INVESTIGATING ORGANIZATIONAL LEARNING WITH A CORPORATE SYSTEM MODEL USING ARTIFICIAL INTELLIGENCE PROCEDURES[a]

Roger I. Hall

Drake Centre for Management Studies 418
University of Manitoba
Winnipeg R3T 2N2, Canada

ABSTRACT

An Artificial Intelligence (AI) model that mimics the behavioral processes of managerial policy making is outlined. The model takes an equation set representing a System Dynamics (SD) corporate model and interprets it as a surrogate *cognitive map* of the organization's domains. The model seeks policies to satisfy the goals of all departments or, where this is not feasible, the goals of the dominant departments only. These policies are used to drive the SD model for a simulated year and the results are fed back to affect organizational learning, that in turn affects the policies adopted for the next period, and so on. Experiments can be run to investigate the effects of performance on organizational learning and *vice versa.*

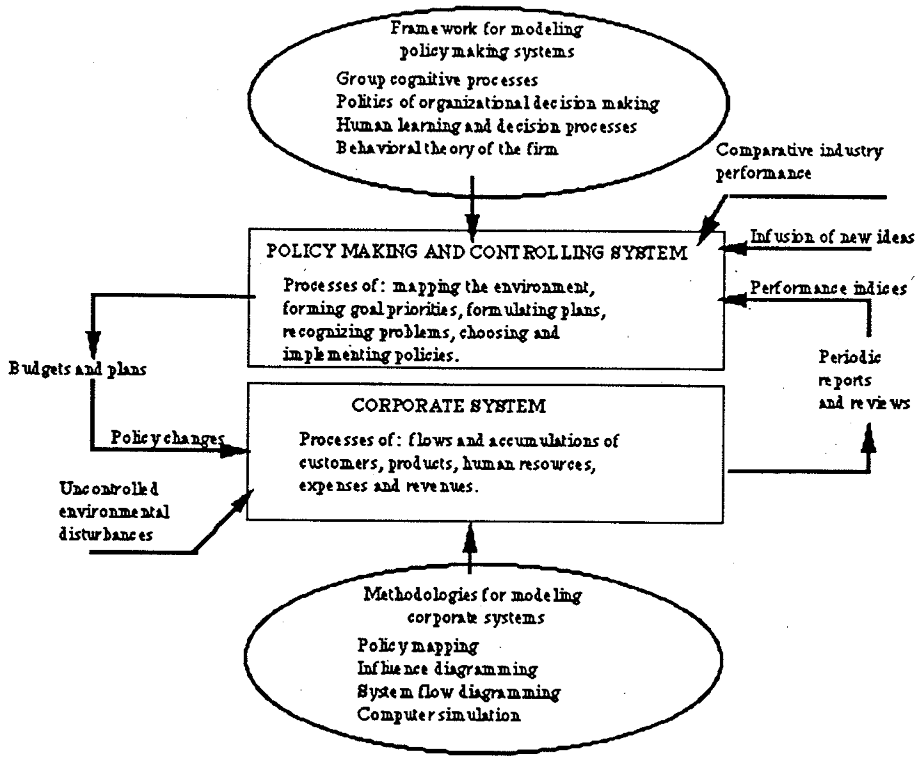
THE RESEARCH QUESTION

Using an analogy with human anatomy, Corporate System Models can be viewed as comprising two distinct parts (figure 1): a corporate system (the body), and a controlling and policy making system (the brain). Whereas the corporate system can be modeled using System Dynamics as a kind of expert system framework for assembling and connecting stocks and flows, the controlling and policy making system is often absent or represented by relatively simple graphical functions or conditional statements. The actual process of making policy decisions involves learning from the results, revising mental maps, formulating budgets to help identify problems and a socio-political process for forming policies to correct the problems. The resulting decisions impact on the corporate system together with uncontrolled environmental disturbances, such as economic booms and depressions, to create new results and new organizational learning and so on. The micro processes of decision making move the organization through time to create macro events such as growth, decay, crises and reorientations.

The relationship among performance, organizational learning, and policy making in an institutional setting is a matter of some research interest. What, for instance is the effect of adding departments, or blinding the decision makers to certain causal relations that cross departmental or environmental boundaries, or changing subtly the culture of the organization in terms of the priorities for achieving certain goals and the beliefs in certain key cause-effects, or spurious uncontrollable events bringing a windfall increase or loss of sales. Such insights might also help managers to understand better the effects of their organization's structure and style of decision making on performance and *vice versa.*

[a] This project is supported by a Strategic Research Grant from the Social Sciences and Humanities Research Council of Canada.

Figure 1 A representation of the interactions between the policy and corporate systems



A research project to aid this research was undertaken to design and program a model of group policy making that could be used to drive a corporate system model. The model incorporates socio-political, social psychological and group cognitive processes (Hall,1984) as an Artificial Intelligence (AI) designed in the tradition of building machines that think and act like people (Newell and Simon, 1966)[1]. The purpose of this AI is to mimic the way groups of managers make policy decisions. It is not intended to make optimal policy decisions but rather to assist in generating insight and organizational learning by aiding the users to explore the mutual interaction between the policy making behaviors of groups of managers and the behavior of the corporate system they seek to control. Appendix A contains a listing of the behavioral assumptions included in the model.

AN OVERVIEW OF THE AI

The AI is programmed in HyperTalk using the HyperCard facility of the Macintosh. HyperTalk has the advantages of being able to launch programs in structured languages such as C and BASIC, and to pass data to and from a corporate simulation model programmed in system modeling language Stella™, and then to launch it. For the less

[1] A more complete description of the the basic design can be found in Hall (1990).

sophisticated programmer, designing a series of visual interactive screens that prompt the user for information is quite easily accomplished with HyperCard. This model was programmed with the aid of two undergraduate students.

The AI procedures are designed to interpret a SD corporate system (e.g., a firm and its significant environments), form policies for certain problem situations (e.g., poor growth or financial loss), construct operating statements and budgets frameworks for reporting and controlling, make decisions by implementing the policies previously formed, learn from the results (the operating statements), and reformulate the policies where required. The AI is contained in three parts (HyperCard stacks): (I) policy inference procedures, (II) a reviewing, planning and forecasting framework, and (III) decision making procedures.

Part I Policy Inference Procedures

The user is prompted to select a SD corporate model and the AI procedures will import the equations representing the corporate system. The AI procedures will then convert the set of equations or influences into a surrogate *cognitive map*[2] and infer causality between variables named by the user as *policy variables* and *goals*[3], and formulate policies (which policy variables to change and in which direction) for different general problem situations. In searching for acceptable policies, the AI employs psychological, social and political behavioral processes that mimic the way groups make sense of complex and potentially conflictful situations (see appendix B). Experiments can be run, for example, to see what kinds of policies are likely to be adopted (i) under different organizational structures by adding or subtracting departments, (ii) with different levels of perception by modifying the influence links in the cognitive map, and (iii) with different initial beliefs in causality where opposing influences exist. If the corporate system model under analysis is programmed in Stella™ (version 2.1) which can run under StellaStack™, then the user can proceed to Parts II and III.

Part II **Reviewing, Planning and Forecasting Framework**

The AI procedures will prompt the user to identify certain operating variables from the model, and then will construct operating statement and budget type forms for use later in organizing, presenting and storing the end-of-period results. The budget uses the protocols listed in appendix A.

Part III **Decision Making Procedures**

The AI procedures will launch the corporate model under StellaStack™ with the initial policies provided by the AI procedures in Part I. The end-of-period results will be transferred to the operating statements and converted into budgets using the frameworks supplied in Part II. Policies will be evoked from Part I to solve any obvious gaps between the aspiration levels for goals and the performance predicted by the budget. The outcome will be decisions to increase or decrease the policy variables (such as prices). The amount of change needed to close the budgetary gaps will be computed using the current values of the sensitivities (e.g., price-demand or volume of production-unit cost) learnt from the

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[2] A parsing routine converts the equations representing the corporate system into (i) a list of variables in alphabetic order,and (ii) a list of bivariate influences in the form variable x influences variable y positively or negatively in a correlational sense.

[3] A depth-first with backtracking path finding algorithm (after Tarjan, 1972) is used to identify all the paths (representing lines of arguments) from the named policy variables to the named goals. It also finds the feedback loops embedded along the paths. See Hall, Aitchison and Kocay (1991) for a more detailed description.

past. The AI procedures will pass these decisions to the corporate model and launch it for another period , and so on until the end of the prescribed simulation run is reached. The period-by period results will be stored for analysis later.

Learning takes place in terms of changes to the forecast levels of key operational variables such as *sales* and aspirational levels for goals such as *profits* based on past experience. Where more than one policy exists for solving a budgetary problem, a selection is made on the basis of previous success (*positive hits*). A crisis, such as financial loss, can trigger off a re-evaluation of the policies provided by Part I, leading to a reorientations in goal priorities, and a change in the beliefs in causality for key environmental relations, and the adoption of new policies. The simulation will then continue with these reordered conditions representing a strategic change.

AN ILLUSTRATION OF THE AI

The corporate system model of a magazine firm shown in figure 2 will be used to demonstrate the *policy inference procedures* of part I of the AI. The AI requires a file of equations representing the model. The current version of the AI requires a text file of equations without time subscripts as produced by selecting *save equations* from the Stella™ menu. Selected screens generated by the AI HyperCard stack, as it prompts the user and interprets the model, are shown in figure 3. The final screen shows the policies derived under the assumptions provided to alleviate problems with (i) both corporate goals of profit and revenue dissatisfied, (ii) either one of the corporate goals dissatisfied and (iii) both corporate goals oversubscribed.

A list of potential experiments with the model is summarized in appendix C. A progress report on the results of these experiments will be given at the conference.

Figure 2 Part of a corporate model of a MAGAZINE FIRM built with Stella™

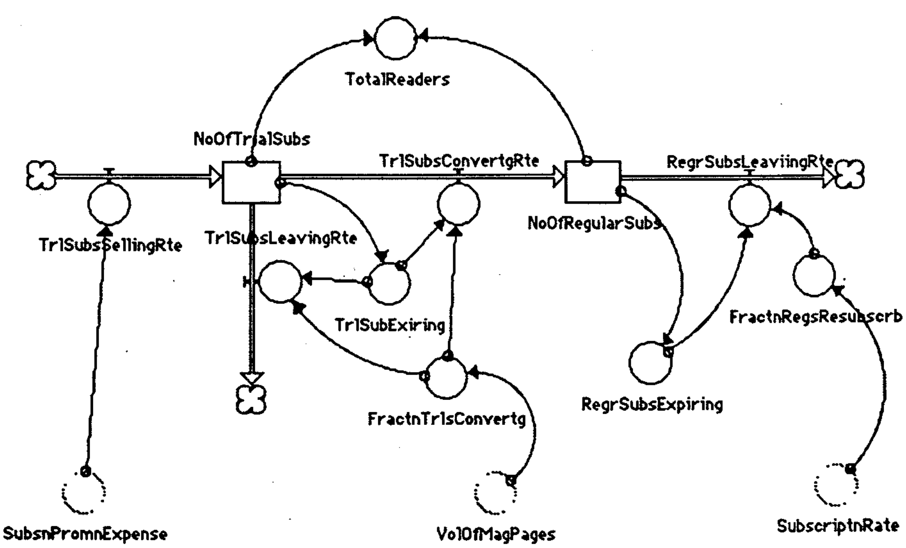
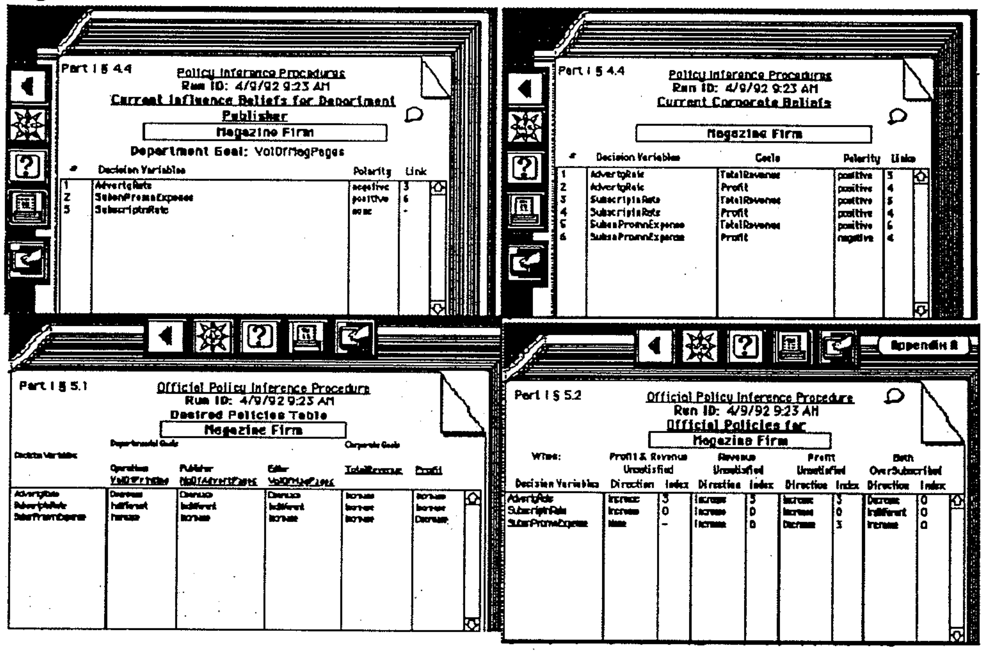


Figure 2 Continued



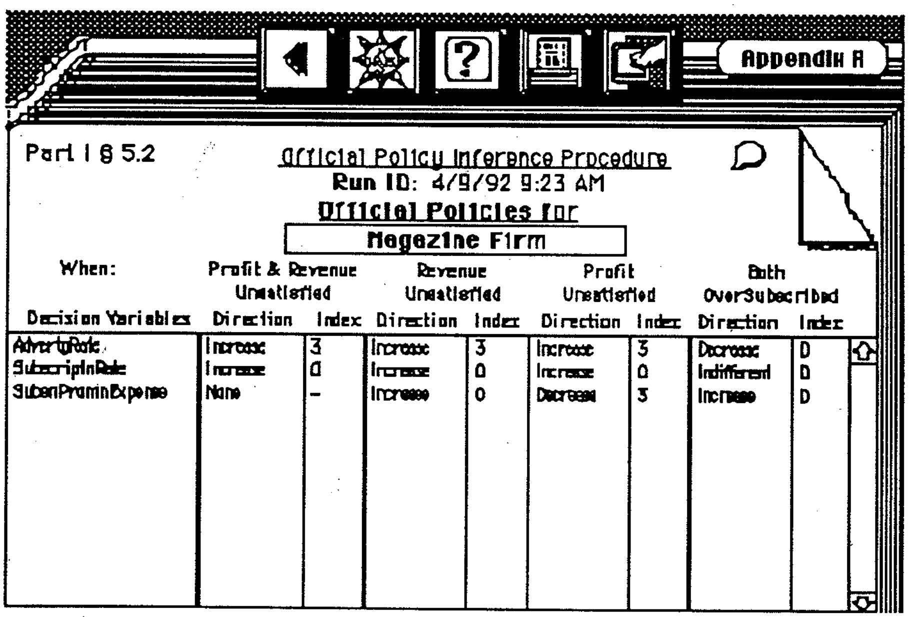
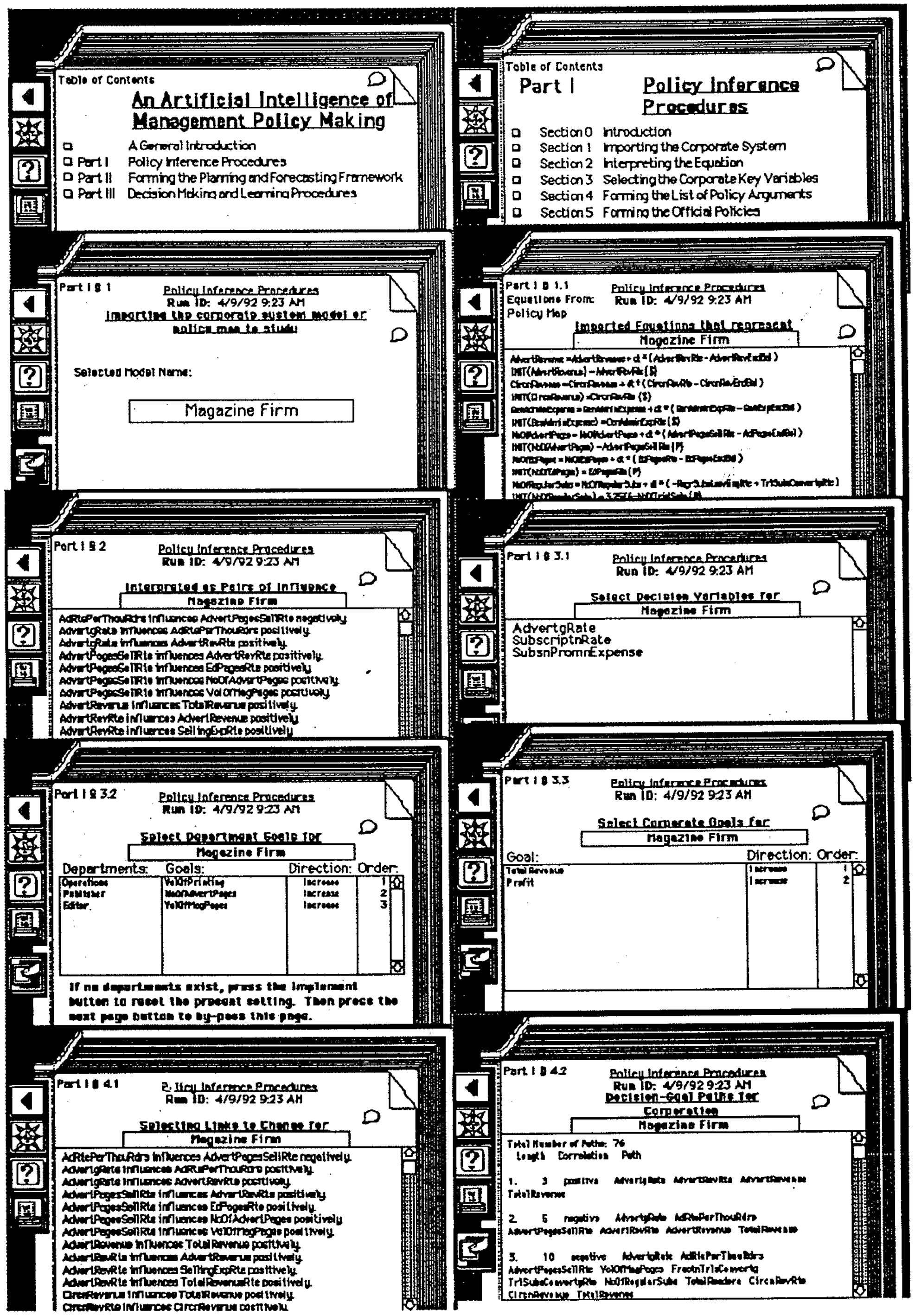


Figure 3 Illustrations of the AI screens when interpreting a corporate model



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APPENDICES

Appendix A Behavioral Assumptions Built into the AI Policy Making Model

Organizational learning takes place in terms of:
1. Policies are validated by the number and intensity of *positive hits* (policies that worked). *Negative hits* (policies that did not have any positive effects) are largely overlooked until the onset of a crisis.
2. Cost sensitivities and market price elasticities are updated by correlating changes in outcomes (results) with changes in inputs. No relations are updated unless the changes to both the results and inputs are at least a *just noticeable difference* of 2% and in the direction expected.
3. Aspiration levels for goals are based on a mixture of *hopes and expectations* as follows:
   a. if performance is improving, adjust the forecasts by *anchoring and adjusting* (anchor on current performance and adjust with an exponentially smoothed trend from past performance),
   b. if performance is deteriorating, use current performance increased by a *just noticeable difference.*

Budgeting uses the following protocols:
1. Forecasts of market-related variables (e.g., sales) are based on *anchoring* on current performance and adjusting with an exponential trend based on past performance rather than using demand curve analysis.
2. The framework of the budget is a simple *proforma* financial operating statement.
3. Individual budget lines are estimated with simple operating logic (e.g., the extension of volume of production by the current unit cost to provide the production cost).

Recognizing problems is based on:
1. Performance gaps (problems) are defined by the difference between budgeted and aspiration levels of the corporate goals of revenue and profit (whether a shortfall or a surplus).
2. Performance gaps of the corporate goals are solved simultaneously where common policies exist; otherwise one at a time in a politically determined order (see appendix B).
3. Where more than one feasible policy exists, then the one with the highest *positive hit rate* (success in use) is selected.

Appendix B Policy Finder Protocols (after Hall, 1984)

Different combinations and depth of search strategies are used depending on the type of problem and the ease of finding a solution. The basic search strategies consist of a *politically motivated search* for policies that advance the goals of as many departments as is possible in the order of their dominance under the limits imposed for meeting the primary corporate goals. When there is conflict, the process leads to satisfying the more dominant departments at the expense of the less dominant by removing successively the constraints imposed by the politically weaker departments until a policy is found. The search is made to solve problems (unsatisfactory performance) with (1) both the primary corporate goals of *revenue* and *profit* simultaneously, (2) the primary corporate goal of *revenue* without any *profit* goal constraint, (3) the primary corporate goal of *profit* without any *revenue* goal constraint, and (4) the primary corporate goals are over-subscribed by diverting the slack into advancing the dominant department's goals and as many as possible of the remaining departmental goals simultaneously.

Protocol 1: Search for policies to satisfy both corporate goals simultaneously
For each decision variable in the *table of desired policies*:

1.1 Check for a policy that satisfies both the primary corporate goals simultaneously. If such a policy does not exist (i.e., the desired policies are opposed), or if there is no policy (i.e., both desired policies are "indifferent") skip to the next decision variable, or if all decision variables have been processed, skip to the next protocol.

1.2 Count the number of dissatisfied departments with desired policies that are opposite to this policy. Store this number as an *index of dissatisfaction* with the chosen policy.

Protocol 2: Search for policies using a sequential attention to corporate goals.
First sequence - satisfy revenue corporate goal only
For each decision variable in the *table of desired policies*:

2.1.1 Check for a policy that satisfies the primary corporate goal of *revenue*.. If such a policy does not exist (i.e., the desired policy is "indifferent") skip to the next decision variable, or if all decision variables have been processed, skip to the next protocol. Otherwise, store the policy as a *revenue only* satisfying policy in the *table of official policies* .

2.1.2 Count the number of dissatisfied departments with desired policies that are opposite to this policy. Store this number as an *index of dissatisfaction* with the *revenue only* policy.

Second sequence - satisfy profit corporate goal only
For each decision variable in the *table of desired policies*:

2.2.1 Check for a policy that satisfies the primary corporate goal of *profit*.. If such a policy does not exist (i.e., the desired policy is "indifferent") skip to the next decision variable, or if all decision variables have been processed, skip to the next protocol. Otherwise, store the policy as a *profit only* satisfying policy in the *table of official policies*.

2.2.2 Count the number of dissatisfied departments with desired policies that are opposite to this policy. Store this number as an *index of dissatisfaction* with the *profit only* policy.

Protocol 3: Search for slack absorbing policies when both primary corporate goals are over-subscribed

For each decision variable in the *table of desired policies*:

3.1 Check for a policy that satisfies the goal of the dominant department. If the policy is "indifferent", choose the desired policy of the next dominant department, and so on. Store the policy as a *slack absorption* policy in the *table of official policies*.

3.2 Count the number of dissatisfied departments with desired policies that are opposite to this policy. Store this number as an *index of dissatisfaction* with the *slack absorption* policy.

All policy conflicts should now be resolved.

Appendix C Experimenting with the Policy Inference AI

A list of possible experiments that could be carried out to probe the behavior of the Policy Inference Procedures.

What policies might emerge from the following experiments and what are their implications for the future direction of the organization?

1. Add and delete *departments* together with their respective *goals* representing changes in organizational structure.
2. Cut selected links in the *pairs of relations* that span environmental boundaries to represent a lack of insight by the managers about how parts of the product-market system works.
3. Select different initial beliefs in causality where opposing beliefs exist to represent different previously environment-driven learning.
4. Modify the protocol used in the *policy finder* to represent different types of organizations, such as: (i) one dominant department or internal culture, (ii) several equally politically strong departments, or (iii) a consensual style of management.
5. Run different combinations of these experiments to represent *best* and *worst case scenarios*.