Structured Modeling for Efficient Treatment of Uncertainty in Complex Problems

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Abstract. The paper deals with three key issues of model-based support for policy-making: (1) Structured modeling technology supporting the whole modeling process, especially collaborative development of complex models by interdisciplinary teams; (2) Methods and tools for policy analyses to cope with inherent endogenous uncertainties and risks with potential catastrophic consequences, proper representation of abrupt changes, spatial and temporal distributional heterogeneities, vulnerabilities, and robust solutions; (3) Methodology and tools for integrated model analysis aimed at combining the capabilities of different methods (such as various types of simulation, optimization, multicriteria model analysis, sensitivity analysis) with data mining technology.

1 Context

Because of the unquestionable success of mathematical modeling in problem solving, various modeling paradigms[1] have been intensively developed over the last few decades. In this, to a great extent case-study-driven process, a growing tendency to focus on specific methodologies and tools was observed. As a result, different types of models were developed (e.g., static, dynamic, continuous, discrete, deterministic, stochastic, set-membership, fuzzy) for a possibly best representation of different problems by a selected type of model. Moreover, different methods of model analysis (e.g., simulation, optimization, soft simulation, multicriteria model analysis) have been developed as the best-possible support for various types of model analyses for different purposes and/or users.

Due to space considerations we cannot comment more specifically on particular modeling paradigms. Such comments, and a more extensive bibliography, can be found in e.g., [26, 33]. We restrict the further discussion to two types of problems for which there are no established modeling methods and tools: first, proper treatment of endogenous uncertainty, and adequate modeling of spatial and temporal heterogeneity; second, methodology for development and analysis of models built to support analysis and solution of complex problems. Both of these two issues are characterized below.

Policy-making issues which address global change pose new challenging methodological problems for proper treatment of uncertainty. The prediction of overall global climate changes requires not only a prediction of the climate system, but also an evaluation of endogenous socioeconomic, technological, and environmental processes and risks. Traditional approaches rely on real observations and experiments. Yet, there are no adequate observations in existence for new problems, and learning-by-doing experiments may be very expensive, dangerous, or simply impossible. The main issue is the lack of historical data on potential abrupt irreversible changes occurring on extremely large spatial, temporal, and social scales. Moreover, extreme events playing such a decisive role are, on average, evaluated as improbable events during a human lifetime. A 1000-year disaster (i.e., an extreme event that occurs on average once in 1000 years) may, in fact, occur tomorrow. Thus, it is not rational to perform a proper evaluation of complex heterogeneous global-change processes on ”average”. The traditional models in economics,

[1] A scientific paradigm, as defined by Kuhn [22], embodies the consensus of a scientific community on an approach to a class of problems. A more detailed discussion on modeling paradigms is presented in [25].

insurance, risk-management, and extreme value theory are based on exact predictions and evaluations.[2] For example, the established extremal value theory deals primarily with independent events and assumes that these events are quantifiable by a single number [10]. Catastrophes are definitely not events that can be quantified in this sense. They have significantly different spatial and temporal patterns and induce heterogeneity of losses and gains which exclude the use of average (aggregate) characteristics. Globally, an average resident may even benefit from some climate-change scenarios, while some regions may be simply wiped out.

The most important scientific challenge in addressing the above summarized problems is to develop proper methods for comparative analysis of the feasible decisions and to design robust policies with respect to the uncertainties and risks involved. Although exact evaluations are impossible, the preference structure among decisions can be a stable basis for a relative ranking of alternatives. This issue is discussed in more detail in [20] along with other open research problems related to proper treatment of irreducible uncertainty, catastrophic risks, spatial and temporal heterogeneity, downscaling, and discounting.

Global-change policy-making needs to be supported also by diversified analyses of complex interdisciplinary problems which in turn requires an adequate modeling technology, i.e. application of all pertinent modeling paradigms in an integrated manner. However, the modeling state-of-the-art does not support multi-paradigm modeling. Each modeling paradigm embodies a great deal of accumulated knowledge, expertise, methodology, and general-purpose modeling tools specialized for solving various problems peculiar to each modeling paradigm, such as GAMS, AMPL, AIMMS, MPL, and object-oriented modeling systems (e.g., ASCEND). Such tools have been developed over the years and will continue to be developed and used for applications that can be adequately supported by a corresponding modeling paradigm. However, there are problems, and the corresponding models (such as RAINS [1]) that demand modeling technology that cannot be provided by general-purpose tools.

1.1 Science and policy context

The modeling processes supporting policy making have to meet the strong requirements of: credibility, transparency, replicability of results, integrated model analysis, controllability (modification of model specification and data, and various views on, and interactive analysis of, results), quality assurance, documentation, controllable sharing of modeling resources through the Internet, and efficient use of resources on computational Grids.

Dantzig summarized in [6] the opportunities and limitations of using large-scale models for policy making. Thanks to the development of algorithms and computing power today's large-scale models are at least 1000-times larger; thus, large-scale models of the 1970s are classified as rather small today. This, however, makes the Dantzig's message relevant to practically all models used today, not only for policy-making but also in science and management.

Today's models are not only much larger. The modeled problems are more complex (e.g., by including representation of knowledge coming from various fields of science and technology), and many models are developed by interdisciplinary teams. The complexity, size, model development process, requirements for integrated model analysis form the main arguments justifying the needs for the new modeling methodology. More detailed arguments (including an overview of the standard modeling methods and tools) supporting this statement are available in [25].

One of the most important issues in decision making (not only in policy-making) is a proper treatment of uncertainty. A thorough scientific policy analysis of on-going socio-economic, technological and environmental global change processes raises new methodological problems that challenge traditional approaches and demonstrate the need for new methodological developments for proper treatment of inherent, practically irreducible uncertainties and "unknown" risks that may affect at once large territories and communities. Large-scale potential catastrophic impacts and the magnitudes of the uncertainties that surround them particularly dominate the climate-change policy debates [21, 24, 27, 29, 30, 34]. A more detailed discussion of the relevance of a proper treatment of uncertainty to policy making is presented in [20].

[2] E.g., standard insurance theory essentially relies on the assumption of independent, frequent, low-consequence (conventional) risks, such as car accidents, for which decisions on premiums, claims estimates and the likelihood of insolvency can be calculated from rich historical data.

1.2 Integrated modeling approach

The presented overview of the needs and the state-of-the-art shows the limitations of traditional modeling methods and general-purpose modeling tools developed to deal with one of the standard problem-types through a particular modeling paradigm. The requirements summarized in Section 1.1 demand a qualitative jump in modeling methodology: from supporting individual modeling paradigms to supporting a *Laboratory World*[3] in which various models are developed and used to learn about the modeled problem in a comprehensive way. The truth is that there are no simple solutions for complex problems, thus learning about complex problems by modeling is in fact more important than finding an *"optimal"* solution. Such a Laboratory World requires integration of various established methods with new (either to be developed to properly address new challenges, or not yet supported by any standard modeling environment) approaches needed for an appropriate (in respect to the decision-making process, and available data) mathematical representation of the problem and ways of its diversified analyses. Therefore, to be able to adequately meet the demand for advanced modeling support one indeed needs to develop and apply novel modeling methodologies.

This paper outlines the advances in three areas of modeling methods and tools:

- Structured modeling supporting the whole modeling cycle of complex problems by interdisciplinary teams working at distant locations (Section 2).
- Proper treatment of irreducible uncertainty, catastrophic risks, spatial and temporal heterogeneity, downscaling, and discounting (Section 3).
- Methodology and tools for integrated model analysis aimed at combining the capabilities of different methods (such as various types of simulation, optimization, multicriteria model analysis, sensitivity analysis) with data mining technology (Section 4).

2 Structured Modeling Technology (SMT)

The development, maintenance and exploitation of models are composed of interlinked activities, often referred to as a *modeling process*. Such a process should be supported by modeling technology that is a craft of systematic treatment of modeling tasks using a combination of pertinent elements of science, experience, intuition, and modeling resources, the latter being composed of knowledge encoded in models, data, and modeling tools. Thus the key to a successful modeling undertaking is defined by the appropriate choice of *"a combination of pertinent elements"*. This can only be achieved through long-term and efficient collaboration of researchers advancing disciplinary methodology with those progressing modeling methodology, the latter keeping contacts with recent developments in operations research.

The complexity of problems, and the corresponding modeling process are precisely the two main factors that determine requirements for modeling technology that substantially differs from the technologies successfully applied for modeling well-structured and relatively simple problems. In most publications that deal with modeling, small problems are used as an illustration of the presented modeling methods and tools. Often, they can also be applied to large problems. However, as discussed above, the complexity is characterized not primarily by the size, but rather by: the requirements of integrating heterogeneous knowledge, the structure of the problem, and the requirements for the corresponding modeling process. Moreover, efficient solving of complex problems requires the use of a variety of models and modeling tools; this in turn will require even more reliable, re-usable, and shareable modeling resources (models, data, modeling tools). The complexity, size, model development process, and the requirements for integrated model analysis form main arguments justifying the need for the new modeling methodology.

Unfortunately, modeling resources are fragmented, and using more than one paradigm for the problem at hand is too expensive and time-consuming in practice. Geoffrion [17] formulated the principles of structured modeling thus providing a methodological framework for the integration of various paradigms. However, the proposed integrating framework has been to a large extent ignored, and most modeling paradigms have been developed somewhat separately.

Low productivity of model-based work compared with high productivity of data-based work has already been

[3] Originally proposed by Dantzig, see e.g. [6, 19].

discussed in [17]. In the case of databases, DBMSs are mature and well-established, and there is a broad agreement on the definitions of the abstract data models, as well as on the operations (e.g., those featured in SQL) to be supported for working with these data. This broad agreement has made it possible to efficiently use data from different sources because DBMS products of high quality are available and widely used. It is therefore strange that professional-quality DBMS techniques are not routinely used in most modeling systems, especially since it is generally agreed that dealing properly with models of a realistic size requires the use of modern DBMS technology; moreover, the DBMS technology has advanced immensely and is now well integrated with the Web.

Continuous progress in the foundations of modeling, and in database management, and new opportunities emerging from the network-based, platform-independent technologies offer a solid background for providing the desired modeling support needed for management, policy makers, research, and education. Arguments supporting this statement are summarized e.g., in [5, 7, 8, 9, 15, 18, 31]. However, modeling technology is still at the stage where data-processing technology was before the development of DBMS. The data-management revolution occurred in response to severe problems with data reusability associated with file-processing approaches to application development. DBMSs make it possible to efficiently share not only databases but also tools and services for data analysis that are developed and supplied by various providers and made available on computer networks [23]. Data processing was revolutionized by the transition from file processing (when data was stored in various forms and software for data processing had to be developed for each application) to DBMS. The need to share data resources resulted in the development of DBMSs that separate the data from the applications that use the data. The modeling world has not yet learned this lesson: almost every modeling paradigm still uses a specific format of model specification and data handling.

Structured Modeling Technology (SMT) described in [25] has been developed for meeting such requirements. SMT supports distributed modeling activities for models with a complex structure using large amounts of diversified data, possibly from different sources. A description of SMT is beyond the scope of this paper, therefore we only summarize its main features:

- SMT is Web-based, thus supporting *any-where, any-time* collaborative modeling.
- It follows the principles of Structured Modeling proposed by Geoffrion, see e.g., [17]; thus it has a modular structure supporting the development of various elements of the modeling process (model specification, (subset of) data, model analysis) by different teams.
- It provides automatic documentation of all modeling activities.
- It uses a DBMS for all persistent elements of the modeling process, which results in efficiency and robustness; moreover, the capabilities of DBMSs serve efficient handling of both huge and small amounts of data.
- It assures the consistency of: model specification, meta-data, data, model instances, computational tasks, and results of model analysis.
- It automatically generates a Data Warehouse with efficient (also for large amounts of data) structure for:
  - ⋆ data, and tree-structure of data updates,
  - ⋆ definitions of instances,
  - ⋆ definitions of of preferences for diversified methods of model analysis,
  - ⋆ results of model results,
  - ⋆ logs of all operations operations during modeling process.

  This conforms to the requirement for persistency of all elements of the modeling process.
- It exploits computational grids for large amounts of calculations.
- It also provides users with easy and context sensitive problem reporting.

Thus SMT supports the entire modeling process composed of:

- Analysis of the problem and a development of the corresponding model (symbolic) specification.
- Collection and verification of the data to be used for calculating the model parameters.
- Definition of various model instances (composed of a model specification, and a selection of data defining its parameters).
- Diversified analyses of instances.
- Documentation of the whole modeling process.

More detailed arguments (including overview of the standard modeling methods and tools) supporting this statement are available in [25].

3 Coping with Endogenous Uncertainty and Risks

Global socio-economic, technological, and environmental changes raise new scientifically challenging problems requiring new concepts and approaches. These problems are characterized by inherent endogenous uncertainties and risks, large temporal-spatial scales and heterogeneities, interdependencies and nonlinear interactions that may potentially lead to abrupt changes with irreversible catastrophic impacts.

Traditionally, scientific approaches to uncertainty rely on observations, repetitive experiments and predictions. However, for new problems historical data may not be available and experiments may be extremely costly and dangerous, leading to poor evaluations and predictions.

A key task in these cases is to design robust policies with respect to uncertainties and risks on various temporal and spatial dimensions. In particular, an important task is the development of integrated stochastic models that combine reduced spatial catastrophe generators, multiagent accounting frameworks, vulnerability modules, risk reducing and risk spreading decisions together with fast adaptive Monte Carlo optimization. These models allow for the design of robust policies which take into account uncertainties in an explicit and consistent way by using *hard* data from historical observations, the results of possible experiments, model simulations, *soft* expert opinions and perspectives of future learning. In contrast to statistical robustness an essential feature of robust decisions is their sensitivity (responsiveness, discontinuity) to low probability extreme events. In other words, robust strategies cannot be rationally evaluated by ignoring extreme events, e.g., by using average values. To achieve such responsiveness new approaches to a joint decision and data analyses are required. Traditionally, input data is analyzed independently of the goal for a forthcoming decision analysis. However, decisions may cancel out effects of uncertainties and often require only specific details of inputs. Therefore, a joint data and decision analysis may significantly reduce the data requirement, if the latter is coupled with the goals and feasibility of decisions. One also needs to properly address the spatial and temporal distributional aspects (such as change in incomes or productivity, exposure to risks) for various agents; this in turn requires application of diversified criteria (including fairness and equity considerations).

The main issue is the lack of historical data on potential abrupt irreversible changes occurring on extremely large spatial, temporal, and social scales. Extreme events playing a decisive role in such changes are, on average, evaluated as improbable events during a human lifetime. Moreover, it is impossible to research all the details connected with such events in order to achieve good enough predictions and evaluations required by the traditional models in economics, insurance, risk-management, and extreme value theory. For example, standard insurance theory essentially relies on the assumption of independent, frequent, low-consequence (conventional) risks, such as car accidents, for which decisions on premiums, claims estimates and the likelihood of insolvency can be calculated via rich historical data. Existing extremal value theory also deals primarily with independent events and assumes that these events are quantifiable by a single number [10]. Catastrophes are definitely not quantifiable events in this sense. They have significantly different spatial and temporal patterns and induce heterogeneity of losses and gains which exclude the use of average (aggregate) characteristics. Globally, an average resident may even benefit from some climate-change scenarios, while some regions may be simply wiped out.

The most important scientific task in this situation is to perform a comparative analysis of the feasible decisions and to design robust policies with respect to the uncertainties and risks involved. Although exact evaluations are impossible, the preference structure among decisions can be a stable basis for a relative ranking of alternatives.

3.1 Integrated catastrophic risk management

Catastrophic risk management is a complex interdisciplinary problem requiring knowledge of environmental, natural, financial, and social systems. Their burden is unevenly distributed, debatable in scope, and yet not well matched to policy makers. A decision-making process requires the participation of various agents and stake holders: individuals, governments, farmers, producers, consumers, insurers, investors, etc. The perception by all these actors of catastrophes, goals and constraints with respect to these rare/high consequence events is very diversified. The scarcity of historical data is an inherent feature and a major challenge in designing strategies for dealing with rare catastrophes. Thus, catastrophic risks create new scientific problems requiring integrated approaches, new concepts, and tools for risk management. The role of models enabling the simulation of possible catastrophes and estimating potential damages and losses becomes a key task for designing mitigation and adaptation programs.

Below we outline the model developed for supporting an integrated decision-making process. This model supports the analysis of spatial and temporal heterogeneity of various agents (stake holders) induced by mutually dependent losses from extreme events. The model addresses the specifics of catastrophic risks: limited information, the need for long term perspectives and geographically explicit models, and a multi-agent decision-making structure. The model combines geographically explicit data on the distribution of capital stocks and economic values in infrastructure and agriculture in a region with a stochastic model generating magnitudes, occurrences, and locations of catastrophes. Using advanced stochastic optimization techniques, the model, in general, supports the search for, and the analysis of robust optimal portfolios of exante (land use, structural mitigation, insurance) and expost (adaptation, rehabilitation, borrowing) measures for decreasing regional vulnerability measured in terms of economic, financial, and human losses as well as in terms of selected welfare growth indicators.

The integrated catastrophe management model consists of three major modules:
• a catastrophe module,
• an engineering vulnerability module, and
• an economic multi-agent module.

The catastrophe module simulates a natural phenomenon using a model, which is based on the knowledge of the corresponding type of event represented by a set of variables and relations between them. For example, for a hurricane model the variables are the radius of the maximum winds, or the forward speed of the storm. For an earthquake model that simulates the shaking of the ground these are epicenter locations, magnitudes of earthquakes, Gütenberg-Richter laws, or attenuation characteristics. For a flood these are precipitation curves, water discharge, river characteristics, etc. The catastrophe models used in IIASA's case studies are based on the Monte Carlo dynamic simulations of geographically explicit catastrophe patterns in selected regions (a discussion of these models is beyond the scope of this paper but can be found e.g., in [2, 3, 4, 11, 14, 16, 32]). A catastrophe model, in fact, compensates for the lack of historical data on the occurrence of catastrophes in locations where the effects of catastrophes may have never been experienced in the past.

The engineering module is used to estimate the damages that may be caused by the catastrophes. Shaking intensities, duration of standing water, water discharge speed or wind speeds are what engineering modules take from the catastrophe modules to calculate potential damages. The engineering modules use vulnerability curves and take into account the age of the building, and the number of stories in order to estimate the damages induced by the simulated disaster.

The economic multi-agent model used in our case studies is a stochastic dynamic welfare growth model (see, e.g., [12, 13]). This model maps spatial economic losses (which depend on implemented loss mitigating and sharing policy options) into gains and losses of agents: a central government, a mandatory catastrophe insurance (a catastrophe pool), an investor, individuals (cells or regions), producers (farmers), etc,,

Catastrophe and vulnerability GIS-based modeling coupled with multi-agent models is still not widely used. However, it is becoming increasingly important:
• to governments and legislative authorities for better comprehending, negotiating and managing risks;
• to insurance companies for making decisions on the allocation and values of contracts, premiums, reinsurance arrangements, and the effects of mitigation measures;
• for households, industries, farmers for risk-based allocation of properties and values;
• for scientific communities involved in global change and sustainability research.

A catastrophe can ruin many agents if their risk exposures are not appropriate. To design safe catastrophic risk management strategies it is necessary to define location specific feasible decisions based on potential losses generated by a catastrophe model. Some of these decisions reduce the frequencies (likelihood) and magnitudes of catastrophic events (say, land-use decisions) and redistribute losses and gains at local and international levels (say, pools, insurance, compensation schemes, credits). Different catastrophic scenarios in general, lead, to different decision strategies. The number of alternative decisions may be very large, and the straightforward *if-then* evaluation of all alternatives is not practicable (because it may easily require more than 100 years of computations).

The important question is how to by-pass limitations of the *if-then* analysis and find a combination of strategies, which would be the ”best” strategy for all possible catastrophes. In [13] it was shown that the search for ”robust” optimal decisions can be done by incorporating stochastic Spatial Adaptive Monte Carlo optimization techniques into catastrophic modeling that enables the design of desirable robust solutions without evaluating all possible alternatives.

4 Integrated Model Analysis

Model analysis is probably the least researched element of the modeling process.This results from the focus that each modeling paradigm has on a specific type of analysis. However, the essence of model-based decision-making support is precisely the opposite; namely, to support diversified ways of model analysis, and to provide efficient tools for various comparisons of solutions. Such an approach can be called Integrated Model Analysis.

A typical model for supporting decision-making has an infinite number of solutions, and users are interested in analyzing trade-offs between a manageable number of solutions that correspond to various representations of their preferences, often called the preferential structure of the user. Thus, an appropriate integrated analysis should help users to find and analyze a small subset of all solutions that correspond best to their preferential structures that typically change during the model analysis. Structured Modeling Technology provides the computational technology framework for the analysis, but there are three types of problems that call for innovative research:

1. integration of various paradigms of model analysis,
2. extracting knowledge from large sets of solutions,
3. efficient solution of computational tasks (either resource demanding, or numerically difficult, or large sets of simple jobs).

We briefly summarize each of them below.

For a truly integrated problem analysis one should actually combine different methods of model analysis, such as: classical (deterministic) optimization (and its generalizations, including parametric optimization, sensitivity analysis, fuzzy techniques), multicriteria model analysis, stochastic optimization and Monte Carlo simulations, classical simulation, soft simulation, and several of its generalizations (e.g. inverse simulation, softly constrained simulation). However, no modeling tool supports such a complete analysis, and development of separate versions of a model with tools supporting different modeling paradigms is typically too expensive. Thus we aim at finding a satisfactory solution to this problem.

The second research challenge is to develop and implement a methodology for a comprehensive analysis of large sets of solutions. We explore the applicability of various data mining and knowledge engineering techniques, and either adapt some of them, or develop new methods to extract and organize knowledge from large sets of solutions, and supply users with this knowledge in a form that will help further problem analysis.

The third set of research issues is related to efficient and robust organization of computational tasks typically needed for large-scale models, and includes:

- Efficient support for handling a large number of results, possibly coming from various types of analyses of large models.
- Adaptation of specialized optimization algorithms for badly conditioned problems.
- Support for exploiting the structure of huge optimization problems that need to be solved on computational grids.

5 Concluding remarks

Models play a key role for designing robust policies. Any policy analysis focuses attention on situations where processes can be affected or controlled by decisions that should be selected in the best possible manner. In this paper we discussed various facets of robustness assuming that the policy analysis problem is formulated as a basic optimization model with given sets of goals and feasible decisions. In reality these sets are also uncertain and they can be specified through a dialogue of users with a system of models, where optimization models create only some blocks of a complex overall accounting system. Advances in modeling and computational methods [26] allow us to create a ”laboratory world” [19], where we can test new policies never implemented in reality. This ”learning-by-modeling” dialogue of users with models requires specific robust optimization methods which are able to properly evaluate effects of rare extreme events. These methods also maintain a consistency of outcomes under the changing environment of the ”laboratory world” where goals and sets of feasible solutions of optimization models are subject to permanent changes dependent on views of users, new information and gained experience from real life implementation. Special attention is required for the analysis of these issues in the future.

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