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Editors

Uncertainty and Environmental Decision Making

A Handbook of Research and Best Practice

Springer

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Preface

The 21st century promises to be an era dominated by international response to certain global environmental challenges such as climate change, depleting biodiversity and biocapacity as well as general atmospheric, water and soil pollution problems. Consequently, Environmental decision making (EDM) is a socially important field of development for Operations Research and Management Science (OR/MS). Uncertainty is an important feature of these decision problems and it intervenes at very different time and space scales. The *Handbook on "Uncertainty and Environmental Decision Making"* provides a guided tour of selected methods and tools that OR/MS offer to deal with these issues. Below, we briefly introduce, peer reviewed, chapters of this handbook and the topics that are treated by the invited authors.

The first chapter is a general introduction to the challenges of environmental decision making, the use of OR/MS techniques and a range of tools that are used to deal with uncertainty in this domain.

Chapter 1. Filar and Haurie present a broad overview of Operations Research and Management Science methods and models used to support Environmental Decision Making under uncertainty. They first outline challenges and pitfalls of OR/MS applications to EDM. Subsequently, they classify different sources of uncertainty and show how stochastic reasoning pervades some fundamental issues raised in EDM and environmental economics. In particular, they discuss issues related to discounting and intergenerational equity. A selection of concepts and techniques is surveyed that enable the modeler to better understand and manage uncertainty in EDM. Finally, it is shown how the methods of stochastic control, stochastic programming, robust optimization and statistical emulation in meta-modeling can be used to shed some light on difficult issues arising in EDM under uncertainty.

The next two chapters present application of stochastic or robust programming methods to techno-economic modeling of energy/environment interactions.

Chapter 2. Labriet, Loulou and Kanudia consider a large scale, partial equilibrium, technology rich global 15-region TIMES Integrated Assessment Model (ETSAP-TIAM). They apply the well-known method of stochastic programming in extensive form to assess climate policies in a very uncertain world. The main uncertainties considered are those of the Climate Sensitivity parameter, and of the rate of economic development. They argue that the stochastic programming approach is well suited to the treatment of major uncertainties, in spite of the limitation inherent to this technique due to increased model size when many outcomes are modeled. The main advantage of the approach is to obtain a single hedging strategy while uncertainty prevails, unlike in the case of classical scenario analysis. Furthermore, the hedging strategy has the very desirable property of attenuating the (in)famous "razor edge" effect of Linear Programming. It thus arrives at a more robust mix of technologies to attain the desired climate target. Although the example treated uses the classical expected cost criterion, the authors also presents, and argue in favor of, altering this criterion to introduce risk considerations, by means of a linearized semi-variance term, or by using the Savage criterion. Risk considerations are arguably even more important in situations where the random events are of a "one-shot" nature and involve large costs or payoffs, as is the case in the modeling of global climate strategies. The article presents methodological details of the modeling approach, and uses realistic instances of the ETSAP-TIAM model to illustrate the technique and to analyze the resulting hedging strategies.

Chapter 3. Babonneau, Vial and Apparigliato show how traditional approaches to optimization under uncertainty, in particular stochastic programming, chance-constrained programming or stochastic dynamic programming, encounter most severe numerical difficulties. This is because models in this area are large and complex, already in their deterministic formulation. In this chapter the authors introduce a relatively new method, known as robust optimization, as an alternative to traditional methods and formulations. Through an illustrative example, they suggest ways of putting robust optimization to work in environmental and energy optimization models.

Traditionally, both short term weather and longer term climatic conditions have been regarded as sources of uncertainty in great many human endeavors. Nowadays, it is widely believed that anthropogenic induced climate change will impact not only long term trends such as global warming and sea level rise but also frequency and severity of the southern oscillation effect as well of extreme events such as hurricanes, droughts and floods. Consequently, the next three chapters focus on certain important consequences of uncertainty inherent in weather patterns, the El-Nino phenomenon and the anticipated climate change.

Chapter 4. Naylor and Mastrandrea provide a framework for using climate information in the design of policy to manage risks for agriculture, rural economic growth, and food security. They highlight several tools of analysis that can be applied in the context of both climate variability and global climate change. The concepts are developed through a case study of the rice sector in Indonesia a country directly affected by climate variability related to El Nino Southern Oscillation events. The risk assessment model is based on the probability of climate events, critical thresholds of damage related to those events, and the role of policy in reducing climate-related impacts on agricultural systems. Because risk assessment involves estimations of both the probability of climate events and the expected consequences of those climate events, Bayesian analysis is applied to show how climate information can be used to update subjective probabilities over short- and long- time scales. Bayesian updating can help reduce the chances that policymakers will make the wrong policy decision given all of the available information. However, the chapter demonstrates that - even with the help of these tools - Type I and Type II errors in policymaking will always be present and hence need to be estimated and incorporated in policy planning.

Chapter 5. Barrieu and Scaillet give a short introduction to weather derivatives. They discuss the purposes for which they were created, describe the markets on which they are exchanged, and how they are used to promote agricultural risk transfer in developing countries via the World Bank program. They also treat some specific issues such as basis risk, pricing and design.

Chapter 6. Ambrosi, Hourcade, Hallegatte, Lecocq, Dumas and Minh Ha Duong examine the consequences of various attitudes towards climate damages through a family of stochastic optimal control models (RESPONSE): cost-effectiveness for a given temperature ceiling; cost-benefit analysis with a pure preference for current climate regime and full cost-benefit analysis. The choice of a given proxy for climate change risks is regarded as more than a technical option. It is essentially motivated by a degree of mistrust of the legitimacy of an assessment of climate damages and the possibility of providing, in due course, reliable and non controversial estimates. The authors' results demonstrate that: (a) for the early decades of abatement, the difference between various decision-making frameworks appears to matter less than the difference between stochastic and non stochastic approach given the cascade of uncertainty from emissions to damages; (b) in a stochastic approach, the possibility of non-catastrophic singularities in the damage function is sufficient to significantly increase earlier optimal abatements; (c) a window of opportunity for action exists up to 2040: abatements further delayed may induce significant regret in case of bad news about climate response or singularities in damages.

One fundamental problem underlying attempts to apply OR/MS methods to environmental decision making stems from the fact that human development processes, typically, operate on much shorter time scales than natural processes of the biosphere. Consequently, the next two chapters exploit tools of decision analysis, utility theory and optimal control theory to model the ensuing difficulties that are caused by the need to make environmental policy decisions that affect disparate periods of time and under conditions where new information becomes available during the periods affected by these policies.

Chapter 7. Bahn, Haurie and Malhamé present an application of stochastic control or stochastic game methods to the modeling of climate policy timing. The authors first propose a stochastic control approach for a cost-effectiveness model where two sources of uncertainty are included. In a second part they use a similar stochastic control approach for a cost-benefit model where only the uncertainty on the access to a clean technology is taken into account. Finally, they show how these models could be extended to a game theoretic framework, assuming non-cooperative behavior of two groups of countries, under a treaty imposing a coupled constraint on atmospheric concentrations of greenhouse gases.

Chapter 8. De Lara and Gilotte consider an agent taking two successive decisions under uncertainty. After the agent's first decision, a signal is revealed providing information about the state of nature and then the second decision is taken accordingly. Suppose that the agent is an expected utility maximizer. The precautionary effect holds when, in the prospect of future information, his optimal initial decision is smaller (more conservative?) than without such a prospect. Indeed, the first decision is usually a scalar representing consumption, so that precaution is identified with less consumption. The authors introduce the second-period value of information as a function of the initial decision and show that, when this function is decreasing, namely, the precautionary effect holds true. More generally the condition enables the comparison of optimal decisions related to different signals, not necessarily comparable. It also ties together and clarifies many conditions for the precautionary effect that are scattered in the environmental economics literature. A practical illustration with Nordhaus's DICE model is included.

Whenever stochastic phenomena impact on a decision making processes, probability distributions, moments, or other key parameters of the most important random variables need to be modeled. Consequently, the final three chapters present methods that combine statistical and decision analyses that can support a variety of environmental management problems.

Chapter 9 Chiera, Filar, Gordon and Zachary present an analysis of two separate single-indicator forecasting methods for the El Nino Southern Oscillation phenomenon, based on the oscillation persistence. The authors use the southern oscillation index (SOI) of pressure, to forecast in short time scales of $4-8$ months. A Bayesian approach is used in order to explore SOI persistence and compare results to a Taylor Series expansion (control method). The authors find that signal persistence is important when forecasting more than a few months and the techniques presented provide a relatively simple approach to environmental risk forecasting in situations where the underlying phenomenon exhibits substantial amount of persistence.

Chapter 10. Boland develops a model to generate synthetic sequences of half hourly electricity demand. The generated sequences represent possible realizations of electricity load that may occur in a region under consideration. Each of the components included in the model has a physical interpretation. These components are yearly and daily seasonality which were modelled using Fourier series, weekly seasonality modelled with dummy variables, and the relationship with current temperature described by polynomial functions of temperature. Finally the stochastic component was modelled with ARMA processes. The temperature series was modelled in a similar fashion. The stochastic modelling was performed to build probability distributions of the outputs to calculate probabilistic forecasts. As one application several summers of half hourly electricity demand were generated and from them the value of demand that is not expected to be exceeded more than once in ten years was calculated. Additionally, the bivariate temperature and demand model was used in software designed to optimize the orientation of photovoltaic cells to match demand.

Chapter 11. Gabriel, Vilalai, Sahakij, Ramirez, Peot describe recent modeling efforts to identify factors that lead to high biosolids odor levels associated with advanced waste water treatment plants (AWTP). These factors can be broken down into two groups: (i) those that are beyond the control of the AWTP such as ambient temperature, (ii) those that are controllable such as the number of centrifuges in operation, the amount of lime used, etc. The authors summarize their findings relative to different statistical models that predict biosolids odor levels based on either subjective or analytic measurements from the District of Columbia Water and Sewer Author (DCWASA). These models take into account a host of factors to predict biosolids odor levels and are then used to generate a relevant probability distribution for odor levels using Monte Carlo simulation. Such probability distributions will guide AWTP managers relative to where to send the biosolids products taking into account the likelihood of high levels and thus indirectly, possible complaints from those living or working near the reuse sites. The authors also describe recent efforts in also optimizing the operations of the AWTP and distribution network to balance both biosolids odors and costs. The resulting multiobjective optimization models are computationally challenging due to their size and non-convexities. The discussion presented also shows how to handle stochasticity directly within such optimization models.

Adelaide (Australia), Chêne Bougeries (Switzerland), June 2009

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Contents

Chapter 1
OR/MS and Environmental Decision Making under Uncertainty

Jerzy A. Filar and Alain B. Haurie

Abstract In this chapter we present a broad overview of Operations Research and Management Science (OR/MS) methods and models used to support Environmental Decision Making (EDM) under uncertainty. We first survey the challenges and pitfalls frequently accompanying OR/MS applications to problems involving environmental issues. We consider and classify generic sources of uncertainty in quantitative models involving life support systems. We show how stochastic reasoning pervades some fundamental issues affecting decision making pertaining to the natural environment and environmental economics, in particular those related to discounting and intergenerational equity. We then discuss a selection of concepts and techniques that enable us to better understand and manage uncertainty in EDM. Finally, we indicate how the methods of stochastic control, stochastic programming, robust optimization and statistical emulation in meta-modeling can be used to shed light on some difficult issues arising in environmental decision making under uncertainty. This general discussion constitutes a preparation for the forthcoming chapters of this book.

1.1 Introduction

Since its inception during the second world war, the subject of Operations Research has grown rapidly and adapted itself repeatedly in order to answer an ever growing array of important problems. Links with Management Science broadened its reach beyond military logistics and engineering applications to those of business and management. Subsequently, aided by the explosive growth of computing power

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and information technology, its domain of interest expanded even further to include problems of manufacturing systems, communications, operations management, decision support systems, financial systems and many others. Loosely speaking, we shall refer to the multi-disciplinary subject that had so evolved as OR/MS (short for Operations Research & Management Science).

For the purpose of this contribution, we shall think of OR/MS as a body of largely quantitative models and techniques aimed at identifying a best (or, at least, an adequate) course of action out of a, possibly enormous, set of alternative courses of action. In this context, the course of action adopted influences the performance of some complex "system" and may lead to benefits such as profits, efficiency, enhanced productivity as well as to a wide range of possible costs (e.g., operational costs, failures, or waste).

In recent years, concerns about our society's impact on natural environment – fuelled by global problems such as climate change, loss of biodiversity and spread of pollution – have opened many new opportunities for OR/MS practitioners. As industries and regulatory agencies are beginning to show real interest in minimizing adverse impacts of human development processes on the natural environment a whole new set of problems waiting to be analyzed has emerged. While some of these problems are readily amenable to existing OR/MS techniques, many possess novel characteristics that require special attention and development of new techniques to produce meaningful results when analyzed from the OR/MS perspective. While some of these characteristics will be discussed in more detail in subsequent sections, two that form a recurrent theme throughout this volume are highlighted at this preliminary stage.

U: *Uncertainty.* Typically, a coupling of environmental impacts with a business or an engineering decision making problem dramatically increases uncertainty concerning a number of important issues. These range from uncertainty concerning the natural variability of certain biological and physical phenomena, through uncertainty related to the understanding of impacts of the selected courses of action on these phenomena, to the uncertainty generated by a combination of disparate analytical tools to the study of the problem of interest.

TSA: *Time Scales' Asynchrony.* Arguably, at the core of most controversies regarding environmental protection lies the problem of lack of "synchronization" between the time scales of human development processes and the natural processes of the biosphere. Typically, the former are relatively short time scales while the latter are much longer.

The bulk of this volume is devoted to quantitative, fundamentally mathematical, modelling paradigms capable of capturing certain essential interactions between human development activities and the natural environment. Hence, it is worthwhile to briefly discuss whether the problems encountered are, indeed, suitable for mathematical modeling.

A relatively recent survey article (36) presents the minimal requirements that situations studied should possess in order to make mathematical modeling meaningful. The characterization of these requirements is not simple because the boundaries of what can be achieved with mathematical models are constantly pushed back. Nonetheless, three principles were identified capturing what might be called an analyst's common sense which, if violated, raise questions as to whether mathematical modelling is appropriate in these situations. These criteria are:

- The presence of (at least some) variables that can be quantified and (ideally) observed and measured, or of data from which such variables could be extracted
- The presence of some understanding of relations between quantifiable variables or of, at least, a need to discover such relations empirically
- The presence of data, experimental designs, or other procedures to be used to validate the model.

The preceding requirements may appear to be so obvious as to be taken for granted and yet, there are many important situations where one or more of these requirements are very difficult to satisfy. Fortunately, in our case, the first two requirements are generally – albeit separately – satisfied for both the business/industrial activities and the environmental phenomena of interest.

For instance, the operations of airlines and airports constitute a classic example of success of OR/MS techniques from the strictly business/industrial application perspective. Hence, there is ample information available concerning demand for flights, optimal scheduling and impacts of schedules on airlines' profitability. Furthermore, atmospheric and environmental scientists can supply much information concerning greenhouse gas emissions, energy consumption, waste generated, or embodied energy associated with airlines' operations.

Thus the main problem, in our case, appears to be with the third requirement. If, for instance, we seek an "optimal adaptation or a mitigation strategy" by air travel industry to the problems of, say climate change, we are immediately confronted by lack of historical data as well as the difficulty of testing hypotheses concerning environmental benefits, if any, of the proposed courses of action. Consequently, the problem some OR/MS analysts may initially have considered as a relatively routine, bi-objective, trade-off situation now becomes clouded in uncertainty and confounded by the dramatic difference between the time scale of a typical business planning cycle and that of the response time of the "deep layer" of the oceans!

Despite the preceding, cautionary, introduction the thesis advanced in this contribution and explicitly or implicitly supported in most of the other chapters is that challenges to the successful application of OR/MS techniques to environmental decision making are not insurmountable. Indeed, uncertainty needs to be understood and intelligently managed so as to minimize risks. Similarly, time scales' asynchrony between human development processes and the natural processes of the biosphere needs to be acknowledged, quantified, and used as a basis for building a societal consensus concerning the forthcoming tradeoffs that, hopefully, will be made in a well planned manner that is consistent with an enlightened society.

The remainder of this chapter is organized around the discussion of the following main issues.

1. New challenges and pitfalls to OR/MS applications.
2. The sources of uncertainty in environmental modeling.

3. Stochastic reasoning for some fundamental issues.
4. Different ways to deal with uncertainty: stochastic control and stochastic programming, statistical analysis and statistical emulation, robust optimization.

1.2 New challenges and pitfalls to OR/MS applications to EDM

In this section we present Environmental Decision Making (EDM) and highlight some of the difficulties that have to be overcome when applying OR/MS method to this new domain of application. We give here a list of the main difficulties that we have identified:

- Interactions between physical, biological, economic and technological systems.
- Choice of performance criteria (e.g., public or private welfare, or a mixture of these)
- Susceptibility of extreme events
- Time scales (short to very long)
- Memory effects
- Limitation of statistical analysis
- Danger of inaction for viability
- Ethics of uncertainty and intergenerational equity.

1.2.1 From natural resource management to EDM

Environmental Decision Making (EDM) offers new challenges to OR/MS. Indeed, environmental management is a socially important domain and the situation could be compared to the one, in the early 1940's, at the beginning of modern OR era. At that time the challenge was to help solve the huge logistical problems of war operations around the globe, or to help design better antisubmarine or anti-aircraft weapons (see (59)) . As mentioned in the Introduction, the methods of modern OR developed since WW2 have used powerful mathematical tools, in particular those related to convex analysis to produce efficient decision support tools which were then successfully implemented in private or public organizations and corporate management under the generic name of Management Science (MS). Currently the state of the environment and its possible evolution is viewed as a global threat which requires the development of efficient and operational decision support systems adapted for EDM. Controlling local pollution and improving waste management in mega-cities, managing scarce water resources, controlling ocean pollution, and, of course, mitigating anthropogenic climate change are the big challenges of this century. These are also new challenges to decision analysis which are as encompassing and urgent as the ones of WW2. We believe that OR/MS can address them by adapting its current techniques or by developing radically new ones, using again some recent developments in applied mathematics, in particular those related to the modeling of earth systems and those dealing with uncertainty in optimization.

The development of OR/MS applications to deal with decision problems involving the rational use of natural resources is not a recent phenomenon. In 1781, the French mathematician Gaspard Monge defined the problem of "Déblais & Remblais" (or the moving of earth mass with the least possible amount of work), having in mind some applications to military engineering (building defense walls). This problem is often considered as one of the very early attempts to apply mathematical reasoning to logistics and it was used by Kantorovich in 1942 for one of the first applications of linear programming. Moving earth efficiently would be considered today as an environmental management problem. Since the early days of modern OR/MS, the applications to energy management have been numerous and ever growing. This is a domain which is indeed closely related to environmental management, in particular when one is dealing with hydro systems. The efficient exploitation of water systems involves an environmental system, typically a river basin, which is modeled and its management is optimized using the techniques of OR/MS. However it is only recently that environmental constraints or objectives have been explicitly introduced in decision models for private or public organizations. The great debates concerning the management of air quality or waste in urban communities, and more recently the international negotiations concerning climate policy have triggered the development of an ensemble of decision support systems for EDM using the methods of OR/MS. In particular E^3 models which deal with the three dimensions of energy, economics and the environment have been developed in the realm of activity analysis models over the last few decades.

1.2.2 Cost-effectiveness vs cost-benefit analysis

The first challenge posed by EDM is to formulate models permitting an assessment of environmental policies. Environmental impacts of human activities often arise in the form of a deteriorating "free good", like air or water quality, climate, etc. In order to integrate the environmental dimension in the decision making of firms or public organizations we must, in one way or another, define a cost for environmental degradation or a price for environmental quality. In economic terms this is equivalent to defining a surrogate market for the environmental goods. Optimization models can be used to do that. Economists distinguish two main approaches, called *cost-effectiveness* and *cost-benefit* analysis, respectively. To illustrate these let us consider the problem of assessing climate policies.

In a cost-effectiveness approach, for example, one would define a constraint on the total emissions of greenhouse gases (GHG) that would be compatible with maintaining climate change within tolerable limits. For instance, the official goal of the climate policy in the EU (in 2008) was to limit the global average temperature increase to 2 ^{o}C, considering that a higher temperature increase would cause irreparable damage to ecosystems and to the economy. To compare climate policies one could then try to compute their relative costs with respect to attaining that goal[1]. In this approach the difficulty lies in the correct modelling of the environmental constraint. For example, to know if an emission program will satisfy the goal of 2 ^{o}C, one must use a climate model that is an imperfect description of the state of nature. Therefore, even if the problem seemed to be well posed, it remains plagued with an important risk; in this particular case it would be the risk of not reaching the goal.

Consider now the cost-benefit approach. It is well illustrated, in the climate change context, by the DICE family of models developed by Nordhaus, in particular by the original DICE94 model (see (20)). In that approach an integrated economic model is proposed where both the cost of abatement and the benefits of reducing climate change are combined in the evaluation of the utility function of a representative decision maker (in that case it is the consumer in the economy). This elegant integrated approach also suffers from many pitfalls that are mainly related to uncertainty and imperfect knowledge. The evolution of climate is a random process, the impact of climate change on economic production is also very uncertain. On top of that, since the change in climate is a process that will extend over decades or even centuries, the utility function of the decision maker should include the welfare of both the constituency of the current generation, and also that of the forthcoming generations. There is therefore a question of inter-generational equity and the attitude of current decision makers toward this equity issue is uncertain.

1.2.3 Activity analysis models and uncertainty

The integration of environmental constraints into energy models generally follows the cost-effectiveness paradigm. In the late 70's as a consequence of the first oil crisis and the creation of the IEA[2] several models of the energy system, based on the paradigm of linear activity analysis, have been developed to assess the new technologies and energy forms that could be used to replace oil and oil-based technologies in a perspective of a durable shortage. A few years later the shortage of oil was less an urgent problem, but the global environmental impact of energy systems became an important concern.

The bottom-up E^3 models integrate within a large scale linear programming formulation, a technology rich description of energy supply, a representation of the emissions of the main atmospheric pollutants and GHGs, a representation of the adaptation of the demand for energy services to the energy prices (price elasticity of demands). Among the most successful models in that class one may cite MARKAL, developed by the ETSAP[3] consortium under the aegis of the IEA and MESSAGE, developed at the IIASA[4]. In its most recent avatars, MARKAL has been succeeded

[1] More precisely one would consider the addition in cost compared with a business as usual situation where no environmental concern would have to be taken into consideration.

[2] International Energy Agency which is run by the OECD.

[3] Energy Technology Systems Analysis Program.

[4] International Institute of Applied Systems Analysis, Laxenburg, Austria.

by TIMES[5] and TIAM[6] which allow the use of stochastic programming to deal with uncertainty, as shown in one chapter of this book[7].

1.2.4 Meta-modeling: interactions between physical, bio-chemical, economic and technological systems

In EDM, one typically has to organize a production or a logistic process so that it supplies the requested service while the environmental impact of these activities is maintained in a tolerable region. The modeling of the logistic part is similar to what has been developed since the early days of OR/MS; the difficulty lies in the representation of environmental impacts, the delimitation of a "tolerable region" and the integration of this concept as a meaningful set of constraints in the EDM. The representation of air quality or climate change dynamics, for example, rely on very complex numerical models which represent atmospheric dynamics and chemistry. The inclusion of this information in an EDM requires the development of what has been called a "meta-model" in (50) and (21) whose authors proposed an EDM for air quality management in urban regions. The problem to solve could be formulated as follows:

> Find the optimal development and use of the energy system to satisfy the demand for energy services in a given urban region (transportation, residential and commercial heat and cooling, industrial heat, electricity usage etc.) which would maintain the air quality at an acceptable level, according to meaningful indicators.

The proposed "meta-model" is combining an activity analysis model describing the energy and technology choices made to provide the needed services in an urban region and an air quality simulation model representing some typical ozone pollution episodes that might occur. The latter are typically caused by the emission of precursor pollutants, like NO_x and $VOCs$ and are generated by these technology choices. The meta-model is set in an optimization framework corresponding to a cost-effectiveness approach. In the rest of this section we outline the main features of this approach.

1.2.4.1 Modeling atmospheric dynamics and chemistry

Consider first the air quality model (AQM). Air quality is the result of a complicated process. Pollution episodes are due to many different factors (e.g., atmospheric dynamics, complex chemistry, generally incomplete knowledge about urban and biogenic emissions and others). Since numerical air quality models are capable of in-

[5] The Integrated MARKAL-EFOM System.

[6] The TIMES Integrated Assessment Model.

[7] M.Labriet, M. Loulou and A. Kanudia, Modeling Uncertainty in a Large scale integrated Energy-Climate Model, this book.

corporating many of these factors, they constitute a reasonable approach to first understanding and, ultimately, controlling air pollution. The processes represented in a typical comprehensive air quality model include the chemistry leading to the formation and destruction of pollutants, the dispersion (transport and diffusion) and the deposition. The inputs of such models are the emissions of harmful pollutants and their precursors, meteorological fields (wind speed and direction, turbulent coefficients, temperature and density), and ground characteristics (topography, land use etc.). The outputs are the concentrations of harmful air pollutants, such as ozone and particulate matter, the deposition of acids on land and water, visibility degradation, and, eventually, the potential exposure of humans to various species of interest. This is summarized in Figure 1.1.

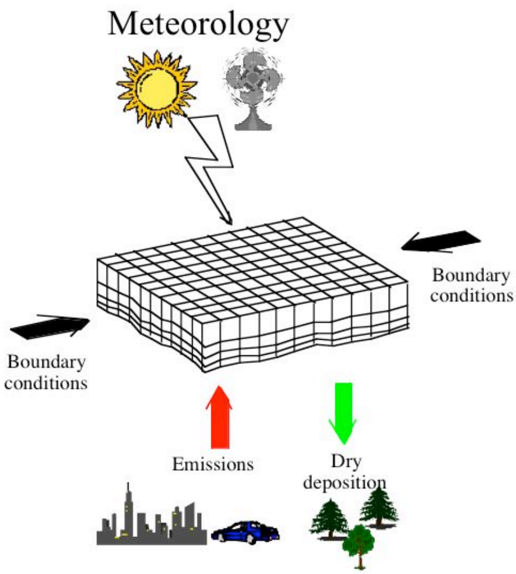

Fig. 1.1 : Input and output of a typical comprehensive air quality model

A typical air quality model is the atmospheric diffusion model found in the California/Carnegie Institute of Technology (CIT) airshed model (82), (80) or the *Transport and Photochemistry Mesoscale Model* (TAPOM) implemented at the Swiss Federal Institute of Technology at Lausanne (EPFL), and at the Joint Research Center of Ispra (JRC-Ispra) (83).

These models solve a mass conservation equation for each pollutant which can be summarized by the distributed parameter system for all species i

$$\frac{\partial c_i}{\partial t} + \nabla \cdot (U c_i) = R_i(T, J, H, \mathbf{c}) + \sum_{j=1}^{3} \frac{\partial}{\partial s_j} (\sum_{\ell=1}^{3} K_{j\ell}(s) \frac{\partial c_i}{\partial s_\ell}) + E_i, \tag{1.1}$$

where c_i is the mean concentration of species i, $\mathbf{c}$ denotes the aggregate concentration vector of all species[8], U is the wind velocity vector, $\nabla \cdot (Uc_i)$ denotes the divergence in the space variables $s = (s_1, s_2, s_3)$, $\bar{K}(s) = (K_{j\ell}(s); j, \ell = 1,2,3)$ is the second order turbulent diffusivity tensor, $R_i(\cdot)$ is the rate of reaction of specie i due to chemistry, T the temperature, J a function defining the solar flux, H the humidity, and the vector of concentrations c. E_i is the elevated source rate of emissions of species i, and t is the time.

These dynamic equations are complemented by the boundary conditions that describe the influence of the rest of the world on the domain $S \subset \mathbb{R}^3$ under consideration. These boundary conditions[9] are expressed as

$$Uc_i - \bar{K}\nabla c_i = Uc_i^b, \quad s_1 \text{ or } s_2 = 0, \quad \text{(horizontal inflow)} \tag{1.2}$$

$$-\nabla c_i = 0, \quad s_1 \text{ or } s_2 = s_{max}, \quad \text{(horizontal outflow)} \tag{1.3}$$

$$v_i^g c_i - K_{33}\frac{\partial c_i}{\partial s_3} = E_i^g, \quad s_3 = 0, \quad \text{(ground emissions dispersion)} \tag{1.4}$$

$$-\frac{\partial c_i}{\partial s_3} = 0, \quad s_3 = H, \quad \text{(top of model domain)} \tag{1.5}$$

where v_i^g is the dry deposition velocity for species i and E_i^g is the ground level emission rate.

1.2.4.2 Air Quality Indicators.

Air quality in a region S depends on the evolution of the concentrations of some chemicals – typically refereed to as "species" – in space and time during critical episodes. We shall focus on ozone (O_3) in this application. Ozone concentrations are functions of the emission schedule of all species, as indicated in the system (1.1-1.5). We summarize this dependence in the notation $c(t,s;\bar{E}^g,\bar{E})$, $t \in [0,\Upsilon]$, $s \in S$ for the concentration of ozone at location s at time t of a critical episode. Here we use the notation $\bar{E}^g = (E_i^g : \text{all species } i)$, $\bar{E} = (E_i : \text{all species } i)$.

To gauge air quality one defines some performance criteria, or indices, based on the concentrations of ozone during representative critical episodes[10]. There are several possibilities to define such criteria. A simple way is to measure the maximum concentration of ozone over the region S during a weather episode of duration $\Upsilon > 0$. That is, we define

$$P^{max}(\bar{E}^g,\bar{E}) = \max_{(t,s)\in[0,\Upsilon]\times S} c(t,s;\bar{E}^g,\bar{E}). \tag{1.6}$$

Another option for air quality performance indices would be to select a threshold level for each specie, say $\theta(s), s \in S$, and consider the average over the threshold

[8] Typically TAPOM considers more than 60 species in its chemistry module

[9] The horizontal inflow and outflow conditions assume that the wind is diagonal across the domain volume, originating from $s_1 = s_2 = 0$ and exiting the domain at $s_1 = s_2 = s_{max}$.

[10] Typically an episode has a duration of a few days with characteristic weather conditions.

(AOT) criterion defined by

$$P^{AOT}(\bar{E}^g, \bar{E}) = \frac{1}{\Upsilon \times |S|} \int_0^{\Upsilon} \int_S \max(0, (c(t,s;\bar{E}^g,\bar{E}) - \theta(s)))\, ds\, dt \tag{1.7}$$

in which $|S|$ denotes the volume of the region S. This criterion only considers the regions in which the concentration exceeds the threshold level. Still a third choice could be the mean square AOT. That is,

$$P^{SAOT}(\bar{E}^g, \bar{E}) = \frac{1}{\Upsilon \times |S|} \int_0^{\Upsilon} \int_S |\max(0, (c(t,s;\bar{E}^g,\bar{E}) - \theta(s)))|^2\, ds\, dt. \tag{1.8}$$

We observe that all of the above air quality indices have the form

$$P^*(\bar{E}^g, \bar{E}) = \mathscr{P}(c(\cdot,\cdot;\bar{E}^g,\bar{E})) \tag{1.9}$$

in which $\mathscr{P}$ is a real-valued, convex functional defined on the space of functions that contains the solutions of the dynamical system, that is the distribution over time and space of the concentrations of species. We further notice that in the case when the dynamics described by (1.1) is linear (i.e., when the chemical reactions R are linear in $\mathbf{c}$) then the air quality indices $P^*(\cdot,\cdot)$ ($* = \max$, AOT, or SAOT) are convex functionals of the emission rates $(\bar{E}^g, \bar{E})$.

1.2.4.3 Techno-economic model

Now consider the Techno-economic model (TEM) which describes the logistical aspect of this EDM. Activity analysis models have been developed to assess global long-term energy and environmental policies at national and regional levels. The MARKAL model (1), (21) , which will be used in this study, is an archetypal TEM that has been implemented in more than 16 countries, and in the context of urban environment management in Sweden (85) and Switzerland (42). In these models, the energy system is represented through a network of technologies extracting, transforming and using energy carriers to provide the energy services needed by the economy. The technologies used to satisfy these energy services are the main emitters of primary pollutants. More precisely there is a close relationship between the modeling of energy flows in a production economy and the tracking of pollutant emissions, since they are both determined by the choice of technologies made to satisfy the demand for different products and services. In activity analysis models, economic activities are represented as resources transformers. Each activity is thus characterised by its level of use and the technical coefficients that describe the resources input and output characterising the technology involved in the activity. An activity may bear a cost or contribute some profit (or more generally some utility). Using the appropriate optimization formulation, activity analysis models can be imbedded in different types of market structures (competitive, oligopolistic, and monopolistic).

There have been many successful applications of the above paradigm in the energy sector, starting with the representation of oil refineries, and more recently the representation of the interactions between the energy sector and the rest of the economy (69). These models are particularly well suited for the analysis of environmental management policies and for the design of market based instruments (MBI). As said before, the technologies (activities) are transforming resources and as a byproduct they emit pollutants. A global emission constraint can be imposed on the economic system under consideration. This translates into a higher cost for achieving the production goals of the system.

In brief the structure of the TEM is a mathematical programming model, usually a linear program, that can be written as follows

$$\min g = \gamma x \tag{1.10}$$

$$\text{s.t}$$

$$Ax = a \tag{1.11}$$

$$x \geq 0$$

where x is the vector of activity levels, γ is the vector of economic coefficient (interpreted here as costs). Here A is the matrix of technical coefficients and a is the right hand side of the constraints. Basically, a TEM minimizes an objective function which represents the total discounted system cost. This is the discounted sum over a time horizon (typically 35 to 45 years) of the operation, investment and maintenance cost of all technologies involved in the energy production and usage. The minimization of that function is done subject to four main categories of constraints that express the following principles:

1. an installed capacity (inherited or resulting from investment) is needed to operate a technology;
2. existing capacity is transferred over time periods subject to life duration of equipment;
3. the useful demand has to be satisfied;
4. the energy balance has to be respected (consumption + export = production + import) for each energy form at each time period.

1.2.4.4 Coupling the two types of models

Time-scale issue.

To combine the two approaches (AQM and TEM) we have to deal with the previously mentioned times scales' asynchrony (TSA). This is because techno-economic multi-period model which encompasses a planning horizon of several decades with discrete time steps of five years, while the air quality simulation model has a time horizon of a few days with time steps of usually 15 to 60 minutes. These two time scales have to be made compatible in order to permit a coherent dialogue between the two models.

A way to deal with TSA is to associate an average air quality index with a typical emissions inventory resulting from a technology mix selected by the TEM for each 5 year planning period. The average air quality index is obtained from simulation runs obtained from the AQM over a fixed set of weather episodes. These weather episodes represent the typical meteorological conditions favorable to high air pollution levels (64), (29). Emission control strategies are tested against these selected episodes in order to derive an air quality response that is representative of the average meteorological conditions leading to high levels of pollution. Note that the average air quality indices obtained from these simulations now have a time-scale corresponding to a year. Indeed, we take the statistically relevant weather episodes in a year and we simulate the ozone concentrations resulting from the average daily emission inventory resulting from the activities decided for the TEM.

Therefore a constraint imposed on this average quality index will have a time-scale compatible with the techno-economic model. Indeed there is a considerable latitude in the construction of this average yearly air quality index and in the selection of a sample of weather episodes to be used in simulations. This is a source of uncertainty that will be necessary to handle through sensitivity analyses or some form of robust programming (a concept that will be discussed shortly).

Creating an emission inventory as an input for the AQM

The emissions sources are mostly related to a subset of economic activity sectors. In the TEM, these activities are typically traffic, heating and air conditioning systems and power plants. Let $u_i(k,\alpha,x)$ denote the primary pollutant i emissions level due to the activities in sector α in period k given the decision vector x. Let $f_i(t,s,k,x)$ be the total emissions level of pollutant i at time t at location s in period k. We assume that the distribution in time and space is obtained from the activity pollution level $u_i(k,\alpha,x)$ via an exogenously defined *dynamic emissions map* $\nu(t,s,k,\alpha)$ according to the linear transformation

$$f_i(t,s,k,x) = \sum_{\alpha \in A} \nu(t,s,k,\alpha) u_i(k,\alpha,x). \tag{1.12}$$

The above *dynamic emissions map* converts the global annual emissions for the whole domain into hourly emissions on the spatial mesh of the geographical information system which produces the input for the AQM.

An auxiliary TEM with emission limits

Our aim is to solve a problem where a constraint on air quality is added to the TEM. As shown above, the air quality constraint is complicated and involves simulations done with a detailed numerical model. A much simpler model would be obtained if we could replace the constraint on air quality by a constraint on emission levels for primary pollutants.

For each primary pollutant i, each sector α and each period k, one defines an upper bound vector $U = \{U_i(k,a)\}_{i,k,a}$ where $U_i(k,\alpha)$ is a limit on the total emissions of pollutant i due to activities in sector α, in period k. We can now define the function $h(U)$ as the solution of the following mathematical programming problem:

$$h(U) = \min \gamma x \tag{1.13}$$

$$\text{s.t}$$

$$Ax = a$$

$$u_i(k,\alpha,x) \leq U_i(k,\alpha) \quad k = 1,\ldots,K, \quad \alpha \in A. \tag{1.14}$$

$$x \geq 0.$$

where the constraints are indexed over all primary pollutants i. This mathematical programming problem reduces to an easily solved linear programming problem if one assumes constant emissions rates for the different activities (technologies) entering the model. The function $h(U)$ is thus representing the minimal cost to achieve the program of sectoral emissions of primary pollutants, represented by the upper bounds U.

The Meta-Model as an upper level program.

As we are interested in the air quality resulting from the ozone concentration, we now define a second auxiliary problem, involving an environmental constraint $P(k,U)$ that is computed via the AQM, for the emissions level corresponding to U at period k. This leads us to introduce a nonlinear program that can be written as:

$$\min \quad h(U) \tag{1.15}$$

$$\text{s.t}$$

$$P(k,U) \leq P_{\max}, \tag{1.16}$$

where $h(U)$ has been defined in Eq. (1.13) and the function $P(k,U)$ is typically representing an AOT_{60} or peak ozone index calculated for typical episodes at the successive periods k of the planning horizon. The whole difficulty of the method resides now in the identification of the functions $h(U)$ and $P(k,U)$.

We call the program (1.15)-(1.16) a "Meta-Model" because both parts, the objective function in (1.15) and the constraints in (1.16) are obtained from complex sub-models which are run separately in their own time and geographical scale, either as optimization or numerical simulation tools.

1.2.4.5 How to solve the Meta-Model

In (21) it was shown how solving the program (1.15)-(1.16) could be approached with an oracle-based optimization method (see (43), (10)). The Analytic Center Cutting Plane method is implemented to send queries either to the TEM with emissions constraints to obtain "optimality cuts" or to the AQM to obtain "feasibility cuts" which delineate a shrinking localization set in the U space where the optimum must be found.

In (50), for the same problem, a different approach was used. In particular, a statistical emulation of the response of the complex AQM and an air quality index to an emission program were used to build surrogate constraints that can be tackled directly in the program (1.15)-(1.16).[11]

This rather detailed description of a model of air quality management has permitted us to show some of the critical difficulties of combining techno-economic models and earth science models. We have also seen that recent advances in optimization methods, in particular the oracle-based optimization techniques, provide a way to deal with meta-models where some constraints are obtained from running complex numerical simulation models. Indeed, these simulations are approximate description of the chemical or physical processes that are involved and, therefore should include in the approach an explicit consideration of the possible errors, or more precisely, of the confidence intervals of the indicators obtained.

1.2.4.6 Extension to other EDMs and the possible role of robust optimization

The Meta-Modeling approach described above for a problem of air quality management has also been applied to build an integrated assessment model for global climate policies. In particular, (13), (30) develop a meta-model composed of an optimal economic growth model on one side and a general circulation climate model of intermediate complexity on the other side. In these applications, also reported in (11), the coupling of the optimal economic growth model and the climate 3-D circulation model was also achieved through the use of ACCPM, an oracle based convex optimization method.

A very interesting and promising approach, to deal with the uncertainty which is inherent in these complex simulations of environmental systems, is to build statistical emulations of the response of climate system to some variations in key parameters, using, for example Kriging techniques ((63), (68), (79)).

We refer to (24) for a description of the use of statistical emulation in climate models and to (81) for the implementation of robust optimization in meta-models obtained from complex computer simulations. For robust optimization, which is presented in one chapter of this book[12] we refer to (15) or (17)). It is our contention that robust optimization allied to statistical emulation of complex environmental models will play an important role in the development and implementation of meta-models for EDM, in particular in the domain of air quality management and climate policy assessment.

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[11] The interested reader can find the implementation and the results obtained through these approaches in (50).

[12] Robust Optimization for Energy-Environment Planning, F. Babonneau, J.-P. Vial, R. Apparigliato. This book.