VALIDATION AND UNCERTAINTY IN ANALYSIS DECISION SUPPORT

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Contents

Summary

This contribution discusses the concepts of validity and uncertainty in Decision Support System (DSS). In the development of any DSS, validation and uncertainty analysis are critical steps. Environmental problems are not only complex and multi-factorial, but also carrying, in most cases, a large amount of uncertain information. Uncertainty management must therefore be incorporated in environmental DSS and the evaluation process is not complete without uncertainty analysis. Validation is also part of the support system's evaluation and is designating the process of establishing the usefulness and relevance for the decision-making model for the intended application. Different approaches for assessing model validity, validation techniques and the relation between validation, verification and evaluation, together with different types and sources of uncertainty in environmental DSS and methods of representing and managing uncertainty are reviewed.

1. Introduction

Decision Support Systems (DSSs) are increasingly used in environmental problem solving and decision making. To decide which action or intervention has to be taken if the amount of air or water pollution is exceeding a pre-defined limit or to plan and managed water resources or to face natural disasters, there is an acute need of accurate, in time and reliable information. The decision-maker has to know what are the polluting sources and substances, the result of chemical analysis, what are the costs associated with different intervention scenarios, the map of the gas pipes and electricity cables etc. The quality of the decision will be affected if this huge amount of different types of information is not available. Therefore DSSs are necessary and extremely useful. However, when speaking about environmental DSSs one must not forget that in this field decisions can and probably will affect the life of one or more individuals. The effect of a decision can be immediate, in the near future or a long term one. It is expected that the use of DSSs will enhance the quality of the decision making process. Therefore, it is of decisive importance to develop accurate, reliable, performing systems. Unless it has been properly evaluated, a DSS should not be used in practice, for in environmental applications the risk is present. The evaluation process is not an easy one. No matter how sophisticated the software solution of a DSS is, or how performing the computer is on which the system is implemented, a DSS has an "Achilles heel" - the model. The model is a reflection of reality and environmental problems' "reality" is extremely complex, with many inter-related factors, some of which, as the social and political ones, are difficult to quantify. All the actors involved in a decision process that uses a DSS, from developers and decision-makers or agents to all those affected by the decisions, are concerned with whether the model is a "good" one and its results are "correct". Schlesinger has defined model validation as the confirmation that a computerized model possesses a satisfactory range of accuracy consistent with its intended application. It must be noted here that DSS model validation is including model verification that refers to the correctness of the computer program of the computerized model and its implementation. Validation general aspects are discussed in Section 2.

Environmental problems are also characterized by the presence of imperfect, i.e. imprecise or uncertain, information. The different aspects of imprecision and uncertainty, and the importance of uncertainty analysis in the context of environmental decision models are presented in Section 3. The types and sources of uncertainty together with methods to represent and handle uncertain knowledge, from classical probabilities to fuzzy sets are finally discussed. Section 4 is considering the relationship between validation and uncertainty analysis. The last section gives the conclusions and future possible advances.

2. Validation of Decision Support Systems

The validity of a DSS is determined considering how useful and relevant is the decision model for a predefined purpose. The purpose of a DSS may be to answer to a set of questions, to select the best features from a collection or to predict future values for some parameters. An important issue in a DSS validation process is to have a description of: who will use the system, for what kind of problems, and how frequently, and how knowledge is represented in the DSS model? That means that the validity of a

model is restricted to a certain area and it is necessary to clearly identify and specify the validity range of a model. For each output variable the required degree of accuracy should be specified. During validation, the output generated by the model will be compared against real data. For example, if the output is represented by values of random variables, statistical characteristics as central tendency indicators and standard variance are used to determine the validity.

Validation data sets are built up and together with calibration data are used to minimize the differences between model output and given sets of observed data. In this sense it can be said that validity is context and purpose sensitive. A model may be valid for a certain set of testing conditions and invalid for another. The central question in validation studies is to determine the objective reference by which the system is substantiated as valid or invalid. A DSS is considered valid if the conceptual model is valid, the computerized model and its implementation are correct and if data used in model development are adequate and correct.

The substantiation that the computerized model and its implementation are correct is often labeled as model verification. DSS credibility or acceptability is another concept related to validation and verification. A DSS is said to be credible or accepted if the potential users are confident in the system's outputs and are willing to use it.

2.1. Validation Process

Validation of a DSS, i.e. data and model validation and verification, is considered a recurrent process and it is recommended to be embedded in the model development process. A first version of a model is adjusted several times until the desired valid model is obtained. For environmental problems, that are complex and require high confidence in the model due to the consequences of an invalid model, validation may be not only time consuming but also very expensive.

Sargent and Shannon have considered the situation when instead of determining the absolute validity of a model; evaluation procedures are carried on until obtaining sufficient confidence that the model is valid for its purpose. Cross-validation is a procedure that uses a reduced number of representative data sets in order to calibrate and validate the model. The data collection is repeatedly split in subsets of calibrated and validated data. The prediction error for a new situation is estimated by the average of the observed prediction error over the data subsets. A tuning operation can be performed in order to achieve a certain balance between the validation process cost and the value assigned by the user to the model.

The validation process can be conducted in three different manners:

- During the model development process, the development team conducts validation tests and other evaluations and decides, in a subjective way, whether the model is valid or not.
- An independent party - a third party, not connected with the development team or the DSS users, decides upon validity. This approach is often called independent verification and validation (IV&V) and it is usually performed after the model

development. Many authors considered that the IV&V approach is not worth the effort and they recommend including it in the model development process. However this is raising two problems. First the cost of the validation will be increased and second, in the case of complex problem model development that may takes years of effort, the independent party evaluation may decrease in objectivity. Moreover, as human experts are involved in the evaluation, an iterative feedback procedure must be established in order to reduce the inter-observer variability, for example an adapted Delphi technique.

- The use of a scoring system. According to this approach, subjective scores are assigned to the different aspects of the validation process. These scores are then combined to obtain category scores and the overall score of the model. A conventional passing score is established and the validity of the model is considered with respect to this threshold; if the overall score of the model is greater that the passing score, the model is validated. This approach has several weak points. We have been used to consider scoring systems as objectives evaluation means so there will be a natural tendency to forget that the assignment of scores is subjective and that the passing score is, in the best situation, a reflection of an average behavioral pattern. Also the use of an overall model score is hiding the real value of the individual evaluated items, possible ending in ignoring defects of the model.

The scoring system validation approach is quite infrequently used in practice. In general the validation process is conducted by the developers' team in parallel with the model development, exception the very costly projects, when the third party approach is preferred.

Considering the validation process embedded in the model development, we have to consider the following sub-processes: conceptual model validation, computerized model verification, operational validation and data validation. The conceptual model validation consists in determining whether the assumptions and theories used are correct and that the real world problem is reflected with sufficient accuracy. Computerized model verification refers to the correctness of the computer program describing the model and to its implementation.

The largest part of validation procedures are concerned with establishing the operational validity of the model, i.e. to determine if the "living" model is working well and in accordance with the purpose of the DSS for the domain of application. Data validity is defined as the substantiation that the data used in model building, testing, experimentation and evaluation are adequate and correct.

During the development phase of a DSS, the decision model is reviewed and tuned in an iterative manner. The development team performs validations and verifications for every iteration. The most used validation techniques are described in the following section. There are no standard procedures for the selection of the technique to be used and in practice common sense and available resources prevail.
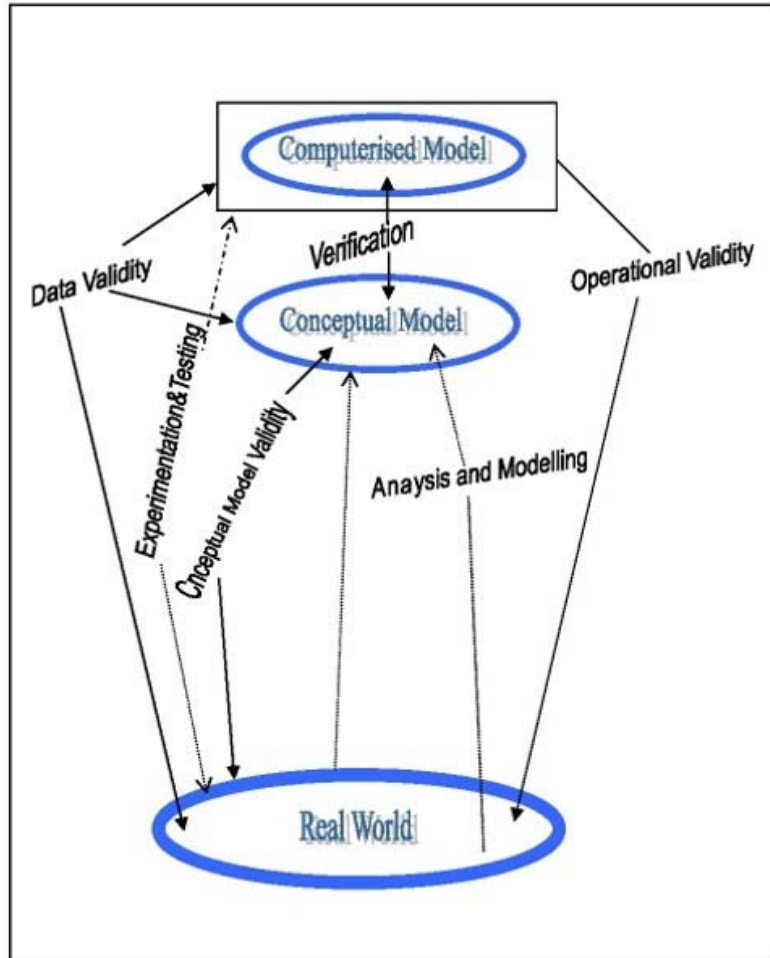
Figure 1 DSS Validation Process

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Biographical Sketch

Ioana MOISIL was born in Bucharest, Romania, in 1948. She received the M.Sc. in Mathematics at the University of Bucharest, in 1971, the scientific grade in Statistical, Epidemiological and Operation Research Methods Applied in Public Health and Medicine at the Universite Libre de Bruxelles, in Belgium, in 1991 and the Ph.D. in Mathematics at the Romanian Academy in 1997. Dr. Moisil is a Senior Researcher and a Professor at the Department of Computer Science of the "Lucian Blaga" University of Sibiu. She is the author / co-author of eight books and over 70 scientific papers. She is vice-president of the HIT Foundation – Health Informatics and Telematics and of the Romanian Medical Informatics Society. Her scientific interests include modeling and simulation, model validation and performance evaluation, uncertainty management, artificial intelligence and healthcare telematics.