A PERSPECTIVE ON MODELING, DATA, AND KNOWLEDGE

Robert G. Sargent, Ph.D.

Department of Electrical Engineering and Computer Science

Syracuse University

Syracuse, NY 13244

315-443-4348

rsargent@syr.edu

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Bibliographical Note:

Robert G. Sargent is a Professor Emeritus of Syracuse University. Dr. Sargent's current research interests include the methodology areas of modeling and discrete event simulation, model validation, and performance evaluation. He was one of the first individuals to initiate the modeling of computer systems for performance evaluation and this work included the analysis of system data. Most of his research contributions have been in the methodology areas of simulation including the modeling area, computational speedup, statistical output analysis, verification and validation, visual interactive simulation systems, and the theory of simulation. He has developed numerous validation techniques, approaches, and methodologies and also graphical views of how Verification and Validation (V&V) relate to the modeling process. His paper "Verification and Validation of Simulation Models" received one of the Winter Simulation Conference 40th anniversary landmark paper awards in 2007.

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Abstract

This paper presents and discusses the problem solving methodology used in operations research. The advantages presented using this methodology include (1) the development of a problem statement, (2) the construction and use of a causal mathematical model based on system knowledge, and (3) the data requirements determined from the steps of the methodology. Also discussed is how this methodology differs from the method of first collecting significant amounts of data then attempting to develop models from that data.

Two major types of models, causal and empirical, are compared and discussed; this includes the strengths and weaknesses of each type. This paper also discusses why causal models are preferred, the importance of understanding that *causal models contain system relationships and empirical models contain data relationships*, and the different kinds of graphical and mathematical models for each model type. Different kinds of data and measurement scales for data are also described. System knowledge, needed for developing causal models, is discussed and depicted in a table containing different levels of system knowledge and types of system knowledge.

The modeling process and obstacles that may arise during this process are described. The importance of validation of models, model solutions, and model theories is stressed. Lastly, the use of domain experts in problem solving is discussed including why it should be one of the approaches considered for solving social system problems.

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I. INTRODUCTION

This paper was written at the request of the National Academies' National Research Council (NRC) for the workshop "Unifying Social Frameworks" sponsored by the Office of Naval Research and hosted by the NRC on August 16-17, 2010. The paper is to address the question ***Methods, Tools, Frameworks and Models: What are the strengths and weaknesses of "categories" of approaches for different "kinds" of knowledge and data?*** The question is open to one's interpretation and is to be answered based on one's personal expertise and interest.

My expertise and experience is in Operations Research. Much of my academic research focused on developing practical methods and techniques in various methodology areas of modeling and simulation, including validation. Earlier academic research included developing models for system performance evaluation, especially of computer systems, which included statistical analysis of computer system data. For over twenty-five years, the U.S. Air Force supported my academic research and applied work on military problems. I have taught a variety of operations research, statistics, and system performance courses. Experience doing academic research, solving real world problems for the military and industry, and teaching provides the foundation for my views presented in this paper.

The approach to problem solving that I use is the operations research methodology of problem solving (Ackoff, 1956; Hiller et al., 1986; Jensen et al., 2003). The first step is to develop a problem statement by formulating the problem. This requires data regarding the situation or system under investigation. The second step is to construct (develop) a mathematical model for the problem. This again requires data about the situation or system under investigation. The third step is to obtain a solution to the model. This frequently requires iterations among the earlier steps. The fourth step is to test (validate) the model and solution. This step also needs data on the system or situation being modeled. If the model or solution is found to be unsatisfactory, then one must iterate back to an earlier step. Testing continues until a satisfactory model and solution is obtained, iterating as needed. (Note: it is possible that a satisfactory model and solution cannot be obtained.) The fifth step is to establish controls over the solution. It is possible that some aspect, variable, or input of the system (or situation) may change or a model assumption made no longer holds causing the solution to become unsatisfactory. Thus, controls must be established to know when a change has occurred that requires a new problem solution. The final step is to develop an implementation method to use the solution developed for the problem.

It is important to note that in the operations research method of problem solving, the data requirements are determined by what data are needed in the various steps of the methodology. Thus, only the data required needs to be collected. It is also important to note that this method differs from at least one interpretation of the question we are asked to answer—namely, determining what types of models with their strengths and weaknesses can be obtained from different "kinds" of collected data. This latter approach requires collecting, storing, and maintaining data that may not be needed. It is usually expensive and time consuming to collect, store, and maintain data.

This author believes the question that was asked of this paper is the reverse of what should be addressed; namely, what should be addressed is 'What kinds of data, knowledge, and tools are needed to develop different types of models?' This question would apply to the operations research problem-solving method given above. The reminder of this paper discusses different aspects of both the question asked and the question suggested in this paragraph. Also included is a section on 'domain expert approach', which discusses the use of domain experts in problem solving instead of using only models.

II. DATA

Data generally refer to some collection of numbers, characters, images, or audios that are unprocessed. Knowledge is obtained from data by interpreting the data or through processing the data. (Various kinds of knowledge are needed for modeling such as the different system variables, the relationships between and among the system variables, the causal relationships, and the system theories.)

It is important in modeling to know about different scales of measurement that can be used for data. There are four common measurement scales: nominal, ordinal, interval, and ratio. (These scales were initially developed for statistical analysis.) Nominal scale, the lowest level scale, is where data can be only be classified into mutually exclusive categories and the categories have no relative ordering. The next level scale is the ordinal scale and here data can only be classified into mutually exclusive categories and there is rank order among the categories. The next level of scale is the interval scale where the distance between numbers or units on the scale is equal over all levels of the scale and no absolute zero point exist. An example of an interval scale is the Fahrenheit (or Centigrade) scale of temperature. The ratio scale is the highest level scale; its distance between numbers or units on the scale equal over all levels of the scale and there is a meaningful absolute zero point. This scale allows for the interpretation of ratio comparisons. An example of an ratio scale is the height of individuals where we can say an individual who is six feet tall is twice as tall as an individual who is three feet tall (a ratio comparison).

The type of data that can be obtained on the system or situation is extremely important and must be considered when developing a model. If, for example, the only data available on a variable is the direction (plus/minus or increase/decrease) that it takes under different conditions, we have a qualitative variable. This will usually restrict the type of model that may be developed to a qualitative model. If both the direction and magnitude of a variable can be obtained, we have a quantitative variable. Quantitative models usually require all of its variables to be quantitative.

It is expensive to collect, store, and maintain data. Using the operations research problem-solving method is a cost effective approach for data because this method determines the minimal data that needs to be collected and stored. Collected data should be stored in a database. Data stored can be structured or unstructured. Data stored in a database using a data model are usually referred to as structured data. Such data could be observations on variables of a system. Data stored not using a data model are usually referred to as unstructured data. Examples of unstructured data are audios, videos, web pages, and unstructured text such as the body of an e-mail message. Structured data are what is commonly used in the operations research problem-solving method. There are software tools and processes that can convert unstructured data into structured data under certain situations. (There are also tools and processes to convert qualitative data into quantitative data under certain situations; one example is the Analytic Hierarchy Process (AHP) discussed in Section VII.)

Data are needed for different purposes using the operations research problem-solving method described above. Data are required to develop the problem statement, system understanding and theories, the model, and model solution as well as to test (validate) the model and solution, and to utilize during the model's use in operations.

III. **MODELS**

A model is an abstraction of some system or situation. Since a model is an abstraction of some system, this means that one-hundred percent of the system is not included in a model. A model is developed for a specific purpose. This means then that there can be several models of the same system with different models having different purposes. Furthermore, there can be different levels of abstraction of a system. Models having a higher level of abstraction are simpler than models having lower level of abstractions as these latter models contain more detail. Higher level models may not be able to describe the system adequately for the model's desired purpose or to provide the information desired. Lower level models may be too complex to develop or to allow development of solutions for them. All developed models should be validated to ensure they are correct for the purpose of the model.

There are three classes of models: analog, iconic (physical), and symbolic. We are only interested in symbolic models in this paper. Symbolic models use symbols. (See Table 1 for a breakdown of symbolic models.) There are two major types of symbolic models: causal models and empirical models. Causal models use and contain the causal relationships that occur in the system. System knowledge is required to develop this class of models, which consists of the system variables and their relationships with each other, causal relationships, system theories, etc. Empirical models are models developed purely from system data (observations) and use relationships found among the data (system theories, etc. are usually not used). *It is extremely important to understand the difference between these two types of models: causal models contain system relationships and empirical models contain data relationships.* Causal models are preferred since they contain how the system works. With causal models, one can hopefully detect if some aspect, variable, or input of the system changes or a model assumption made no longer holds in order to know that the model and solution may have become inappropriate—whereas with an empirical model this is usually not possible. *This distinction is important.*

Causal and empirical models can be either a graphical (visual) model or a mathematical model. Graphical models are models that use graphical symbols to show relationships that describe a system or some aspect of a system. Mathematical models use symbols, logic, and equations to describe their relationships and allow for analytic or numerical solutions. There are two kinds of mathematical models used for causal models:

analytic models and simulation models. An analytic model consists of a set of equations that characterize a system. A simulation model 'mimics' the operating behavior of a system and contains the system's functional relationships. Experiments are performed on this mimic by 'running' ('operating') the mimic. There are different kinds of graphical models used for causal models; usually, however, these are some kind of network (graph) model. Two examples are PERT networks (Hiller et al., 1986) and control flow graph models (Sargent, 1996).

Table 1. Symbolic Models

TYPE	FORMALISM	KIND
Causal	Graphical	• Network • Others
	Mathematical	• Analytic • Simulation
Empirical	Graphical	• Network • Others
	Mathematical	• Regression • Neural Network • Others

Empirical models are usually descriptive models. Mathematical models that are empirical models contain mathematical equations that describe relationships found among the data contained in a subset of a data set of observations of some system. Two common kinds of mathematical models used for empirical models are (statistical) regression models and neural network models. There are different kinds of graphical models used for empirical models; they are, however, usually some kind of network (graph) model. An example is a network drawn from a set of observations of some system where each node represents an individual contained in the set of observations, and the edges (branches) represent any communication that occurred between individuals that are contained in the set of observations.

IV. SYSTEM KNOWLEDGE

In order to build (construct/develop) causal models for problem solving, scientific knowledge of the system is required. The amount of (scientific) system knowledge determines what kind of causal model can be developed. Table 2 presents a high level view of levels of system knowledge versus different kinds of system knowledge. Five levels of system knowledge from 'none' to 'complete' are listed horizontally across the table. Different kinds of system knowledge are displayed vertically down the table. The table cells contain the level of knowledge. Variables indentified qualitatively or quantitatively refer to those system variables that have been indentified and determined to be either qualitative or quantitative. (If a variable is quantitative, then it is also qualitative since a quantitative variable contains the data/information needed for a variable to be qualitative.) Causal relationships can be qualitative, quantitative or both qualitative and quantitative. If some causal relationship is known quantitatively, then that causal relationship is also known qualitatively because qualitative understanding is included in quantitative understanding. It is desirable to know the theories of how a system and its sub-systems work; these are referred to as the system theories.

Table 2. System Knowledge

	SYSTEM KNOWLEDGE				
	NONE	LITTLE	SOME	CONSIDERABLE	COMPLETE
VARIABLES INDENTIFIED • Qualitative	none	Some	All	all	all
• Quantitative	none	none/few	some/most	all	all
CAUSAL RELATIONSHIPS • Qualitative	none	Some	Most	all	all
• Quantitative	none	none/few	some/most	most/all	all
SYSTEM THEORIES	none	none/few	Some	most	all

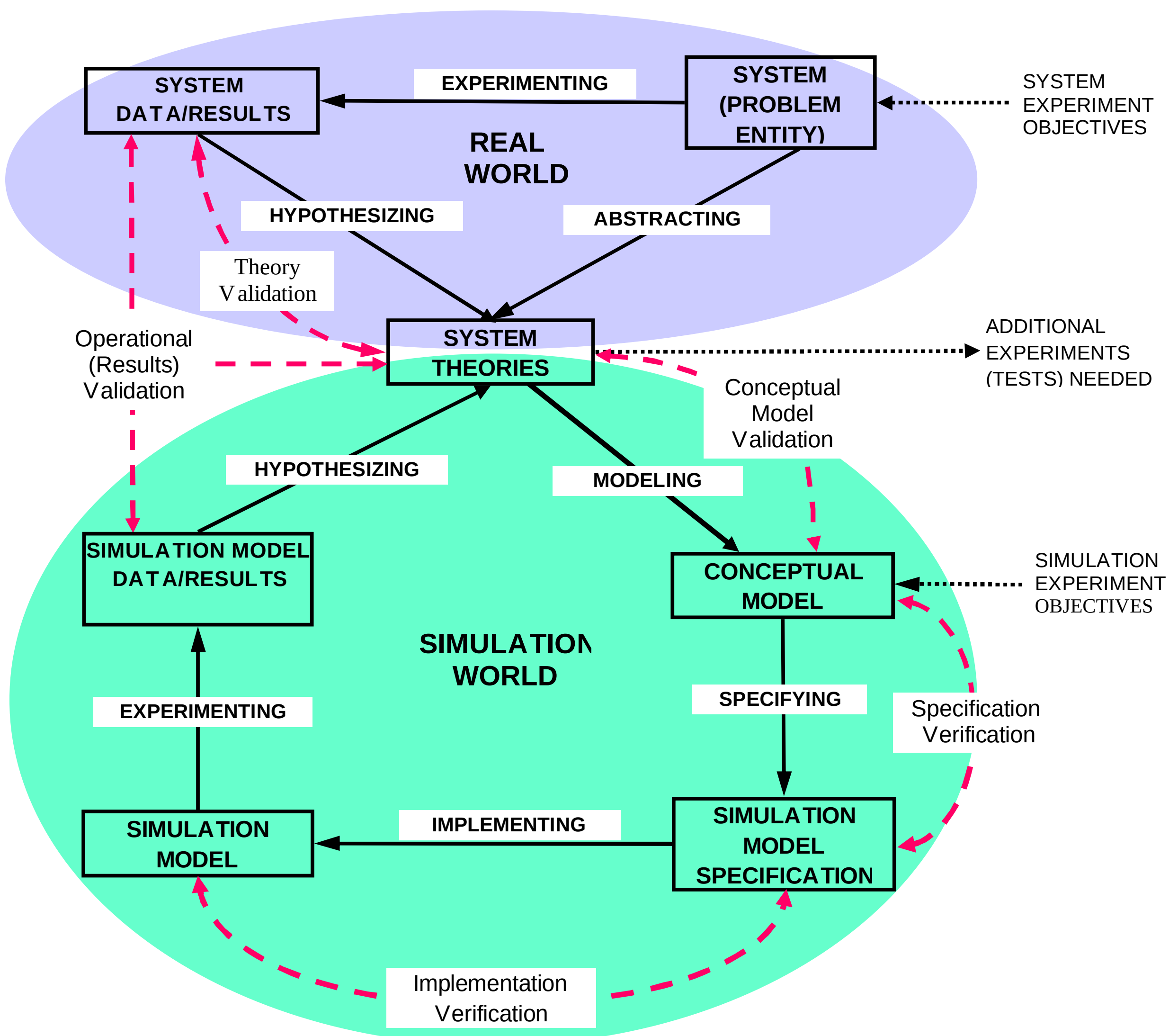
When one proceeds to solve a problem using the operations research problem-solving method, system knowledge is used in the first two steps: formulating the problem and developing the model. To develop a 'reasonable' qualitative causal model, system knowledge must be at 'some' or more. To develop a 'reasonable' quantitative causal model, system knowledge must be at 'considerable' or more. Since quantitative causal models are usually desired, we will restrict our discussions to quantitative models. If the system knowledge is not at 'considerable' or more, a choice must be made on how to proceed. Various approaches are discussed in the next section, which is on modeling.

Further development of system knowledge frequently occurs. The time required to make advances in system knowledge varies over a large range and usually depends on the system of interest. Systems vary from being simple to complex and some types of systems take much longer to learn about than others. On occasion additional system knowledge can be obtained quickly and thus can be done as part of solving a specific problem. Most often, however, the time required to obtain additional system knowledge takes a considerable amount of time—months or years—especially if a large amount of research is required. (Developing system knowledge on most social systems will probably take a very long time.)

In developing additional knowledge, recall the eighty percent rule, which says that eighty percent is usually sufficient enough for most problems. If we view the system knowledge column of 'considerable' in Table 2 as the eighty percent mark, this is what the goal of system knowledge should be. Recall that if we have 'considerable' system knowledge on a system, a 'reasonable' quantitative causal model should be able to be constructed. Too often, individuals want complete system knowledge of a system or a perfect model that requires complete system knowledge. This is usually not necessary and takes considerable time and money to accomplish—if it is ever reached.

To develop additional system knowledge, research must be performed on the system. Perhaps additional system variables must be identified, additional causal relationships determined, or new system theories developed. Figure 1 (Copyrighted figure taken from Sargent, 2001 and 2009) shows how system theories are developed. Note that system theories can be hypothesized from a model as well as from the system. It is extremely important to note that *new system theories must be validated.* The same process shown for developing system theories also applies for determining causal relationships. (Further discussion of this figure is contained in Sargent, 2001 and 2009.)

Figure 1. Representations of Real World and Simulation World with Verification and Validation



V. MODELING

In modeling a system to solve a specific problem, one should abstract the system to have a parsimonious model that will address the problem being studied. A parsimonious model is as simple as possible containing the fewest number of variables, simplest and fewest causal relationships, etc. while being able to serve its purpose. Having a parsimonious model should be a goal no matter what type of model is being developed.

One should strive to have a causal model (revisit Tables 1 and 2). Constructing a causal model requires sufficient system knowledge on the system. The preferred type of causal model is an analytic model with the preferred solution being analytic; and if an analytic solution cannot be found, then hopefully a numerical solution can be obtained, which is usually a numerical algorithm. If an analytic model and its solution cannot be developed, then hopefully a discrete-event simulation model can be developed. If a simulation model cannot be developed, then a decision must be made on how to proceed. This decision depends on the reason(s) why a causal model cannot be developed.

If the reason that a causal model cannot be developed is due to the lack of system knowledge, then one needs to determine if sufficient system knowledge can be developed to construct a causal model within the desired time-frame for obtaining a problem solution. If the answer is yes, then this is what is usually done. If the answer is no, then the next question to be asked is, what level of causal model is being attempted to be constructed? We do not need a perfect model; often, the eighty percent rule works meaning that a 'reasonable' model gives a satisfactory answer to our problem. Recall from the System Knowledge Section that 'considerable' system knowledge should be sufficient to construct a 'reasonable' model. Hopefully, a 'reasonable' causal model can be constructed. If this is not possible, then another decision must be made.

There are two major causes why a 'reasonable' causal model cannot be constructed: (1) the model complexity being required to solve the problem does not allow a causal model and solution to be developed, and (2) there is a lack of sufficient system knowledge to develop a causal model. Model complexity can be caused by several things. Some examples are: (a) the 'curse of dimensionality'—too many variables or attributes needed in the model; (b) 'mixture of types of variables'—the combination of continuous and discrete variables is required and possibly has two types of discrete variables, one type with two outcomes and the other type with numerous outcomes; (c) 'problem solution requirement'—the solution is required to have integer values or a combination of solution values of which some must be integers and others can have continuous values; and (d) the problem requires a complex model.

To proceed in trying to develop a causal model, one can move into using the 'increment method of modeling' where a simple causal model is developed initially and more complex causal models are developed over time as it becomes possible to develop more complex causal models. Simpler causal models can be developed in several ways. One way is to reduce the scope of the problem to reduce the scope of what is required of a causal model. A second way is to develop the most complex causal model possible based on available system knowledge. A third way is to abstract at a higher level to obtain a simpler causal model. A fourth way is to do some aggregation. The reason that one might use the increment method of causal model development is that the simple causal model initially developed may give a better solution to the problem than the current solution method. Then, as one is able to increment the causal model to a better causal model for the problem, a new model solution is developed that hopefully gives a better problem solution.

It is possible that a causal model cannot be developed, in which case one must decide how to proceed in solving the problem. One approach is to attempt development of an empirical model. But, sufficient data must be available to attempt to develop an empirical model. There are major weaknesses in using empirical models in problem solving and it is possible that an empirical model cannot be developed. (Empirical models are discussed in Section VI.). Another approach to problem solving is to have system knowledgeable experts (humans) use established domain expert methods to obtain problem solutions instead of using models. Sometimes using system knowledge experts leads to better problem solutions than using empirical models; this latter approach is discussed in a Section VII.

In modeling, it is extremely important to remember that any model and solution developed must be validated to ensure that it is correct. This is part of any modeling procedure and much has been written about model validation (for discussion of validating simulation models, see Sargent, 2009).

VI. EMPIRICAL MODELS

There is a school of thought that believes models should be developed directly from data. Significant amounts of data are first collected and then models are developed directly from the data with little or no use of system knowledge. These types of models are called empirical models as was discussed in Section III (revisit Table 1). Some individuals believe this way of modeling should be the preferred choice for model development. This author does not believe this approach is the preferred way to proceed in modeling, including for modeling social systems. Instead, this author believes the preferred approach is to use the operations research method discussed in the previous sections.

Wanting to develop models directly from data reminds me of the story of the boy looking for a pony in the manure pile. The boy is asked why he is digging through the manure pile and he answers that with such a large pile of manure, there must be a pony somewhere. The boy at least has an objective: trying to find a pony. I find there are two types of people trying to develop models directly from data: (1) those who are attempting to solve problems—they have problem statements—and (2) those that are looking for models, but have no problem they are trying to solve. Those in the initial group may have limited success. Those in the latter group I do not understand; furthermore, I believe they are wasting resources in attempting to find models that have no purpose.

There are two types of data: structured and unstructured. Empirical models are usually developed from structured data. Recall that empirical models are usually descriptive models. Graphical empirical models, especially networks or graphs, are frequently useful for communicating about, gaining insights into, and developing understanding of simple systems. They are often less useful for complex systems because the networks become too complex. Mathematical empirical models contain mathematical equations that use data relationships found in data sets. Considerable data are usually required to develop mathematical empirical models. A subset of the data set is used to develop an empirical model, and a different subset of the dataset is used to test (validate) the developed empirical model.

There are different kinds of mathematical empirical models with two common kinds being the (statistical) regression models and the neural network models. Regression models have requirements on the data that are used to develop them. Neural network models also have requirements on data used to develop them; however, their data assumptions requirements are usually less than what is required for regression models. It is important to understand that mathematical empirical models are mathematical models that use data relationships found in the set of data used to develop the empirical model.

A major weakness of empirical models is that it is impossible to know, when using an empirical model on a different data set, if anything in the new data set has changed from the data subset initially used to develop the model. For example, if the data is coming from a system and something in that system changes, there is no way to tell from the new data that it is different from the data used to develop the empirical model. Consider for example the following simple system: data is kept on whether a man's dog howls each night as a string of zeros and ones—one if the dog howls that night and zero if it does not. Also, a string of zeros and ones are kept each night on whether the moon shines on the dog—one if the moon shines that night on the dog and zero if it does not. There is a perfect match between the zeros and ones in the two strings, which results in a simple empirical model. The man, who happens to be blind, is told that if his dog howls any night that means the moon is shinning on the dog as this is what the empirical model says occurs. One night the dog howls but the moon is not out. The reason the dog howled is because a helicopter flew over the dog and its spotlight shinned on the dog causing the dog to howl. Both the model and the man are blind to what actual happened as both say the moon was shinning.

Other weaknesses of empirical models, especially mathematical empirical models, are difficulties that may be caused by (1) the determination of which variables to use, (2) a mixture of variable types (qualitative/quantitative or discrete/continuous), (3) the curse of dimensionality, (4) the lack of sufficient number of observations on some specific variables, and (5) an overwhelming amount of data in the data set such that no data relationships can easily be found.

Empirical models have uses but their uses are limited. Their use should usually be limited to situations where it is known that the system will not change (a static system), which will hopefully result in the data not changing. (An example of this might be using an empirical model to predict if an individual will get a disease based on a set of specific measures of that individual, where the empirical model was developed from a large data set of specific measures.) If the system being studied is dynamic (i.e., the system is changing over time), then the data of such a system would be expected to change over time and thus an empirical model would probably not be appropriate. (Probably many of the social systems fall into this latter category of being dynamic.) It is usually difficult to develop empirical models and often they cannot be developed. Use of system knowledge sometimes helps in developing empirical models but many people do not like to use empirical models because of the weaknesses discussed above.

Unstructured data are generally not useful for developing models. This type of data lends itself to certain types of analysis; e.g., looking for certain types of content. Sometimes certain types of analysis may help obtain system understanding. An example of this might be determining the number of different content types in mutually exclusive categories (or, alternatively, different types of actions taken). There are software tools that can convert certain types of unstructured data into structured data in specific situations. The resulting structured data can sometimes be used for developing empirical (and causal) models.

VII. DOMAIN EXPERT APPROACH

An alternative to using only models in problem solving is to use domain experts. A domain expert is an individual who is extremely knowledgeable in some domain, or topic. These experts might be experts on the system, the problem being addressed, etc. These experts then address the problem using methods that have been established for use in problem solving. Two examples of these methods are the Analytic Hierarchy Process (AHP; Saaty, 1980) and the Delphi Method (Hiller et al., 1986). AHP provides a comprehensive and rational framework for structuring a decision to a decision problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions. The Delphi Method helps experts reach for a consensus on an answer to a specific question (see http://en.wikipedia.org/wiki/Delphi_method) These two methods have received extensive use in problem solving.

One such use of these methods is in a methodology developed to optimally design console panels (Sargent et al., 1997). Domain experts and the Delphi method are used to develop a ranking of mutually exclusive groups of components, in other words, to convert a set of groups from a nominal scale to an ordinal scale. Domain experts and AHP are used to handle the cognitive relationships between the panel operator and panel components to obtain a ratio scale set of weights for 'component groups' that is used in an optimization model. Note the use of three measurement scales discussed in Section II.

Problem solving methodologies to solve specific problems can be developed using domain experts that are scientifically based. These methodologies may or may not include the use of one or more models. This approach of using domain experts as part of the problem-solving methodology sometimes (1) provide solutions to problems faster than using only models and (2) lead to better solutions than can be obtained from using single complex causal models or from empirical models because issues that have not been included in a model can be considered by the experts. Using the domain expert approach to solve problems in social frameworks might be much more productive than trying to use a pure modeling approach.

VIII. SUMMARY

The operations research methodology for problem solving was presented in Section I. The factors that are extremely important about this methodology and differentiate it from many other problem-solving methodologies are as follows: (1) operations research methodology starts with the development of a problem statement (step 1 of the methodology), (2) it uses a causal model constructed for the problem using system knowledge (step 2 of the methodology), and (3) its data requirements are determined from the steps of the methodology. This methodology differs considerably from first collecting significant amounts of data then attempting to develop models from that data. In Section II, different kinds of data and different types of measurements scales for data were discussed, both of which are important in modeling.

Discussed in Sections III, V, and VI were two major types of models (causal and empirical), including the strengths and weaknesses of each type and why causal models are preferred. In Section IV, system knowledge and need for developing causal models was discussed along with how to develop additional system knowledge. The process of modeling was described in Section V including obstacles that can occur during modeling. In Section VII, the use of domain experts for solving problems instead of using only models was discussed noting that this approach can sometimes provide better and faster solutions than using only models.

An interview with Robert E. Foster, retiring Director of BioSystems, DoD, is published in the Spring 2010, Issue No. 5, HSCB (Human Social Culture Behavior) Newsletter. Some quotes from his comments on the HSCB Modeling Program:

(1) "… models and the science …, not work-station tools, should be our foci."

(2) "Stick to developing theory and models but don't forget to attend to the data issues."

(3) "… keep the 80%, five-year solution as an acceptable goal in contrast to setting goals based on 20 year-to-perfection delusions."

I agree with most of what Robert E. Foster said in this interview about the HSCB Modeling Program. Regarding the first quote, please note the emphasis on developing science and models—not collecting significant amounts of data for building empirical models. Regarding the second quote, I hope this includes using data to validate models and theory. Regarding the third quote, I believe he is too optimistic in believing sufficient theory can be developed in five years to have eighty percent solutions.

I strongly believe it is highly desirable for the HSCB modeling program and other programs involved with the types of problems being addressed by this workshop to start supporting the development of approaches using domain experts as discussed in Section VII. I believe good solutions can be obtained to some of the problems of interest considerably faster using the domain expert approach rather than waiting for the theory (system knowledge) and only models to be developed. For example, a good solution exists to the problem of optimally designing console problems (Sargent et al., 1997) discussed in Section VII using domain experts to solve two of the steps in the design process. Here, domain experts and AHP are used to handle cognitive relationships; and domain experts and the Delphi Method are utilized for developing rankings of component groups. This is done instead of probably waiting decades for theory (system knowledge) and models to develop for handling the cognitive relationships and the ranking of component groups in a solution that uses only models.

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