also a potentially useful organization: algebraic equations, ordinary differential equations, partial differential equations, integral equations, predicate logic, etc. Models might also be classified according to how well they turn the input information into output information. For models expressed as mathematical equations, the best way to turn input information into output information may reduce to the best method (e.g., analytical, numerical) to solve that equation. (Many texts on engineering modeling organize models in this way because they focus on how to solve models, rather than on defining which model is best for a given problem.)

Though these model classification schemes have their uses, they are not appropriate for a design model taxonomy. A designer is not usually interested in whether a model is a symbolic model, an ordinary differential equation, or is solved using separation of variables—although these issues are of interest when the designer has to consider the cost of executing a model and the value of the information returned. Of primary importance to the designer is the information produced *by* the model. Thus, any useful design model taxonomy should be based on the information produced by the model.

We propose that a design model taxonomy rests on four primary classes:

1. the type of output information;
2. the type of input information;
3. the model's parameter uncertainty characteristics; and
4. the model's structural uncertainty characteristics.

These four primary classes represent the three critical aspects of a model: the types of input and output information, and the information uncertainty. Each of these classes needs to be further refined to provide a complete model taxonomy. We will explore this initial classification scheme below and suggest some further decompositions. Also, we will explain parametric and structural uncertainties, and make the case for treating them as different classifications.

Output information is what the designer seeks. Input information is what is needed to produce the desired output information. Here, input and output information parallel the ***Find?*** and ***Given?*** steps of the principled modeling questions of delineated previously. Input and output information are further classified using the same taxonomy. We propose that the first sub-taxonomy for input and output information is the taxonomy presented above as the six knowledge state layers. For example, the information we have or want is first classified as a perceived need, function, physical phenomenon, embodiment, artifact type, or artifact instance. The five representation languages are used (often in combination) to represent the information. Still, in a complete model taxonomy, each of these information stages must be further decomposed or classified.

As an example of further classifications for these information stages, we briefly review a taxonomy for function. For categorizing function, the *Functional Basis* (FB) has proven useful and stable [28-30]. The FB was originally developed to determine which functions occurred frequently in various product domains and how the execution of these functions related to customer satisfaction with a product.

The FB describes function in terms of a verb noun pair, such as *convert energy* where the verb is the function and the noun is a flow. The FB consists of three class primary flows: material, signal and energy. The material level is further decomposed into five secondary categories and an expanded list of tertiary categories. The signal class has two further specified secondary categories, with an expanded list of tertiary categories. The energy class has 13 further specified secondary categories, with an expanded list of tertiary categories. Functions are also decomposed into class, secondary, and tertiary classifications. The function set contains eight class (primary) categories. The eight secondary categories are: branch, channel, connect, control magnitude, convert, provision, signal and support. Clear definitions have been developed for all of the flow and function categories (see [28] for a more complete discussion).

The FB represents a significant effort on the part of a multiple researchers at different institutions. This effort indicates that developing complete taxonomies for each of the model information classes represents significant work. Nevertheless, the stability of the FB indicates that detailed information taxonomies can be developed. Though the FB is also a dynamic taxonomy, no additional functions have been added and no definitions have been revised in the last three years. The FB has proven useful for concept generation methods, product architecture design methods, modeling strategies, and failure prediction. Current research efforts built on the FB include coordinating mathematical models with function and extensions, which better support computer-aided design [31, 32].

The third and fourth classification schemes for the model taxonomy are based on the information uncertainty characteristics of the model. Note that we use the term uncertainty characteristic, not just uncertainty. The uncertainty output of a model is a result of multiple factors. We are interested in the way the model contributes to, or interacts with, other factors to produce output uncertainty. The way in which a model contributes to, or interacts with, other factors is a property of the model, thus it is both critical and feasible for model classification. The third and fourth classification schemes relate partially to the ***Assume?***, ***Predict?***, ***Valid?***, ***Verified?***, and ***Improve?*** questions of the principled modeling questions presented earlier.

The third classification scheme is the parameter uncertainty characteristic of the model. The parameter uncertainty characteristic is the relationship between uncertainty in input information and output information. The parameter uncertainty characteristic of a model depends only on uncertainty in input information. The parameter uncertainty characteristic of a model assumes that the causal structure of the model could predict the future with perfect clarity if not for errors in input information. For example, perhaps our interest is the kinetic energy (KE) of some rigid body of some mass (m) moving with some velocity (v). The kinetic energy model in this case is

$$KE = \frac{1}{2} m v^2 \tag{1}$$

Even if we assume that this model represents underlying causality with perfection, there is still uncertainty in the energy based on the uncertainty in knowledge of mass and velocity. Also, the uncertainty in output information, in this case energy, responds differently with uncertainty in mass and velocity.

In the case of simple parametric models such as Eq. (1), developing the model uncertainty characteristics between input and output information is straightforward. For more complex relationships, developing the model uncertainty characteristic may be more challenging. In either case, understanding the parametric uncertainty characteristic is important as the model is used in design. If the designer needs to know the kinetic energy within 20% of its true value to make a decision with sufficient confidence in the outcome, what quality of knowledge must the designers have about mass and velocity?

Similarly to the decomposition of information types such as function, parameter uncertainty characteristics need to be further decomposed. Developing these classifications remains as future work. Possible classification schemes include linearity, non-linearity, bounded, unbounded, and other factors. Also as possible classification schemes could include magnitudes of a signal to noise (S/N) ratios between the different input and output information. The specific form of the S/N ratio could be as used by Taguchi [33]. Such data could be simply stored in a matrix such as shown in Table 1. Such knowledge would allow a designer to quickly assess the potential error incurred from using a particular model. Also, overall magnitude metrics such as the square of the matrix in Table 1 could be used as a representation of the overall model parametric uncertainty.

Table 1. Knowledge base for potential classification scheme for parameter uncertainty characteristic. S/N is the signal to noise ratio between the corresponding input information ($input\_i$) and output information ($output\_i$).

	$input\_i_1$	$input\_i_2$	$\cdots$	$input\_i_n$
$output\_i_1$	$S/N_{1,1}$	$S/N_{1,2}$	$\cdots$	$S/N_{1,n}$
$output\_i_2$	$S/N_{2,1}$	$\cdots$	$\cdots$	$\cdots$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$output\_i_n$	$S/N_{n,1}$	$\cdots$	$\cdots$	$S/N_{n,n}$

The fourth classification is the structural uncertainty characteristic of the model. The structural uncertainty characteristic of a model is the relationship between output information and both input information not included in the model structure and, or, an incorrectly represented causal relationship between input and output information. We return to our kinetic energy example. If the designer is interested in the kinetic energy of some rigid body moving with some velocity, Eq. (2) could be used to the relationship between desired output information and needed input information. However, there is structural error in the model. If the velocity of the object is near the speed of light (c), a more appropriate model would be

$$KE = mc^2 \left(\frac{1}{\sqrt{1 - (v/c)^2}} - 1 \right) \tag{2}$$

Alternatively, the object may have some rotational velocity (ω) that had not been included as input information. In this case, a more appropriate model would be

$$KE = \frac{1}{2} m v^2 + \frac{1}{2} I \omega^2 \tag{3}$$

In the case of the neglected rotational velocity, both the rotational velocity and the inertia I are additional needed input information.

There are many different potential sources of structural uncertainty. In cases where we use the structure of Eq. (1), we are assuming that potentially relevant factors will not change the output information enough to impact our decision. Essentially, we are saying v/c and ω are small and have negligible impact on KE.

In other cases, the structural uncertainty is more closely tied to a limited scientific understanding of the causal relations. For example, fatigue diagrams commonly used to determine the strength of some material after a certain number of cycles of loading are empirical models. These models also exhibit some structural uncertainty. In many cases, this structural uncertainty is well represented using probabilistic methods.

Developing the sub-classification scheme for model structural uncertainty characteristic is a challenging problem. The above examples may point toward potential classification schemes. One classification scheme could be the impact of neglected terms. Another scheme could be models that are empirical and are well modeled probabilistic. A complete sub-classification for structural uncertainty remains future work. Nevertheless, the structural uncertainty of a model is a key feature of model and needs to be included in the general model taxonomy.

Model structural and parameter uncertainty share important similarities. In terms of creating uncertainty in model output information, they are equivalent. Nevertheless, they are separate classification schemes because the parameter uncertainty indicates to the designer the requirements for input information quality and the structural uncertainty indicates that the designer may need to acquire additional, and distinctly different, input information. We see these as two different tasks and thus the separate classification of structural and parameter uncertainty.

We admit that developing the sub-classification schemes for parameter and structural uncertainty present some challenging, yet interesting problems. Nevertheless, a classification based on information uncertainty characteristic can be constructed: there is a difference between knowing the uncertainty and classifying things based on uncertainty. For example, we devise a classification for marbles based on color and size without knowing the color and size of any particular marble. By developing a scheme to classify uncertainty characteristics, we hope to improve our fundamental understanding of uncertainty in models. With this deeper understanding, we are better able to store and retrieve the uncertainty in previously-used models. Building on such past knowledge, we can better assess the uncertainty in new models. Additionally, if the designer had some idea about the uncertainty characteristic of a model, it might help a designer select the correct model, gather more input information before modeling, and make decisions with some palpable hope for a good outcome rather than just being satisfied with having executed proper mathematical form in his or her decision making effort.

CONCLUSIONS AND FUTURE WORK: WHERE DO WE GO FROM HERE?

In this paper we have observed the way in which models are used in design. Our goal is to improve engineering design, specifically the way in which models are used in engineering design. To this end, we argue that a design model taxonomy will help to improve our understanding of models and thus our ability to both use them as practicing designers and teach them as engineering educators. As a first step, we propose that a design model taxonomy should be based on both the type and the quality of information it produces. We also stress that the quality of the *outcome* is important since that is *the* underlying point of a design process.

Additionally, we have observed that models of design are useful. Modeling design as a decision-making process helps us clearly think through difficult and uncertain decisions. However, it is insufficient to model design only as a decision-making process. Just as we construct different models to help us better understand natural laws, we need to construct different models of design so that we may better understand it. In many cases, these models will not be simple definitions, but more complex taxonomies of design.

Modeling design as a transformation from perceived need to realized artifact sheds light on the relationship between uncertainty, error, and the resultant iterative nature of design. If we are only making one model to move from one of the six information stages to the next, each model is a simple linear model of the form $y = ax$, and there is 10% error in a and x we end up with 60% error in our realized artifact. In practice, we make many models from one information stage to the next, they are rarely linear (for example, is a sketch model a linear transformation of information?), and 10% error is optimistic for many cases, especially early in design. Without iterating, the error in the desired performance of the realized artifact will be so large that the probability of achieving some desired outcome is very small. In fact, in most cases, it would be hard to defend the artifact as designed. Just as the bike designer used weight models to guide the synthesis of a light frame in the example above, model usage is inherent in this iterative process. We construct a proof of concept or a prototype—and both are models [34]—to verify the feasibility of our design. From this model, we deepen our knowledge of some cause-effect relationship that we had previously modeled mathematically. Then we can refine and calibrate our mathematical model and use it to guide us to better concepts and better proofs of concept.

Models and the information they produce are inseparably interwoven in engineering design. A deeper understanding of models is needed to improve the efficiency of the design process. Further, a deeper understanding of models is needed to improve engineering design education. A compact definition of a model will not produce this understanding, but a taxonomy of models— a *model* of models—offers that potential. Thus, there may be multiple model taxonomies that could benefit engineering design. We argue that the most useful taxonomy of models should be based on how models are used to transform information.

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