Modelling Decision Rules in System Dynamics Models

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Resumen: Este articulo es sobre el modelamiento de "reglas de decisión" como componentes fundamentales de los modelos de simulación y una de las mas difíciles tareas en modelamiento y análisis. Las reglas de decisión en modelos de dinámica de sistemas siguen el método científico, en donde el científico (en este caso, el modelador) hace un esfuerzo en construir adecuadamente el mundo real (en este caso, la representación de decisiones humanas en modelos de dinámica de sistemas). Consecuentemente, este artículo esta organizado siguiendo el método científico. Las reglas de decisión deberían estar basadas de acuerdo con el propósito del modelo y con una teoría de toma de decisiones. Personalmente, creo en que las decisiones humanas fallan en satisfacer la mayoría de las suposiciones de la teoría de selección racional. Por lo tanto, si se desea que los modelos representen sistemas reales, la teoría de racionalidad limitada es una mejor aproximación para la representación de decisiones humanas. Se presentan algunas técnicas para el modelamiento de reglas de decisión de la dinámica de sistemas y de otras escuelas de modelamiento.

Palabras Clave: Reglas de Decisión, Dinámica de Sistemas, Modelamiento

Abstract: This paper focuses on modelling decision rules, fundamental components of simulation models and one of the most difficult tasks in modelling and analysis. Modelling decision rules in system dynamics models follows the process described by the Scientific Method, by which scientists (in this case, modellers) make an effort to construct an accurate representation of the world (in this case, representations of human decisions in systems dynamics models). Consequently, the paper is organized in the light of the scientific method. Decision rules should be shaped by the purpose of the model and be based on a theory of human decision making. I believe that human decision fail to satisfy most of the assumptions of the rational choice theory. This leads to persistent and systematic deviations from the prediction of the rational choice theory. Therefore, if there is an agreement that models should represent reality, the use of bounded rationality theory is a better approximation to model human decisions. Techniques for building decision rules from system dynamics and other modelling schools are presented.

Keywords: Decision Rules, System Dynamics, Modelling

Science is best defined as a careful, disciplined, logical search for knowledge about any and all aspects of the universe, obtained by examination of the best available evidence and always subject to correction and improvement upon discovery of better evidence. What's left is magic. And it doesn't work.
- James Randi

1 INTRODUCTION

This paper focuses on modelling *decision rules*, one of the fundamental components of simulation models. Decision rules represent human decisions in formal models, and are of key importance for the behaviour of dynamic systems. The formulation of decision rules is one of the most difficult tasks in modelling and analysis [Mass and Senge (1978)]. The purpose of this essay is to survey the literature on this challenging topic and explore the available methods to formulate decision rules in System Dynamics models.

Modelling decision rules in system dynamics models follows the process described by the *Scientific Method*, by which scientists (in this case, modellers) make an effort to construct an accurate representation of the world (in this case, representations of human decisions in systems dynamics models). Consequently, the paper is organized in the light of the scientific method. There are five basics according to wikipedia[1] , which are Observation, Hypothesis/Prediction, Experimentation, Conclusion and Evaluation, and Repetition. Thus, the paper provides the appropriate information for the modeller to build the decision rules based on those fundamental steps.

First I present some formal *definitions* of decision rules. Second, I present *theories* on modelling decision rules of human decisions. Third, I present various *methods* to establish the decision rules, where both principles and techniques from various disciplines are considered. Fourth, issues on structure validation and parameter estimation are presented, followed by a discussion and some personal comments.

2 DEFINITION OF DECISION RULE

A large number of modelling schools have appeared based on the scientific method, the advances of computers, and the mathematical models [Meadows (1976)]. Each school hase created their own needs, methods and languages. In particular, simulation models of dynamic systems constitute a subset of computer modelling methodologies. They represent reality in terms of multiple non-linear differential equations. Simulation models of dynamic systems have two basic building blocks: *Stocks* (state variables) and *flows* (rate variables). Flows represent the rate of change in stocks and stocks accumulate flows. Thus, flows are the derivatives of stocks.

Flows describe not only natural processes but can also represent human decisions. In general, flows are the variables that control all system states. Examples of flows are valves in chemical plants, the birth rate of a population, and the acquisition of equipment. While the flows that represent natural process are generally clearly established by physical laws; human decision making does not have a unified theory for its representation. The representation of human decisions by the use of mathematical functions is often referred to as decision rules in simulation models.

A human decision is not an instantaneous process. It is a process that takes time and can be compared to cooking: you take ingredients, you mix and boil them and, after a certain period of time, you have the result - hopefully, a good meal. Human decisions are made by individuals or groups of people in organizations, they make use of available information, involve cognitive and social processes, and after a while there is a result -the decision. The time could be seconds, days, weeks, months, or years, according to the type of problem and institution surrounding the decision. The process of making decisions is not usually modelled explicitly; the process is not part of the decision rule, only the end result. Since the final decision takes time, the decision rule may not represent the flow variable, it represents the indicated flow. The actual flow variable is then the indicated flow with a delay (thus, decision rules are mathematical functions which take the available information and transform it with the decision rule into an indicated flow; which is delayed in order to get the flow or final action in the model). Thus, the decision rule and the delay makes up a simplified representation of the dynamics of the decision process (see Figure 1).

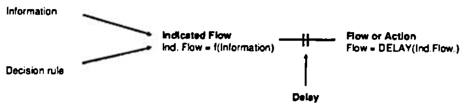

Figura 1: Decision rule's definition in simulation of dynamical systems models

Often, more than one single flow in a model is influenced by human decisions. In that case, decision rules must be formulated for all those flows.

3 HOW TO FORMULATE THE DECISION RULES? AVAILABLE THEORIES

Natural processes are normally modelled according to the laws of physics. Similarly, human decisions should be modelled according to the available theories of human behaviour. We identify two main streams of theories which are in sharp contrast to each other. On the one hand, there is the standard neoclassical theory of rational choice that claims that decision makers maximize utility making use of full information about current stocks. An extension of this theory even claims that decision makers have unbiased expectations about the future [Muth (1961); Lucas and Sargent (1981)]. On the other hand, there is the bounded rationality theory [Simon (1979)] which proposes that human's rationality is limited. This theory is extended by propositions of rules of thumb or heuristics [Tversky and Kahneman (1987)]. Quite often these heuristics lead to persistent and systematic departures from rationality when they are applied in complex dynamic systems [Sterman (2000)].

Rational choice has been the dominant theory in economics. Rational choice theory assumes perfect knowledge of all the available policy alternatives, complete knowledge of the possible results that will follow from all alternatives and certainty in the decision maker's about present and future outcome of these consequences. The decision maker has the ability to compare those consequences, no matter how diverse and heterogeneous they are. Moreover, [Muth (1961, p. 316)] asserts that that "*expectations, since they are informed*

[1]Wikipedia: open-content online encyclopedia (www.wikipedia.org).

predictions of future events, are essentially the same as the predictions of the relevant economic theory".

In contrast, bounded rationality theory assumes that people seek procedures that transform decision problems into tractable ones [Simon (1979)]. One example is to look for choices that are satisfactory rather than optimal. Another example is to replace abstract and/or global goals by tangible subgoals. Simon describes two fundamental concepts of the bounded rationality theory: *search* and *satisficing*. The theory postulates that "*the decision maker had formed some aspiration as to how good an alternative he should find. As soon as he discovered an alternative for choice meeting his level of aspiration, he would terminate the search and choose that alternative*" [Simon (1979, p. 503)]. Thus, in some cases the decision maker has to search for the choices and then make a decision which *satisfies* her desires. Bounded rationality theory has accumulated empirical evidence about its validity [Lovell (1986); Tversky and Kahneman (1987); Sterman (1989*a*); Kampmann (1990); Dwyer, Williams, Battalio and Mason (1993); Levine (1993); Aggarwal and Mohanty (1995); Diehl and Sterman (1995); Cashin, McDermott and Scott (2002)].

The decision rules embody the assumptions about the degree of rationality of decision makers. The problems addressed by the system dynamics discipline include dynamic complexity, non-linearities, and delays. It has been demonstrated that full rationality is unlikely to be observed in such problems [Sterman (1989*a*); Kampmann (1990); Paich and Sterman (1993); Diehl and Sterman (1995); Conlisk (1996); Moxnes (2004)]. Instead, these experimental tests have shown that decision rules based on the bounded rationality theory are closer to reality [Sterman (2000)].

Bounded rationality theory includes also feedback concepts in social sciences as presented in [Richardson (1991)]. The hierarchies in system structure can be summarized as:

Closed boundary
 Feedback loop structure
  Level and rate substructure
   Goal, observation, discrepancy, and action as the sub-substructure within rates

According to [Forrester (1968), decisions are part of feedback loops:

"***Principle 4.2-1. Decisions always within feedback loops:*** *Every decision is made within a feedback loop. The decision controls action which alters the system levels which influence the decision. A decision process can be part of more than one feedback loop.*"

In the same reference, Forrester presents also the foundations of modelling decision rules based on feedback theory, particularly applied to system dynamics models. In the following quote note that a decision rule is the same concept and has the same meaning as "policy statement" or "rate equations" [Forrester (1968, Sec. 4.4):

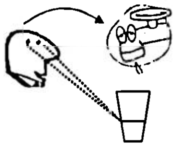

Figura 2: Feedback Loop

"*A rate equation is a policy statement. That is, the rate equation tells how a "decision stream" (or "action stream") is generated. "Rate equation" and "policy", as used here, have the same meaning. A policy describes how the available information is used to generate decisions. "Decision stream" and "action stream" are equivalent because, as used here, the decision and the action are one and the same. Any delays and discrepancies between the deciding and the doing that we might expect from the common usage of the words would involve level equations in a model. So the policy, or rate equation, tells how to compute the rate (the flow into some level) based on the values of levels and constants*".

As an example, think of a person filling a glass of water from the tap. Initially, she looks at the glass and opens the tap. Once she sees that the glass is about to be full she decides to close the tap. The final water level in the glass is not necessarily the exact "desired" one, but it satisfies her wishes. It is precise enough for her and there is any need for exact optimisation. Figure 2 illustrate the feedback loop. This is a simple feedback loop compared to most real life tasks, where many feedback loops may have to be taken into account.

While rational expectations theory is identified as normative, bounded rationality theory is identified as descriptive [Simon (1979)]. Currently, both theories coexist and are under the microscope to find out which one is the most appropriate. The validity of these theories is an empirical question. Different answers have been given without consensus or agreement so far. At least, there are some cases where the rational expectations theory fail and bounded rationality in the form of heuristics involving feedback theory is more likely to explain the decisions [Sterman (1989*a*); Sterman (1989*b*); Kampmann (1990); Paich and Sterman (1993); Diehl and Sterman (1995); Moxnes (1998*a*); Moxnes (1998*b*); Moxnes (2000)]. These tests have been performed in decision making type of problems that are normally addressed by the system dynamics field. While the rational expectations theory claims that the actors have "perfect foresight", feedback theory is open to more elaborate decision rules which involve not only the foresight as a function of the current states but also the current states themselves. Note that the theory of rationality limits itself to traditional models which have analytical solution; hence they frequently ignore the importance of dynamics, non-linearity, measurement errors and ambiguity. Simon (1979, p. 496) states that "*The classical theory of omniscient rationality is strikingly simple and beautiful. Moreover, it allows us to predict (correctly or not) human behaviour without stirring out of our armchairs to observe what such behaviour is like*". If reality is more complex than assumed in classical theory, rationality ends up as a simplified view of the decision maker. Thus, in practical terms of modelling, it is a simplified *decision rule* with a questionable validity.

From the above, one may suspect that rational theory explains well simple cases, while it fails with increasing complexity. In simple feedback systems, the behaviour could be identical under decision rules formulated with either rational choice or bounded rationality theory, given that people can easily see the "rational" decision. In the example (see Figure 2) rational choice and bounded rationality may offer the same results. However, when the complexity of the system is increased, and more loops become important in the decision making problem, the theory of rational choice does not work any longer and rationality is degraded. People misperceive the role of accumulation, delays, and nonlinearities in the systems. In these cases, bounded rationality theory offers a better explanation of the system's behaviour. Those cases are very often in decision making problems, with strong implications in model behaviour. Models based on rational choice theory normally converge to equilibrium points; while models based on bounded rationality frequently produces unstable and cyclical behaviour.

According to the system dynamics literature, the purpose of a model is to analyse a problem and this purpose should shape the formulation of the decision rule. The decision rule should be based on a theory of human decision making. I believe that human decisions fail to satisfy most of the assumptions of the rational choice theory, which leads to persistent and systematic deviations from the predictions of such theory. Therefore, if there is an agreement that models should represent reality, bounded rationality theory should be used to model human decisions. The following quote summarizes the reasons to choose bounded rationality, based on a literature survey Conlisk (1996, p. 692):

"*Why bounded rationality? In four words (one for each section above): evidence, success, methodology, and scarcity. In more words: Psychology and economics provide wide-ranging evidence that bounded rationality is important (Section I). Economists who include bounds on rationality in their models have excellent success in describing economic behaviour beyond the coverage of standard theory (Section II). The traditional appeals to economic methodology cut both ways; the conditions of a particular context may favour either bounded or unbounded rationality (Section III). Models of bounded rationality adhere to a fundamental tenet of economics, respect for scarcity. Human cognition, as a scarce resource, should be treated as such (Section IV).*"

The use of rational choice theory could still be valid to study some problems. For example, rational choice could eventually work as benchmark to compare with other realistic decisions, or it can also explain human decision in simple problems where rational choice theory may be valid. System dynamics generally subscribes to the bounded rationality theory and in particular to feedback theory. However, it should have clearly open doors to the use of rationality in cases where is required.

Thus, being conscious about the theory behind the modelling process helps to improve the discipline itself and therefore the quality of models, as is claimed by Meadows (1976): "Computer modelling could be more effective, both as a science and as a useful art, if each modeller could recognize the assumptions behind his own modelling school and could understand and respect the assumption behind other schools".

4 METHODS FOR BUILDING *DECISION RULES*

How can modellers identify a function that defines a decision rule? How should they quantify the parameters in the decision rule? There are different methodological approaches available that the modeller can use to build decision rules. Personal experiences with similar problems, different theories about the topic, expert knowledge, historical data and different sources of information described by Forrester (1980), are among the possible methodological approaches.

Let's start with Forrester's definition of decision rule [Forrester (1968)], as a pioneer of the system dynamics field. He argues that the *decision rule* is determined by four components or sub-structures: a goal, an observed condition of the system, something to express the discrepancy between the goal and the observed condition, and a way to take the action based on the discrepancy. This process is presented in Figure 3, and is supported by the *Principle 4.4-1* [Forrester (1968)]:

"***Principle 4.4-1. Goal, observation, discrepancy, and action-system sub-substructure:*** *A policy or rate equation recognizes a local goal toward which that decision point strives, compares the goal with the apparent system condition to detect a discrepancy, and uses the discrepancy to guide action.*"

Some of the features defined to the decision rules are:

i) It is instantaneous in its behaviour,

ii) It is a pure algebraic expression that states the

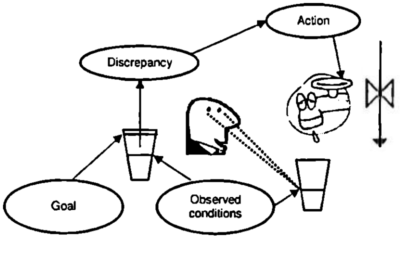

Figura 3: Components of a Decision Rule

present flow rate in terms of the present information,

iii) It is free of lags and time-dependent distortion (all time-dependent changes are created by the level equations).

Forrester (1994) argues that in order to represent policies and decision making, all kinds of information should be used. It includes not only numerical data, but also other rich sources of information such as mental models (which are built up from experience and observation), and written information. There is not always data available about important structures or variables. Forrester argues that omitting these data is less scientific and less accurate than using one's best judgment to estimate their values. "*To omit such variables is equivalent to saying they have zero effect probably the only value that is known to be wrong!*" [Forrester (1961, p. 57)].

Decision rules depend only on level variables and/or constants in the model, and not on other decision rules. The decision rules do not depend on time or own past variables as is presented in *Principle 4.3-6.*

"***Principle 4.3-6. Rates depend only on levels and constants:*** *The value of a rate variable depends only on constants and on present values of level variables. No rate variable depends directly on any other rate variable. The rate equations (policy statements) of a system are of simple algebraic form; they do not involve time or the solution interval; they do are not dependent on their own past values.*"

Forrester's presentation may seem dogmatic with no room for other alternatives to model decisions. For example, it is not recommended to use information about other rates. In principle Forrester is right since rates cannot be measured instantaneously (measurement of rates depend on accumulation devices). However, in practice they could be known by the decision maker.

However, Forrester's position is not the only view about modelling decision rules in system dynamics. In particular, *Business Dynamics* [Sterman (2000)] has become a frequently used reference by system dynamics modellers. In the chapter about modelling decision making, Sterman rather than presenting a dogmatic statement about the nature and composition of the decision rules, presents a collection of principles that should be followed. The decision rule is made according to assumptions about the degree of rationality of the decision maker. Thus, there is a wide range of possibilities: from decisions based on the rational choice theory to bounded rationality. This gives room to include within the decision rules the rational expectations theory. He points out that decision rules should follow the following five principles:

1. The Baker Criterion: the input information to all decision rules in models must be currently available to the real decision makers. It implies that the future is unknown, and that forecasting must be done based only on current and historical information. The actual and perceived conditions of the system may be different due to reporting delays, slow update of beliefs, etc.

2. Decision rules should conform to managerial practice, therefore all variables and relationships should have a real world meaning.

3. Desired and actual conditions should be distinguished, and it is necessary to represent the physical constrains to the realization of the desired conditions.

4. Decision rules should be robust under extreme conditions.

5. Equilibrium should not be assumed and stability may (or may not) emerge from the interaction of the elements of the system.

Sterman presents certain mathematical functions[2], which normally satisfy the principles stated above. Those functions could be used as decision rules. The decision rules should be customized for each case, depending on the purpose of the model, the time horizon, etc. Others advice to follow are: i) All outflows require a first order control, ii) avoid IF ... THEN ... ELSE formulations, and iii) disaggregate net flows. Richardson and Pugh (1981) present other mathematical functions to consider for decision rules, and they also point out

[2]These templates are the following: Fractional Change in Rate, Adjustment to a Goal, The Stock Management structure: Rate = Normal Rate + Adjustment, Flow = Resource * Productivity, Y = Y^* * Effect of X_1 pm Y * Effect of X_2 pm Y * ... * Effect of X_n pm Y, Y = Y^* + Effect of X_1 pm Y + Effect of X_2 pm Y + ... + Effect of X_n pm Y, Fuzzy MIN (MAX) Function, Floating Goals, Nonlinear Weighted Average, Modeling Search: Hill-Climbing Optimization, Resource Allocations

that the list is not exhaustive, and it is open to try new ideas as well.

The trial-and-error method fits into the iterative modelling process [Homer (1996); Sterman (2000)]. System dynamics modelling is also a feedback process that goes through constant iteration, constant questioning, testing, and refinement. It can be understood as a trial and error method, which includes the decision rules. In fact, the decision rule, or what is also called the policy, is a hit-or-miss process from a wide range of options [Coyle (1996)]. The modeller should develop the skill to choose the proper function and adapt it to the model in order to test the chosen option. It must be chosen according to the information/action/consequences feedback theory and take into account the two major components: *structure* and *parameters*. The structure is the form of the equation and the links on the influence diagram. The parameters, for a given structure, are the numerical values.

Frequently, system dynamics use particular practices in order to improve models. *Group model building* is an example. This practice involves the client within the modelling process in order to facilitate and improve models. This fact could apparently be a natural source to formulate decision rules. Group model building does not have the model construction as its primary goal. However, the clients aid model building, hence the decision rules formulation. It combines different techniques according to the stage in the modelling process. Decision rules are defined in the model formulation stage. In this stage, group model building calls the attention to dimension consistency through the whole model. Some qualitative data may need special units, sometimes just for the model, that requires especial discussion between the modeller and the clients [Vennix (1996)]. Although, the current literature on group model building does not provide hints and methods to be used directly in the decision rules formulation, some ideas and methodologies may be useful. Due to the fact that those methodologies are mostly taken from the knowledge elicitation techniques, it will be explained later on.

Due to the growth of the field of experimental economics, research on dynamic problems addressed by the system dynamics methodology has increased. Laboratory experiments with real subjects have been done in order to understand problems associated with decision making, and the data have been used to analyze the heuristics people use to make decisions and to estimate decision rules, which are used in simulation models. The basic idea is to have a controlled environment where the subjects make decisions, generally motivated by economic rewards. Afterwards, hypothetical decision rules are tested by direct observations. The literature of simulation models with experiments is increasing, examples are [Sterman (1989*a*); Paich and Sterman (1993); Moxnes (1998*a*); Rassenti, Reynolds, Smith and Szidarovszky (2000)]. Details about the methodology are framed in Friedman and Sunder (1994).

Decision rules cannot be determined from aggregate statistical data, but it must be done by first hand data by using techniques such us experimental economics [Smith (1982); Sterman (1988); Rassenti et al. (2000)]. It should be done through observation of the actual decision making in the field itself, by the use of laboratory experiments in which managers operate simulated systems. With first hand information, the modeller may be able to infer the appropriate decision rule. According to Mass and Senge (1978), first, there must be a prior hypothesis regarding the causes of the changes in the dependent variable (output of the decision rule). The hypothesis should be based on observed phenomena and/or prior theories, which identify the variables believed to be significant determinants of change in the dependent variable. The hypothesis should also specify how these determinants are to be combined. Second, the initial prior hypothesis must be tested under the available empirical information and refined if needed. Some examples are [Sterman (1989*b*); Rassenti et al. (2000)].

System dynamics has grown as a modelling school, taking advantage of the latest computing capabilities. Simultaneously, other modelling schools have emerged. Some of those address problems where human decisions are involved. Therefore, it represents a source for different techniques to formulate decision rules. Following, I present some alternative methodologies that could be used in the system dynamics field.

Experts systems have a different purpose than simulation models. This methodology is used to suggest decisions automatically, and eventually to make decisions. Consistent with the name, the expert systems are built from expert knowledge. The experts provide direct data about decisions. Thus, it makes experts systems a natural source of methodologies to build decision rules. Expert systems have used a number of *Knowledge Elicitation* [KE] techniques, mostly designed to elicit rules. Decision rules are called procedural knowledge in the field of expert systems and knowledge elicitation [Moody, Richard and Blanton (1996)].

KE techniques are methods and practices of acquiring knowledge about specific topics from different sources, such as experts in the field, and/or published literature. KE is one of the most important tasks of the expert systems field. Any particular technique might be adapted according to the nature of the situation, the domain knowledge, and the availability of experts [Dawood (1996)]. KE techniques focus basically on the use the expert knowledge [Hoffman, Shadbolt, Mike and Gary (1995)].

There is a great diversity of KE techniques. KE has a variety of goals such as generation of cognitive specifications for jobs or task, mitigation of human error in domains with pressure and risks, skill remediation, etc. [Hoffman et al. (1995)]. They also present a complete methodological analysis of KE from experts. They classify KE techniques into *analysis of familiar task*, *interviews*, and *contrived techniques*. Following, I present a description of different KE techniques based on their literature survey.

4.1 Analysis of Familiar Task

This category of techniques investigates what is the experts' behaviour in their usual problem solving or decision-making tasks. It studies decision *in situ*, i.e., analysis of people's behaviour when they make decisions in real life.

Documentation analysis: It is the first step in the search of knowledge from experts. It refers to the review of all information in documents (text, manuals, course, etc.) or any other sort of records. It is not just having information flow from documents, "the researcher's analysis of the documents can involve specific procedures that generate records or analyses of the knowledge contained in the documents". This process may be time-consuming, but indispensable in some cases.

Task analysis: consists of the task or jobs of the subjects "on-line" or "in situ". Other suggestive names are job analysis, structural analysis, and task description, etc. The task analysis is explored by using "Think Aloud Problem-Solving/Protocol Analysis". The subjects are asked to do their regular tasks. In the meantime, they are asked to "think aloud" about the problem and describe what they are doing. This information is recorded and analysed subsequently. The actions are grouped by common features to seek for common patterns. It is recommended to take into account possible biased answers by differences in verbal expressiveness, which may lead to differences in perception of the actions. Task analysis is also studied by the use of *test cases*. With this technique, the experts are asked to describe how they behave in certain cases. Test cases are used to confront experts with past decisions and observe their reasoning of past experiences. It is also recommended alternative techniques for task analysis such as *tough cases* and *atypical cases*. With these techniques, the expert is confronted with particularly difficult or challenging cases, and may eventually be more revealing if the experts are observed making decisions in common or routine problems. The technique has been used extensively in fields such as medical diagnosis, physics, computer programming, and accounting.

4.2 Interviews

The interviews are the second major category of KE techniques. An interview is a question/answer arrangement, where the interviewer gets information from the interviewed. According to the nature of the questions, interviews can be unstructured or structured. The first takes the form of open dialog with the expert, with questions such as "Tell me everything about Y." The idea is to get to know the expert's reasoning. It is useful to observe the kind of knowledge and then, follow up with structured interviews. Problems with the unstructured interview are that the expert can get away of the desired track, or the expert can assume that the elicitor has knowledge a priori. Interviews in general have been widespread, hence recommendations and literature available from many different fields helps to improve the skills.

The second is the structured interview, also called "focus". Those interviews are planned and well defined. Structured interview goes directly to the point and reduce the time spent compared with unstructured interview. In general, there are two formats of structured interviews *Domain-Specific Probe Questions* and *Generic Probe Questions*. In the domain-specific probe questions, the elicitor prepares fixed questions; hence the interviewer requires a prior knowledge about the topic. In generic probe questions, the elicitor relies on a set of generic questions[3], which have specific functions.

Additional companying material is part of the interviews. It helps with the structure of the interview. The companying material could be *test cases*, *first-pass knowledge base*, and *event recall interviews*. The test cases have the same form as described on the analysis of familiar tasks. The first-pass knowledge base is basically a list of prepositions that express many of the core concepts, the definitions of terms, and the procedural rules about the topic. The list is normally taken from the task analysis activities or initial interviews. Finally, event recall interview look for questions that "try to go through the events in reverse order" and try to recall an incident from different perspectives. Occasionally, the interviews can also be fruitful when they are performed in groups. In group interviews, the interviewer normally seeks for common knowledge and agreements among the group of experts.

4.3 Contrived Techniques

According to some psychological research, expert knowledge and reasoning can be revealed by deliberate modification of the familiar tasks. Demonstration about

[3]Examples of probe set questions applicable to decision rules, are: "Why would you do that?", "How would you do that?", "What would you do at each step on this procedure?", "When would you do that?", "Is [the rule] always the case?", "What alternatives [to the prescribed action or decision] are there?", "What if it were not the case that [currently true conditions]"

with experiments such as asking chess masters "to recall game boards in which the pieces had been randomly arranged", or "making bridge players adhere to altered rules". The controversy arises about how much of those departures are legitimate or fruitful to elicit knowledge. It is argued that contrived tasks may make the experts uncomfortable or may reflect reasoning strategies that are not the real behaviour. Some of the contrived techniques are describe below.

Decision analysis: it is a set of procedures including decision aiding, risk analysis, probability and utility modelling based, etc. It seeks, in many cases, for evidences about the sequence of steps in their usual decision making by generating the following list:

(a) elements of the problems,

(b) causal relationship,

(c) kind of problems faced,

(d) features of each type of problems,

(e) decisions involved in each type of problems,

(f) confidence in judgments or hypothesis of the problem solver,

(g) consequences of each decisions,

(h) quality of the analysis.

From the steps listed above, the elicitor may possible develop mathematical functions and key concepts about expert's reasoning, and therefore generate their decision rules.

Group decision making: there are different methodologies to analyze decision making problems, when the decisions are made by groups. One of them is "*brainstorming*", where the participants are asked to generate many different ideas without any sort of criticisms or refining. Another one is "*consensus decision making*", where the group is challenged to find the "best" group solution by assessing advantages and disadvantages of the possible solutions. A last example is "*nominal group*", where the individuals perform independent ranking of given alternative solutions.

Rating and sorting tasks: the technique is sometimes included with familiar tasks. It basically seeks for rating and sorting alternative solutions by the experts. It has been used in cases that look for key variables, judgement about reasoning and strategic behaviour of experts on different fields, etc. Some authors have used the technique to explore particular hypothesis, rather than eliciting expert knowledge. The way to apply the technique varies according to the particular problem. Given the nature of this technique, statistical tools may be useful to compare different expert's results.

Constrained Processing and Limited Information Problems: In this technique, the experts' experience that their familiar routines are constrained in some ways, for instance, the expert may be asked to follow a particular strategy or make decisions under limited information. There are recommendations to use this technique together with interruption analysis, where the expert is interrupted during certain tasks to answer questions such as "What were you just doing?" or "What was just going on?" or "What would you have done just then if ...?"

Graph Constructions: A conceptual graph is a representation of relationships or links between elements or variables. The experts are asked to draw graphs of a particular relationship. These sorts of representations are commonly used in Artificial Intelligence[4].

This is not the only classifications of KE techniques in the literature. For instance Coffey, Canas, Hill, Carff, Reichherzer and Niranjan (2003) made a distinction between direct and indirect techniques. Direct techniques are referred to as those where interactions with one or more domain experts occur, while indirect techniques seek for the knowledge from texts, reports or any other documentation.

It is agreed that different KE techniques may elicit different types of knowledge. Thus, procedural rules and heuristics (which is our interest) could best be elicited by "think-aloud" problem solving, task analysis, and interviews based on memory probe questions. Above, I have described the techniques, however the literature is vast and more detailed material is available.

4.4 Alternative Methodologies

A number of techniques are emerging from different modelling schools, which may be included in system dynamics models, and therefore models could turn to be adapted into hybrid systems[5]. In fact, a particular computational modelling technique could be used as a decision rule itself. This approach is analogous to the methodological approach of laboratory experiments. In an experiment, the modeller asks real people to make decisions based on a model and afterwards infers about the decision rule used by people on this purpose. Some of the alternative modelling schools are listed below:

[4]Similar kinds or representations between variables are also frequently used in system dynamics models, where non-linear relationships are easily represented by conceptual graphs.

[5]There are many different definitions for hybrid systems. In this paper, I refer to hybrid systems as a computer model that uses more than one problem-solving modelling school in order to solve a problem.

Neural Networks
Regression techniques
Data reduction techniques
Fuzzy logic
Genetic algorithms
Case-based reasoning
Expert systems
Decision trees
Artificial Intelligence
Agents based simulation
Multi-criteria analysis

Each of those schools is complex and diverse; therefore there may be different definitions and descriptions for them. It is not the intention here to describe other computer modelling schools. What I want to point out is that hybrid systems may be useful to model human decisions in system dynamics models, by making use of alternative computational techniques instead of endogenous decision rules. The modeller may go deeply into the literature in case of the use of those techniques.

Next I will present some elements to the test of the *decision rules*. It includes not only the traditional statistical validation methodology, but also tests for consistency with the theory and the system dynamics theory.

5 TESTING THE *DECISION RULES*

The decision rules are part of the system dynamics models. Therefore, decision rule validation in particular is part of system dynamics model validation in general. A number of publications have referred in different ways of validation in general [Forrester (1961); Forrester and Senge (1980); Homer (1983); Barlas (1996); Sterman (2000)], however, the focus here is only on the decision rules. Thus, we provide information about how to test the hypothesized decision rule in order to be consistent with the scientific method.

An explicit direct test of the decision rule is presented by Sterman (2000). After the statement of a hypothesis (decision rule) based on a theory, the mathematical expression that defines the decision rule is tested by using statistical methods with empirical evidence. It has also been used by Moxnes (1998*a*). In particular, Sterman (2000) proposes the use of "partial model tests" in order to determine the intended rationality in decision rules. It is an explicit test of the decision rule. In this technique "*each organizational function or decision point is isolated from its environment until the environment is consistent with the mental model that underlies the decision rule. The subsystem can then be challenged with various exogenous patterns in its inputs.*"

Within the current system dynamics literature, it is argued that one should perform many tests of model structure and behaviour not possible with other types of models, and that there is no single test to make "the validation" of the model][Forrester and Senge (1980)]. The various tests have been used and restated in different sources e. g. Sterman (2000), and some of them have also been implemented in the system dynamics software [Peterson and Eberlin (1994)]. In general, the decision rules, as a part of the system dynamics models must satisfy all the proposed tests, and in particular, the tests done for the isolated decision rules. Those tests are listed next [Sterman (2000)]:

5.1 Test of Model Structure

Structure-verification test: it includes the verification of the model assumption, and therefore also the *decision rules.*

Parameter-verification test: the decision rules' parameters should be confronted numerically and conceptually with the parameters in real life.

Extreme-conditions test: for example, the shipments must be zero in the inventory of a commodity is zero; and if there are no houses in a city, then the decision to immigrate must be strongly discouraged.

Boundary-adequacy (structure) test: it is necessary to develop a convincing hypothesis relating proposed model structure to a particular issue addressed by a model.

Dimensional-consistency test: measurement units must be consistent not only for the decision rules, but also for the whole model.

5.2 Tests of Model Behaviour

All the tests related to model behaviour (behaviour-reproduction, behaviour-prediction test, behaviour-anomaly test, family member test, surprise-behaviour test, extreme-policy test, boundary -adequacy (behaviour) test, behaviour-sensitivity test) are applicable to the *decision rules*. Thus, in the sense that these rules are important for the overall behaviour of the model.

5.3 Tests of Policy Implications

The tests of policy implications are done in order to build confidence in a model's implications for policy. Since the policies are represented in models through decision rules, this test could be used to see the robustness of the policy implications when changes are made. It includes the system-improvement test, changed-behaviour-prediction test, boundary-adequacy (policy) test, and policy-sensitivity test.

Classical statistical goodness-of-fit tests have also been used to test decision rules, particularly when data are obtained directly from experiments. The hypothetical decision rule is tested by using classical statistics [Sterman (1989*a*); Moxnes (1998*b*)]. In particular Mass and Senge (1978) present a detailed case to carry on single-equation statistical tests, based on the comparison between individual model equation and model behaviour test through the use of the popular t-test of parameter "significance" and the partial correlation coefficient.

A particular method of analysis is the "premise description", which is used to analyse the bounded rationality of policies or decision functions (decision rules) in a system dynamics model. The method has a particular stress on the process and cognitive limitations assumed in the decision making [Morecroft (1985)]. This method of analysis is also useful for testing the decision rule. A quote of the method description is Morecroft (1985):

"*The modeller starts with a diagram of the model system showing the network of interlinked decision functions. He then describes the equations of each decision function, drawing attention to the way factoring and local goals simplify rational choice, how authority and culture influence the content and interpretation of information streams, and how routine and cognitive limitations influence the collection, processing, and transmission of information. At the back of his mind the modeller has the notion of objective rationality as a yardstick. This yardstick raises questions of why some information is available in a decision function and other is not, why bias is present. The answer to these questions naturally point to empirically observed organizational processes that stem from bounded rationality.*"

6 FINAL COMMENTS

Since the decision rules are part of the model, they should follow the principles of the model itself. Thus, the purpose of the model should shape the formulation of the decision rule. Once the modeller has the purpose of the model clear, it is necessary to choose the methodology or strategy to build the decision rules. The decision rule should also be based on a theory of human decision making. I believe that human decision fail to satisfy most of the assumptions of the rational choice theory. This leads to persistent and systematic deviations from the prediction of the rational choice theory. Therefore, if there is an agreement that models should represent reality, the use of bounded rationality theory is a better approximation to model human decisions.

The Scientific method is based on hypothesis formulation and testing. Here, I presented the particular case of the formulation of decision rules as a part of formal system dynamics models. The presentation is intended to fulfil the requirements of the scientific method in both hypothesis formulation and testing. A decision rule is a hypothesis formulation of a theory. Since we are dealing within the field of system dynamics modelling, the principles of the field should shape the formulation of decision rules, which include the thinking, methodolo-

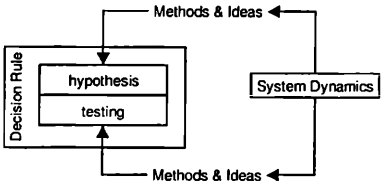

Figura 4: Decision Rules Definition in Simulation of Dynamical Systems Models

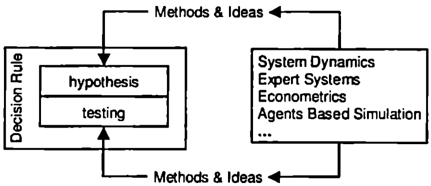

Figura 5: Decision Rules: Formulation and Testing within Different Computer Modelling Schools

gies and particular techniques. The hypothesis testing should be also done according to the system dynamics principles.

Forrester's early view of system dynamics may seems very dogmatic with respect to the decision rule based on feedback theory as a part of bounded rationality. Even though there is some influence and use of other computer schools on modelling decision rules, I think that the vision is still narrow (see Figure 4) and should open much more to other computer modelling schools.

System dynamics is understood to be part of a wider range of computer simulation schools of thought, all of them oriented towards problem solving [Meadows (1976)]. The computer modelling schools were influenced by the computer evolution, mathematical models and the scientific method. Even though the schools have developed independently, common roots lead to the possibility of sharing techniques, in particular for the case of decision rules. The decision rules are clearly identifiable across the schools as presented in the paper with suggestive names such as: procedural rules, decision functions, etc. Thus, the hypothesis formulation and testing of the decision rules in system dynamics models could use techniques taken from other fields as is presented in the Figure 5. In fact, some of the techniques currently used in system dynamics models are taken from other fields. I have presented a bunch of alternative techniques that may improve the models by improving the decision rules formulation and testing.

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