3. Modelling Methods for Evaluating Alternatives

3 Modelling Methods for Evaluating Alternatives

Water resources systems are characterized by multiple interdependent components that together produce multiple economic, environmental, ecological and social impacts. Planners and managers working to improve the performance of these complex systems must identify and evaluate alternative designs and operating policies, comparing their predicted performance with the desired goals or objectives. These alternatives are defined by the values of numerous design, target and operating policy variables. Constrained optimization together with simulation modelling is the primary way we have of estimating the values of the decision variables that will best achieve specified performance objectives. This chapter introduces these optimization and simulation methods and describes what is involved in developing and applying them in engineering projects.

1. Introduction

Water resources system planners must identify and evaluate alternative water resources system designs or management plans on the basis of their economic, ecological, environmental, and social or political impacts. One important criterion for plan identification and evaluation is the economic benefit or cost a plan would entail were it to be implemented. Other criteria can include the extent to which any plan meets environmental, ecological and social targets. Once planning or management performance measures (objectives) and various general alternatives for achieving desired levels of these performance measures have been identified, models can be developed and used to help identify specific alternative plans that best meet those objectives.

Some system performance objectives may be in conflict, and in such cases models can help identify the efficient tradeoffs among these conflicting measures of system performance. These tradeoffs indicate what combinations of performance measure values can be obtained from various system design and operating policy variable values. If the objectives are the right ones (that is, they are what the stakeholders really care about), such quantitative tradeoff information should be of value during the debate over what decisions to make.

Regional water resources development plans designed to achieve various objectives typically involve investments in land and infrastructure. Achieving the desired economic, environmental, ecological and social objective values over time and space may require investments in storage facilities, including surface or groundwater reservoirs and storage tanks, pipes, canals, wells, pumps, treatment plants, levees and hydroelectric generating facilities, or in fact the removal of some of them.

Many capital investments can result in irreversible economic and ecological impacts. Once the forest of a valley is cleared and replaced by a lake behind a dam, it is almost impossible to restore the site to its original condition. In parts of the world where river basin or coastal restoration activities require the removal of engineering structures, water resources engineers are learning just how difficult and expensive that effort can be.

The use of planning models is not going to eliminate the possibility of making mistakes. These models can, however, better inform. They can provide estimates of the different impacts associated with, say, a natural unregulated river system and a regulated river system. The former can support a healthier ecosystem that provides a host of flood protection and water quality enhancement services. The latter can provide more reliable and cheaper water supplies for off-stream users and increased hydropower and some protection from at least small floods for those living on flood-prone lands. In short, models can help stakeholders assess the future consequences, the benefits and costs, and a multitude of other impacts associated with alternative plans or management policies.

This chapter introduces some mathematical optimization and simulation modelling approaches commonly used to study and analyse water resources systems. The modelling approaches are illustrated by their application to some relatively simple water resources planning and management problems. The purpose here is to introduce and compare some commonly used methods of (or approaches to) modelling. This is not a text on the state-of-the-art of optimization or simulation modelling. In subsequent chapters of this book, more details will be given about optimization models and simulation methods. More realistic and more complex problems usually require much bigger and more complex models than those developed in this book, but these bigger and more complex models are often based on the principles and techniques introduced here.

Regardless of the problem complexity or size, the modelling approaches are the same. Thus, the emphasis here is on the art of model development: just how one goes about constructing a model that will provide information needed to solve a particular problem, and various ways models might be solved. It is unlikely anyone will ever use any of the specific models developed in this or other chapters, simply because they will not be solving the specific examples used to illustrate the different approaches to model development and solution. However, it is quite likely that water resources managers and planners will use the modelling approaches and solution methods presented in this book to analyse similar types of problems. The particular problems used here, or any others that could have been used, can be the core of more complex models addressing more complex problems in practice.

Water resources planning and management today is dominated by the use of predictive optimization and simulation models. While computer software is becoming increasingly available for solving various types of optimization and simulation models, no software currently exists that will build those models themselves. What and what not to include and assume in models requires judgement, experience and knowledge of the particular problem being addressed, the system being modelled and the decision-making environment. Understanding the contents of, and performing the exercises for, this chapter will be a first step towards gaining some judgement and experience in model development.

1.1. Model Components

Mathematical models contain algebraic equations. These equations include variables that are assumed to be known and others that are unknown and to be determined. Known variables are usually called *parameters*, and unknown variables are called *decision variables*. Models are developed for the primary purpose of identifying the best values of the latter. These decision variables can include design and operating policy variables of various water resources system components.

Design variables can include the active and flood storage capacities of reservoirs, the power generating capacity of hydropower plants, the pumping capacity of pumping stations, the efficiencies of wastewater treatment plants, the dimensions or flow capacities of canals and pipes, the heights of levees, the hectares of an irrigation area, the targets for water supply allocations and so on. Operating variables can include releases of water from reservoirs or the allocations of water to various users over space and time. Unknown decision variables can also include measures of system performance, such as net economic benefits, concentrations of pollutants, ecological habitat suitability values or deviations from particular ecological, economic or hydrological targets.

Models describe, in mathematical terms, the system being analysed and the conditions that the system has to satisfy. These conditions are often called constraints. Consider, for example, a reservoir serving various water supply users downstream. The conditions included in a model of this reservoir would include the assumption that water will flow in the direction of lower heads (that is, downstream unless it is pumped upstream), and the volume of water stored in a reservoir cannot exceed the

Figure 3.1. These stakeholders have an interest in how their watershed or river basin is managed. Here they are using a physical model to help them visualize and address planning and management issues. Mathematical models often replace physical models, especially for planning and management studies. (Reprinted with permission from Engineering News-Record, copyright The McGraw-Hill Companies, Inc., September 20, 1993. All rights reserved.).

reservoir's storage capacity. Both the storage volume over time and the reservoir capacity might be unknown. If the capacity is known or assumed, then it is among the known model parameters.

Model parameter values, while assumed to be known, can often be uncertain. The relationships between various decision variables and assumed known model parameters (i.e., the model itself) may be uncertain. In these cases the models can be solved for a variety of assumed conditions and parameter values. This provides an estimate of just how important uncertain parameter values or uncertain model structures are with respect to the output of the model. This is called *sensitivity analysis*. Sensitivity analyses will be discussed in Chapter 9 in much more detail.

Solving a model means finding values of its unknown decision variables. The values of these decision variables can define a plan or policy. They can also define the costs and benefits or other measures of system performance associated with that particular management plan or policy.

While the components of optimization and simulation models include system performance indicators, model parameters and constraints, the process of model development and use includes people. The drawing shown in Figure 3.1 illustrates some interested stakeholders busy studying their river basin, in this case perhaps with the use of a physical model. Whether a mathematical model or physical model is being used, one important consideration is that if the modelling exercise is to be of any value, it must provide the information desired and in a form that the interested stakeholders can understand.

2. Plan Formulation and Selection

Plan formulation can be thought of as assigning particular values to each of the relevant decision variables. Plan selection is the process of evaluating alternative plans and selecting the one that best satisfies a particular objective or set of objectives. The processes of plan formulation and selection involve modelling and communication among all interested stakeholders, as the picture in Figure 3.1 suggests.

The planning and management issues being discussed by the stakeholders in the basin pictured in Figure 3.1 could well include surface and groundwater water allocations, reservoir operation, water quality management and infrastructure capacity expansion.

2.1. Plan Formulation

Model building for defining alternative plans or policies involves a number of steps. The first is to clearly specify the issue or problem or decision(s) to be made. What are the fundamental objectives and possible alternatives? Such alternatives might require defining allocations of water to various water users, the level of wastewater treatment, the capacities and operating rules of multipurpose reservoirs and hydropower plants, and the extent and reliability of floodplain protection from levees. Each of these decisions may affect system performance criteria or objectives. Often these objectives include economic measures of performance, such as costs and benefits. They may also include environmental and social measures not expressed in monetary units. (More detail on performance criteria is contained in Chapter 10.)

To illustrate this plan formulation process, consider the problem of designing a tank to hold a specific amount of water. The criterion to be used to compare different feasible designs is cost. The goal in this example is to find the least-cost shape and dimensions of a tank that will hold a specified volume, say V, of water.

The model of this problem must somehow relate the unknown design variable values to the cost of the tank. Assume, for example, a rectangular tank shape. The design variables are the length, L, width, W, and height, H, of the tank. These are the unknown decision variables. The objective is to find the combination of L, W, and H values that minimizes the total cost of providing a tank capacity of at least V units of water. This volume V will be one of the model parameters. Its value is assumed known even though in fact it may be unknown and dependent in part on the cost.

The cost of the tank will be the sum of the costs of the base, the sides and the top. These costs will depend on the area of the base, sides and top. The costs per unit area may vary depending on the values of L, W and H; however, even if those cost values depend on the values of those decision variables, given any specific values for L, W and H, one can define an average cost-per-unit area. Here we will assume these average costs per unit area are known. They can be adjusted if they turn out to be incorrect for the derived values of L, W and H.

These average unit costs of the base, sides and top will probably differ. They can be denoted as C_{base}, C_{side} and C_{top} respectively. These unit costs together with the tank's volume, V, are the parameters of the model. If L, W, and H are measured in metres, then the areas will be expressed in units of square metres and the volume will be expressed in units of cubic metres. The average unit costs will be expressed in monetary units per square metre.

The final step of model building is to specify all the relations among the objective (cost), function and decision variables and parameters, including all the conditions that must be satisfied. It is often wise to first state these relationships in words. The result is a word model. Once that is written, mathematical notation can be defined and used to construct a mathematical model.

The word model for this tank design problem is to minimize total cost where:

- Total cost equals the sum of the costs of the base, the sides and the top.
- Cost of the sides is the cost-per-unit area of the sides times the total side area.
- Cost of the base is the cost-per-unit area of the base times the total base area.
- Cost of the top is the cost-per-unit area of the top times the total top area.
- The volume of the tank must at least equal some specified volume capacity.
- The volume of the tank is the product of the length, width and height of the tank.

Using the notation already defined, and combining some of the above conditions, a mathematical model can be written as:

$$\text{Minimize } Cost \tag{3.1}$$

Subject to:

$$Cost = (C_{base} + C_{top})(LW) + 2(C_{side})\,(LH + WH) \tag{3.2}$$

$$LWH \geq V \tag{3.3}$$

Equation 3.3 permits the tank's volume to be larger than that required. While this is allowed, it will cost more if the tank's capacity is larger than V, and hence the least-cost solution of this model will surely show that LWH will equal V. In practice, however, there may be practical, legal and/or safety reasons why the decisions with respect to L, W and H may result in a capacity that exceeds the required volume, V.

This model can be solved a number of ways, which will be discussed later in this and the next chapters. The least-cost solution is

$$W = L = [2C_{side}\,V/(C_{base} + C_{top})]^{1/3} \tag{3.4}$$

$$\text{and } \quad H = V/[2C_{side}\,V/(C_{base} + C_{top})]^{2/3} \tag{3.5}$$

$$\text{or } \quad H = V^{1/3}[(C_{base} + C_{top})/2C_{side}]^{2/3} \tag{3.6}$$

The modelling exercise should not end here. If there is any doubt about the value of any of the parameters, a sensitivity analyses should be performed on those uncertain parameters or assumptions. In general these assumptions could include the values of the cost parameters (e.g., the costs-per-unit area) as well as the relationships expressed in the model (that is, the model itself). How much does the total cost change with respect to a change in any of the cost parameters or with the required volume V? How much does any decision-variable change with respect to changes in those parameter values? What is the percent change in a decision-variable value given a unit percent change in some parameter value (what economists call *elasticity*)?

If indeed the decision-variable values do not change significantly with respect to a change in the value of an uncertain parameter value, there is no need to devote more effort to reducing that uncertainty. Any time and money available for further study should be directed toward those parameters or assumptions that substantially influence the model's decision-variable values.

This capability of models to help identify what data are important and what data are not can guide monitoring and data collection efforts. This is a beneficial attribute of modelling often overlooked.

Continuing with the tank example, after determining, or estimating, all the values of the model parameters and then solving the model to obtain the cost-effective values of L, W and H, we now have a design. It is just one of a number of designs that could be proposed. Another design might be for a cylindrical tank having a radius and height as decision-variables. For the same volume V and unit area costs, we would find that the total cost is less, simply because the areas of the base, side and top are less. We could go one step further and consider the possibility of a truncated cone, having different bottom and top radii. In this case both radii and the height would be the decision-variables. But whatever the final outcome of our modelling efforts, there might be other considerations or criteria that are not expressed or included in the model that might be important to those responsible for plan (tank design) selection.

2.2. Plan Selection

Assume P alternative plans (e.g., tank designs) have been defined, each designated by the index p. For each plan, there exist n_p decision variables x_j^p indexed with the letter j. Together these variables and their values, expressed by the vector $\boldsymbol{X}^p$, define the specifics of the pth plan. The index j distinguishes one decision-variable from another, and the index p distinguishes one plan from another. The task at hand, in this case, may be to find the particular plan p, defined by the known values of each decision-variable in the vector $\boldsymbol{X}^p$, that maximizes the present value of net benefits, $B(\boldsymbol{X}^p)$, derived from the plan.

Assume for now that an overall performance objective can be expressed mathematically as:

$$\text{maximize } B(\boldsymbol{X}^p) \tag{3.7}$$

The values of each decision-variable in the vector $\boldsymbol{X}^p$ that meet this objective must be feasible; in other words, they must meet all the physical, legal, social and institutional constraints.

$$\boldsymbol{X}^p \text{ feasible for all plans } p. \tag{3.8}$$

There are various approaches to finding the 'best' plan or best set of decision-variable values. By trial and error, one could identify alternative plans p, evaluate the net benefits derived from each plan, and select the particular plan whose net benefits are a maximum. This process could include a systematic simulation of a range of possible solutions in a search for the best. When there is a large number of feasible alternatives – that is, many decision-variables and many possible values for each of them – it may no longer be practical to identify and simulate all feasible combinations of decision-variable values, or even a small percentage of them. It would simply take too long. In this case it is often convenient to use an optimization procedure.

Equations 3.7 and 3.8 represent a discrete optimization problem. There are a finite set of discrete alternatives. The set could be large, but it is finite. The tank problem example is a continuous optimization problem having, at least mathematically, an infinite number of feasible solutions. In this case optimization involves finding feasible values of each decision-variable x_j in the set of decision variables $\boldsymbol{X}$ that maximize (or minimize) some performance measure, $B(\boldsymbol{X})$. Again, feasible values are those that satisfy all the model constraints. A continuous constrained optimization problem can be written as:

$$\text{maximize } B(\boldsymbol{X}) \tag{3.9}$$

$$\boldsymbol{X} \text{ feasible} \tag{3.10}$$

While maximization of Equation 3.7 requires a comparison of $B(\boldsymbol{X}^p)$ for every discrete plan p, the maximization of Equation 3.9, subject to the feasibility conditions required in Equation 3.10, by complete enumeration is impossible. If there exists a feasible solution – in other words, at least one that satisfies all the constraints – mathematically there are likely to be an infinite number of possible feasible solutions or plans represented by various values of the decision-variables in the vector $\boldsymbol{X}$.

Finding by trial and error the values of the vector $\boldsymbol{X}$ that maximizes the objective Equation 3.9 and at the same time meet all the constraints is often difficult. Some type of optimization procedure, or algorithm, is useful in such cases. Mathematical optimization methods are designed to make this search for the best solution (or better solutions) more efficient. Optimization methods are used to identify those values of the decision-variables that satisfy specified objectives and constraints without requiring complete enumeration.

While optimization models might help identify the decision-variable values that will produce the best plan directly, they are based on all the assumptions incorporated in the model. Often these assumptions are limiting. In these cases the solutions resulting from optimization models should be analysed in more detail, perhaps through simulation methods, to improve the values of the decision-variables and to provide more accurate estimates of the impacts associated with those decision-variable values. In these situations, optimization models are used for screening out the clearly inferior solutions, not for finding the very best one. Just how screening is performed using optimization models will be discussed in the next chapter.

The values that the decision-variables may assume are rarely unrestricted. Usually various functional relationships among these variables must be satisfied. This is what is expressed in constraint Equations 3.8 and 3.10. For example, the tank had to contain a given amount of water. In a water-allocation problem, any water allocated to and completely consumed by one user cannot simultaneously or subsequently be allocated to another user. Storage reservoirs cannot store more water than their maximum capacity. Technological restrictions may limit the capacities and sizes of pipes, generators and pumps to those commercially available. Water quality concentrations should not exceed those specified by water quality standards or regulations. There may be limited funds available to spend on water resources development projects. These are a few examples of physical, legal and financial conditions or constraints that may restrict the ranges of variable values in the solution of a model.

Equations or inequalities can generally express any physical, economic, legal or social restrictions on the values of the decision-variables. Constraints can also simply define relationships among decision-variables. For example, Equation 3.2 above defines a new decision-variable called *Cost* as a function of other decision-variables and model parameters.

In general, constraints describe in mathematical terms the system being analysed. They define the system components and their inter-relationships, and the permissible ranges of values of the decision-variables, either directly or indirectly.

Typically, there exist many more decision-variables than constraints, and hence, if any feasible solution exists, there may be many such solutions that satisfy all the constraints. The existence of many feasible alternative plans is a characteristic of most water resources systems planning problems. Indeed it is a characteristic of most engineering design and operation problems. The particular feasible solution or plan that satisfies the objective function – that is, that maximizes or minimizes it – is called *optimal*. It is the optimal solution of the mathematical model, but it may not necessarily be considered optimal by any decision-maker. What is optimal with respect to some model may not be optimal with respect to those involved in a planning or decision-making process. To repeat what was written in Chapter 2, models are used to provide information (useful information, one hopes), to the decision-making process. Model solutions are not replacements for individuals involved in the decision-making process.

3. Modelling Methods: Simulation or Optimization

The modelling approach discussed in the previous section focused on the use of optimization methods to identify the preferred design of a tank. Similar methods can be used to identify preferred design-variable values and operating policies for multiple reservoir systems, for example. Once these preferred designs and operating policies have been identified, unless there is reason to believe that a particular alternative is really the best and needs no further analysis, each of these preferred alternatives can be further evaluated with the aid of more detailed and robust simulation models. Simulation models address '*what if*' questions: What will likely happen over time and at one or more specific places if a particular design and/or operating policy is implemented?

Simulation models are not limited by many of the assumptions incorporated into optimization models. For example, the inputs to simulation models can include a much longer time series of hydrological, economic and environmental data such as rainfall or streamflows, water supply demands, pollutant loadings and so on than would likely be included in an optimization model. The resulting outputs can better identify the variations of multiple system performance indicator values: that is, the multiple hydrological, ecological, economic and environmental impacts that might be observed over time, given any particular system design and operating policy.

Simulating multiple sets of values defining the designs and operating policies of a water resources system can take a long time. Consider, for example, only 30 decision-variables whose best values are to be determined. Even if only two values are assumed for each of the 30 variables, the number of combinations that could be simulated amounts to 2^{30} or in excess of 10^9. Simulating and comparing even 1% of these billion at a minute per simulation amounts to over twenty years, continuously and without sleeping. Most simulation models of water resources systems contain many more variables and are much more complex than this simple 30-binary-variable example. In reality there could be an infinite combination of feasible values for each of the decision-variables.

Simulation works when there are only a relatively few alternatives to be evaluated, not when there are a large number of them. The trial and error process of simulation can be time consuming. An important role of optimization methods is to reduce the number of alternatives for simulation analyses. However, if only one method of analysis is to be used to evaluate a complex water resources system, simulation together with human judgement concerning which alternatives to simulate is often, and rightly so, the method of choice.

Simulation can be based on either discrete events or discrete time periods. Most simulation models of water resources systems are designed to simulate a sequence of discrete time periods. In each discrete time period, the simulation model converts all the initial conditions and inputs to outputs. The duration of each period depends in part on the particular system being simulated and the questions being addressed.

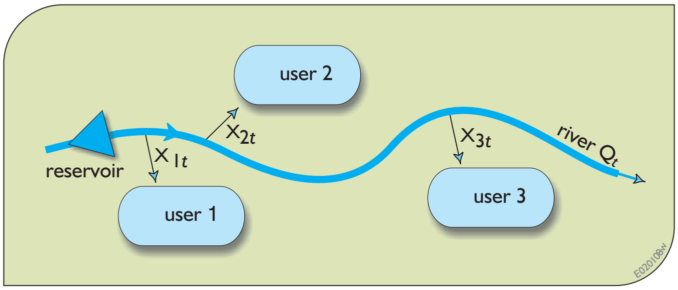

Figure 3.2. Reservoir-water allocation system to be simulated.

3.1. A Simple Planning Example

Consider the case of a potential reservoir releasing water to downstream users. A reservoir and its operating policy can increase the benefits each user receives over time by providing increased flows during periods of otherwise low flows relative to the user demands. Of interest is whether or not the increased benefits the water users obtain from an increased flow and more reliable downstream flow conditions will offset the costs of the reservoir. This water resources system is illustrated in Figure 3.2.

Before this system can be simulated, one has to define the active storage capacity of the reservoir and how much water is to be released depending on the storage volume and time period; in other words, one has to define the reservoir operating policy. In addition, one must also define the allocation policy: how much water to allocate to each user and to the river downstream of the users given any particular reservoir release.

For this simple illustration assume these operating and allocation policies are as shown in Figure 3.3. Also for simplicity assume they apply to each discrete time period.

The reservoir operating policy, shown as a red line in Figure 3.3, attempts to meet a release target. If insufficient water is available, all the water will be released in the time period. If the inflow exceeds the target flow and the reservoir is at capacity, a spill will occur. This operating policy is sometimes called the 'standard' operating policy. It is not usually followed in practice. Most operators, as indeed specified by most reservoir operating policies, will reduce releases in times of drought in an attempt to save

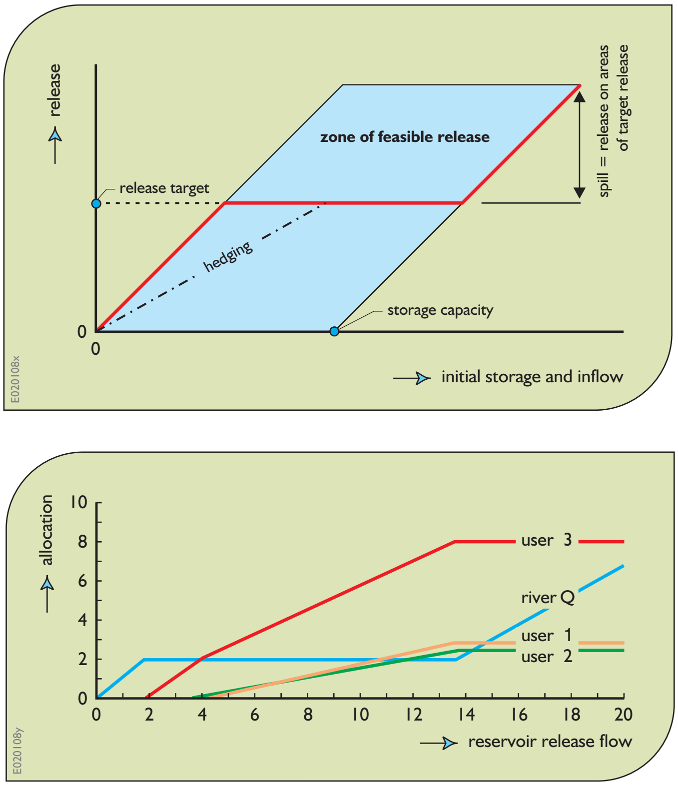

Figure 3.3. Policy defining the reservoir release to be made as a function of the current storage volume and current inflow and the reservoir release allocation policy for the river flow downstream of the reservoir. The blue zone in the reservoir release policy indicates the zone of feasible releases. It is physically impossible to make releases represented by points outside that blue zone.

some water in the reservoir for future releases in case of an extended period of low inflows. This is called a hedging policy. Any reservoir release policy, including a hedging policy, can be defined within the blue portion of the release policy plot shown in Figure 3.3. The dash–dot line in Figure 3.3 is one such hedging function.

Once defined, any reservoir operating policy can be simulated.

3.2. Simulation Modelling Approach

The simulation process for the three-user system shown in Figure 3.2 proceeds from one time period to the next. The reservoir inflow, obtained from a database, is added to the existing storage volume, and a release is determined from the release policy. Once the release is known, the final storage volume is computed and this becomes the initial volume for the next simulation time period. The reservoir release is then allocated to the three downstream users and to the river downstream of those users as defined by the allocation policy. The resulting benefits can be calculated and stored in an output database. Additional data pertaining to storage volumes, releases and the allocations themselves can also be stored in the output database, as desired. The process continues for the duration of the simulation run. Then the output data can be summarized for later comparison with other simulation results based on other reservoir capacities and operation policies and other allocation policies. Figure 3.4 illustrates this simulation process.

It would not be too difficult to write a computer program to carry out this simulation. In fact, it can be done on a spreadsheet. However easy that might be for anyone familiar with computer programming or spreadsheets, one cannot expect it to be easy for many practicing water resources planners and managers who are not doing this type of work on a regular basis. Yet they might wish to perform a simulation of their particular system, and to do it in a way that facilitates changes in many of its assumptions.

Computer programs capable of simulating a wide variety of water resources systems are becoming increasingly available. Simulation programs together with their interfaces that facilitate the input and editing of data and the display of output data are typically called decision support systems. Their input data define the components of the water resources system and their configuration. Inputs include hydrological data and design and operating policy data. These generic simulation programs are now becoming capable of simulating surface and groundwater water flows, storage volumes and qualities under a variety of system infrastructure designs and operating policies.

3.3. Optimization Modelling Approach

The simple reservoir-release and water-allocation planning example of Section 3.1 can also be described as an optimization model. The objective remains that of maximizing the total benefits that the three users obtain from the water that is allocated to them. Denoting each user's benefit as B_{it} ($i = 1, 2, 3$) for each of T time periods t, this objective, expressed symbolically is to:

$$\text{maximize total benefits} = \sum_{t}^{T} \{B_{1t} + B_{2t} + B_{3t}\} \qquad (3.11)$$

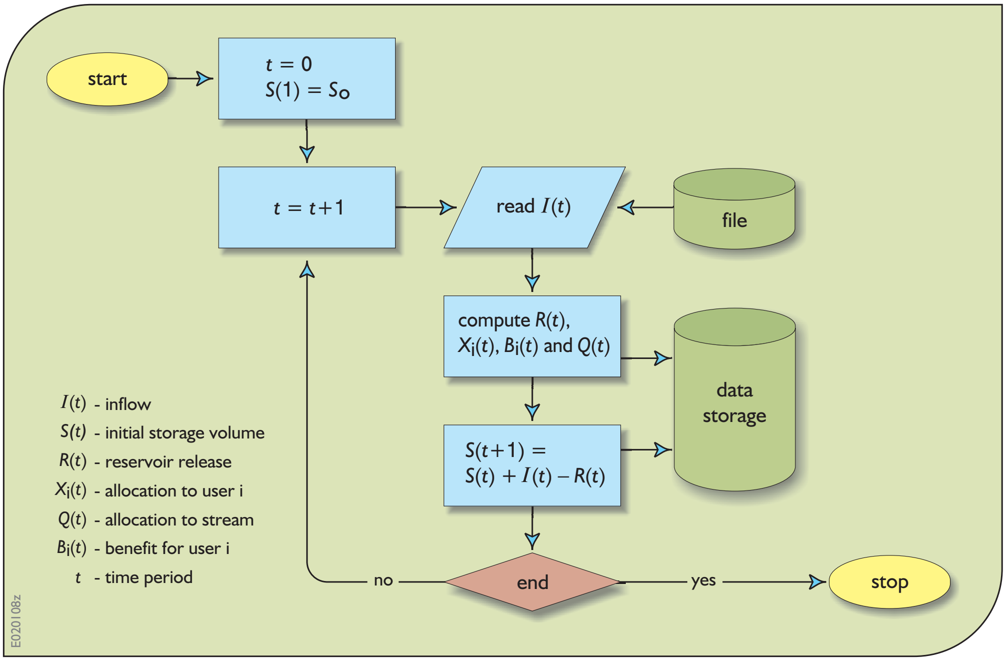

Figure 3.4. Flow diagram of the reservoir-allocation system simulation process. The simulation terminates after some predefined number of simulation time steps.

The benefit, B_{it}, for each user i in each time period t depends on the amount of water, X_{it}, allocated to it. These benefit functions, $B_{it} = B_{it}(X_{it})$, need to be known and expressed in a form suitable for solution using the particular optimization solution algorithm selected. The unknown variables include the allocations, X_{it}, and associated reservoir releases R_t for all periods $t = 1, 2, 3, \ldots, T$. Assuming there is no significant incremental runoff between the upstream reservoir and the sites where water is diverted from the river, the amounts allocated to all users, the sum of all X_{it} in each period t, cannot exceed the amount of water released from the reservoir, R_t, in the period. This is one of the optimization model constraints:

$$R_t \geq X_{1t} + X_{2t} + X_{3t} \tag{3.12}$$

The remaining necessary constraints apply to the reservoir. A mass balance of water storage is needed, along with constraints limiting initial storage volumes, S_t, to the capacity, K, of the reservoir. Assuming a known time-series record of reservoir inflows, I_t, in each of the time periods being considered, the mass-balance or continuity equations for storage changes in each period t can be written:

$$S_t + I_t - R_t = S_{t+1} \quad \text{for } t = 1, 2, \ldots, T;$$
$$\text{If } t = T, \text{ then } T+1 = 1. \tag{3.13}$$

The capacity constraints simply limit the unknown initial storage volume, S_t, to be no greater than the reservoir capacity, K.

$$S_t \leq K \quad \text{for } t = 1, 2, \ldots, T. \tag{3.14}$$

A one-year analysis period with $T = 12$ time periods of one month each in combination with three allocation variables, X_{it}, a storage variable S_t, and a release R_t, variable in each period t, includes a total of sixty unknown decision-variables. The job of the optimization solution procedure is to find the values of these sixty variables that will satisfy the objective, Equation 3.11, that is to say, maximize total benefits, and at the same time satisfy all of the thirty-six constraint equations and inequalities as well.

In this example the reservoir inflows, I_t, its storage capacity, K, and each user's benefit functions, B_{it}, are assumed known. In some cases such information is not known. Nor were other purposes, such as hydropower, flood control, water quality or recreation considered in this example, to mention only a few possible extensions. Such conditions and extensions will be considered in later chapters.

3.4. Simulation Versus Optimization

Unlike simulation models, the solutions of optimization models are based on objective functions of unknown decision-variables that are to be maximized or minimized.

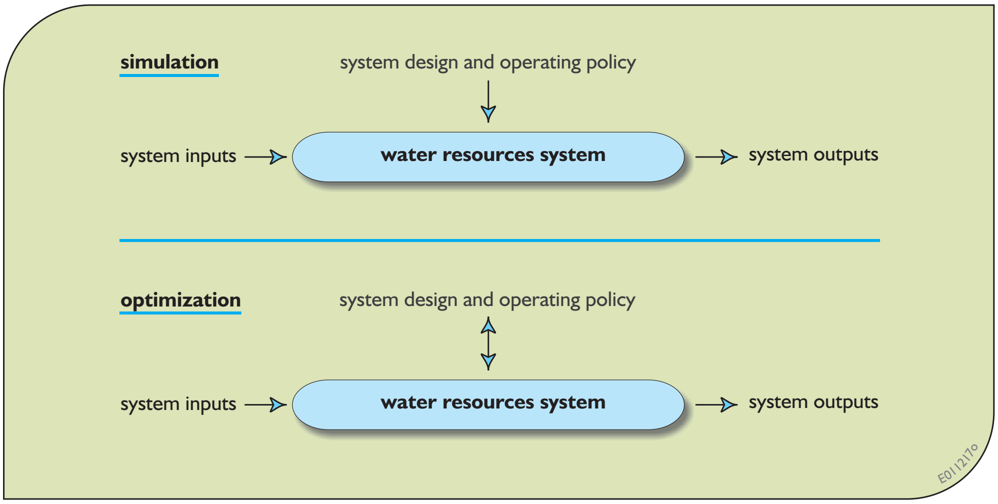

Figure 3.5. Distinguishing between simulation and optimization modelling. Simulation addresses '*what if*' questions; optimization can address '*what should be*' questions. Both types of models are often needed in water resources panning and management studies.

The constraints of an optimization model contain decision-variables that are unknown and parameters whose values are assumed known. Constraints are expressed as equations and inequalities. The tank model (Equations 3.1, 3.2 and 3.3) is an example of an optimization model. So is the reservoir water-allocation model, Equations 3.11 to 3.14. The solution of an optimization model, if one exists, contains the values of all of the unknown decision-variables. It is mathematically optimal in that the values of the decision-variables satisfy all the constraints and maximize or minimize an objective function. This 'optimal' solution is of course based on the assumed values of the model parameters, the chosen objective function and the structure of the model itself.

The procedure (or algorithm) most appropriate for solving any particular optimization model depends in part on the particular mathematical structure of the model. There is no single universal solution procedure that will efficiently solve all optimization models. Hence, model builders tend to model water resources systems by using mathematical expressions that are of a form compatible with one or more known solution procedures. Approximations of reality, made to permit model solution by a chosen optimization solution procedure (algorithm), may justify a more detailed simulation to check and improve on any solution obtained from that optimization. Simulation models are not restricted to any particular form of mathematics, and can define many relations including those not easily incorporated into optimization models.

One of many challenges in the use of optimization modelling is our inability to quantify and express mathematically all the planning objectives, the technical, economic, and political constraints and uncertainties, and other important considerations that will influence the decision-making process. Hence at best a mathematical-model of a complex water resources system is only an approximate description of the real system. The optimal solution of any model is optimal *only with respect to the particular model*, not necessarily with respect to the real system. It is important to realize this limited meaning of the word 'optimal,' a term commonly used by water resources and other systems analysts, planners and engineers.

Figure 3.5 illustrates the broad differences between simulation and optimization. Optimization models need explicit expressions of objectives. Simulation models do not. Simulation simply addresses 'what-if' sceanarios – what may happen if a particular scenario is assumed or if a particular decision is made. Users must specify the values of design and operating decision-variables before a simulation can be performed. Once these values of all decision-variables are defined, simulation can help us estimate more precisely the impacts that may result from those decisions. The difficulty with using simulation alone for analysing multiple alternatives occurs when there are many alternative, and potentially attractive, feasible solutions or plans and not enough time or resources to simulate them all. Even when combined with efficient techniques for selecting the values of each decision-variable, an enormous computational effort may still lead to a solution that is still far from the best possible.

For water resources planning and management, it is often advantageous to use both optimization and simulation modelling. While optimization will tell us

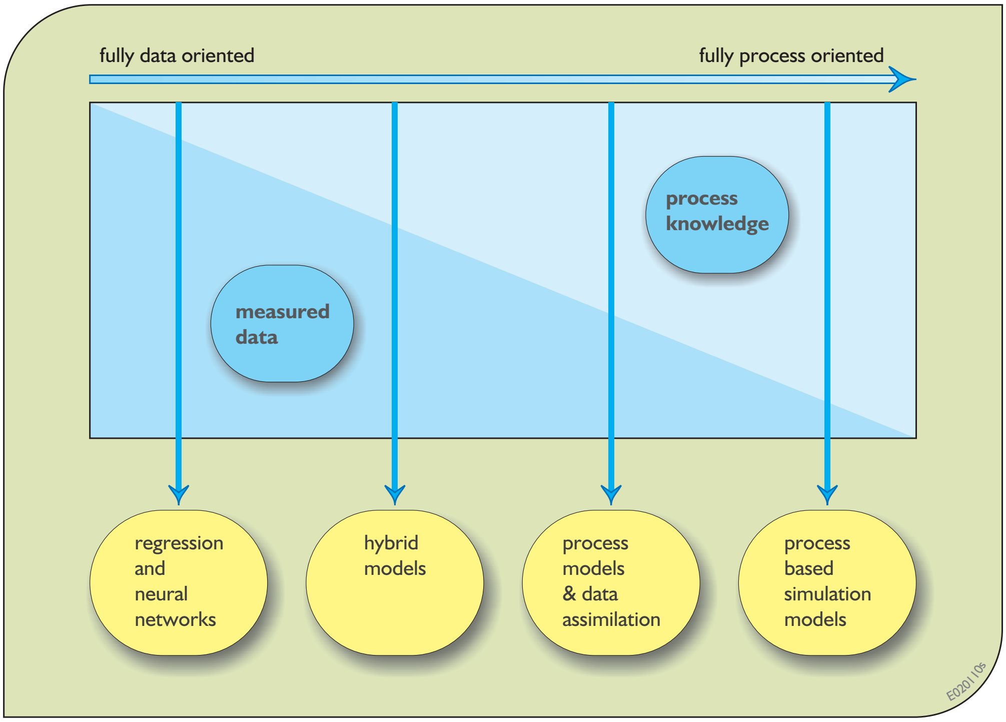

Figure 3.6. Range of simulation models types based on the extent to which measured field data and descriptions of system processes are included in the model.

what we should do – what the best decision is – that solution is often based on many limiting assumptions. Because of this, we need to use optimization not as a way to find the best solution, but to define a relatively small number of good alternatives that can later be tested, evaluated and improved by means of simulation. This process of using optimization to reduce the large number of plans and policies to a few that can then be simulated and better evaluated is often called preliminary screening.

3.5. Types of Models

3.5.1. Types of Simulation Models

Simulation models can be statistical or process oriented, or a mixture of both. Pure statistical models are based solely on data (field measurements). Pure process-oriented models are based on knowledge of the fundamental processes that are taking place. The example simulation model just discussed is a process-oriented model. It incorporated and simulated the physical processes taking place in the system. Many simulation models combine features of both of these extremes.

The range of various simulation modelling approaches applied to water resources systems is illustrated in Figure 3.6.

Regressions, such as that resulting from a least-squares analysis, and artificial neural networks are examples of purely statistical models. As discussed in Chapter 6, a relationship is derived between input data (cause) and output data (effect), based on measured and observed data. The relationship between the input and the output variable values is derived by calibrating a black-box or statistical model with a predefined structure unrelated to the actual natural processes taking place. Once calibrated, the model can be used to estimate the output variable values as long as the input variable values are within the range of those used to calibrate the model.

Hybrid models incorporate some process relationships into regression models or neural networks. These relationships supplement the knowledge contained in the calibrated parameter values based on measured data.

Most simulation models containing process relationships include parameters whose values need to be estimated. This is called model calibration. Calibration requires measured field data. These data can be used for initial calibration and verification, and in the case of ongoing simulations, for continual calibration and uncertainty reduction. The latter is sometimes referred to as data assimilation.

Other simulation model classifications are possible. Simulation models can be classified based on what the model simulates: on the domain of application. Today one can obtain, or develop, computer programs written to simulate a wide variety of water resources system components or events. Some of these include:

- water quantity and/or quality of rivers, bays, estuaries or coastal zones
- reservoir operation for quantity and/or quality
- saturated and/or unsaturated zone groundwater quantity and/or quality
- precipitation runoff, including erosion and chemicals
- water system demands, supply distribution and treatment
- high-water forecasting and control
- hazardous material spills
- morphological changes
- wastewater collection systems
- wastewater purification facilities
- irrigation operations
- hydropower production
- ecological habitats of wetlands, lakes, reservoirs and flood plains
- economic benefits and costs.

Simulation models of water resources systems generally have both spatial and temporal dimensions. These dimensions may be influenced by the numerical methods used, if any, in the simulation, but otherwise they are usually set, within the limits desired by the user. Spatial resolutions can range from 0 to 3 dimensions. Models are sometimes referred to as quasi 2- or 3-dimensional models. These are 1 or 2-dimensional models set up in a way that approximates what takes place in 2- or 3-dimensional space, respectively. A quasi-3D system of a reservoir could consist of a series of coupled 2D horizontal layers, for example.

Simulation models can be used to study what might occur during a given time period, say a year, sometime in the future, or what might occur from now to that given time in the future. Models that simulate some particular time in the future, where future conditions such as demands and infrastructure design and operation are fixed, are called stationary or static models. Models that simulate developments over time are called dynamic models. Static models are those in which the external environment of the system being simulated is not changing. Water demands, soil conditions, economic benefit and cost functions, populations and other factors do not change from one year to the next. Static models provide a snapshot or a picture at a point in time. Multiple years of input data may be simulated, but from the output statistical summaries can be made to identify what the values of all the impact variables could be, together with their probabilities, at that future time period.

Dynamic simulation models are those in which the external environment is also changing over time. Reservoir storage capacities could be decreasing due to sediment load deposition, costs could be increasing due to inflation, wastewater effluent discharges could be changing due to changes in populations and/or wastewater treatment capacities, and so on.

Simulation models can also vary in the way they are solved. Some use purely analytical methods while others require numerical ones. Many use both methods, as appropriate.

Finally, models can also be distinguished according to the questions being asked and the level of information desired. The type of information desired can range from data of interest to policy-makers and planners (requiring relatively simple models and broader in scope) to that of interest to researchers desiring a better understanding of the complex natural, economic and social processes taking place (requiring much more detailed models and narrower in scope). Water management and operational models (for real-time operations of structures, for example) and event-based calamity models are somewhere between these two extremes with respect to model detail. The scope and level of detail of any modelling study will also depend on the time, money and data available for that study (see Chapter 2).

3.5.2. Types of Optimization Models

There are many ways to classify various types of constrained optimization models. Optimization models can be deterministic or probabilistic, or a mixture of both. They can be static or dynamic with respect to time. Many water resources planning and management models are static, but include multiple time periods to obtain a statistical snapshot of various impacts in some planning period. Optimization models can be linear or non-linear. They can consist of continuous variables or discrete or integer variables, or a combination of both. But whatever type they are, they have in common the fact that they are describing situations where there exist multiple solutions that satisfy all the constraints, and hence, there is the desire to find the best solution, or at least a set of very good solutions.

Regardless of the type of optimization model, they all include an objective function. The objective function of an optimization model (such as Equation 3.11 in the example problem above) is used to evaluate multiple possible solutions. Often multiple objective functions may be identified (as will be discussed in Chapter 10). But at least one objective must be identified in all optimization models. Identifying the best objective function is often a challenging task.

Optimization models can be based on the particular type of application, such as reservoir sizing and/or operation, water quality management, or irrigation development or operation. Optimization models can also be classified into different types depending on the algorithm to be used to solve the model. Constrained optimization algorithms are numerous. Some guarantee to find the best model solution and others can only guarantee locally optimum solutions. Some include algebraic 'mathematical programming' methods and others include deterministic or random trial-and-error search techniques. Mathematical programming techniques include Lagrange multipliers, linear programming, non-linear programming, dynamic programming, quadratic programming, fractional programming and geometric programming, to mention a few. The applicability of each of these as well as other constrained optimization procedures is highly dependent on the mathematical structure of the model. The following Chapter 4 illustrates the application of some of the most commonly used constrained optimization techniques in water resources planning and management. These include classical constrained optimization using calculus-based Lagrange multipliers, discrete dynamic programming, and linear and non-linear programming.

Hybrid models usually include multiple solution methods. Many generic multi-period simulation models are driven by optimization methods within each time period. (The CALSIM II model used by the State of California and the US Bureau of Reclamation to allocate water in central California is one such model.)

Each of a variety of optimization modelling types and solution approaches will be discussed and illustrated in more detail in subsequent chapters. In some cases, we can use available computer programs to solve optimization models. In other cases, we may have to write our own software. To make effective use of optimization, and even simulation, models one has to learn some model solution methods, since those methods often dictate the type of model most appropriate for analysing a particular planning or management problem or issue.

To date, no single model type or solution procedure has been judged best for all the different types of issues and problems encountered in water resources planning and management. Each method has its advantages and limitations. One will experience these advantages and limitations as one practices the art of model development and application.

4. Model Development

Prior to the selection or development of a quantitative simulation model, it is often useful to develop a conceptual one. Conceptual models are non-quantitative representations of a system. The overall system structure is defined but not all its elements and functional relationships.

Figure 3.7 illustrates a conceptual model, without indicating what each box represents, defining relationships between what land and water managers can do and the eventual ecological impacts of those actions.

Once a conceptual model has been quantified (expressed in mathematical terms), it becomes a mathematical model. The model's equations typically include state and auxiliary variables, parameters and other model components.

The values of the model's parameters need to be determined. Model calibration involves finding the best values for these parameters. It is based on comparisons of the model results with field measurements. Optimization methods can sometimes be used to identify the values of all model parameters. This is called model calibration or identification. (Illustrations of the use of optimization for estimating model parameter values are contained in Chapters 4 and 6).

Sensitivity analysis (Chapter 9) may serve to identify the impacts of uncertain parameter values and show which parameter values substantially influence the

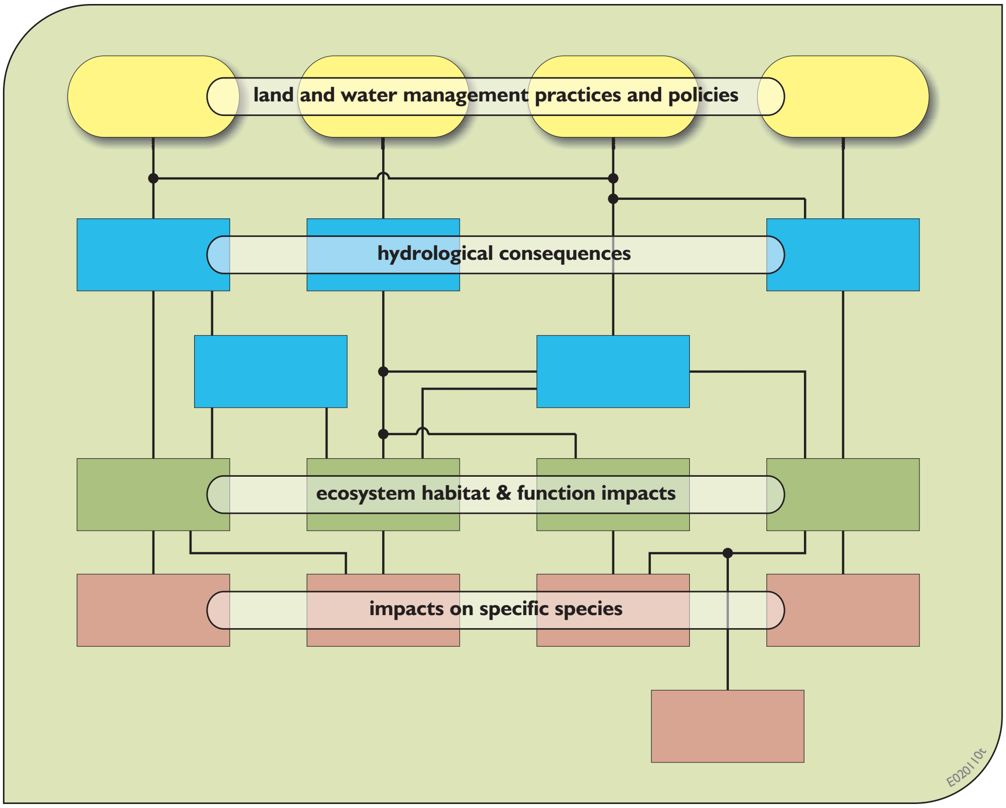

Figure 3.7. An example of a conceptual model without its detail, showing the cause and effect links between management decisions and specific system impacts.

model's results. Following calibration, the remaining uncertainties in the model predictions may be quantified in an uncertainty analysis as discussed in Chapter 9.

In addition to being calibrated, simulation models should also be validated or verified. In the validation or verification process the model results are compared with an independent set of measured observations that were not used in calibration. This comparison is made to verify whether or not the model describes the system behaviour sufficiently correctly.

5. Managing Modelling Projects

There are some steps that, if followed in modelling projects, can help reduce potential problems and lead to more effective outcomes. These steps are illustrated in Figure 3.8 (Scholten et al., 2000).

Some of the steps illustrated in Figure 3.8 may not be relevant in particular modelling projects. If so, these parts of the process can be skipped. Each of these modelling project steps is discussed in the next several sections.

5.1. Creating a Model Journal

One common problem of model studies once they are underway occurs when one wishes to go back over a series of simulation results to see what was changed, why a particular simulation was made or what was learned. It is also commonly difficult if not impossible for third parties to continue from the point at which any previous project terminated. These problems are caused by a lack of information on how the study was carried out. What was the pattern of thought that took place? Which actions and activities were carried out? Who carried out what work and why? What choices were made? How reliable are the end results? These questions should be answerable if a model journal is kept. Just like computer-programming documentation, this study documentation is often neglected under the pressure of time and perhaps because it is not as interesting as running the models themselves.

5.2. Initiating the Modelling Project

Project initiation involves defining the problem to be modelled and the objectives that are to be accomplished.

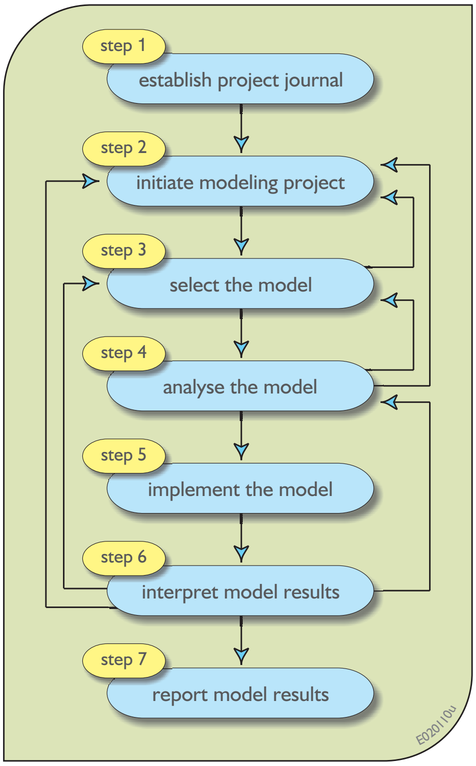

Figure 3.8. The modelling project process is an iterative procedure involving specific steps or tasks.

There can be major differences in perceptions between those who need information and those who are going to provide it. The problem 'as stated' is often not the problem 'as understood' by either the client or the modeller. In addition, problem perceptions and modelling objectives can change over the duration of a modelling project.

The appropriate spatial and time scales also need to be identified. The essential natural system processes must be identified and described. One should ask and answer the question of whether or not a particular modelling approach, or even modelling in general, is the best way to obtain the needed information. What are the alternatives to modelling or a particular modelling approach?

The objective of any modelling project should be clearly understood with respect to the domain and the problem area, the reason for using a particular model, the questions to be answered by the model, and the scenarios to be modelled. Throughout the project these objective components should be checked to see if any have changed and if they are being met.

The use of a model nearly always takes place within a broader context. The model itself can also be part of a larger whole, such as a network of models in which many are using the outputs of other models. These conditions may impose constraints on the modelling project.

Proposed modelling activities may have to be justified and agreements made where applicable. Any client at any time may wish for some justification of the modelling project activities. Agreement should be reached on how this justification will take place. Are intermediate reports required, have conditions been defined that will indicate an official completion of the modelling project, is verification by third parties required, and so on? It is particularly important to record beforehand the events or times when the client must approve the simulation results. Finally, it is also sensible to reach agreements with respect to quality requirements and how they are determined or defined, as well as the format, scope and contents of modelling project outputs (data files) and reports.

5.3. Selecting the Model

The selection of an existing model to be used in any project depends in part on the processes that will be modelled (perhaps as defined by the conceptual model), the data available and the data required by the model. The available data should include system observations for comparison of the model results. They should also include estimates of the degree of uncertainty associated with each of the model parameters. At a minimum this might only be estimates of the ranges of all uncertain parameter values. At best it could include statistical distributions of them. In this step of the process it is sufficient to know what data are available, their quality and completeness, and what to do about missing or outlier data.

Determining the boundaries of the model is an essential consideration in model selection. This defines what is to be included in a model and what is not. Any model selected will contain a number of assumptions. These assumptions should be identified and justified, and later tested.

Project-based matters such as the computers to be used, the available time and expertise, the modeller's personal preferences, and the client's wishes or requirements may also influence model choice. An important practical criterion is whether there is an accessible manual for operating the model program and a help desk available to address any possible problems.

The decision to use a model, and which model to use, is an important part of water resources plan formulation. Even though there are no clear rules on how to select the right model to use, a few simple guidelines can be stated:

- Define the problem and determine what information is needed and what questions need to be answered.
- Use the simplest method that will yield adequate accuracy and provide the answer to your questions.
- Select a model that fits the problem rather than trying to fit the problem to a model.
- Question whether increased accuracy is worth the increased effort and increased cost of data collection. (With the advances in computer technology, computational cost is rarely an issue except perhaps for some groundwater management problems.)
- Do not forget the assumptions underlying the model used and do not read more significance into the simulation results than is actually there.

5.4. Analysing the Model

Once a modelling approach or a particular model has been selected, its strengths and limitations should be studied in more detail. The first step is to set up a plan for testing and evaluating the model. These tests can include mass (and energy) balance checks and parameter sensitivity analyses (see Chapter 9). The model can be run under extreme input data conditions to see if the results are as expected.

Once a model is tested satisfactorily, it can be calibrated. Calibration focuses on the comparison between model results and field observations. An important principle is: the smaller the deviation between the calculated model results and the field observations, the better the model. This is indeed the case to a certain extent, as the deviations in a perfect model are only due to measurement errors. In practice, however, a good fit is by no means a guarantee of a good model.

The deviations between the model results and the field observations can be due to a number of factors. These include possible software errors, inappropriate modelling assumptions such as the (conscious) simplification of complex structures, neglect of certain processes, errors in the mathematical description or in the numerical method applied, inappropriate parameter values, errors in input data and boundary conditions, and measurement errors in the field observations.

To determine whether or not a calibrated model is 'good', it should be validated or verified. Calibrated models should be able to reproduce field observations not used in calibration. Validation can be carried out for calibrated models as long as an independent data set has been kept aside for this purpose. If all available data are used in the calibration process in order to arrive at the best possible results, validation will not be possible. The decision to leave out validation is often a justifiable one especially when data are limited.

Philosophically, it is impossible to know if a model of a complex system is 'correct'. There is no way to prove it. Experimenting with a model, by carrying out multiple validation tests, can increase one's confidence in that model. After a sufficient number of successful tests, one might be willing to state that the model is 'good enough', based on the modelling project requirements. The model can then be regarded as having been validated, at least for the ranges of input data and field observations used in the validation.

If model predictions are to be made for situations or conditions for which the model has been validated, one may have a degree of confidence in the reliability of those predictions. Yet one cannot be certain. Much less confidence can be placed on model predictions for conditions outside the range for which the model was validated.

While a model should not be used for extrapolations as commonly applied in predictions and in scenario analyses, this is often exactly the reason for the modelling project. What is likely to happen given events we have not yet experienced? A model's answer to this question should also include the uncertainties attached to these predictions. Beck (1987) summarized this dilemma in the following statement: 'using scientifically based models, you will often predict an incorrect future with great accuracy, and when using complex, non-identifiable models, you may be capable of predicting the correct future with great uncertainty'.

5.5. Using the Model

Once the model has been judged 'good enough', it may be used to obtain the information desired. One should develop a plan on how the model is to be used, identifying the input to be used, the time period(s) to be simulated, and the quality of the results to be expected. Again, close communication between the client and the modeller is essential, both in setting up this plan and throughout its implementation, to avoid any unnecessary misunderstandings about what information is wanted and the assumptions on which that information is to be based.

Before the end of this model-use step, one should determine whether all the necessary model runs have been performed and whether they have been performed well. Questions to ask include:

- Did the model fulfill its purpose?
- Are the results valid?
- Are the quality requirements met?
- Was the discretization of space and time chosen well?
- Was the choice of the model restrictions correct?
- Was the correct model and/or model program chosen?
- Was the numerical approach appropriate?
- Was the implementation performed correctly?
- Are the sensitive parameters (and other factors) clearly identified?
- Was an uncertainty analysis performed?

If any of the answers to these questions is no, then the situation should be corrected. If it cannot be corrected, then there should be a good reason for this.

5.6. Interpreting Model Results

Interpreting the information resulting from simulation models is a crucial step in a modelling project, especially in situations in which the client may only be interested in those results and not the way they were obtained. The model results can be compared to those of other similar studies. Any unanticipated results should be discussed and explained. The results should be judged with respect to the modelling project objectives.

The results of any water resources modelling project typically include large files of time-series data. Only the most dedicated of clients will want to read those files, so the data must be presented in a more concise form. Statistical summaries should explicitly include any restrictions and uncertainties in the results. They should identify any gaps in the domain knowledge, thus generating new research questions or identifying the need for more field observations and measurements.

5.7. Reporting Model Results

Although the results of a model should not be the sole basis for policy decisions, modellers have a responsibility to translate their model results into policy recommendations. Policy-makers, managers, and indeed the participating stakeholders often want simple, clear and unambiguous answers to complex questions. The executive summary of a report will typically omit much of the scientifically justified discussion in its main body regarding, say, the uncertainties associated with some of the data. This executive summary is often the only part read by those responsible for making decisions. Therefore, the conclusions of the model study must not only be scientifically correct and complete, but also concisely formulated, free of jargon, and fully understandable by managers and policy-makers. The report should provide a clear indication of the validity, usability and any restrictions of the model results. The use of visual aids, such as graphs and GIS, can be very helpful.

The final report should also include sufficient detail to allow others to reproduce the model study (including its results) and/or to proceed from the point where this study ended.

6. Issues of Scale

Scaling aspects play an important role in many modelling projects. Four different types of scales can be distinguished: the process scale, the information scale, the model scale and the sampling scale. Each of these is discussed below.

6.1. Process Scale

Most hydrological processes vary over space and time. The scale on which the process variations manifest themselves is referred to as the process scale. Spatially, process scale can vary from the movement of small granules of sediment, for example, to the flooding of large river basins or coastal zones. All kinds of intermediary scale processes can be found, such as drainage into ditches of runoff from parcels of land, transport of sediment in brooks and flow movements in aquifers.

Various temporal scales can also be distinguished, varying from the intensity of rain in less than a minute to the change in landscape in geological time. Many process descriptions require a spectrum of scales. Such is the case, for example, in the simulation of interdependent surface and groundwater quantity and quality processes taking place in a watershed.

6.2. Information Scale

Information scale is the spatial and temporal scale of the information required. Generally, a strategic water resources manager (for example the local, regional or national government) needs information on a scale relative to their responsibilities and authorities. This level of information is likely to differ from the level desired by operational water managers dealing with day-to-day issues.

Information at scales smaller than what is needed is seen as being 'noise'. Information at scales larger than what is needed is not relevant or helpful. For local organizations (e.g., water boards) concerned with runoff, for example, there is no need to collect information on individual raindrops. The important spatial variances are usually within a range varying from hundreds of metres to hundreds of kilometres. Larger-scale variations (differences between precipitation in the Netherlands and Russia or between North and South America, for example) are rarely if ever relevant. The information scale depends on the task set for the water planner or manager.

6.3. Model Scale

Model scales refer to their spatial and temporal discretization. The model scales determine the required data interpolation and aggregation.

If the temporal and spatial scales of the problem have not been defined clearly enough, this can affect the later phases of the modelling process negatively. If the model scale chosen is too large, this may result in too general a schematization and relevant details might not be derived from the results. If the chosen model scale is too small, irrelevant small-scale variations can lead to non-optimal calibrations for the large-scale variations.

In large, spatially distributed models in particular, it is vital that the scale and the number of independent parameters (degrees of freedom) are chosen on the basis of the available data. If too many parameters are included

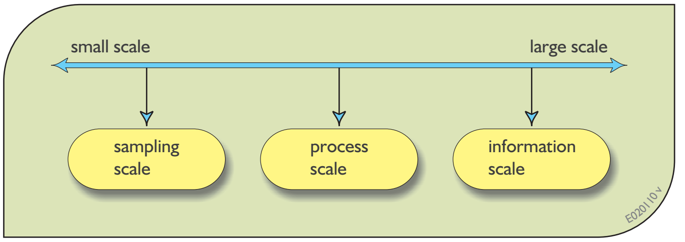

Figure 3.9. Relationships among various scale types.

in a model, there is a risk of it appearing to work well but being unsuitable for interpolation or prediction. This can actually only be determined if adequate measuring data are available having a measurement frequency at least equal to the chosen modelling time step. This must be taken into account when selecting or constructing the model, as there is otherwise the risk that the model cannot be calibrated adequately.

6.4. Sampling Scale

Sampling scale is the scale at which samples are taken. The sampling spatial scale can vary from 'point observations' (for example, a temperature measurement at a certain location at a certain time) to area observations (using, for example, remote sensing images). The density of the measuring network and the sampling or measuring and recording frequency determine the sampling spatial and temporal scales.

6.5. Selecting the Right Scales

Modellers must choose the model scale in such a manner that the model provides information at the required information scale, taking into account the process scales present, in combination with the spatial and temporal sampling scales. It is possible that situations will occur that are impossible to model just because of these scale issues.

The relationship between the types of scales is represented in Figure 3.9. The relative level of detail is given on the horizontal axis, from considerable detail on the left to much less detail on the right.

To show that the various types of scales may not be mutually compatible, consider the following three examples.

Example 1: *The information scale is different from the process scale*

Water resources planning studies are typically carried out at a river basin or watershed scale. From a hydrological (process) point of view, this makes sense because it enables a comprehensive analysis (including upstream and downstream impacts), makes it easier to develop a water balance for the study area, and reduces the amount of information needed at the borders of the study area. However, most decision-makers are not interested in results at river basin or watershed scale; they want to know what these results mean for their province, municipality or city. This conflict of scales can be solved by a well-considered selection of the (sub)watersheds that will be considered in the study and a post-processor that translates the results at these process scales into the required administrative scales.

Example 2: *The information scale is smaller than the process scale*

Imagine that a water resources manager wants to evaluate alternative anti-dehydration measures on the groundwater level over a period of five years. Thus the required information scale is a five-year period. However, the groundwater level is characterized by a very slow response. The relevant temporal groundwater-level process scale is around fifteen to twenty years. Whatever management alternative is implemented, it will take fifteen to twenty years to determine its impact. Thus, regardless of the choice of measuring frequency (sampling scale) and the model scale, it is impossible within the five-year period of interest to arrive at information on the groundwater-level changes as a consequence of anti-dehydration measures.

Example 3: *The sampling scale is larger than the process scale and information scale*

Assume it is necessary to estimate the change in concentrations of certain substances in the soil and groundwater in an urban area. The information spatial scale is one to two decimetres. This corresponds to the spatial variation of cohesion processes that take place in the soil and groundwater aquifer. However, logistic and budgetary considerations make it impossible to increase the spatial sampling density to less than a measurement site every few hundred metres. As the spatial sampling scale is much larger than the spatial process scale, useful interpolations cannot be made.

7. Conclusions

This chapter has reviewed some basic types of models and presented guidelines for consideration when undertaking a modelling project. Generic models for water resources system analyses are increasingly becoming available, saving many organizations that need model results from having to develop their own individual models. While many readers of this book may get involved in writing their own models, most of those involved in water resources planning and management will be using existing models and analysing and presenting their results. The information provided in this chapter is intended to help model users plan and manage effective modelling projects as well as improve the reproducibility, transferability and usefulness of model results.

8. References

BECK, M.B. 1987. Water quality modeling: a review of the analysis of uncertainty. *Water Resources Research*, No. 23, pp. 1393–1442.

SCHOLTEN, H.; WAVEREN, R.H. VAN; GROOT, S.; GEER, F.C. VAN; WÖSTEN, J.H.M.; KOEZE, R.D. and NOORT, J.J. 2000. *Good modelling practice in water management, proceedings hydroinformatics 2000*. Cedar Rapids, Iowa, International Association for Hydraulic Research.

Additional References (Further Reading)

ABBOTT, M.B. 1999. Introducing hydroinformatics. *Journal of Hydroinformatics*, Vol. 1, No. 1, pp. 3–20.

BISWAS, A.K. (ed.). 1997. *Water resources: environmental planning, management, and development*. New York, McGraw-Hill.

BOBBA, A., GHOSH, S.; VIJAY, P. and BENGTSSON, L. 2000. Application of environmental models to different hydrological systems. *Ecological Modelling*, Vol. 125, pp. 15–49.

BOOCH, G. 1994. *Object-oriented analysis with applications*. Redwood City, Benjamin Cummings.

CHAN, H.W. and LAM, P.F. 1997. Visualizing Input and output analysis for simulation. *Simulation Practice and Theory*, Vol. 5, No. 5, pp. 425–53.

EDSALL, R.M.; HARROWER, M. and MENNIS, J.L. 2000. Tools for visualizing properties of spatial and temporal periodicities in geographic data. *Computers & Geosciences*, Vol. 26, No. 1, pp. 109–18.

FEDRA, K. and JAMIESON, D.G. 1996. An object-oriented approach to model integration: a river basin information system example. In: K. Kowar and H.P. Nachtnebel (eds.), *Proceedings of the HydroGIS'96 Conference, No. 235*, Vienna, IAHS Press. pp. 669–76.

GUARISO, G. and WERTHNER, H. 1989. *Environmental decision support systems*. New York, Ellis Horwood-Wiley.

HO, J.K.K. and SCULLI, D. 1997. The scientific approach to problem solving and decision support systems. *International Journal of Production Economics*, Vol. 48, No. 3, pp. 249–57.

HUFSCHMIDT, M.M. and FIERING, M.B. 1966. *Simulation in the design of water resource systems*. Cambridge, Mass., Harvard University Press.

LAM, D.C.L.; MAYFIELD, C.I. and SAWYNE, D.A. 1994. A prototype information system for watershed management and planning. *Journal of Biological Systems*, Vol. 2, No. 4, pp. 499–517.

LAM, D. and SWAYNE, D. 2001. Issues of EIS software design: some lessons learned in the past decade. *Environmental Modeling and Software*, Vol. 16, No. 5, pp. 419–25.

LAW, A.M. and KELTON, W.D. 2000. *Simulation modeling and analysis*, 3rd edn. Boston, Mass., McGraw-Hill.

LOUCKS, D.P.; STEDINGER, J.S. and HAITH, D.A. 1981. *Water resources systems planning and analysis*. Englewood Clifts, N.J., Prentice Hall.

MAASS, A.; HUFSCHMIDT, M.M.; DORFMAN, R.; THOMAS, H.A.; MARGLIN, S.A. and FAIR, G.M. 1966. *Design of water resources systems*. Cambridge, UK, Harvard University Press.

REITSMA, R.F. and CARRON, J.C. 1997. Object-oriented simulation and evaluation of river basin operations. *Journal of Geographic Information and Decision Analysis*, Vol. 1, No. 1, pp. 9–24.

RIZZOLI, A.E. and YOUNG, W.J. 1997. Delivering environmental decision support systems: software tools and techniques. *Environmental Modeling & Software*, Vol. 12, No. 2–3, pp. 237–49.

RIZZOLI, A.E.; DAVIS, J.R. and ABEL, D.J. 1998. Model and data integration and re-use in environmental decision support systems. *Decision support systems*, Vol. 24, No. 2, pp. 127–44.

SARGENT, R.G. 1982. Verification and validation of simulation models. In: F.E. Cellier (ed.), *Progress in modelling and simulation*, pp. 159–69. London and elsewhere, Academic Press.

SARGENT, R.G. 1984a. A tutorial on verification and validation of simulation models. In: S. Sheppard, U. Pooch and D. Pegden (eds.), *Proceedings of the 1984 winter simulation conference*, pp. 115–21. Piscataway, N.J., Institute of Electrical and Electronics Engineers.

SARGENT, R.G. 1984b. Simulation model validation. In: T.I. Ören, B.P. Zeigler and M.S. Elzas (eds.), *Simulation and model-based methodologies: an integrative view*, pp. 537–55. Berlin and elsewhere, Springer-Verlag (No. 10 in the series: NATO ASI Series F: Computer and Systems Sciences).

SINGH, V.P. (ed.). 1995. Computer models of watershed hydrology. Littleton, Colo., Water Resources Publications.

SUN, L. and LIU, K. 2001. A method for interactive articulation of information requirements for strategic decision support. *Information and Software Technology*, Vol. 43, No. 4, pp. 247–63.

VAN WAVEREN, R.H.; GROOT, S.; SCHOLTEN, H.; VAN GEER, F.C.; WÖSTEN, J.H.M.; KOEZE, R.D. and NOORT, J.J. 1999. *Good modelling practice handbook: STOWA report 99–05*. Lelystad, the Netherlands, Dutch Dept. of Public Works, Institute for Inland Water Management and Waste Water Treatment (report 99.036).

YOUNG, P. 1998. Data-based mechanistic modeling of environmental, ecological, economic and engineering systems. *Environmental Modeling & Software*, Vol. 13, pp. 105–22.

YOUNG, W.J.; LAM, D.C.L.; RESSEL, V. and WONG, J.W. 2000. Development of an environmental flows decision support system. *Environmental Modeling & Software*, Vol. 15, pp. 257–65.

ZEIGLER, B.P. 1976. *Theory of modelling and simulation*. Malabar, Fla, Robert E. Krieger.

ZEILER, M. 1999. *Modeling our world: the ESRI guide to geodatabase design*. Redlands, Calif., ESRI.