Mathematical Modeling for Coping with Uncertainty and Risk*

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Coping with uncertainty in decision-making, especially for integrated management of risk, requires the analysis of various measures of outcomes resulting from applying alternative policy options. Policy options include various exante measures (such as mitigation, different arrangements for risk spreading) and expost measures aimed at reducing and sharing losses. The outcomes of implementing a given set of policy measures are typically measured by various indicators such as exante and expost costs, benefits from mitigation measures, welfare, quality of the environment, and indicators of risk exposure (value at risk, insolvency). The amount of data and relationships for any risk management problem are far too complex to be analyzed based solely on experience and/or intuition. Therefore, mathematical models have become a key element of decision-making support in various policy processes, especially those aimed at integrated management of disaster risk.

This chapter outlines methodological, social, and technical problems related to the development of novel methods for such models, and illustrates applications of such methods by case studies done at IIASA.

1. Introduction

Everybody has to cope with uncertainty and to manage various risks in he world that is changing more and more rapidly clearly stretching the social fabric. One of the dominant driving forces is efficiency, which has led to globalization, increased dependency among more diversified systems, a reduction in many safety (both technological and social) margins, and other factors which contribute to increased vulnerability.[1] However, faster development has its price. Traditional societies developed slower but in a more robust way, i.e., the consequences of wrong decisions or natural catastrophes were limited to rather small communities. Nowadays, the consequences of wrong decisions may be wider (even global and long-term) and more serious. Even at the family level, faster development has its price. There is a great deal of stress caused by the demand to be the best, a much lower tolerance for failure, and by various risks (e.g., a substantial decrease of future pension, or of loosing a single source of family income). Less people are successful in competitive societies than in egalitarian societies. This is not only a

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[1]A recent example is a faulty switch in a power station that resulted in a lack of electricity for dozens million people.

moral problem but in the longer term it reduces the security, safety, and reliability of three types of interlinked systems: human, economic, and technological.

A secure, safe, and reliable society requires a rational and timely decision making. However, decision making is becoming more and more difficult because decision problems are no longer well-structured problems that are easy to solve by intuition or experience supported by relatively simple calculations. Even the same type of problems that used to be easy to define and solve, are now much more complex because of the globalization of the economy, and a much greater awareness of its linkages with various environmental, social, and political issues. Moreover, decision-making is done for the future, which always is uncertain. Thus, any decision-maker needs to cope with uncertainty in order to rationally manage various risks.

Rational decision making typically requires:

- a representation of relationships between decisions and outcomes (the consequences of applying a decision),
- understanding the uncertainties related to various representations of such relationships,
- a representation of preferential structures (measures of tradeoffs between various outcomes) of the stake holders (persons and/or institutions affected by the consequences of implementing decisions),
- an assessment of the temporal and spatial consequences of implementing a selected decision,
- an assessment of various risks related to either implementing a (best at the moment) decision or postponing making a decision (until a possibly better decision can be made),
- a procedure (conventionally called DMP – Decision Making Process) for selecting *the best* solution (decision), and
- a procedure for involving stake holders in the DMP, and for communicating decisions to stake holders.

It is not practicable to attempt to deal with all these issues for any given decision problem. Each of these elements has a large number of methods and corresponding tools and an attempt to fully exploit the capabilities of many of them is doomed to failure. Different decision problems and the associated DMP have different characteristics, which call for focusing on implementing a selection of methods and tools. However, there are some common characteristics of model-based support for decision making, and a selection of these are discussed in this chapter.

2. Context

2.1. Common background

Before focusing on coping with uncertainty and risk management issues in decision making for complex problems, let us briefly consider a (theoretically simple) commonly known and well-structured problem: a decision by an individual to buy a car. From a methodological perspective, this is a multicriteria (with a small number of criteria) problem of a selection from a small set of alternatives. The alternatives are rather well defined and criteria are easily interpreted by a person making the decision. There are several methods supporting decision making in such situations, and yet the problem is typically solved using intuition and experience rather than any analytical tool. It is interesting to note that the same problem is solved in a different way by different future owners of a car, and the same person may take very different decisions that even he/she cannot explain using the criteria that are believed to completely define the tradeoffs. Different approaches taken by different persons is explained by the concept of *Habit-*

ual Domain introduced by Yu [1]. Different solutions (each believed to be *the best*) to the same choice problem show that even for a simple decision problem it may be impossible to precisely define a complete set of criteria and tradeoffs between them.

While a choice of a car is typically done without using any analytical tools, intuition and experience alone cannot be used for the analysis of (typically infinite number of) solutions to complex problems. Therefore, modern decision makers typically need to somehow integrate knowledge from these various areas of science and practice, and this can practically be done only by using a mathematical model. Unfortunately, the culture, language, and tools developed for knowledge representation in the key areas (such as the economy, engineering, environment, finance, management, social and political sciences) are very different. This observation is known to everybody who has ever participated in teamwork with researchers and practitioners who have backgrounds in different areas. Given the great heterogeneity of knowledge representation in various disciplines, and the fast growing amount of knowledge in most areas, the need for efficient knowledge integration for decision support remains a challenge that deserves to be addressed. More detailed discussion of these topics can be found in [2–4].

2.2. Model-based decision-making support

Safe, secure and reliable societies cannot be realized without model-based support for analyzing and solving complex problems organized in a way that is transparent not only for scientists and experts. For any complex decision problem models are necessary not only to support a decision-making process but also to enhance public understanding of problems and the proposed solutions. As this chapter focuses on supporting decision making, we only briefly comment on the role of models in public information. By now it is commonly agreed that the provision of information is critical to public acceptance, and that in reality some commonly discussed problems are actually incorrectly understood. Selected issues of modeling for knowledge exchange are discussed in [3]. The relevance of this publication for policy making is illustrated e.g., by Sterman [5], who points out that although the Kyoto Protocol is one of the most widely discussed topics, most people believe that stabilizing emissions at near current rates will stabilize the climate. Current debates (some accompanied by strikes) on pension system reforms in several European countries also clearly show a wide misunderstanding of the consequences of population structure dynamics on economies in general and on pension systems in particular. These, and many other problems, can also be explained to the public by adapting relevant models for use in presentations that the public can understand. Unfortunately, various models developed for policy-making problems use different assumptions, and often different sets of data; therefore a comparative analysis of their results can at best be done and understood by a small community of modelers. The need for public access to knowledge pertinent to policy-making will certainly grow, see e.g., [6], who discusses access to environmental information; thus the role of models in public life will also grow accordingly. Multidisciplinary and interdisciplinary modeling will grow in importance for the next generation society, see e.g., [7], for which a knowledge-based economy will become a major driving force for development. Models can represent knowledge as both synthesized and structured information, which can be verified by various groups of model users, see e.g., [4,8–10].

Making rational decisions for any complex problem requires various analyses of tradeoffs between conflicting objectives (outcomes) that are used for measuring the results of applying various policy options (decisions). There are three issues related to a proper model-based support: first, developing a model that represents the relations between decisions and outcomes, second, supporting analyses of tradeoffs between conflicting objectives, and third, organizing participation of stake holders in selected activities of the whole modeling process.

Models, when properly developed and maintained and equipped with proper tools for their analysis, can integrate relevant knowledge that is available from various disciplines and sources. While the substance of various environmental models is obviously different, many modeling methods and portable tools for model generation and analysis are applicable to problems of different origins. Many such models pose additional challenges owing to the large amount of data, complex relations between variables, the characteristics of the resulting mathematical programming problems, and requirements for comprehensive problem analyses. Such challenges have motivated the development of advanced modeling technology for supporting the whole modeling cycle. This includes model specification, data management, generation of model instances (composed of a selected model specification and data defining parameters and sets for compound variables), various methods of analyses of instances, and documentation of the whole modeling process. A modeling technology that supports this approach to model-based decision-making support is summarized in Section 3.1.

2.3. Uncertainty and risk

As outlined above, integration of knowledge for model-based decision support is a complex problem even without considering the two other elements of decision making, which are the key characteristics of many problems, namely, uncertainty and risk.

About 200 years ago Laplace argued that the world was completely deterministic, i.e., if we knew the current state of all the elements of the universe (from large bodies to atoms) and a set of scientific laws, then we could predict all events (including human behavior) with certainty. This implies that uncertainty is a consequence of our incomplete knowledge and will evaporate if knowledge becomes complete. This doctrine of scientific determinism was strongly resisted by many people, but it remained the standard assumption of science for over 100 years until a sequence of discoveries in physics proved that developments in science can increase uncertainty. In 1926 Heisenberg proved that the product of three attributes of a particle (the uncertainty in the position, the uncertainty in velocity, and the mass) can never be smaller than the Planck's constant. This was the first proof that uncertainty cannot be reduced below a certain level. Since 1933 Kolmogorov developed probability theory in a rigorous way from fundamental axioms; in 1954 he published a fundamental work on dynamic systems, where he also demonstrated the vital role of probability theory in physics, and of apparent randomness in systems believed to be deterministic.

We should distinguish between two types of uncertainty related to a considered phenomena:

- epistemic uncertainty: due to incomplete knowledge (which ranges from deterministic knowledge to total ignorance) of the phenomena,
- variability uncertainty: due to the inherent variability (i.e., natural randomness) of the phenomena, e.g., natural processes; human behavior; social, economic, technological dynamics; and discontinuities (or fast changes) in some of these processes.

While the epistemic uncertainty can be reduced provided that there is time and resources to do so, the variability uncertainty should be adequately addressed in any rational decision-making process. Further on we will discuss *variability uncertainty* for which we will use the term *uncertainty*.

The most common treatment of the variability uncertainty is through one of the following three paradigms of probability defined as:

- ratio of favorable events to the total number of *equally likely* events (Laplace),
- long-run frequency of the event, if the experiment was repeated *many* times (von Mises),
- a measure of a subjective degree of certainty about the event (Bayes, Keynes).

The first two paradigms assume that probability is an attribute of the corresponding event (or object), the third one is based on beliefs. However, a properly used probability is part of the additive set theory built by Kolmogorov on a set of mathematical axioms. Unfortunately, countless applications of probability theory do not conform to these axioms.

There are two pitfalls when using probability in decision making under uncertainty:

- Incorrect calculation of probabilities (e.g. applying the Laplace's paradigm to events that are not equally likely; or violating assumption of von Mises by: counting frequency from observations of events that occurred under different conditions, or by using a small sample of data, or by interpreting as data results provided by various models based on related data, or by multiple use of the same data each interpreted[2] as independent events). Probability defined as the relative frequency is equal to the limit of an infinite sequence, and it is rarely proved to what extent it is related to the relative frequency inferred from a finite subset of the infinite sequence.
- Correct probabilities provide a good basis for frequently repeated decision making provided neither the probability distribution nor payoffs change substantially (because this is a condition for a good approximation of an infinite sequence of decisions by a finite subsequence), and one wants to optimize a total expected outcome (defined as a sum of payoffs weighted by their probabilities). However, as demonstrated already in 1739 by Bernoulli's St Petersburg paradox (see for e.g., [11]), maximization of an expected outcome (or utility) is not rational for situations where a decision is made only once, or when for a sequence of decisions the consequences of each decision should be evaluated separately.

For rational decision making under uncertainty one needs to evaluate the risks associated with implementing a decision. The is no common agreement (not to mention a lack of an underlying rigorous mathematical theory) on the definition of risk. We adapt here (after [12]) the following definition: *Risk is a situation or event in which something of human value (including humans themselves) has been put at stake and where the outcome is uncertain*. Risk has a wide range of connotations (e.g., related to fears, concerns, uncertainties, thrills or worries) but there are unifying features that portray the meaning of risk. Whatever the variation in connotation, risk implies the possibility (as opposed to a predetermination) of some outcome. Risk thus implies uncertainty about an outcome, and can only be measured if one knows all the possible outcomes and the probability of each outcome occurring.

However, measuring risk is still a challenging problem, especially for risks related to rare events with high consequences, conventionally called catastrophic risks that are characterized by so-called heavy-tail distributions (moreover, such distributions are typically multi-modal and often the expected value of losses corresponds to an event which cannot occur). To illustrate this problem let us recall that investment risk is typically measured by a standard deviation (denoted by σ) of returns from that investment. Standard deviation is still commonly used as a primary measure of risk ignoring the facts showing that it is often not adequate. For example, the 1929,

[2]Wittgenstein described this as buying several copies of a newspaper to increase a probability that a news is true.

1987, 2000/2001 stock market crashes were each about a 10σ event; thus each would (under Gaussian statistics) only happen once in the lifetime of Earth.

Risk is not only difficult to measure but it is (especially low-probability risks) difficult for the public and most decision makers to understand (see e.g., [13]). Probably the most frequent question illustrating this is: “why have we had three 100-year floods during the last 10 years?” Hence building a common (for stake holders with different habitual domains) understanding of risk is another challenging problem.

2.4. Stake holders, temporal and spatial scales

So far we have not considered the other three elements of decision making, namely stake holders, and temporal and spatial scales. Due to space limitation we can only outline the scope of related problems by considering the problem of climate, which is a global common good. Climate change is driven by a combination of natural and anthropogenic processes, where the strongest impact of the latter is a function of the collective GHG emissions and sinks of all individuals and all human activities. Climate change is still far too complex a problem to be precisely modeled. However, there is strong evidence that anthropogenic activities may cause irreversible and abrupt climate change. Consequently, there is growing understanding for the need for action aimed at limiting the anthropogenic impact on climate change.

Although the problem is global, responsibilities are place specific and lie with all individuals, private and public organizations, and all nations. These stake holders have different characteristics (e.g., assets, priorities, obligations), see e.g., [14]. Response policies and measures are local while the consequences are long term and global, and therefore a concerted effort by all stake holders is necessary for achieving the global goal in a rational way. Moreover, there are many scientific uncertainties related to climate, and there are very diverse opinions on the scientific treatment of epistemic and variability uncertainties, and on the approaches to embracing it in the science-policy interface (see e.g., [15,16]), and on assessing and communicating uncertainties to the public [17]. Generally, uncertainty may justify inaction until epistemic uncertainty is reduced thus providing a better basis for making more efficient decisions. However, the time needed for reducing uncertainty may be (infinitely) long, and postponing some actions may either result in irreversible and abrupt changes or will require substantially more demanding solutions. While there are extremely different opinions on whether or not climate related actions should actually be taken without any further delay, the consequences of embracing uncertainty as an excuse for inaction in other areas of decision making are commonly known.

The long-time horizon and the global nature of the climate problem, together with the scientific uncertainties they present, pose special challenges for decision makers who have to balance potentially demanding actions for averting global long-term risks against other more immediate (and typically local with a short time horizon) human development demands. These three types of tradeoffs (global vs local, short term vs long term, uncertain vs perceived to be certain) are the major challenges for actual implementation of the necessary measures by politicians, whose constituencies have primarily local and short-term preferences. Model-based decision support is the only way to rationally identify various measures related to climate change, and to support various analyses of tradeoffs between the costs of the measures and their consequences for reducing the anthropogenic impact on global change. This is the only way to provide scientifically based and politically neutral input to policy-making processes, which needs to be conducted in a participatory fashion, involving many research institutions interacting with potential users, i.e., decision makers, various groups of experts, and stake holders.

2.5. Risk management

Before discussing active risk management one should point out the alternative *wait-and-see* strategy, i.e., hoping that an unfavorable event will not occur, and react only, if it indeed will be the case. Contrary to common believes such a strategy may have rational (see e.g. [12] for arguments and case studies) explanations.

Active risk management is typically composed of two interrelated sets of actions:

- reducing the risk by mitigation, adaptation, and diversification measures,
- applying financial instruments (insurance, hedging, catastrophe funds, contingency credits, catastrophe bonds).

Reducing risk is well established in well organized societies, and in the longer term it is the most rational action. However, its implementation requires resources and luck (to be able to implement the measures before the first catastrophe will occur). There is typically a limit beyond which a further reduction of risk is more expensive than the application of an appropriate combination of financial instruments. In addition to traditional financial instruments there are ideas of a new financial order [18] that aim at an integrated management of all types of economic risk.

Risk management requires the analysis of tradeoffs between outcomes (criteria) expressed in different units. The most common approach is to convert (typically for computations only) such multicriteria problem into a single-criterion optimization problem. Such an approach has serious, but not commonly recognized, limitations (see e.g. [19]). Therefore it is worth mentioning a truly multicriteria optimization of decision making under risk [20].

3. Model-based support for coping with uncertainty and risk

3.1. Modeling for decision-making support

Mathematical modeling for decision-making support is the process of creating, analyzing, and documenting a model, which is an abstract representation of a problem developed for finding a possibly best solution for a decision problem. The role of models in modern decision making that is shared by the author of this chapter is discussed in detail in [21] along with the methodology and tools for model-based decision-making support, and several applications to complex environmental policy-making problems. A more diversified collection of methods and applications is presented in [22], and a more focused discussion of selected elements of modeling for decision support, and an updated bibliography is provided in [19].

A mathematical model describes the modeled problem by means of variables, which are abstract representations of these elements of the problem, which need to be considered for the evaluation of the consequences of implementing a decision (typically represented by a vector composed of many variables). More precisely, such a model is typically developed using the following concepts:

- decisions (inputs) $\boldsymbol{x}$, which are controlled by the user;
- external decisions (inputs) $\boldsymbol{z}$, which are not controlled by the user;
- outcomes (outputs) $\boldsymbol{y}$, used for measuring the consequences of implementation of inputs;
- relations between decisions $\boldsymbol{x}$ and $\boldsymbol{z}$, and outcomes $\boldsymbol{y}$; such relations are typically presented in the form:

$$\boldsymbol{y} = \boldsymbol{F}(\boldsymbol{x}, \boldsymbol{z}), \tag{1}$$

where $\boldsymbol{F}(\cdot)$ is a vector of functions.

The concise formulation (1) of a model specification[3] may be misleading for those who are unaware of the complexity of the process of model specification. Each model represents a part of knowledge that is relevant for analysis of the given decision problem. Thus, the model must be confined to a well-defined area of interest, it can only be valid for a specific purpose, and the real phenomena is always only partially to represented by the model. Consider, for example, modeling a cup of coffee. Very different models are suitable for studying various aspects, e.g., how something (sugar, cream) is dissolved in the cup's content, or under what conditions the cup might break from thermal stresses, or what shape of cup is most suitable for use in aircraft, or how a cup of coffee enhances different people's productivity. An attempt to develop a model to cover all these aspects, and represent all the accumulated knowledge on even such a simple topic would not be rational.

To define a purpose for modeling one needs to analyze if and how a model can contribute to finding a better solution that can be found without a model. This, in turn, implicitly sets the requirements for a selection of input and output variables, and a specification of functions (1) that define relations between variables. Because of the unquestionable success of modeling in problem solving, various modeling paradigms have been intensively developed over the last few decades. Thus, different types of models (characterized by types of variables and relations between them) were developed (e.g., static, dynamic, continuous, discrete, linear, nonlinear, deterministic, stochastic, set-membership, fuzzy, soft constraints) with a view to best representing different problems by a selected type of model. Each modeling paradigm embodies a great deal of accumulated knowledge, expertise, methodology, and modeling tools specialized for solving various problems peculiar to each modeling paradigm.

Although several well-developed modeling paradigms exist it is not easy to select the one that is the best for the problem at hand. Moreover, for a selected paradigm a modeler must find a way of avoiding too much detail while preserving the essential features of the specific problem. Finally, even for a selected set of variables and relations there are often several ways of introducing auxiliary variables and defining the relations, which might be equivalent (i.e., the results of the model analysis should be the same[4]) but different specifications may result in substantial differences in efficiency of the whole modeling process (especially, when difficult optimization problems are solved during the model analysis, see e.g., [22,23]).

Thus, an appropriate model specification for any non-trivial problem requires a combination of knowledge, experience, intuition, and taste. Therefore, modeling remains and will remain an art. More discussion on the art of modeling can be found in [24].

However, not only model specification but also its use in decision-making process is a more complex issue than typically perceived. In particular, model analysis is probably the least-discussed 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 various ways of model analysis, and to provide efficient tools for comparisons of various solutions. Thus, we outline now a way

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[3]Actually any complex model contains also auxiliary variables (typically a vast majority of variables in a large model are the auxiliary variables) defined and used in order to make the model easier to develop, analyze, and maintain. However for the sake of brevity we don't introduce auxiliary variables here.

[4]The differences may however occur because of numerical characteristics of the underlying computational problems.

in which a model that adequately represents the relations between the decisions and the outcomes (used for measuring the corresponding consequences) can be used for finding decisions that fit best the preferences of the decision makers.

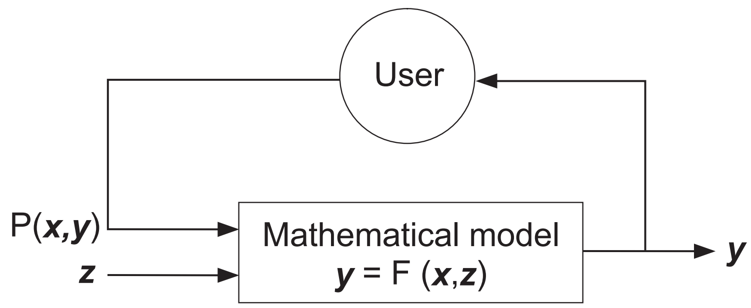

Figure 1. A typical structure when using a mathematical model for decision-making support.

A typical structure when using models for decision-making support is illustrated in Figure 1. The basic function of *Decision Support System* (DSS) is to support the user in finding values of his/her decision variables that will result in a solution of the problem that fits best to the preferences of the user.

A typical decision problem has an infinite number of solutions, and users are interested in those that correspond best to their preferences represented here by a *preferential structure* $P(\boldsymbol{x}, \boldsymbol{y})$ of the user. A preferential structure takes different forms for different ways of model analysis, e.g., for:

- Classical simulation, it is composed of given values of input variables;
- Soft simulation, it is defined by desired values of decisions, and by a measure of the distance between the actual and desired values of decisions;
- Single criterion optimization, it is defined by a selected goal function and by optional additional constraints for the other (than that selected as the goal function) outcome variables;
- Multicriteria model analysis, it is defined by an achievement scalarizing function, which represents the tradeoffs between the criteria used for the evaluation of solutions.

A preferential structure typically induces partial ordering of solutions obtained for different combinations of values of inputs, and in a well-organized modeling process preferential structure is not included in the model, but is defined during the model analysis phase, when users typically modify their preferences substantially. In fact, a well-organized model analysis phase is composed of several stages, see e.g., [19], each serving different needs; thus, typically, not only are different forms of $P(\cdot)$ used for the same problem but also different instances of each of these forms are defined upon analysis of previously obtained solutions.

Such an approach to use models for supporting decision making differs substantially from the (traditional) OR routine of representing a decision problem as a mathematical programming problem, e.g., in the form:

$$\hat{\boldsymbol{x}} = \arg\min_{\boldsymbol{x} \in X_0} \mathcal{F}(\boldsymbol{x}), \tag{2}$$

which provides optimal decisions $\hat{\boldsymbol{x}}$. Countless number of actual applications shows, however, that for most complex problems it is not possible to adequately define a $\mathcal{F}(\boldsymbol{x})$ (that represents preferences of decision makers) nor a set of feasible solutions X_0. In fact, various types of mathematical programming problems are typically defined during the analysis phase; thus, optimization continues to play a crucial role in model-based decision support. However, optimization in supporting decision making for solving complex problems has quite a different role from its function in some engineering applications (especially real-time control problems) or in very early implementations of OR for solving well-structured military or production planning problems. This point has already been made clearly e.g., by Ackoff [25], and by Chapman [26], who characterized the traditional way of using OR methods for solving problems as composed of the following five stages: describe the problem; formulate a model of the problem; solve the model; test the solution; and implement the solution. The shortcomings of such an approach are discussed in many other publications, some of which are overviewed in [21].

Thus, model-based support for decision-making for complex problems has to meet much more demanding requirements (than those adequate for problems of type (2), which are adequate for well-structured, relatively simple decision problems) for the underlying modeling process, which is by far more complex than a process of model development for well-structured decision problems. These requirements demand also a new technology of modeling, such as the *Structured Modeling Technology* (SMT) discussed in detail in [27].

Models for the integrated management of catastrophic risk are not only complex but also possess specific features, which are discussed below. Thus, their presentation below serves two purposes. First, it illustrates the actual complexity of such models and justifies the reasons why the general-purpose modeling tools, and the traditional OR approach to model analysis cannot be successful in such cases. Second, it provides enough details about such models and the corresponding modeling process to help in the development of this type of approach for supporting decision-making process for similar type of problems.

3.2. Integrated catastrophic risk management

3.2.1. Background

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.

3.2.2. The integrated catastrophe management model

The model consists of three major submodels:

- a catastrophe module,
- an engineering vulnerability module, and
- an economic multi-agent module.

The catastrophe module simulates natural phenomenon using a model based on the knowledge of the corresponding type of event, which is 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's location, 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 Monte Carlo dynamic simulations of geographically explicit catastrophe patterns in selected regions (a discussion of these models is beyond the scope of this chapter but can be found e.g., in [28–34]). 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., [35]). 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 may easily require more than 100 years.

3.2.3. Adaptive Monte Carlo optimization

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 [35] 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. The model is composed of elements with the following functionality:

- Initial values for policy variables are input into the Catastrophe Model.
- The Catastrophe Model generates catastrophes and induced direct and indirect damages.
- The efficiency of the policies is evaluated with respect to the performance indicators of the agents, e.g., insurers, insured, governments, etc.
- If these do not fulfill the requirements, goals and constraints, they are further adjusted in the Adaptive Feedbacks submodel. In this manner it is possible to take into account complex interdependencies between damages at different locations, available decisions and resulting losses and claims.

The crucial question is the use of appropriate risk indicators (measures, metrics), e.g., to avoid bankruptcies of agents. Catastrophic losses often have multimodal distributions, and therefore the use of mean values (e.g., expected costs and profits) may be misleading. Roughly speaking, we cannot think in terms of aggregate regional losses and gains as the sum of location specific losses and gains (e.g., if the mean value is substituted by the median). In our model we apply economically sound risk indicators such as bankruptcy of insurers, expected shortfall of insurers’ risk reserve, and overpayments and underpayments by individuals. These indicators are used together with so-called stopping times to direct the analysis towards the most destructive scenarios.

3.2.4. Case studies

The adequacy of the outlined methodology was tested in a number of case studies. In its first application, the integrated model analyzed the insurability of risks in the Irkutsk region in Russia, which is exposed to the risk of earthquakes (see e.g. [28,31]) results demonstrated the model’s capability of generating insurance strategies that are robust with respect to dependencies and uncertainties induced by the catastrophes, thus reducing the risk of bankruptcy to the insurers.

The second case study (see e.g., [36]) in a seismic-prone Italian region illustrated the need for a joint effort by multiple stake holders in managing the catastrophes. It emphasized that neither the market nor the government may be considered as the efficient mechanism for catastrophic risk management. Only some form of a public-private partnership would be appropriate. Also, it illustrated that the policy options suggested by stake holders may often be misleading and result in even higher losses. Only comprehensive model-based analysis of dependencies between the timing of catastrophes occurrences, damages, claims, goals, and constraints of agents can assist towards loss-reduction management.

In the third case study [32], the integrated model evaluated an insurance program for mitigating and sharing losses due to severe floods in the Upper Tisza region in Hungary. In this study special attention was given to the evaluation of strategies robust against a variety of floods. Such strategies are composed of a public multi-pillar flood loss-spreading program involving partial compensation to flood victims by the central government, the pooling of risks through mandatory public insurance on the basis of location-specific exposures, and a contingent exante credit to reinsure the pool's liabilities. A complementary (more focused on social and policy-making issues) description of this case study is given in [37].

4. Uncertainty, risk, and modern societies

After discussing the methodological background of model-based support for risk management, and presenting in more detail one selected approach and related applications, we summarize other IIASA's research activities pertinent to risk management.

The Risk, Modeling, and Society Project has a long history of research on the economic and social implications of technological, health, and other risks to modern societies. Major projects have been carried out on this broad, interdisciplinary topic, including: the perception of risks to technological disasters, the institutional aspects of risk policy making [38], the equity issues of siting locally unwanted facilities [39], and the role of expertise in risk policy making [40].

Recent activities focus on the design of instruments and model-based democratic procedures for effectively and equitably reducing and redistributing the risks of extreme events, with special emphasis on transition and developing countries. A survey of global experience with respect to the financial aspects of disasters shows that the victims of extreme natural events, despite insurance and public solidarity, are primarily the households and businesses suffering the losses [38]. A project funded by the British Association of Insurers carried out 7 case studies of major disasters in Asia, Europe, and the US, which showed that country practices differ greatly on how the financial risks are absorbed, whether privately through insurance arrangements and/or publicly through social solidarity. This study also investigated the incentive links between risk sharing and preventive measures to reduce the losses.

This theme of risk sharing and loss reduction for extreme events has now become topical at the global level, especially since the IPCC prediction that extreme weather events will worsen with climate change. A current concern is helping developing and transition countries adapt to weather extremes. Many governments of poor countries face budgetary restrictions in reducing disaster losses and providing postdisaster relief and reconstruction, and governments of very poor and very disaster-prone countries, for example, Honduras, the Philippines, and China, face such enormous risks that regions can be set back years in their development. In collaboration with the Inter-American Development Bank, IIASA has contributed to the development of a proactive, integrated disaster risk management strategy [41] with special emphasis on developing tools for the financial management of these risks, and exploring whether disaster hedges could become a new form of assistance from the North to the South [42].

How risks are reduced and shared is a value-laden, policy issue, which was addressed by the risk assessment project for managing flood risks in the Upper Tisza river basin. This activity combined information technology (presented in Section 3.2) with public participation through stake holder interviews, surveys, and stake holder workshops [43,44].

The work on risk financing in transition- and developing countries has recently received recognition in the climate negotiations community, in particular in the UNFCCC activities on insurance and risk assessment in the context of climate change and extreme weather events. Moreover, the IIASA model-based research on financial risk management is now used in collaborative activities with the World Bank and the Inter-American Development Bank to take account of catastrophic events in country development plans.

IIASA has also made several activities addressing problems of social security. Here, we outline only the optimization-based analysis of social security under uncertainties and risks.

In most cases the social security system is the main determinant of population welfare. Dominating in major OECD countries the PAYG (pay-as-you-go) system is nowadays put under stress by rapidly changing demographic conditions, aging, characterized by lowering fertility and increasing longevity. Besides this, instabilities in financial markets, economic distress, inflation and devaluation often produce grave impacts on sources financing retirement. Major questions to explore are:

- What is essential for the efficient functioning of the system?
- Can the existing systems survive in the current demographic and economic environment?
- How can the transition from PAYG to funded pension systems work?

In many OECD countries a combination of the PAYG and funded pension systems is being discussed. Criteria for evaluation of various combinations include: the least cost for the transition, the least burden on various population groups (e.g., retirees, and contributors to the systems), the least costly financial measures to aid the transition, for example, through international/national borrowing.

The broad range of uncertainties inherent to social security problems necessitate the explicit introduction and treatment of uncertainties and risks into the social security simulation model, and the formulation and development of an optimization based approach to the analysis of social security systems [45,46].

The social security simulation model [45] is a compromise between a purely actuarial model and an overlapping generations general equilibrium model. It deals with production and consumption processes coevolving with birth-and-death processes of involved agents, e.g., region-specific households subdivided into single-year age groups, firms, governments, financial intermediaries, including pension systems and insurance. The production function of the model allows to track incomes expenditures, savings and dissavings of agents, as well as intergenerational and interregional transfers of wealth. The stochastic optimization approach [46] combines this model together with a rolling horizon stochastic optimization procedure which allows to explicitly and realistically treat the underlying uncertainties with the goal of maximizing social welfare (consumption of workers and retirees) by fine-tuning the mix of the transfer based PAYG and capital reserve finance funded social security schemes.

The social security simulation model of IIASA was applied in a multidisciplinary study of population aging in Japan [47]. This study was made possible by financial support from the Economic and Social Research Institute of the Japanese Cabinet Office as part of its Millenium Project. The general conclusions of the studies are slowing per capita growth, a declining national saving rate, rising social contribution rates (subject to the assumption of no change in labor force participation rates or the calculation of pension, health, and long-term care benefits), and reduction in net foreign assets. While disposable income of both the elderly and the working-age population are expected to rise (i.e., living standards will continue to improve), the assumptions of the model translate into an eventual decline in the living standards of the young relative to those of the elderly. This is, of course, subject to our assumption that the main mechanism for adapting to the rising costs of pensions and health is increasing payroll contribution rates. This picture is typical for all rapidly aging regions of the world among which Japan may be leading the way, but other countries must surely follow.

We close this overview of selected IIASA's activities related to treatment of uncertainty and to risk management by providing references to selected publications (but not repeating publications already cited in this chapter) addressing pertinent methodological issues:

- An introduction to measuring risk [48].
- New measures of risk [49].
- Stochastic optimization for design of catastrophic risks portfolios [50–52].
- Tradeoffs between security and growth [53].
- Exante and expost financial stabilization of long term growth [54].
- Catastrophic risk management [55].
- The role of insurance in risk transfer [56].
- Modeling for financial optimization [57].
- Numerics of financial management [58].

5. Conclusions

Coping with uncertainty, and rational risk management for any complex decision-making situation is a complex process, and there are no simple (and adequate) solutions to truly complex problems. Moreover, the impact of inadequate risk management may be not only significant but also global. Complexity and global impact require two types of cooperation:

- among stake holders at different locations and of different type (central and local governments, enterprises, NGO's, individuals);
- between researchers from various fields that need to contribute to building objective, model-based support for decision-support.

There is a wealth of knowledge and experience that can contribute to rational risk management. However, these resources are fragmented, and often in incompatible forms. Integrating such resources is part of a wider, and even more challenging problem, namely integrating fragmented knowledge to appropriately serve the knowledge society. This new type of society can actually be safe, secure, and reliable only, if decisions on various levels will be made in a concerted way using integrated knowledge.

Due to the unquestionable success of modeling in problem solving, various modeling paradigms 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. Each modeling paradigm embodies a lot of accumulated knowledge, expertise, methodology, and modeling tools specialized for solving many of the problems belonging to each modeling paradigm. However, these resources are fragmented, and using more than one paradigm for a problem at hand is too expensive and time consuming in practice. The *Structured Modeling* of Geoffrion provides a methodology for unifying different paradigms, and for structuring the modeling process, which is the necessary condition for effective modeling of complex systems. The Structured Modeling Technology (SMT) provides modular tools for structured modeling, and supports also the key requirements for good modeling practice, see e.g., [5,21,22,25,27,59–62] for a discussion of various key elements of such practices, and of some typical modeling pitfalls.

Modeling, especially of large and/or complex problems requires a combination of knowledge, craft, and art. Model-based support for policy making issues is by far more complex than modeling for solving better-structured problems, e.g., in engineering applications. Not only are models for policy making more complex than models of well-structured problems, but there are more demanding requirements for the whole modeling process, which in turn needs to be transparent and well documented.

This chapter aims at sharing the knowledge and experience developed during the long-term development of several complex models, and at providing basic information about several actually applications of model-based support for coping with uncertainty and risk, and about SMT which supports the whole modeling process for model-based decision-making support. SMT responds also to the challenging requirements for the modeling process, which will be growing in the near future when more and more policy-making processes will utilize model-based problem analysis and decision-making support.

Finally, this chapter provides an extensive list of references that aim to provide pointers for further reading for those new to some of the concepts presented and who may therefore find the presentation too sketchy.

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