System Dynamics Modelling Analysis Techniques
A Pragmatical Appraisal

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ABSTRACT

This paper reviews techniques that may assist the system dynamics modeller in defining variables and functional relationships, parameter estimation, validation, sensitivity and policy analysis. The evaluation was made in the context of a water resources management modeling effort for the Guadiana basin in Algarve and based on scientific, economic and operational criteria. In general, it was difficult to point out the most appropriate technique but rather recommend combinations of methods for each modeling stage.

INTRODUCTION

Several techniques have been developed in the past for each of the traditional system dynamics modeling stages: definition of variables and functional relationships, parameter estimation, validation, sensitivity and policy analyses.

This paper attempts to assess those techniques in the context of their application to a water resources management modeling effort for the Guadiana basin in Algarve. The assessment is made following scientific, economic and operational criteria. The goal is to screen for the most suitable methods in a pragmatic application of the system dynamics approach.

WATER RESOURCES MANAGEMENT MODELING

Guadiana's model is inspired in a previous work of the authors (see Camara et al., 1984). It basically consists of three interacting sub-models: sub-model I defines how much water is available; sub-model II computes how much water is demanded; and sub-model III, feeds-back into sub-models I and II, through a set of management equations.

Guadiana's model has been developed in four interacting stages: (1) definition of variables and functional relationships; (2) parameter estimation; (3) validation; and (4) sensitivity analysis. After establishing the model validity, to serve as a plausible predictive tool, policy analyses were then conducted. The process is represented in Figure 1.

Two perspectives were considered in the definition of variables: a strictly system dynamics view; and a management view. From the system dynamics perspective, variables were divided into level (i.e., precipitation, population), rate (i.e., runoff rate, potential evapotranspiration rate) and auxiliary. The latter were either the result of algebraic decomposition of rate variables or simple counters (i.e., water deficit or superavit conditions). From the management standpoint, variables were divided into control (i.e., some rate variables) and impact variables (i.e., some level and auxiliary variables).

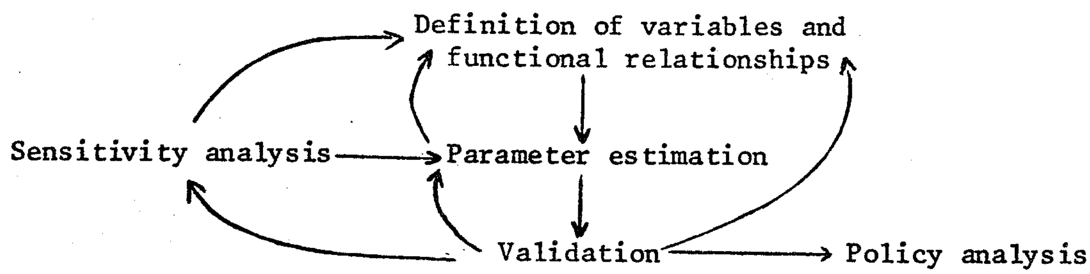

Figure 1 - Guadiana's Basin System Dynamics Modeling Stages

Functional relationships were defined using traditional system dynamics type equations and applied theoretical, empirical (i.e., rational method to estimate runoff) and ad-hoc information (i.e., luxury tourism water consumption).

Parameter estimation foccused essentially on rate equations. Validation was concerned with the model's variables, functional relationships and parameters adequacy. Sensitivity analysis was applied throughout the modeling exercise, guiding parameter estimation and helping validation and policy analysis. The latter stage consisted of evaluating sets of valuations of control variables upon a set of impact variables, defining an objective function.

ASSESSMENT OF SYSTEM DYNAMICS MODELLING TECHNIQUES

In this section, the most common techniques available for each of the system dynamics modeling stages are presented and basically evaluated from scientific (reliability), economic (computational costs and data requirements) and operational (ease of application) standpoints.

Definition of Variables and Functional Relationships

Techniques for the definition of variables and functional relationships and their application to Guadiana basin modeling are summarized in Table 1. A general scientific, economic and operational assessment is synthesized in Table 2. It may be observed that none of the methods is sufficient to define the model's variables and functional relationships. Rather, the use of a combination of methods is necessary.

Parameter Estimation

There are two kinds of available data to perform parameter estimation: (1) disaggregate data (i.e., information about events and items below the level of aggregation of model variables); and (2) aggregate data, corresponding to level type variables.

For both classes of data there are three available kinds of techniques: (1) direct techniques; (2) indirect techniques; and (3) probabilistic techniques. In Table 3, observations on these techniques are included. Table 4 synthesizes a basic scientific, economic and operational assessment of the parameter estimation methods reviewed.

Table 1

Techniques for the Definition of Variables and
Functional Relationships and their Application to Guadiana Model

Techniques	Observations	Application to Guadiana Model
Type I- Define variable and funct. relationships		
Cluster Analysis (Morrison, 1967)	identification of functional rel. between variables and their magnitude but not their representation. Extensive and intensive data needs	analysis of essential comp. of demand model (sub-model II)
Analysis of principal components (Morrison, 1967)	quantitative analysis of funct. rel. Decomposition and present. of funct. rel. components relative magnitude. Do not enable math. repres. of funct. rel. Extensive and intensive data needs	same as in cluster analysis
Adjacency matrices (Cristofides, 1975)	Identification of funct. rel. of variables direct. or indirectly connected. May be translated in digraph form.	preliminary analysis leading to the causal diagram
Application of Kirchoff laws (Davis and Kennedy, 1970)	identification of the magnitude of relationships between var. not directly connected, based on a weighed model. Like a pre-sensitivity analysis	not utilized. Sensitivity analysis was preferred
Type II- Define specific funct. relationships		
Curve fitting (χ^2, Kolgomorov-Smirnov tests) (Shannon, 1975)	fitting hypothesized math. expressions to sampled data sets. Limited to the behaviour verified in the sampled universe	used to define tourism growth equations
Harmonic analysis of time series components (Box and Jenkins, 1976)	allowing by analyzing time series components and trends, represent. the behav. of a funct. rel., that behav. determinant factors and its type of action. Extensive and intensive data needs	used to analyze luxury tourism evolution
Time wavelet composition of time series (Robinson, 1967)	derivation of the behaviour of a funct. relationship after introd. perturb. and/or stimula, by wavelet composition	used to analyze and represent luxury tourism evolution subject

(Cont.)

Table 1 (Cont.)

Techniques	Observations	Application to Guadiana Model
		to perturb. and or stimula
Catastrophe theory (Sinha, 1981)	representing funct. rel. suffer. sudden quantitative and qualitative changes which are not discontinuities	applyed to the components of economic growth in dem. model

Table 2

Scientific, Economic and Operational Assesment of Structure Identification Methods

Techniques	Scientific Reliab.	Comp. Costs	Data Req.	Ease of Appl.
Cluster anal.	+	+	++	o
Anal. prin. co.	++	+	++	o
Adj. matrices	+	o	o	++
Kirchoff laws	++	+	+	+
Curve fitting	+	+	++	+
Harmonic anal.	++	+	++	o
Wavelet comp.	++	+	++	o
Catast. theory	++	+	++	o

Criteria:
++ - high
+ - average
o - low

Table 3

Parameter Estimation Techniques and their Application to Guadiana Model

Techniques	Observations	Application to Guadiana Model
Direct Methods Algebraic estimation Extended algebraic estimation (Eyckoff, 1971)	used considering data withouth measurement errors; equation without errors	applied in both cases: disagregate and aggregate data
Indirect Methods Least-squares control methods (Peterson, 1976) (Graham, 1980) (Box and Jenkins, 1976)	used considering data without measurement errors; equation errors. Simulation reinitialized at each data point	applied in both cases: disaggregate and aggregate data
Probabilistic Methods Bayesian estimation Maximum likelihood estimation Other related methods (Eyckoff, 1974) (Box and Jenkins, 1976)	used considering data and equation errors. Simulation reinitialized at each data point	applied in the case of disaggregate data aggregate data was insufficient

Table 4

Scientific, Economic and Operational Assessment of Parameter Estimation Methods

Techniques	Scientific Reliab.	Comp. Costs	Data Req.	Ease of Appl.
Disaggreg. data				
Direct methods	o	+	+	++
Indirect meth.	+	++	+	+
Probabilistic	++	++	++	o
Aggreg. data				
Direct methods	+	+	+	++
Indirect meth.	+	++	+	+
Probabilistic	++	++	++	o

From Tables 3 and 4, one may observe that there are substantial advantages in the use of probabilistic methods from a scientific standpoint. They are however data intensive and extensive methods. Thus, one normally applies indirect methods, which represent a compromise option between direct and probabilistic methods.

Validation

There are two typical validation stages: (1) internal—to assure that the model performs the way it was intended; and (2) external—comparing the input-output transformation of the model and the real world system. The latter stage is obviously not always possible. Most common validation methods and their application in the Guadiana study are summarized in Table 5. Their scientific, economic and operational assessment is included in Table 6.

From Tables 5 and 6, one may see that most validation efforts should tend to be only Type I plus Turing testing procedures. This was also the case of the Guadiana water resources model.

Sensitivity Analysis

Sensitivity analysis is usually performed by introducing perturbations in the parameter and functional relationships integrating the model. Its two main objectives are: the evaluation of precision required in the parameter estimation stage; and the design of robust models with functional relationships plausible even for extreme conditions. Thus sensitivity analysis may be performed at two levels: parameter sensitivity and noise sensitivity.

Parameter sensitivity analysis

Parameter sensitivity may be conducted: locally--to evaluate the behaviour of the system subject to infinitesimal changes in the parameter values, being altered isolatedly; and globally--to assess the behaviour of the system considering finite and simultaneous changes of its parameter values. Table 7 synthesizes the available methods for local and global sensitivity analyses and their application to the Guadiana basin model. Table 8 includes a scientific, economic and operational evaluation of these methods. Despite its computational costs, conventional parameter sensitivity analysis is still preferable in local sensitivity analysis, specially if applied after preliminary rational screening of sensitive parameters.

Noise sensitivity analysis

Noise sensitivity analysis is used to assess the validity of the model's structure. A noise term R is added to the function $f(x)$ $(f'(x)=f(x)+R)$. R may be continuous, random, wave like or intermittent.

In the conventional method a run of the noise free system and several runs of the perturbated system are performed. Then, function $dx=f'(x)-f(x)$ is evaluated.

In the perturbation method, function $d(x)$ is analytically defined as referred above.

Table 5

Validation Methods and their Application to Guadiana Model

Techniques	Observations	Application to Guadiana Model
<u>Type I--Internal Validation</u>		
Traces	to perform logical checking of the program	applied in comp. prog. stage
Sensitivity analysis (Mass and Senge, 1976) (Bell and Senge, 1980)	to verify plausibility of behaviour under extreme conditions	applied after comp. prog. stage
<u>Type II--External Validation</u>		
Statistical testing univariate or multivariate parametric tests (F, t and Z) (Shannon, 1975) (Zeigler, 1976)	hypothesis testing. Only if observations are not auto-correlated	not applied. Insufficient data available
Turing test (Shannon, 1975)	consists of asking people who are knowledgeable about the system if they can discriminate between system and model outputs and why	applied in a limited extent due to limitat. on system data
Spectral analysis (Shannon, 1975)	comparison of spectra between model and system output to construct confidence bands. Assumes that the time series are covariance stationary which is not always true	not applied. Insufficient data available

Table 6

Scientific, Economic and Operational Assessment
of Validation Methods

Techniques	Scientific Reliab.	Comp. Costs	Data Req.	Ease of Appl.
Traces	+	+	o	+
Sensitivity Analysis	+	++	o	+
Statistical testing	++	++	++	+
Turing test	+	o	+	+
Spectral Analysis	++	++	++	o

Table 7

Local and Global Parameter Sensitivity Analysis and their Application to the Guadiana Basin Model

Techniques	Observations	Application to Guadiana Model
Local sensitivity analysis		
Conventional method (Sharp, 1976)	parameter are changed in each run and one compares these outputs with results obtained with the perturbation-free system. High computational requirements. Often used after a preliminary screening of sensitive parameters. May also be applied, submitting the parameters to random changes	used after preliminary screening of sensitive par.
Perturbation method (Sharp, 1976)	consists of the analitical definition of the function d(x)= f(x)-f(x+dx) (dx--the perturbation of x) using partial diff. and simplification methods. The analysis is done by computing d(x) instead of f(x) and f(x+dx), as described in the conventional meth. Requires mathematical expertise. After these preliminary calculations, computational needs are low	not applied due to extensive preliminary work required
Global sensitivity analysis		
Conventional Perturbation (Sharp, 1976)	use of conventional/perturbation local sensitivity analysis methods in connection with minimization routines, allowing for the deter. of the parameter changes leading to minimal system alterations	not used due to comp. req.
Qualitative stability analyses (adapted from May,	consists of a matrix transcription of causal diagram, where a zero	

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Table 7 (Cont.)

Techniques	Observations	Application to Guadiana model
1975)	coefficient represents the nonexistence of connection between two variables. criteria to evaluate stability may be inspired in the work of May. They are not however fully operational at present time	not applied due to the flaws of the method

Table 8

Scientific, Economic and Operational Assessment of Parameter Sensitivity Analysis Methods

Techniques	Scientific Reliab.	Comp. Costs	Data Req.	Ease of Applicat.
Conventional	++	++	o	++
Perturbation	++	+	o	o
Qual. Stab. Analysis	o	+	o	++

The advantages and disadvantages of these methods from scientific, economic and operational standpoints are similar to the ones pointed out for the parameter sensitivity analysis case (see Table 8).

Sensitivity analysis appears therefore as a method to be applied before parameter estimation and as an additional validation test. It may be used also in policy analysis, as one can consider a policy as a perturbation introduced in the system which will change its behaviour. As suggested further on, sensitivity analysis will help in the assessment of the "degrees of promise" (in terms of objective achievement) of a control variable valuation.

Policy Analysis

If the model developed is valid for its purpose (and all the previous techniques are intended basically to increase and test the model's validity) there are two essential problems in the policy analysis stage:

1. To define from the possible strategies (strategy=set of valuations for control variables), those to be tested (i.e., define the number of runs of the model). This screening has to be made, as the number of valuations for each control variable is large and enormous the number of resulting combinations of those valuations.

2. To determine the optimal strategy, for each set of development goals, based on the impact variables values obtained with the model for each strategy.

For the first problem, the authors found that there are no adequate techniques and propose that: (1) a value should be assigned to each control variable based on its level of "promise" in terms of objective function achievement. This assessment may be done by a pannel of experts or through preliminary sensitivity analysis; (2) each control variable valuation will be then represented as a node with a weight equal to its "promise" level; (3) a network may then be formed, each path representing a strategy; and (4) applying a k-shortest path algorithm to this network, one may thus eliminate numerous alternative strategies from further analysis and define a relatively small number to be assessed with the model. This method was applied in the Guadiana basin modelling effort and proved to be reliable, inexpensive and easy to use.

To evaluate the strategies, one has to solve a multiobjective programming problem. This has been done in system dynamics modelling by at least two authors: Gardiner and Ford (1980) and Camara et al. (1984).

Gardiner and Ford considered that every policy experimented with ,in simulation runs has valuesin terms of its impacts on a number of different dimensions. These dimensions are derived from the analysis of the impact variables trajectories (i.e., peak values, time lags). A multi-attribute utilitymeasurement technique is then applied to discover those values, one dimension at a time, and then aggregate them across dimensions using a suitable aggregation rule and weighing procedure.

Camara et al method considers that for each strategy one obtains trajectories for the different impact variables IV. These trajectories may be represented for a simulation period T as vectors $[IV^k]T$. Then:

1. For each strategy j, vectors $[IV^k\ T]j$ are translated into a vector $[IV^k]j$. This is done by dividing simulation period T into sub-periods t1, t2, t3, ...,tn, synthesizing sub-vectors $[IV^k]ti$ into a scalar, by computing the summation, mean, mode, maximum or minimum for the values of $[IV^k]ti$, depending on the nature of IV^k, assigning weights wti to the sub-periods to assess their relative importance, and finally calculating $[IV^k]j=\Sigma wti.[IV^k]ti,j, \forall k$.

2. Using a value path display approach and the calculated $[IV^k]j$, define the non-inferior strategies j. If there is a superior strategy, the optimization stops.

3. If there is no superior strategy, $[IV^k]j$ are normalized, weights wIV are defined for each IV, and then $\Sigma wIV.IV^k$ is computed for each j, the largest of these values corresponding to the optimal strategy.

Both methods are simple, inexpensive and have a common flaw: subjective weighing procedures. Their treatment of the time dimension is however different. Gardiner and Ford consider trajectories as moving pictures with a number of dimensions. Camara et al. take trajectories as vectors that can be aggregated into scalars, using well known compression mechanisms. In both cases, there are obvious problems: it may be difficult to discover meaningful dimensions in trajectories (Gardiner and Ford); the assignment of weights to time periods is highly subjective (Camara et al.). They should be used therefore depending on the circumstances.

SUMMARY AND CONCLUSIONS

This paper attempted to assess techniques that may assist the system dynamics modeller in defining variables and functional relationships, parameter estimation, validation, sensitivity and policy analyses. The evaluation was made in the context of a water resources management modeling effort for the Guadiana basin and based on scientific, economic and operational criteria.It was concluded that:

1. To define variables and functional relationships none of the methods reviewed is sufficient; rather the use of a combination of methods is necessary.

2. For parameter estimation, least-squares and control methods are the most suitable in practical applications.

3. In validation efforts, sensitivity analysis and Turing tests are recommended in conditions of data scarcity.

4. Sensitivity analysis is a method to be applied before parameter estimation, as an additional validation test and also in preliminary stages of policy analysis. Conventional methods are preferable if applied after a preliminary screening of sensitive parameters.

5. Approaches to policy analysis in system dynamics are based on interfaces between the simulation model and multiobjective programming. The methodologies available have the drawbacks common to many multiobjective decision

methods: they rely on subjective weighing procedures.

6. Finally, one should note that the different modeling stages are not isolated compartments. There is rather a continuous interaction, being some analysis techniques suitable for more than one modelling phase.

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