Decision Support Systems for Environmental Problems at Different Scales*

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Contents

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Summary

The article presents three Decision Support Systems (DSS) applied to complex problems of natural environment management of different scale, namely regional water quality management, land use planning, and European air quality management. These problems are not only of different scale but the way the described DSSs are used are also very different. Nevertheless, these three applications have a number a common characteristics of the applied methodological background of multi-objective decision support and its applications to environmental decision-making problems described in article 4.20.4.1.

The article provides insights to these problems which might be interesting to specialists working in the respective fields. It also illustrates various problems related to the development and use of DSSs, which are interested to both users and developers of DSSs.

Glossary

AEZ: Agro-Ecological Zone. The methodology developed by the FAO to assist in finding rational solutions to various problems of land resources appraisal for planning sustainable agricultural development. This involves linking land use options with other development goals in such areas as food production, food self-sufficiency, cash crop requirements, population supporting capacity, issues of soil fertility constraints, soil erosion risks, and land degradation.

AEZWIN. DSS for Land Use Planning based on the AEZ methodology.

DM: Decision Maker. A person, who is responsible for making actual decision. Often this term is used also for experts, advisors, analysts, even researchers, in other words anybody, who uses analytical methods for decision analysis.

DSS: Decision Support System. Specialized software used for analysis of models aimed at supporting decision-making process.

GIS: Geographic Information System. Specialized software used for handling (typically geographic) data and presenting in graphical form various types of data analysis.

GUI: Graphical User Interface. Conventional name and software tools for providing user friendly interface to computer programs.

HDF: The Hierarchical Data Format. Public domain software for platform independent software for storage and handling of huge amount of data.

ISAAP: Interactive Specification and Analysis of Aspiration-based Preferences. Methodology and software for MCMA (described in article 4.20.4.1).

LGP: Length of Growing Period. Method of quantification of moisture conditions. Reference LGP is defined as duration (in days) of the period when temperature permits crop growth and soil moisture supply exceeds half the potential evapotranspiration; it includes the time required to evapotranspire up to 100 mm of soil moisture storage.

LP: Linear Programming. the type of mathematical programming problem, in which the goal function and all constraints are linear.

LP-DIT: Linear Programming Data Interchange Tool. A C++ library for efficient handling data that need to be exchanged between software used for the LP model generation, optimization, and analysis.

LP-MULTI: Linear Programming Multi Criteria Model Analysis Tools., A C++ library for supporting multicriteria model analysis by providing functionality needed for generating parametric optimization problems that provide Pareto solutions having properties that correspond to the user preferences.

LPG: Length of Growing Period. The element of the AEZ approach, which is defined as the period (in days) during the year when water availability and prevailing temperature can sustain crop growth.

LUT: Land Utilization Types. Technical specifications (including management) within a socioeconomic setting under which a specific crop is grown have been defined as Crop suitability assessments, in essence, are based on matching of crop specific adaptability characteristics and crop/LUT ecological requirements with attributes of the components of individual land units.

MCMA: Multi-Criteria Model Analysis. Methodology and corresponding software tools aimed at supporting decision-making by developing and analysis of mathematical models. The analysis supports examination of these parts of Pareto-set that best correspond to preferences of the DM, which are interactively specified by a sequence of selections of aspiration and reservation levels.

MIP: Mixed Integer Problem. An LP problem, in which a subset of variables can take only integer values.

MWWTP: Municipal Waste Water Treatment Plant.

NLP: Nonlinear Programming. the type of mathematical programming problem, in which the goal function and/or some of constraints are nonlinear.

OR: Operations Research (a.k.a. Operational Research). A set of quantitative methods and tools developed to assist analysts and decision-makers in designing, analyzing, and improving performance or operation of systems.

PWL: Piece-Wise Linear Function. A continuous function that is linear except of a finite set of points (where its slope changes). Often used for approximation of non-linear functions in order to make it possible to deal with LP or MIP problem instead of NLP problem.

RAINS. DSSs for effect-focused analysis of policy options for air quality management in Europe and in Asia.

RWQM. DSS for Regional Water Quality Management developed for the Nitra River basin in Slovakia.

1 Introduction

There is a vast diversity of natural environment problems that need to be analyzed for providing sensible help in better understanding these problems and in identification and/or examination of various actions that can result in desired effects. These problems have different characteristics in several dimensions:

- The type of the problem (its nature, scale, required accuracy, time horizon).
- The nature of the decision process.
- The needs for the decision support.

Every DSS, even for same type of problem, needs to be different, in order to correspond well to the needs of the corresponding decision making process. For example, DSSs for a very specific problem of controlling a system of water reservoirs are using very different models, each of them being relevant to a particular water system and the requirement analysis for the corresponding DSS.

Given such a diversity of problems and the corresponding DSSs, it is not possible to even summarize a representative sample of decision support systems for environmental problems in an article. Moreover, short summaries of DSSs would neither be useful for users nor for developers of DSSs. Therefore, this article instead of an oversimplified summary of a larger sample of DSSs presents three DSSs that have been developed for complex environmental problems of different scale. Enough details of each DSS is provided to illustrate several key issues that are relevant to decision support of any complex problem.

The truth is that there are no simple ways of rational solving any complex problem (article 4.20.4.1 provides arguments for this statements). Unfortunately, there are many books and software tools that advertise simple approaches applicable to almost any decision problem. The role of this article is to illustrate the complexity of the development and use of DSSs, which is needed for understanding the possibilities and limitations of model-based decision support by both users and developers of DSSs. A real understanding of these issues requires a more detailed presentation of each problem and the corresponding DSS, and a discussion of several key issues that are of a more general interest for users and developers of DSSs, and are relevant to various (also very different) decision problems.

The three problems and corresponding DSS presented in this article are:

- RWQM, Regional Water Quality Management, applied to the Nitra River basin in Slovakia,
- AEZWIN, Land Use Planning DSS, being applied in several countries in Africa and Asia,

- RAINS, system of models used for analysis of cost-effective policies aimed at improving European air quality that is used for supporting intergovernmental negotiations in Europe.

RWQM uses a rather small and simple MIP type model, but it shows how the classical water quality modeling approaches had to be modified in order to provide the needed support for regional water quality management. AEZWIN uses large-scale LP type models that are composed by users based on a sophisticated system of programs developed for various elements of land use planning. An interesting common feature of RWQM and AEZWIN is that both of them have the same structure of the DSS, and use common modular software tools.

The third DSS, RAINS, uses a complex NLP model, and its implementation and use demonstrate several methodological and technical issues that are relevant to any DSS aimed at rational supporting decision analysis and support for complex environmental problems.

2 Regional Water Quality Management

2.1 The Problem

The scope of the problem considered here is a river basin, or a region composed of several basins, in which untreated or inadequately treated municipal and industrial wastewater emissions should be reduced in order to improve ambient water quality. At each discharge point, one technology out of a set of possible technologies can be implemented in order to meet the desired water quality goals in the region. In this selection of technologies, or strategy development, decision makers must evaluate the trade-offs among a large number of alternatives based on, among other things, effluent and/or ambient water quality standards and goals; capital investment and annual operating costs; and the principles of equity, uniformity, and efficiency.

The traditional approach, as used in developed countries, is based on the selection of generally uniform effluent standards which, in turn, are often based on given technologies. This is the well-known policy of "best available technology". Under such an approach, both ambient water quality standards and budget requirements are considered only indirectly. The following two conditions must be met:

- If effluent standards are defined stringently enough, then ambient water quality will be "good enough".
- Enough money (or willingness to pay) is available to achieve "safe" environmental conditions (without raising the issues of how safe they are and how much should be paid for them).

Unfortunately, such a robust and uniform policy may not be an affordable option for countries and or regions with tight financial resources for which there is a competition of various social needs (like health-care, restructuring of economy, securing pension-system). In such cases various trade-offs between investment and operating costs on one side, and the resulting water quality have to be examined.

2.2 Model Formulation

The model outlined here has been developed for the Nitra River Basin in Slovakia. The river water quality model applied to this case study is quite simple but it was adequate for this application. It is based on the concept of linear transfer coefficients, which are derived from first-order rate equations and the (linear) extended Streeter-Phelps model incorporating dissolved oxygen (DO), carbonaceous oxygen demand, and nitrogenous oxygen demand. Steady-state hydraulics are considered, based on a "critical design flow". Complete mixing downstream of each emission and tributary confluence and uniform flow along the river between these points are assumed.

For the Nitra River basin a set of locations or points is defined, each of which is characterized by at least one of the following:

- An emission point, at which wastewater is discharged. The amount of discharged pollutants depends on the treatment technology chosen in the decision process.
- An abstraction point, at which water is withdrawn from the river. At these points one can consider a "negative" emission, whereby the constituent loads are reduced proportionally to the reduction in river flow.
- A monitoring point, at which concentrations of water quality constituents are compared to given standards.
- A confluence point, which represents the junction of two rivers. Constituent loads are the sum of loads from both rivers.
- A weir point, where DO is added to the river due to the increase in turbulence downstream of a weir or small dam.
- Other points where hydraulic and hydrologic data exist and therefore new travel times and transfer coefficients can be calculated. The loads of constituents do not change at these points.

Each of these points is called a node, denoted by the subscript j. At every node the equations that define water quality (i.e., mass balances of constituents) are given. Overall, four water quality constituents (of which three are real state variables) are considered. In the equations the subscript l is used to denote the respective constituents:

1. DO (dissolved oxygen).
2. CBOD (carbonaceous biochemical oxygen demand).
3. NBOD (nitrogenous biochemical oxygen demand), which is calculated directly from NH_4, assuming that all of the nitrogen consumes oxygen.
4. NH_4 (ammonia).

The decision variables are the treatment technologies to be implemented at the nodes where wastewater emissions occur. These are denoted by x_{jn}, where n is the technology choice at emission node j. These technology options include the option of no treatment (with raw waste concentrations and no cost), as well as the option of maintaining the existing technology (with the operating cost but no investment cost). Only one technology can be implemented at each node, and this logical condition is represented by the following constraint:

$$\sum_{n \in N(j)} x_{jn} = 1 \qquad x_{jn} \in \{0, 1\}, \qquad j \in E, \tag{1}$$

where $N(j)$ is the set of technologies considered for emission node j, and E is the set of nodes where emissions occur.

Auxiliary variables (defined for easier handling of the model and interpreting results from its analysis) in the model include variables related to water quality and variables related to cost. Focusing on the first set, we consider the water quality constituent concentrations resulting from the implementation of the n-th technology at the j-th emission node, em_{jnl} (mg/l). The emission load of the l-th constituent at the j-th node is denoted by e_{jl} (g/s) and is defined by:

$$e_{jl} = q_j \sum_{n \in N(j)} x_{jn} em_{jnl} \qquad l \in \{1,3\}, \qquad j \in E, \tag{2}$$

where q_j (m^3/s) is the waste flow rate. Note that due to equation (1), for each j exactly one out of $N(j)$ binary variables, x_{jn}, will be equal to one while the others will be equal to zero.

Next, the ambient constituent concentrations must be defined. The ambient concentration of DO (mg/l), typically the most important water quality indicator, is affected by several constituents, as well as by its saturation level. The DO concentration (denoted for the j-th node by aq_{j0}) is given by the extended Streeter-Phelps model, analytically integrated stretch by stretch as follows:

$$\begin{aligned} aq_{j0} &= [1/(Q_j + W_j)] * \Big(\sum_{i \in I(j)} \big(b_{i0} + Q_i * (DOsat_j \\ &\qquad - TC_{i0}(DOsat_i - aq_{i0}) - \sum_{l \in \{1,2,4\}} TCp_{il} aq_{il})\big) + ioxy_j \Big). \end{aligned} \tag{3}$$

In this, the set $I(j)$ is composed of indices of nodes located immediately upstream of the j-th node (this set contains two elements for confluence nodes and one element otherwise), aq_{il} (mg/l) are the upstream concentrations of oxygen-demanding constituents (CBOD, NBOD, SOD), and the remaining right-hand side quantities are given (or computed from given data): $DOsat_j$ (mg/l) is DO saturation level at the j-th node, TC_{i0} is a dimensionless transfer coefficient for the DO deficit (defined as $DOsat_i - aq_{i0}$), TCp_{il} are dimensionless transfer coefficients for CBOD, NBOD, and SOD, respectively; Q_j (m^3/s) is the river flow just below node j, W_j (m^3/s) is the withdrawal occurring at the j-th node, b_{i0} (g/s) is the background level of DO entering the river upstream of node j, and $ioxy_j$ (g/s) is the DO emission at node j. Thus, the summation term represents the DO coming from upstream, which consists of oxygen transfer from the upstream node(s) as well as "background" oxygen from groundwater infiltration flow (for simplicity, we assume that background loads of other constituents do not affect DO until the next reach downstream). This upstream mass is then mixed with the DO load from the wastewater emission, $ioxy_j$, hence the division by the total flow $Q_j + W_j$. Calculation of the transfer coefficients has been done on the basis of the Streeter-Phelps equations (exponential terms expressing transformations due to decay and reaeration over the travel time).

Ambient concentrations of the other constituents such as CBOD and NBOD (denoted by aq_{jl}) are defined by:

$$aq_{jl} = \Big(\sum_{i \in I(j)} (b_{il} + TC_{il} aq_{il} Q_i) + e_{jl} \Big) / (Q_j + W_j) \qquad l \in \{1,3\}, \tag{4}$$

where, as in equation (3), the first term in this equation represents the background load of constituent l which accounts for nonpoint or noncontrollable source pollution, the second term represents the load of the constituent l arriving from the upstream reach(es), and the third term represents the emission load of constituent l at node j. Cross-impact transfer coefficients, TCp_{il}, are not included here since these constituents are not affected by the DO level unless anoxic conditions exist.

Based on these ambient constituent concentrations, the following three indices of water quality are defined:

$$DO = \min_{j \in M} (aq_{j0}), \tag{5}$$

$$BOD = \max_{j \in M}(aq_{j1}), \tag{6}$$

$$NH_4 = \max_{j \in M}(aq_{j3}), \tag{7}$$

where aq_{jl} (defined by (3) or (4)) is the ambient concentration of the l-th constituent at node j, and set M contains indices of monitoring nodes.

Finally, several cost variables are defined in the model. Corresponding to the n-th treatment technology implemented at the j-th node are an investment cost IC_{jn} and an operation and maintenance cost OMC_{jn}. The investment costs Inv_j for the j-th emission point are defined by:

$$Inv_j = \sum_{n \in N(j)} x_{jn} IC_{jn} \qquad j \in E. \tag{8}$$

The operation and maintenance costs OM_j are given by:

$$OM_j = \sum_{n \in N(j)} x_{jn} OMC_{jn} \qquad j \in E. \tag{9}$$

The total annual cost (TAC) of each technology is determined from the two previous cost components as:

$$TAC_j = [r(r+1)^m/((r+1)^m - 1)]Inv_j + OM_j \qquad j \in E, \tag{10}$$

where r is a given discount rate, m is a given capital recovery period, and the multiplier of the first term is called the uniform series capital recovery factor. One may also want to consider the sums of respective costs for the whole region:

$$Tot\_Inv = \sum_{j \in E} Inv_j, \tag{11}$$

$$Tot\_OM = \sum_{j \in E} OM_j \tag{12}$$

$$Tot\_TAC = \sum_{j \in E} TAC_j. \tag{13}$$

The treatment alternatives at various MWWTPs, along with the corresponding effluent concentrations and costs, have been designed in separate field studies for each MWWTP. Each alternative was developed on the basis of technological calculations using physical, biological, and chemical processes, as well as their combination. These lead to well-known methods such as mechanical–biological treatment with or without denitrification, mechanical–biological treatment with chemical addition to remove phosphorus and/or to increase the capacity of the plant, biological–chemical treatment with denitrification, and so forth. The alternatives identified also depend on whether upgrading an existing facility or constructing a new plant is considered a viable option.

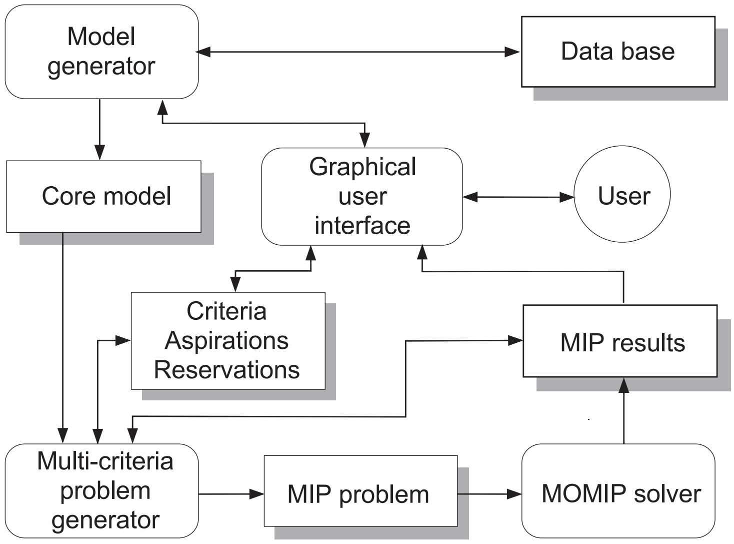

Figure 1: The structure of a Decision Support System for the water quality management in the Nitra River River basin.

2.3 Structure of the DSS

The general structure of a DSS discussed in article 4.20.4.1 is only an outline. In practical applications, specific structures might differ in many details. In order to illustrate the advantages of a modular structure of a DSS, we summarize here the architecture of the DSS developed and applied to the Nitra case study.

The structure of the DSS used for the Nitra River basin case study is illustrated in Figure 1. The implementation of this DSS is based on modular and portable software tools that support the following functions of a DSS:

- A graphical user interface (GUI) for handling all the interaction with the user. It is linked with the MCMA package which handles the definitions of criteria, aspiration, and reservation levels, as well as the generation of a multi-criteria problem. The MCMA includes ISAAP (Interactive Specification and Analysis of Aspiration-based Preferences, outlined in article 4.20.4.1), that is directly linked with LP-MULTI tool, which in turn is a modular tool for handling multi-criteria problems using the approach outlined also in article 4.20.4.1. ISAAP allows for interactive specification of aspiration and reservation levels (and, optionally, for using piece-wise linear membership functions for criteria values between those levels), as well as the changing of a criterion's status. The resulting parametric mixed-integer programming (MIP) problem is based on the core (substantive) model and the aspiration and reservation levels (or on a more precise specification of preferences supported by ISAAP) that represent the current preferential structure of a DM.
- A problem-specific model generator for generating the core model (defined by the relations (1) through (13) generated for each relevant node) that relates wastewater emissions, treatment decisions, and the resulting ambient water quality. It is important to stress again that the core model includes only physical and logical relations, and not the preferential structure of the DM.
- A modular solver for mixed integer programming problems, MOMIP.
- A data interchange tool LP-DIT that provides an easy and efficient way for defining and modifying MIP problems, as well as interchanging of data between a problem generator,

a solver, and software modules that serve for problem modification and solution analysis.

The structure of the DSS for land-use planning presented in the next section is the same as that presented above. Only one substantial module, namely, another problem-specific model generator for generating the land-use core model, had to be developed. Another difference is of a technical nature. The resulting optimization model is of the LP type, therefore another solver (HOPDM, which is an efficient interior point LP solver) is automatically selected by the DSS instead of the MOMIP solver.

Each of these two DSSs has problem-specific utilities for analysis of the results, but the kernel of the software for both DSSs is the same. Additionally, both DSSs can be used on two hardware and operating system platforms, namely, Sun Solaris and MS-Windows (versions for other platforms can be easily developed, because the software is developed with standard C++ and uses a portable library for the GUI).

2.4 Experiences from using RWQM

The results from the Nitra River basin study demonstrate the value of multi-criteria model analysis. Significant trade-offs between the water quality criteria (DO and NH_4 concentrations) and between the cost criteria (investment and total annualized costs) have been identified and evaluated. MCMA helps decision makers to understand these trade-offs when formulating water quality goals, setting budgets, and implementing treatment strategies for the region.

The main advantage of MCMA is the flexibility provided in model examination. Using the MCMA method, one can easily analyze different “regions” of Pareto-efficient solutions. The selection of these regions depends on the preferences of the user expressed in terms of objective (criterion) values, and can be easily changed during the model analysis upon learning about possible efficient solutions. Because the constraints imposed on objectives in traditional single-objective optimization approach are replaced by the selection of aspiration and reservation levels, the risk of infeasibility in model analysis is eliminated, many problems related to sensitivity analysis are reduced, and a larger number of interesting solutions can easily be found. Conversely, the use of MCMA requires an additional methodological background, some experience in interacting with a computer, and more time for the detailed analysis of a larger set of solutions worthy of examination.

These experiences can easily be extended to other types of water management problems because there is a long tradition of using OR methods for various types of water models therefore modeling experience and many models already exist. Applications of MCMA to water management problems used to be limited mainly by a lack of modular tools that facilitate multi-criteria model analysis, which resulted in applications of more traditional methods of model development and analysis. However, the development of the methodology and modular software tools for multicriteria model analysis make it easier to apply advanced decision support methods to other case studies of various problems of water management.

3 Land Use Planning

3.1 The Problem

The increasing human population in developing countries is exerting pressure on finite land resources, frequently causing overexploitation and land degradation. Sectoral and single-objective approaches to planning for the alleviation of this situation have often not been effective, and an integrated approach is required that involves all stakeholders, accommodates the qualities and limitations of each land unit, and produces viable land use options.

Current land use issues in the rural and peri-urban spheres frequently involve environmental versus developmental conflicts. For instance, whether it is preferable to use scarce resources to rehabilitate degraded land or to improve prime agricultural land; whether smallholder settlements will be able to support the expanding population better than large-scale mechanized farming; the threat from encroachment of urban development on to high quality agricultural land, and the most appropriate use of scarce water resources.

In its 1998 revision, the UN medium variant population projection indicates an increase of the world's population to about 8.9 billion by the year 2050, with a possible range between 7.3 and 10.7 billion. Most experts agree that with full and adequate application of modern agricultural technology, the world's land resources could provide sufficient food, fiber, animal feed, biofuel, and timber for such a population increase. In practice, however, there will most likely be acute land shortages in many countries, especially in developing ones.

In response to these articulated needs, the FAO developed a framework of principles and procedures that provide guidance to land use planners, and that can be adapted to local needs. The Guidelines provide an overview of the planning process in ten steps. These are not seen as a recipe for the planning process but rather as a flexible guide and starting point for more detailed local or national procedures. The implementation of these ten steps, although presented here in sequence, are considered to result in an iterative process:

1. Establish goals and ground rules for planning.
2. Prepare an outline of the plan.
3. Identify and structure the problems and opportunities.
4. Identify and design alternative and promising land use types.
5. Evaluate land suitability.
6. Appraise – for alternative land use types – the environmental, economic, and social impacts.
7. Choose the best achievable land use.
8. Plan for change; draw up a final version of the land use plan.
9. Implement the plan (e.g., by using agricultural consulting and tax incentives).
10. Review and revise the plan in view of implementation experience, stakeholders response, or new goals.

The powerful software tools discussed in this section are intended to support planners in the core tasks of planning, i.e., in the execution of steps 5 to 7.

While some of the land use planning objectives are synergetic, several of them are intrinsically antagonistic. Therefore, it is important to understand what level of attainment of the key objectives can be reached, and what the trade-off between them is. Therefore the FAO promotes the integrated planning and management of land resources in cooperation with regional institutions and individual countries as well as land users. Reaching a consensus on land use should be a major objective in the conceptualization of decision support systems (DSSs) for sustainable land use.

Feasible "real world" solutions are compromise solutions, resulting from a trade-off between various conflicting objectives, thus not maximizing single objectives, but finding an efficient and acceptable balance between the requirements of the stakeholders in the land and resources availability. Different kinds of objectives may need to be included, expressing not only economic values of land products but also addressing goals that cannot always be expressed in monetary terms – such as biodiversity, people's preferences, equity, or minimizing risk and uncertainty.

Decision making in land use also involves the consideration of a number of goals that cannot be aggregated into a single criterion to be used as a performance measure for ranking alternatives. Usually models may have to be run a number of times for various specification of preferences, in order to identify a solution that corresponds best to the tradeoffs between attainable goals of a DM.

3.2 The AEZ Land Use Allocation Model

3.2.1 A Summary of the AEZ Methodology

Based on the concepts and needs articulated in the previous section, FAO has developed a methodological framework for assessments of land productivity designed for use in agricultural development planning and natural resources management. AEZ involves the inventory and classification of the land resources in a way meaningful for assessments of the potential of agricultural production systems. This characterization of land resources includes components of climate, soils, and landform, basic for the supply of water, energy, nutrients, and physical support to plants.

The land resources inventory brings together several layers of information on physical environmental resources and allows the creation of unique ecological land units (termed agro-ecological cells) within which landform, soil, and climate conditions are quantified and considered nearly homogeneous. In addition to the soil and climate layers, seven other layers of information have been incorporated in the land resources database, providing information on cash-crop zones, forest zones, parkland areas, location of irrigation schemes, tse-tse infestation areas, administrative boundaries, and a digital elevation model. The individual map layers were digitized and stored in a grid (raster) format of 1085 rows and 900 columns, each grid cell representing an area of one square kilometer.

Crops have climatic requirements for photosynthesis and phenology, both of which bear a relationship to yield. In the AEZ methodology, crops are classified into five climatic adaptability groups according to distinct photosynthetic characteristics. Potential yields for crops, pastures, and fuelwood species by LGP zone were then adjusted considering moisture-related constraints of water stress, weeds, pests and diseases, and workability. Yields refer to single crops that act as building blocks in the formulation of annual cropping patterns and crop rotations. Annual crops are matched to the individual component length of growing periods (in the case of multiple LGPs per year), and perennial crops are evaluated with respect to the average total length of growing period. LGP-pattern evaluation also takes into account the probability weights associated with the historical pattern of occurrence of length of growing periods. This provides a measure of the variability of yields, quantifying potential yields under average, above-average, and below-average moisture conditions.

Many soil characteristics, e.g., natural fertility, salinity, pH, and gypsum content, can be defined in a range that is optimal for a given crop, a range that is critical, and a range that is unsuitable under present technology. These relationships (FAO, 1981) have been applied in the matching of the inventoried soil units with the soil requirements of crops. The soil unit rating relates soil properties to the degree to which crop requirements can be met under a given management practice. Where appropriate, the soil unit rating is modified according to limitations implied by texture evaluation, stoniness, and soil phase evaluation.

For estimating land productivity potential, further consideration has to be given to including multiple cropping, fallow requirements to maintain soil fertility, and production security constraints to reflect risk aversion of subsistence farming under climatic uncertainty. Multiple cropping refers to the intensification of arable land use, both in time and space. The principles of yield increases resulting from a better use of time with crops in sequence is complementary to increases arising from a more efficient use of space with crops in mixture.

Sequential cropping is possible in areas where climatic conditions, temperature, and moisture supply permit crop growth beyond the duration of one crop. The algorithms implemented for land productivity assessment explicitly construct and evaluate all feasible sequential crop combinations, both monoculture and multiculture, by matching individual crop cycle requirements to the relevant component length of growing periods as implied by the LGP pattern.

AEZ assessment is concerned with sustainable agricultural practices. In their natural state, many soils cannot be continuously cultivated without experiencing degradation, manifesting itself in decreased crop yields and deterioration of physico-chemical soil properties. The assumptions on fallow requirements incorporated into the model are formulated for four main groups of crops – cereals, legumes, roots and tubers, banana and sugarcane – and relate to soil unit, thermal zone, and moisture regime.

3.2.2 The core model constraint set

A detailed specification of the AEZ core model for land use allocation is far beyond the scope of this article. Therefore only an outline of the essential features of the model is provided here.

As outlined in Section 3.2.1, each agro-ecological cell was assessed in terms of all feasible agricultural land use options of interest in the analysis. At a given level of input, the productivity assessment records expected production of relevant and agro-ecologically feasible cropping activities, in terms of main produce as well as various by-products (e.g., crop residues and by-products), extents by suitability class, input requirements, and degradation hazard (i.e., potential soil and productivity loss due to water erosion). An application of the AEZ framework constructs an inventory of potential agricultural land use options with relevant quantitative information. Such an inventory is essential for devising optimal land use patterns that take into account physical, socioeconomic, technological, and political objectives and constraints.

A formal model specification is not presented here owing to space limitations. Instead, various sets of constraints are summarized below in a descriptive manner.

A realistic assessment requires a thorough description of relevant constraints to be considered in the selection of optimal land use. These can relate to technological conditions, physical limitations, social, institutional and economic constraints, and political targets. Not all the constraints need to be activated in every scenario, but can be included when appropriate and relevant. Therefore, the following groups of constraints (which is total amount to up to 50,000 constraints) are defined:

- Demand targets by aggregate commodity group.
- Commodity production targets.
- Limits on harvested area.
- Crop-specific land use constraints.
- Total arable land use constraint.
- Production input requirements.

- Crop-mix constraints.
- Human calorie/protein ratio requirements.
- Distribution of livestock population over livestock zones.
- Distribution of livestock systems.
- Constraints on number of animals.
- Livestock feed requirement constraints.
- Zone level production risk constraint.
- Cell use consistency constraint.
- Crop rotation constraints.
- Cell level production risk constraints.
- Environmental impact constraints.

3.2.3 Decision variables

The AEZ core model contains three groups of decision variables that determine optimal agricultural land use, livestock numbers supported, and optimal allocation of feed supplies to different livestock systems, respectively. These three groups are as follows:

- The land use shares, i.e., the share of agro-ecological cell j allocated to a cropping, grassland, or fuelwood activity k.
- The number of animal units of livestock system s kept in zone z.
- The feed ration of feed item h from crop i allocated to livestock system s in period t in zone z.

These variables form the columns of the constraint matrix, the core model activity set. Values of these variables are provided by the solver as the result of solving a parametric optimization problem that is automatically generated in order to compute a Pareto efficient solution corresponding to preferences that are interactively specified by a user.

Values of decision variables and of criteria can be inspected by the user and are then used for generating various reports by the software developed for the AEZ model.

3.2.4 Outcome variables

Typically, six to eight objectives are interactively selected from the set of the following outcome variables to serve as criteria in multi-criteria analysis of the AEZ model:

1. Maximize food output (weighted sum of food energy and protein available for human beings after conversion and processing into food commodities).
2. Maximize net revenue.
3. Minimize production costs.
4. Maximize gross value of output.
5. Minimize weighted sum of arable land use (weight of 1 assigned to crops and fuelwood species and 0.1 to grassland).
6. Minimize area harvested.
7. Maximize food output in bad years (weighted sum of food energy and protein available for human consumption as in outcome 1 above, but evaluated for climatic conditions typical for years with low precipitation levels).
8. Minimize total erosion (total soil loss over all land units).
9. Maximize district self-reliance (defined as minimum of the individual commodity group self-sufficiency ratios, i.e., target production over demand achieved).
10. Minimize erosion at the level of agro-ecological cells (largest soil loss per ha occurring in any used land unit).

The last variable provides an example of an objective that reflects the spatial detail of the GIS resource database. Other examples of variables where the spatial content of the information is important could, for instance, express crop diversification or equity of expected farm incomes.

3.3 DSS for Land Use Planning

As already mentioned in Section 2.3, the functional structure of the AEZWIN DSS is the same as the RWQM DSS illustrated in Figure 1 on page 9. AEZWIN is an acronym for AEZ for Windows, where AEZ is traditionally used for the applied methodology of land resources assessment outlined in previous sections. Apart from some technical issues (analysis of the AEZ model requires the solution of LP problems, whereas the water model is of a mixed integer programming (MIP) type, therefore different solvers are used) the only and obvious difference between these two DSSs is due to their respective core models. This is a strong argument for using a modular structure of a DSS, as discussed in article 4.20.4.1.

Various approaches (discussed in Section 4.3) might be applied to the generation of core models used for model-based decision support. Some models (e.g., the RWQM model used in Section 2) are generated by specialized software that does not require any interaction with the user. However, such interaction is required for the generation of a scenario for the AEZ model. Additionally, the generation of a scenario for the AEZ model requires a selection of various options and processing of data that are pertinent to selected options and that are needed for a corresponding instance of the AEZ model.

A sophisticated system of programs has been developed for this purpose. Figure 2 gives a general overview of the flow and integration of information implemented in the AEZ, whose methodology is summarized in previous sections. This software served originally for the application of linear optimization techniques for analyzing land use scenarios with regard to single-objective functions, such as maximizing agricultural production or minimizing the cost of production under specific physical environmental and socioeconomic conditions and constraints. Now, this software has been linked with a user friendly interface, called AEZWIN, for specifying scenarios that are subject to multicriteria model analysis of land use problems.

AEZWIN part of the DSS for Land Use Planning is marked in Figure 2 by a dashed box. A detailed presentation of all functions of AEZWIN is beyond the scope of this article. In order to illustrate its functionality we present only a list of functions available from the main menu of AEZWIN:

1. *Database*: To import, export, or modify records in the AEZ database, other than a land inventory.
2. *Land resources*: To view inventory files and to calculate, view, and print various statistics from the land resources inventory.
3. *Yields*: To generate maximum attainable yields by agro-climatic zone.
4. *Crop suitability*: To run a single crop suitability assessment and determine the potential arable land for a selected district.
5. *Productivity*: To construct for each agro-ecological cell feasible multiple crop combinations, evaluate crop production options, and filter out the best alternatives for later consideration in district analysis.
6. *Analysis*: To select a district for analysis, generate the AEZ core model specification file, call the LP-solver or perform the multi-criteria model analysis by the MCMA, create reports of district planning scenarios, generate an LP_DIT file.

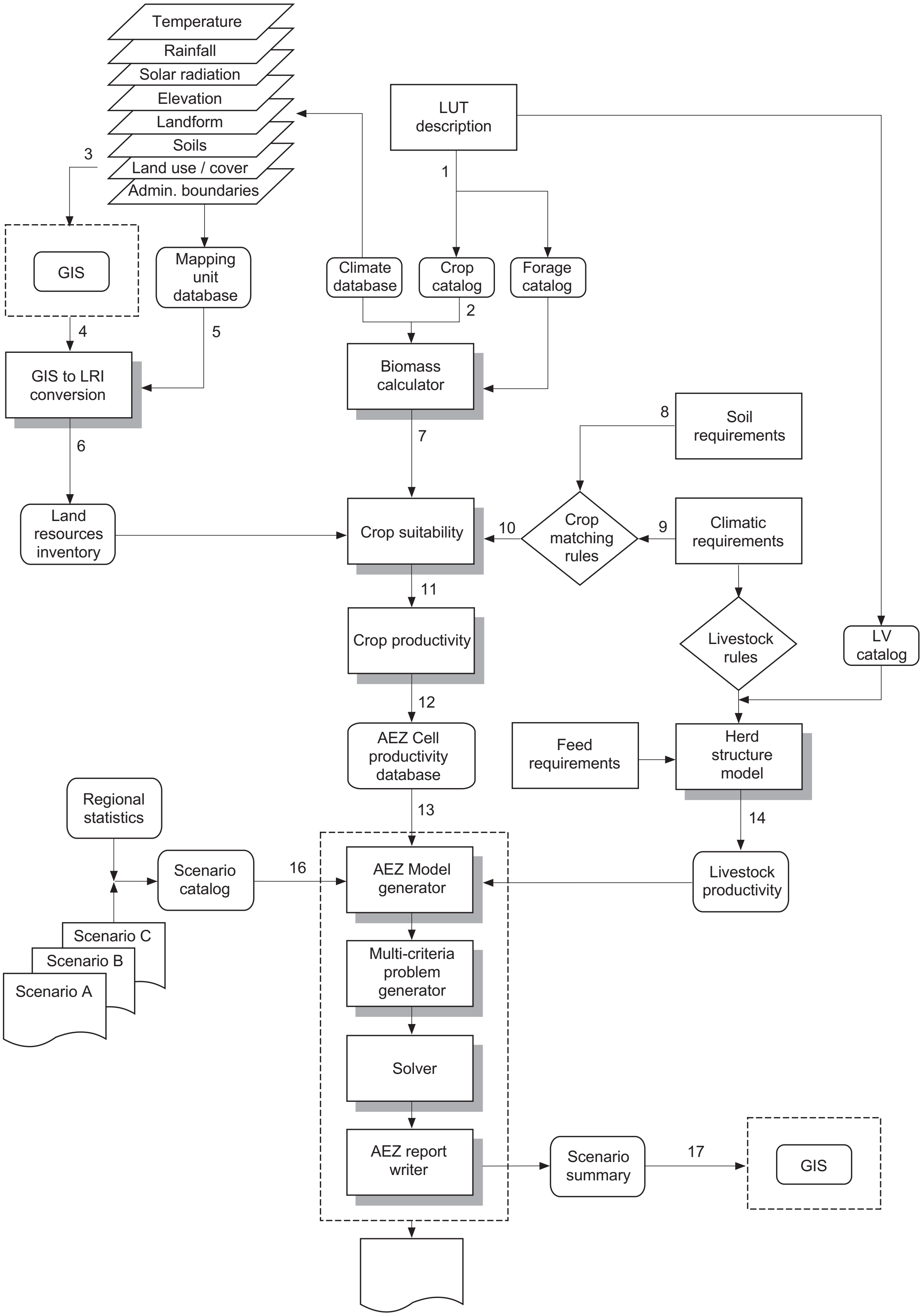

Figure 2: AEZ information flow and integration.

7. *GIS functions*: To display compressed raster maps and to (optionally) transfer control to a GIS system.

3.4 Experiences from using AEZWIN

The approach presented in this section illustrates linking multi-criteria methods of model analysis with GIS land resources databases, which results in a powerful DSS tool in land use decision-making support. A cumbersome approach of converting all but one criteria into constraints and applying a sensitivity analysis of a sequence of single-criterion solutions, as it is necessary in single-criterion optimization, is replaced by an interactive specification of the preferences of the decision maker. Moreover, the simplicity and flexibility of the approach assist the user, during the process of decision-making, to better understand the decision situation. The approach presented is interactive and fast, hence the development of some dozen solutions does not require more than a few hours for a user with a good understanding of the problem.

The user does not need to be experienced in sensitivity analysis and scenario generation techniques, which are necessary for the analysis based on a single-criterion approach. On the one hand, the detailed evaluation of a large number of solutions obtained during multi-criteria model analysis can be much more time-consuming than the evaluation of a smaller number of solutions typically analyzed by single-criterion optimization. On the other hand, the analysis of a large number of solutions corresponding to different areas of the Pareto-efficient set provides a more complete understanding of the problem. Solutions that are close to each other, as obtained in the previous example, can appear confusing at first to the decision maker. The ISAAP tool provides an option for analyzing the history of solutions that helps in selecting solutions. Some users also have difficulty when evaluating more than three criteria visually. Special techniques are provided by ISAAP to facilitate such an evaluation. This can be done by a sequential selection of groups of criteria that are investigated more closely while the remaining criteria are either inactive or their values are stabilized around a target value desired by the user (as selected for each criterion).

The multi-criteria model analysis method can also be used for a more detailed model analysis in two ways that have not been applied so far in the case study reported in this section. The first one is called soft simulation. This is an extension of the traditional simulation allowing a combination of multi-criteria analysis with (soft) setting of values of selected variables. Second, it allows for treatment of a group of constraints as so-called soft constraints, i.e., constraints that can be violated up to a certain bound interactively controlled by the user.

To avoid a misleading conclusion (which, however, frequently arises), namely that the usage of such a DSS package might replace a real decision maker, it should be stressed again that the system is designed to help a decision maker to concentrate on real decision making, while the program takes care of various cumbersome computations involved in the analysis of scenarios and provides information that furthers the analysis of the consequences of different options and alternatives. The user needs to define the various scenarios of interest, changing his/her preferences and priorities when learning interactively about the consequences of possible decisions.

For a successful application of DSSs in land use planning in developing countries, it is necessary to overcome various limitations and difficulties. In many of these countries, lack of data and poor data quality constitute serious limitations to an application of computer-based systems of land resources management. Lack of trained personnel to apply these systems in solving practical problems is another constraint, which often causes the available systems to be underutilized and sometimes not used at all.

4 Air quality management

4.1 The problem

In many parts of Europe the critical levels of air pollution indicators are exceeded and measures to improve air quality in these areas are needed to protect the relevant ecosystems. Several international agreements have been reached over the last decade in Europe to reduce emissions. Negotiations of these agreements have been supported by the analysis of complex models which are outlined in this article. The models help to identify cost effective measures aimed at the improvement of air quality represented by various indicators of acidification, eutrophication, and ground level ozone concentrations. These measures correspond to policies of reductions of NH_3 (ammonia) and SO_x (sulphur oxides), NO_x (nitrogen oxides) and VOC (volatile organic compounds) emissions by various sectors of economies in European countries.

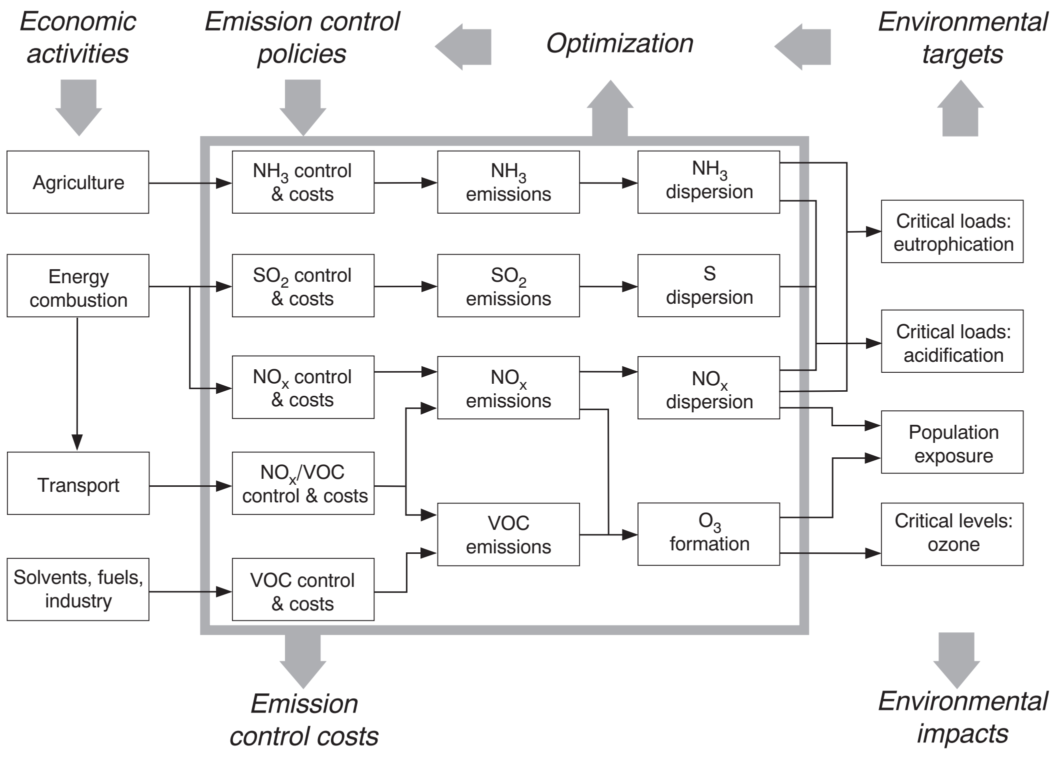

Figure 3: RAINS model structure.

The structure of the RAINS model is outlined in Figure 3. The decision variables are composed of the levels of emissions of NH_3, SO_x, NO_x and VOC by various sectors in each country, which imply the corresponding emission control policies. For each country, and type of emission a cost function is defined. Such a function relates the emission level with the corresponding costs of reducing to this level a sum of various types of emissions caused by activities aggregated (for the purpose of this analysis) for each country in several sectors. Therefore, cost-effective measures can be calculated by a minimization of the cost function that corresponds to the sum of costs related to reductions of all types of considered emissions in all sectors in each country. In order to determine the corresponding environmental impact, emission levels are used as inputs to the three dispersion submodels and to the ozone formation submodel. Studies of the impact of ozone, acidification and eutrophication have resulted in the establishment of critical levels for various air-quality indicators in order to protect agricultural crops and forests. These are determined using a long-term exposure measure, called the *accumulated excess*. Consequently, nine such exposure indices (six for ozone, two for acidification and one for eutrophication) has been defined for each of approximately 600 grids in Europe (called also *receptors*), and accumulated excess PWL (piece-wise linear functions) are defined for each grid and for each type of acidification and eutrophication excess. These indices are used for assessment of environmental effects of the applied emission control policies.

In the mathematical programming terms RAINS is a large (about 30,000 variables and over 30,000 constraints) non-linear model. The original RAINS model, which was a small LP model that dealt only with acidification) can be considered as a small pilot prototype of the current version of RAINS described in this paper. The development of several versions of RAINS made during over ten years were driven by the needs of the negotiators. The first version of RAINS was used for negotiating the sulphur protocol; therefore, it dealt only with a single pollutant. However, it has become clear that a multi-pollutant, multi-effect approach offers substantial environmental and financial advantages. Therefore, to respond to these needs, RAINS has been extended and gradually modified to its current form.

Not only the structure of the RAINS model is complex but also the way in which it is generated and analyzed. Although these problems presented in subsequent sections are of technical nature they are interesting also for users of DSSs because understanding and acceptance of the underlying assumptions and techniques by the users of the DSS are of critical importance for the way in which the results from RAINS can be successfully used as discussed in Section 4.5.

4.2 Specification of the RAINS core model

We shall now briefly comment on the specification of the RAINS model, which can be considered (as illustrated in Figure 3 on page 18) as composed of three mutually linked parts:

- emission control costs and resulted emissions,
- atmospheric dispersion and tropospheric ozone formation models,
- environmental impacts.

Each of these components is backed-up with a large amount of underlying research, which is presented in various specialized publications. Here we can provide only a general overview of these components.

The emission-cost module consists of three parts, estimating current and future levels of emissions of NH_3, SO_x, NO_x and VOC from each considered sector. These estimates are based on national statistics and projections of economic activities taking into account implemented and possible emission control measures and associated costs. These data is used for defining parameters of PWL (piece-wise linear) functions, which map for each considered sector in each country the emission levels of each type of pollutant to the corresponding cost.

The atmospheric dispersion processes over Europe for NH_3, SO_x, NO_x and VOC compounds are modeled using results of the European EMEP model, developed at the Norwegian Meteorological Institute. However, the EMEP model is far too complex to be used for optimization, or even for many scenario analyses. Therefore, an essential requirement of an integrated assessment of the RAINS model is a simplified but reliable description of the dispersion processes in order to represent the source-receptor relationships involved. It is possible to envisage several ways of condensing the results of more complex models to achieve this. One approach is to use statistical techniques to build a simplified model based on the results obtained from a complex mathematical model for a large number of emission reduction scenarios. Such an approach has been implemented for, and is currently used by, the RAINS model. Of course, using simplified source-receptor relationships between the precursor emissions and the various thresholds of corresponding levels/loads results in a lesser accuracy than that assured by the EMEP photo-oxidants model. Therefore, selected results obtained from the simplified model are compared with results from the EMEP model. This is done by running the EMEP model for the emissions obtained from the RAINS model, and comparing the levels/loads values provided by both models.

Another approach to the specification of a simplified ozone formation submodel is based on using fuzzy-rules generation methodology. The simplification method uses fuzzy rule generation methodology to represent numerous results of the EMEP model as a response surface describing the source-receptor relationships between ozone precursor emissions and daily tropospheric ozone concentrations. It has been shown that the fuzzy model provides better predictions of ozone concentrations than the traditional regression model based on all data at each grid. Furthermore, the membership functions obtained appear to be sensible. Based on examination of meteorological data, the different fuzzy rules do seem to describe different meteorological conditions rather well. Unfortunately, the development of a fuzzy model requires manual tuning of parameters for each grid, therefore the model has been developed only for several grids in Europe. For these grids the fuzzy model can be used for examination of daily ozone concentrations caused by a selected emission scenario in a much faster and easier way than by using the much more detailed EMEP model.

4.2.1 Notation

A distinction should be made between a set I of sources of various types of air pollution, and a set J of areas for which various quality indicators are assessed. Conventionally, the names emitter and receptor are used for elements of such sets.

The model definition requires the use of the following indices:

- Index $i \in I$ corresponds to emitters. The numbers of elements in I correspond to the number of countries (about 40).
- Index $is \in S_i$ corresponds to a sector that emits either $\mathrm{NO_x}$ or VOC or a linear combination of them; S_i is a set of sectors in the i-th country. Sets S_i may have up to five elements.
- Index $j \in J$ corresponds to receptors. The numbers of elements in J corresponds to numbers of grids (about 600).
- Index $l \in L$ corresponds to a combination of ozone thresholds and a year. The set L may have up to six elements.
- Index $m \in M$ corresponds to a set of receptors for which balancing of violations and surpluses of targets is defined.

Emission Sectors

Emissions are analyzed for sets of emitters that are located in a certain area, which is typically a country. However, for some types of analysis, sets of NO_x and VOC emitters may be further subdivided into subsets called sectors, in order to account for measures that can be applied to emitters that belong to a sector. In such a case emitters that belong to a particular sector emit either NO_x or VOC or a linear combination of them. A sector is defined by a quadruple:

$$\{is, i, \lambda, \mu\} \tag{14}$$

where is is an integer number that uniquely identifies a sector, an index i corresponds to a country in which emitters belonging to this sector are located, and the following convention is used for the λ member of this quadruple:

$$\lambda = \begin{cases} 0, & \text{if only NO}_\text{x} \text{ is emitted} \\ \text{a negative number,} & \text{if only VOC is emitted} \\ \text{a positive number,} & \text{if both NO}_\text{x} \text{ and VOC are emitted.} \end{cases} \tag{15}$$

Moreover, a (positive) value of λ defines the following relation between the amount of VOC emission corresponding to a unit emission of NO_x:

$$v_{is} = \lambda_{is} n_{is} + \mu_{is} \tag{16}$$

4.2.2 Decision variables

The main decision variables are the annual emissions of the following four types of primary air pollutants from either sectors or countries: (i) n_{is}, annual emission of NO_x from sector is; (ii) v_{is}, annual emission of nonmethane VOC from sector is; (iii) a_i, annual emission of NH_3 from country i; and (iv) s_i, annual emission of SO_2 from country i.

Additionally, optional decision variables are considered for scenarios that allow limited violations of air quality targets. For such scenarios variables corresponding to each type of the considered air quality targets are defined for each receptor. Each variable represents a violation of a given environmental standard. Optionally, violations of targets can be balanced with surpluses (understood as a difference between a target and a corresponding actual concentration/deposition). For reasons of efficiency, one variable is used for both violations of targets and surpluses (positive values represent violations while negative values correspond to a part of a surplus that is used to balance violations of targets).

Therefore, the following decision variables are optionally defined: (i) y_{lj}, violation of ozone exposure targets (surplus, if $y_{lj} < 0$); (ii) ya_j, violation of acidification targets (surplus, if $ya_j < 0$); and (iii) ye_j, violation of eutrophication targets (surplus, if $ye_j < 0$).

4.2.3 Outcome variables

The consequences of applications of computed values of the decision variables are evaluated by the values of outcome variables. However, several auxiliary variables needed for the definitions of outcome variables have to be specified first.

Auxiliary Variables

The annual emission of NO_x (n_i) is defined by:

$$n_i = \sum_{is \in S_i} n_{is}. \tag{17}$$

The annual emission of VOC (v_i) is defined by:

$$v_i = \sum_{is \in S_i} v_{is}. \tag{18}$$

The mean effective emissions of NO_x, including natural sources, experienced at the j-th receptor (en_{lj}) is given by:

$$en_{lj} = \sum_{i \in I} e_{lij} n_i + enn_{lj} \tag{19}$$

where enn_{lj} are given effective natural emissions of NO_x.

The representation of another nonlinear term (nlv_{lj}) defining ozone exposure at the j-th receptor is defined by:

$$nlv_{lj} = \sum_{i \in I} d_{lij} v_i. \tag{20}$$

The coefficients e_{ij}, d_{ij} depend on the meteorology and are obtained from EMEP model calculations.

Definition of Outcome Variables

One outcome variable represents the sum of costs of reductions of emissions; four sets of other outcome variables correspond to various indices of air quality.

Annual costs related to the reduction of a corresponding emission to a certain level are given by a piece-wise linear (PWL) function for each type of emission and for each emitter. Each PWL function is composed of segments defined by pairs of points; each point is composed of the emission level and the corresponding cost of reducing emission to this level. Therefore, a PWL function is defined for each member of sets of NO_x and/or VOC emitters declared by (14) and for NH_3 and SO_2 emitters (the latter for each country). Formally, the following PWL functions define the annual cost related to reducing the level of emission to a level given by argument(s) of the function: $ca_i(a_i)$ for a_i, $cs_i(s_i)$ for s_i, and $c_i(n_i, v_i)$ for n_i and v_i. The term $c_i(n_i, v_i)$ is defined by:

$$c_i(n_i, v_i) = \sum_{s \in S_i} c_s(\cdot) \tag{21}$$

where $c_s(\cdot)$ is a cost function for NO_x or for VOC or for joint NO_x and VOC reduction, depending on $type\_def$ defined by (15).

Each cost function defines its domain by specifying lower and upper bounds for its argument(s). This implicitly defines lower and upper bounds for all emissions that are used as bounds defined in Section 4.2.4. Those bounds may be made tighter by an optional specification of bounds for emissions from countries or sectors.

For the sake of brevity, the sum of costs is defined by:

$$cost = \sum_{i \in I} (ca_i(a_i) + cs_i(s_i) + c_i(n_i, v_i)). \tag{22}$$

Such a function is continuous and convex but it is not smooth. Therefore, in actual implementation it is represented by another function that meets typical requirements of nonlinear solvers.

For each receptor, the following four outcome variables correspond to various indices of air quality:

aot_{lj}, the long-term ozone exposure of the l-th type, is assumed to be a function of the nonmethane VOC and NO_x emissions, v_i and n_i, respectively, from each emitter country i, and the mean "effective" emissions (of NO_x and VOC), en_j, and nlv_j, experienced at the receptor over the period in question. The general model formulation adopted is:

$$aot_{lj} = \sum_{i \in I} (a_{lij} v_i + b_{lij} n_i + \gamma_{lij} n_i^2) + \alpha_{lj} en_{lj}^2 + \beta_{lj} en_{lj} nlv_{lj} + k_{lj}. \tag{23}$$

$ac1_j$, acid deposition of Type 1:

$$ac1_j = tns_j (\sum_{i \in I} tn_{ij} n_i + \sum_{i \in I} ta_{ij} a_i + kn_j) + \sum_{i \in I} ts_{ij} s_i + ks_j. \tag{24}$$

$ac2_j$, acid deposition of Type 2:

$$ac2_j = \sum_{i \in I} tn_{ij} n_i + \sum_{i \in I} ta_{ij} a_i + tss_j (\sum_{i \in I} ts_{ij} s_i + ks_j) + kn_j \tag{25}$$

eu_j, eutrophication:

$$eu_j = \sum_{i \in I} tn_{ij} n_i + \sum_{i \in I} ta_{ij} a_i + kn_j \tag{26}$$

where tn_{ij}, ta_{ij}, ts_{ij} are transfer coefficients for NO_x, NH_3, and SO_2, respectively; kn_j and ks_j are constants for nitrogen and sulphur background depositions; tns_{ij}, tss_{ij} are scaling coefficients that convert acidification coefficients of one type into acidification coefficients of another type, for NO_x and NH_3, and for SO_2, respectively.

Environmental effects caused by acid deposition, excess nitrogen deposition (described by a two-element linear critical loads function), and by eutrophication are evaluated at each receptor by a PWL function that represents an accumulated excess over the threshold of the environmental long-term target:

$aac1_j$, accumulated excess of acidification of Type 1:

$$aac1_j = PWL_j^{ac1}(ac1_j). \tag{27}$$

$aac2_j$, accumulated excess of acidification of Type 2:

$$aac2_j = PWL_j^{ac2}(ac2_j). \tag{28}$$

aeu_j, accumulated excess of eutrophication:

$$aeu_j = PWL_j^{eu}(eu_j). \tag{29}$$

4.2.4 Constraints

Each of the decision variables defined in Section 4.2.2 for $i \in I$ or for $is \in S_i$ is implicitly bounded by a corresponding definition of the domain of the corresponding cost function, which represents costs associated with the reduction of emission (see Section 4.2.3). For some scenarios this domain may be further restricted by a specification of optional bounds.

Violations of targets are constrained at each receptor by corresponding lower and upper limits specified for each target type and for each grid:

$$y_{lj}^{min} \leq y_{lj} \leq y_{lj}^{max}, \tag{30}$$

$$ya_j^{min} \leq ya_j \leq ya_j^{max}, \tag{31}$$

$$ye_j^{min} \leq ye_j \leq ye_j^{max}. \tag{32}$$

The long-term ozone exposure of the l-th type is constrained at each receptor by:

$$aot_{lj} - y_{lj} \leq aot_{lj}^{max} \tag{33}$$

where aot_{lj} is defined by (23) and aot_{lj}^{max} is a given maximum ozone exposure for the l-th threshold at the j-th receptor.

Constraint (33) without the term $-y_{lj}$ represents a so-called hard constraint for long-term ozone exposure and such a formulation is typically used in traditional formulations of optimization problems. It can also be used in the presented model by selecting an option that does not allow for generation of variables y_{lj}. However, assuming hard constraints for air quality targets results in more expensive solutions, which are caused by constraints that are active in only one or two receptors. Introduction of the term $-y_{lj}$ converts a hard constraint into a so-called soft constraint. This allows a violation of a target air quality. Such a violation is: (i) constrained by upper bounds on variables y_{lj}; (ii) compensated by surpluses (i.e., differences between actual exposure and the corresponding target) in other receptors belonging to the same set of receptors (e.g., located in the same country or region); and (iii) controllable by a trade-off between violation of targets and corresponding costs of reducing emissions (see Section 4.4 for details).

Constraints for accumulated excess of the two types of acidification and of eutrophication are defined in a similar way:

$$aac1_j - ya_j \leq aac_j^{max}, \tag{34}$$

$$aac2_j - ya_j \leq aac_j^{max}, \tag{35}$$

$$aeu_j - ye_j \leq aeu_j^{max}. \tag{36}$$

Optionally, violations of targets can be balanced with surpluses of targets over sets of receptors denoted in the following constraints by J_m, where $m \in M$ is the index of a set of receptors. Obviously, lower bounds in conditions (30), (31), and (32) have to be negative in such a case. The balances are represented by the following constraints:

$$\sum_{j \in J_m} wo_{lmj} y_{lj} \leq tbo_{lm} \qquad l = 0, \tag{37}$$

$$\sum_{l=1}^{L} \sum_{j \in J_m} wo_{lmj} y_{lj} \leq \sum_{l=1}^{L} tbo_{lm}, \tag{38}$$

$$\sum_{j \in J_m} wa_{mj} ya_j \leq tba_m, \tag{39}$$

$$\sum_{j \in J_m} we_{mj} ye_j \leq tbe_m, \tag{40}$$

where $wo_{lmj}, wa_{mj}, we_{mj}$ are the given weighting coefficients, $J_m, m \in M$ are sets of receptors, and tbo_{lm}, tba_m, tbe_m are target balances for the m-th set of receptors for the l-th type of ozone exposure, for acidification, and for eutrophication, respectively. The sets J_m are defined implicitly by nonzero elements of sparse matrices wo_l, wa, and we, respectively.

Due to the space limitation we cannot provide here a full specification of the RAINS model and discuss all methodological and technical issues of its implementation. We end the above short summary of the RAINS model specification by outlining two issues of a more general interest, which are accounted for in this model specification:

- The resulting optimization problem has practically non-unique solutions. More exactly, it has many very different solutions with almost the same value of the original goal function. Let's consider two solutions x_1 and x_2 such that:

  $$||c(x_1) - c(x_2)|| < \epsilon \qquad ||x_1 - x_2|| > \delta \tag{41}$$

  where $c(\cdot)$ is a goal function, and ϵ, δ are two positive numbers, small and large, respectively. This is a typical issue for most of large optimization problems, which unfortunately does not attract enough attention because analysts often look only at an optimal solution without analyzing other solutions, which have practically the same value of the goal function. Typically a problem is noticed, if various instances of the mathematical programming problem that differ very little have very different optimal solution (with a practically same value of a goal function).

  There is a simple and practical technique called regularization which provides a suboptimal solution which has additional properties specified by a user.
- A traditional representation of environmental targets by hard constraints would result in the recommendation of expensive solutions, where only few grids have active constraints for environmental targets, and for almost all grids the actual values of indices are substantially lower than the corresponding targets. In order to provide a more complete analysis so called *soft constraints* (with compensation for the violation of original targets in some grids by a larger margin in other grids) can optionally be specified for environmental targets. These results in much cheaper solutions with more uniform differences between environmental targets and actual values of corresponding indices.

4.3 Model generation and data handling

There are basically two approaches to the generation and analysis of a mathematical programming problem. These either develop a problem-specific generator or use a modeling system (such as GAMS, AMPL, AIMMS). There is a number issues that should be considered when selecting one of these approaches. Here we only outline some of them:

- A modeling system greatly simplifies the task of model specification, especially if compared with the amount of resources needed for the development of a model generator using traditional procedural programming languages like Fortran or C. However, the use of C++ substantially reduces this difference, especially with the Standard Template Library (recently included in the C++ standard), and with other class libraries supporting implementations of mathematical programming type of problems.
- A model generator is more efficient in processing the input data needed for model specification. It is also preferred when a more sophisticated check of data consistency is desired.
- A modeling system has limited possibilities for efficient preprocessing of optimization problems. This is not a serious problem for linear models because preprocessing is a standard feature of any good LP solver. However, the preprocessing of non-linear models is much more difficult.

- For a large problem, a good starting point might dramatically decrease the computation time. A computation of such a point is much easier for a problem-specific generator.
- A modeling system greatly simplifies model analysis within the paradigm specific to a given system. However, using different paradigms – such as soft and/or inverse simulation, regularization, soft constraints, multi-criteria model analysis – typically require much additional effort if the particular paradigm is not included into a given modeling system.
- A modeling system releases a modeler from the complex task of providing code for computing the values of non-linear constraints and the non-linear elements of the Jacobian. However, a typical non-linear problem has only a few formulas for the non-linear part. Therefore, one can use e.g. Mathematica for generating C language code for formulas of the Jacobian and for the values of constraints, and then include this code in a class that provides values for particular elements of the Jacobian and for the constraints.
- Finally, for models that are not only run on various platforms but are also widely distributed, a problem-specific generator substantially decreases costs for the users (typically, the cost of a solver plugged into the problem-specific software is a small fraction of the cost of the run-time license for a modeling system).

Taking into account the above summarized points, the problem generator of the RAINS model has been implemented as a problem-specific C++ classes that use a template class library supporting the generation of mathematical programming problems. The generator includes an efficient preprocessor, which dramatically reduces size of the non-linear optimization problem, and does also an instance specific scaling, which results in values of the Jacobian and Hessian that are likely to not cause numerical problems for a non-linear solver.

The approach is conceptually very simple. Each of the above mentioned solvers is available as a library of Fortran subroutines. The generator has C++ classes that are specific for each solver. These classes are inherited from the base classes that handle a common part of the generator. A problem specific report writer processes the results into a form that eases their interpretations. Another class supports a portable interface between C++ and Fortran. Hence, three versions of executables can easily be produced, each composed of the generator, preprocessor, postprocessor and one of the solvers.

A nonlinear solver requires routines that compute values as well as elements of the Jacobian of the non-linear constraints and the goal function. A large part of the total computation time is used for the execution of these functions, therefore the efficiency of their implementation is important. The code for the Jacobian has been generated by *Mathematica* with a prior use of the *FullSimplify* operator, which simplifies the formulas substantially. This is an easy way to generate an efficient and bug-free code.

The RAINS model requires processing a large amount of data coming from various sources, including other complex models. Therefore, the data used is maintained by several DBMS, which are coupled with other applications. For efficient and portable handling of data used in the RAINS model the public domain library HDF has been applied. The basic data structures are handled by a collection of well-tested template C++ classes that are also used for the LP-DIT. A C++ interface class has been implemented for an easy and efficient handling of the used data structures by the HDF library.

Costs of emission reductions discussed above are given as PWL (Piece-Wise-Linear) functions of the corresponding emission levels. PWL functions are not smooth. Therefore, in order to be able to use efficient nonlinear solvers (which require smooth functions), the PWL cost functions are represented by corresponding smooth functions. Due to space limitations, these conversions are not presented here.

Finally, one should notice that the dimensions of the model are not fixed. For some scenarios a part of the constraints and/or variables does not need to be generated. Moreover, the dimensions of the matrices and vectors used in the model definition vary substantially for various types of analysis. Fortunately, properly implemented constructors of C++ template classes handle such problems in a natural and efficient way.

4.4 Analysis of the RAINS model

This Section outlines how a combination of various methods of model analysis has been applied to the RAINS model, which is used extensively for various types of analysis that are needed for supporting international negotiations.

Due to space constraints, we have limited this section to presenting the structure of one cycle of analysis followed by a summary of the implementation of a composite goal function for the RAINS model analysis.

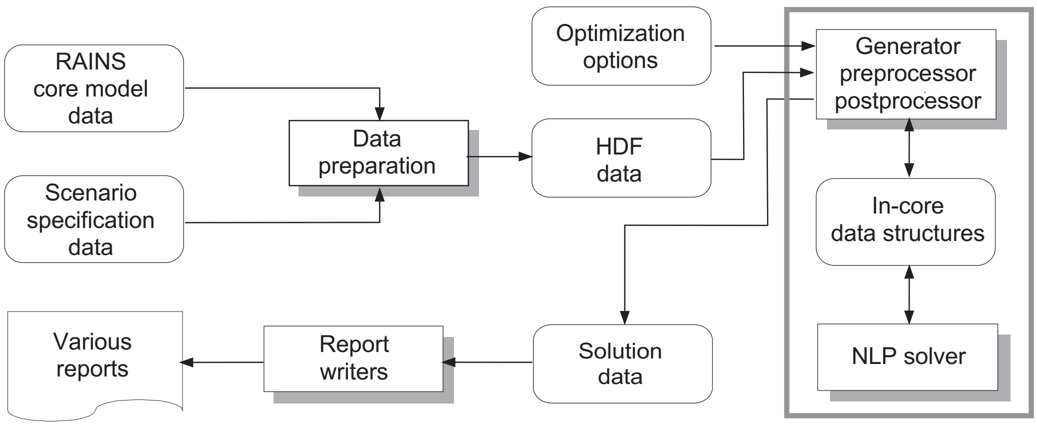

Figure 4: RAINS model analysis cycle.

The structure of one cycle of the RAINS model analysis is outlined in Figure 4. Prior to analysis, a data file is prepared that contains all parameters of the RAINS core model. Another data file with a definition of the parameters for a particular scenario is prepared by specialized software. These two data sets are converted by another specialized program into the HDF format file. Additionally, a user has the possibility to select various options and specify the corresponding parameters (for example, of the composite goal function discussed below) and options (e.g. allowing for soft constraints, requesting the balancing of violations with surpluses) that overwrite the default selections and are used for a definition of a particular instance of the non-linear optimization problem.

The optimization problem is generated and solved by the problem specific model generator linked with a selected non-linear solver library. The generator (which functions are described in Section 4.3) creates the necessary data structures, which are kept in-core and are used for functions that are required by each of the used solvers. Such an approach allows for the efficient generation and solution of the corresponding large non-linear optimization problem. After an optimal solution is found, a postprocessor converts the solution to a form that is convenient for analysis (by "undoing" the actions of the preprocessor and by computing values of variables, which were not generated).

A solution provided by the postprocessor is processed by a specialized report-writer program, which provides various types of information needed for the analysis of a solution.

Afterwards, another scenario is designed based on this analysis and on requests from users. This scenario is used as an input to a new cycle of the analysis.

A particular scenario is defined by many parameters. A minimization of costs related to measures needed for improvement of air quality is a main goal; however, other objectives – such as robustness of a solution, trade-offs between costs and violations of environmental standards – are also important. Therefore, a multi-criteria model analysis has been applied to this case study. A composite goal function (42), which is applied to support the analysis of trade-offs between the following three criteria:

- the minimization of total costs of emissions reduction,
- the minimization of violations of the environmental standards,
- the robustness of solutions.

The following composite criterion function is used:

$$goal\_function = cost + \Theta + \Psi \tag{42}$$

where the *cost* term corresponds to the sum of the costs of emission reductions and Θ and Ψ are regularizing and the penalty term, respectively.

The regularizing term Θ is defined by:

$$\Theta = \epsilon \| z - \bar{z} \|^2 \tag{43}$$

where ϵ is a given positive (not necessarily small) number, z denotes a vector composed of decision variables that correspond to emissions, and $\bar{z}$ is a given vector composed of desired (reference) values of emissions. The role of the term Θ is twofold. First, it helps to avoid large variations of solutions (with almost the same value of the original goal function) for problems that differ very little. Second, it substantially improves the numerical stability of the optimization problem. Additionally, the term Θ can be used for the technique called softly-constrained inverse simulation. Thus, it is possible to analyze trade-offs between minimization of costs and solutions that correspond closely to various given patterns of emissions defined by $\bar{z}$.

The role of the term Ψ is also twofold. First, it serves as a penalty term for optional variables y, ya and ye. Second, it provides regularization for these decision variables, which are not covered by the Θ term. The term Ψ is defined by:

$$\Psi = \sum_{l \in L} \sum_{j \in J} \psi(y_{lj}, \rho_o, \sigma_o) + \sum_{j \in J} \psi(ya_j, \rho_a, \sigma_a) + \sum_{j \in J} \psi(ye_j, \rho_e, \sigma_e) \tag{44}$$

where $\rho_o, \rho_a, \rho_e, \sigma_o, \sigma_a, \sigma_e$ are given positive parameters, and the function $\psi(\cdot)$ is defined by:

$$\psi(x, \rho, \sigma) = \begin{cases} -\rho\sigma x - \rho\sigma^2/2 & \text{for } x < -\sigma \\ \rho/2x^2 & \text{for } |x| \le \sigma \\ \rho\sigma x - \rho\sigma^2/2 & \text{for } x > \sigma \end{cases} \tag{45}$$

Note that $\psi(x, \rho, \sigma)$ is a smooth function that, depending on the parameters ρ and σ, can be used for both purposes that correspond to the role of the term Ψ outlined above. First, it plays a role of a classical quadratic penalty function, if large values of the parameters ρ, σ are selected. Such a function can be used to examine the trade-offs between violations of air quality standards and minimization of costs. Second, it may not be desirable to apply any penalty function for some scenarios in which the balances between violations of environmental targets and surpluses. However, in such cases, it is still necessary to apply regularization in order to deal correctly with the soft constraints optionally defined by introduction of decision variables y_{lj}, ya_j, ye_j. A quadratic function is not suitable for this purpose because often violations and surpluses take small values in some grids and large values in other grids; therefore, it is not possible to find a value of the parameter ρ such that it would allow for large values of violations/surpluses in some grids, while serving as a regularizing term for grids where violations/surpluses may be three orders of magnitude smaller, and a specification of different values of ρ for each of about 600 grids is not practicable. Therefore, when used for regularization purposes alone, the function ψ is defined using small values of both parameters ρ, σ, which implies using a flat piece-wise linear function with a small quadratic segment needed to make such a function smooth. Finally, we would like to point out that the term Ψ provides a similar functionality as the approach commonly known as *soft constraints*.

We summarize the discussion on the form of the goal function (42) by stressing the fact that a properly defined goal function is the key element for achieving two goals, namely providing a tool for a comprehensive problem analysis and assuring possibly good numerical properties of the corresponding optimization problems. The specific form of this model – in particular, the penalty terms for soft constraint violations, the regularizing terms – make it very similar to a multi-objective formulation, as applied e.g. to softly constrained inverse scenario analysis.

4.5 Experiences from using RAINS

Obviously, neither RAINS nor any other complex model provides any "best" solutions. This is simply because, there is a number of problems and trade-offs that are both moral and social. No model can actually answer such questions, and this remains the domain of negotiations. However, models can help the negotiators to concentrate on those parts of the negotiations that should not be represented by a mathematical model. This assistance is provided by various unbiased analyses, such as computation of the consequences of given policies of emission reductions, or advising the values of emission levels that correspond best to given criteria and constraints.

Modern efforts to control air pollution in Europe began in the 1970s, prompted by concerns over acid rain. The convention on Long-Range Transboundary Air Pollution was signed by all European states, USA and Canada in 1979. The convention was negotiated through the UN-ECE (United Nations Economic Commission for Europe), and this convention has become a framework for subsequent efforts to improve air quality in Europe. In 1989, when the sulphur protocol was due for renegotiation, the UN-ECE accepted the RAINS model for use in the negotiations. Most probably, this was the first time when all parties to a major international negotiation accepted one computer model as a key tool in their negotiations. Currently, the RAINS model is used not only by UN-ECE, but also by the Council of EC Environment Ministers. There is also a version of RAINS developed for Asia.

However, the acceptance of the model was just the beginning. The negotiators had to trust the model results and to understand how the model works. The scientists had to understand the political realities and modify the model in order to respond better to the requests of the negotiators. In order to illustrate just one element of this process, let's consider an interpretation of the optimality of a solution. From the scientific perspective, a rational optimality criteria is a minimization of the sum of costs of emission reductions subject to constraints on values of the air quality indices. However, this obviously results in solutions that would oblige some countries and/or industries to make larger emission reductions (which also implies substantial costs) than others. Acceptance of such a solution would certainly distort competition; therefore, negotiators cannot accept such solutions. On the other hand, the RAINS model clearly demonstrates that uniform reductions (which are a sound idea from a political point of view) would not only be much more expensive but also would not result in achieving the desired air quality. Another example of this mutual learning process undertaken by the negotiators and scientists is illustrated by the evolution of the understanding of what the desired air quality should be. For example, the results of extensive research have shown that the critical acid loads should vary substantially between various ecosystems. Therefore, there is no justification to apply uniform environmental requirements for all grids in Europe.

Identification and examination of various cost-effective policy options aimed at improving the air quality in Europe is based on a large-scale complex model, which has been developed over several years by the Transboundary Air Pollution (TAP) project team at IIASA. The team is composed of specialists in various fields who have been collaborating closely with several other groups affiliated at various European institutes. The specifications of the model have been modified over these years in order to better fit the requirements of the users. Due to the size of this nonlinear model no typical interactive multi-criteria model analysis can be applied to its analysis. However, it has been shown how various formulations of single-criterion optimization problems, using some methodological concepts related to multi-objective model analysis, can provide similar advantages for a more complete model analysis.

5 Lessons from the presented DSSs

The presented DSSs serve as an illustration of the methodological and software engineering issues that are relevant to many complex models. They show that the specification, generation, analysis, and maintenance of any complex model require knowledge, experience, and collaboration of interdisciplinary teams.

The compact specifications of three models presented on few pages may give a misleading impression that such models can be developed by few researchers in few months. The contrary is however true. Each of these models is the result of many years of work of teams composed of specialists in various fields who have been collaborating closely with several other groups affiliated at various institutions. Moreover, each model needs huge amount of data that is provided from various specialized studies, many of them based on other complex models and on many field studies.

The development of the presented DSSs has also resulted in implementations of various extensions of traditional OR methods that greatly enhance the usefulness of various modeling methodologies and techniques for policy analysis. In particular, each of these DSSs requires problem-specific software for model generation because no general purpose modeling system is suitable for this application because of its complexity, requirements for efficiency, and distribution. However, although the software is problem-specific, it is built using a number of modular tools that can be easily adapted for other problems.

The article does not present any example of decision support for problems of risk analysis or choices under uncertainty. This has been done on purpose because an adequate treatment of these problems requires at least another article. However, two positions of the annotated bibliography can help readers as a starting point for exploring these types of problems.

The article shows that there are no simple solutions to complex problems. Indeed, no single modeling paradigm alone is sufficiently good enough to identify and analyze relevant policy options. Rather, an integration of various modeling methods and tools is needed to provide the best available support possible to analyze each complex problem. Such a conclusion has a more general value. Indeed, the analysis of any complex problem calls for application of various methods and tools to help identify a variety of different policy options and provide ways to compare the consequences of their implementations. Focusing on a particular modeling paradigm considered to be the most appropriate for a given problem was previously justified by limited hardware and software capabilities. However, lessons learned from the applications of various modeling paradigms to very different types of real-world problems, and the recent abundance of computing hardware and software tools makes it possible to integrate several methods of a model specification and analysis, and to apply them to large and complex problems. Such an integration calls for a collaboration of specialists, who have been concentrated – and therefore have substantial experience – in a particular method. Fortunately, recent developments in both research culture and in hardware that supports cooperative work over the Internet has made such a collaboration substantially easier. Therefore, one should expect that various integrations of different modeling paradigms will be used more broadly to improve decision-making support in a wide range of practical problems.

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6 Bibliography

Below is a selection of 10 key bibliography items. The bibliography has been generated from the BibTEX database using the ACM citation and bibliography styles. It can be easily generated in one of many commonly used styles, if this would help processing this article.

Here are the annotations to each position:

(1): The book describes the scientific basis of the RAINS model of acidification and reviews major findings from using the model. In doing so, the book provides a comprehensive and quantitative overview of the European-scale acidification from a systems analysis perspective.

(2): This book is unique in that it covers the philosophy of model-based data analysis and a strategy for the analysis of empirical data. This is an applied book written primarily for biologists and statisticians using models for making inferences from empirical data. However, it will be useful for readers who are looking for various methods of selection of a good approximating model that best represents the inference supported by the data.

(3): The monograph presenting a proven water management system that can be applied to a wide range of water industry problems. It explains the key principles guiding the water industry and illustrates their applications to current environmental issues with more than 50 case studies.

(4): This book describes the state of the art of risk analysis, a rapidly growing field with important applications in environmental policy making, as well as in engineering, science and management. The book shows how to quantify risk in conjunction with real-world decision-making. It presents basic concepts, and also advanced material, incorporating numerous examples and case studies to illustrate the presented analytical methods.

(5): The book responds to the current European policy discussions to apply air pollution emission trading on a continental scale. Because of the its unique blend of theory and practice, this volume not only provides background of environmental policy instruments in general, and European emission trading in particular, but also offers approaches that can contribute to the discussions on broader applications of emission trading.

(6): The monograph on water resource systems planning and analysis describes the development and application of quantitative modeling methods to various problems of water management. The primary focus of this book is on applications of operations research and system analysis methods to a wide range of actual water management problems.

(7): A collection of articles that describe novel modeling paradigms, including state-of-the-art modeling methods and tools, advanced methods of data analysis, and their applications to various problems of management of natural environment.

(8): Edited composite of several series of lectures on decision making under uncertainty. Unlike most of books on this subject that present the analytical material in a formal mathematical style, this book can be easily understood by readers with a high school level knowledge of mathematics and is interesting also for mathematically trained readers.

(9): This is a comprehensive text which will appeal to students and researchers concerned with any aspect of climate and the study of related topics in the environmental sciences. The book provides a grounding in climate dynamics and the issues involved in predicting climate change. It not only discusses the primary concepts involved but also the mathematical, physical, chemical and biological basis the component models needed to analyze climate change.

(10): The monograph introduces the methodological background and describes various features of the decision environment and the ways in which model-based decision support can help the modern decision making process; it presents the methodology and software tools for building mathematical models and for their multicriteria analysis; the presented methods and tools are illustrated by detailed presentation of four complex environmental applications, including the three models outlined in this article.

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