On Generating Hypotheses Using Computer Simulations

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Abstract

Computational models of complex systems, such as teams, task forces, and organizations can be used to reason about the behavior of those systems under diverse conditions. The large number of integrated processes and variables, and the non-linearities inherent in the underlying processes make it difficult for humans, unassisted by computer simulations, to effectively reason about the consequences of any one action. Computer simulation becomes an important tool for generating hypotheses about the behavior of these systems that can then be tested in the lab and field.

1. **Introduction and Motivation**

The use of formal techniques in general, and computational analysis in particular, is playing an increasingly important role in the development of theories of complex systems such as groups, teams, organizations, and their command and control architectures. One reason for this is the growing recognition that the underlying processes are complex, dynamic, adaptive, and non-linear, that group or team behavior emerges from interactions within and between the agents and entities that comprise the unit (the people, sub-groups, technologies, etc.), and that the relationships among these entities are constrain and enable individual and unit level action. Another reason for the movement to computational approaches is the recognition that units composed of multiple people are inherently computational since they have a need to scan and observe their environment, store facts and programs, communicate among members and with their environment, and transform information by human or automated decision making [Baligh, Burton and Obel, 1990]. In general, the aim of this computational research is to build new concepts, theories, and knowledge about complex systems such as groups, teams, or command and control architectures. This aim can be, and is being met, through the use of a wide range of computational models including computer-based simulation, numerical enumeration, and emulation models that focus on the underlying processes.

A large number of claims are being made about the value and use of computer-based simulation in general and computational process models in particular. These claims appear in articles in almost every discipline. One of the strongest claims is that such computer-based simulation can be used for theory development and hypothesis generation. Simple, but non-linear processes, often

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underlie the team and group behavior. An example of such a non-linearity is the decreasing ability of a new piece of information to alter an agents opinion as the agent gains experience. As the agent gets more and more information that confirms a previously held idea, any information that disconfirms it is increasingly discounted. Such non-linearities make it non-trivial to think through the results of various types of learning, adaptation, and response of teams and groups, particularly in changing environments. Computational analysis enables the theorist to think through the possible ramifications of such non-linear processes and to develop a series of consistent predictions. These predictions are the hypotheses that can then be tested in human laboratory experiments or in live simulations. Thus, computer-based simulation models can be, and have been, used in a normative fashion to generate a series of hypotheses by running virtual experiments.

2. **Virtual Experiments**

One of the most effective ways of generating hypotheses from computational models is by running a virtual experiment. A virtual experiment is an experiment in which the data for each cell in the experimental design is generated by running a computer simulation model. In generating this experiment, standard principles of good experimental design should be followed. The results should then be analyzed statistically. The results of that analysis are the hypotheses that can be examined using data from human laboratory experiments, live simulations, games, field studies, or archival sources. In conducting a virtual experiment and generating a series of hypotheses the followings stages are gone through. Stage 1. Identify core variables. Stage 2. Explore the parameter space. Stage 3. Set non-core variables. Stage 4. Run simulations in virtual experiment. Stage 5. Statistically analyze results. To demonstrate the value of this approach a particular illustrative virtual experiment is described and is used to illustrate each of these stages.

2.1 ***Illustrative Virtual Experiment***

To illustrate how a virtual experiment is done and hypotheses generated, a specific virtual experiment was run using ORGAHEAD [Carley, 1996a; Carley 1998; Carley and Svoboda, 1996; Carley and Lee, 1998]. ORGAHEAD illustrates several aspects of computational process models:

1. ORGAHEAD has been built in a building block fashion by adding on to a base model, additional computational process modules. This building block approach is one of the strongest approaches for building computational models as it enables the designer to validate the model as it is developed and to generate intermediate results.
2. Computational process modules should have face validity. ORGAHEAD, has demonstrated this level of validity and captures the core aspects of unit level architecture.
3. ORGAHEAD, like any computational process model, enables huge numbers of predictions in multiple areas.
4. ORGAHEAD, like any good computational process model is testable.

ORGAHEAD is a computer-based simulation model for reasoning about organizational performance. Performance for units with different command and control architectures and different task environments is predicted. Each member of the organizational unit is modeled as an agent with the ability to learn. In ORGAHEAD the commander can change the C3I architecture in response to various external and internal triggers. Each ORGAHEAD agent may be either a person, a subgroup, or a platform. Agents are boundedly and structurally rational and so exhibit limited attention, memory, information processing capability, and access to information. The performance of the unit is determined by the agent's actions as they process tasks.

ORGAHEAD has been used to make predictions about training, learning, the fragility of organizational success, the type of emergent form, the relative value of different organizational forms, etc. One of the interesting predictions from ORGAHEAD is that organizations can trade individual experience or learning for structural learning. Another finding is that, while all successful organizational forms are similar, their nearest neighbor may be a completely unsuccessful form. Thus small changes in an organization's command and control architecture, small changes in a group's structure, can be devastating.

3. **A Staged Approach to Hypothesis Generation**

In conducting a virtual experiment and generating a series of hypotheses the followings stages are gone through. Stage 1. Identify core variables. Stage 2. Explore the parameter space. Stage 3. Set non-core variables. Stage 4. Run simulations in virtual experiment. Stage 5. Statistically analyze results. To demonstrate the value of this approach a particular illustrative virtual experiment is described and is used to illustrate each of these stages.

3.1 ***Stage 1***

Begin by identifying core variables. Core variables are the parameters or variables of concern. These core variables should be the parameters or model modules which are hypothesized to be the most relevant ones in affecting the dependent variable of interest. An example of a core variable in ORGAHEAD is task complexity.

3.2 ***Stage 2***

Once the parameters have been identified you need to define which values for each parameter will be explored. The choice should reflect concerns with these parameters, and expectations as to where different values of the parameter will effect different system level behavior. In general, two or more values should be chosen for each parameter. For example, for the parameter task complexity we might choose values reflecting low, medium and high complexity. Choosing the parameters and the values defines a virtual experiment. The experiment used here is described in Table 1. These variations of parameters yield 512 different experimental conditions.

3.3 ***Stage 3***

Non core variables should be set to be random, fixed at a level needed for the analysis, or should be set to match conditions known to be true of human groups. For example, ORGAHEAD enables the user to look at units whose size changes over time. In this experiment, however, size is fixed.

3.4 ***Stage 4***

At this point simulations can be run. For each condition, each cell in the table describing your experiment, you should run multiple simulations. This is because there are stochastic elements. If you have a deterministic model you run each condition once. These simulations are your virtual experiment. For example, for the virtual experiment just described each condition was simulated 40 times. In general the number of observations generated via a virtual experiment will be much larger than that generated via a human laboratory experiment, or in a gaming or live simulation situation. For example, the virtual experiment described resulted in 20480 data observations at each point in time.

Parameter	Categories
Task limit	20,000 and 80,000
Task complexity	binary and trinary
Task information	7 and 9
Agent ability	5 and 7
Stressors	Stable and periodic
Unit Size	9, 12, 18, and 36
Shake-ups	1, 2, 3 and 4

Table 1: Summary of Parameters

3.5 ***Stage 5***

Computer-based simulation models generate more data than human laboratory experiments. Nevertheless the results should still be statistically analyzed. Since there is so much data, it is possible to conduct multiple explorations given a single virtual experiment. For example, for the virtual experiment just described first the impact of meta-adaptation strategies on performance was examined then the impact of meta-adaptation strategies on the C3I structure was examined.
For the first analysis, results indicate that, in order of impact, the four factors which most affect sustained performance are: the number of resources available to each agent, the size of the unit, the length of (amount of information in and resources associated with) the task, and the number of shake-ups. These results are summarized in Table 2.

For the second analysis results indicate that increasing organizational size and increasing the task complexity from 7 to 9 bits, reduces the number of re-assignments (who reports to whom) made and increases the number of re-taskings (who is doing what task). The first part of this finding is quite non-intuitive. If there are more people, then the probability of a re-assignment should increase. However, we find this number decreases implying that units are adapting by creating more direct linkages between personnel and task thus reducing the complexities brought on by inter-organizational communication. As a side result the amount of information and the number of resources available to any one individual increases.

Predictor	Coefficient	p value
intercept	0.000000	1.000
Task limit	0.031853	0.000
Task complexity	-0.024068	0.000
Environmental stressors	-0.014568	0.027
Unit size	0.170226	0.000
Agent ability	0.265205	0.000
Task information	0.091118	0.000
Shake-ups	-0.012299	0.063

R^2 (adj) = 10.9%, df = 7, 20472, p<0.001

Table 2. Standardized Regression for Performance.

4. **Summary - Value of Computational Approach to Generating Hypotheses**

Computer-based simulation is a valuable technique for generating hypotheses. As the previous discussion illustrates, application of good experimental design results in data that can be analyzed to generate a wide number of hypotheses all of which are consistent with the underlying processes. Computational modeling allows the analyst to examine a larger number of parameters and to examine values or processes that may be impossible to examine in the human laboratory due to cost or ethical considerations. Computational models are ideally suited to the examination of dynamic systems and to suggesting the long term impacts of new technologies. Another advantage of computational analysis is that they enable an analysis of groups far larger in size than can be analyzed in a field setting. As such, simulations are in essence tools for doing theory development. Computational process models are not, however, a panacea. There are limitations to their usefulness and there are conditions where they are more useful than others. A disadvantage is that such models cannot be used to conclusively demonstrate what people do in novel situations.

The areas where computational process models are most useful are:

1. The system is so complex that even a simple description involves a large number of variables.
2. There are important non-linearities in the processes.
3. The variables interact in multiple ways.
4. There are complex interactions involving three or more variables.
5. The analysts interest is in the dynamics of the system.
6. The team or group being examined is composed of more than 3 personnel.
7. The team or group being examined is engaged in a knowledge intensive tasks.

Historically it was possible to test computational process models by doing a comprehensive analysis of the impact of all parameters. Current process models are sufficiently complex and veridical that a complete sensitivity analysis across all parameters cannot be done; rather, researchers often use response surface mapping techniques, experimental designs and statistical techniques to examine key aspects of the models. One of the key areas of research is how to validate and test these highly complex models.

One technique for validation is hypotheses validation (see also [Carley, 1996b; Carley, Prietula and Lin, 1998]). Once the hypotheses have been generated, they can then be tested in various settings. One issue is what to do if the hypotheses is not validated. There are several reasons that this might occur. Most notably, the model may be wrong or the data may have been collected from a human setting using different measures or different conditions than in the model. Thus the first step is to check and make sure there is a match between the real and virtual world. If there is a match then the model is wrong and needs to be adjusted or discarded.

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