A Typology for C^2 Measures

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Abstract

Numerous measures of the C^2 structure have been developed. The goal is to develop a small meaningful and predictive set. Work in this area, however, has been hampered by a lack of a standard categorization schema. Such a schema is presented herein. This schema is based on the recognition that many aspects of C^2 structures can be represented as graphs.

1. Introduction and Motivation

Measuring and monitoring the C^2 structure requires attendance to numerous aspects of the structure. Decades of research have been spent in an attempt to develop a small set of meaningful and predictive measures. The result has been a plethora of measures ranging in usability, predictability, and meaningfulness. Often, multiple measures have been developed for the same underlying construct - such as span of control. Currently there does not exist a commonly accepted taxonomy for classifying C^2 architectures or a commonly accepted set of measures. Within the organizational theory community debate rages over whether or not such a taxonomy, and the associated measures, is possible, let alone useful. McKelvey [1982] sees a need for such a taxonomy. Some schemes for classifying organizations have been based on strategy [Romanelli, 1989] or product service [Fligstein, 1985]. Other researchers have classified organizations using multiple dimensions, such that one or more measures are used to place an organization along that dimension. For example, Aldrich and Mueller [1982] categorize organizations using the dimensions of technology, coordination, and control.

There are three core difficulties with the standard approach. First there is no unifying scheme for categorizing, contrasting and comparing such measures. Such a unifying scheme would also

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benefit the field by enabling the identification of areas where no measures have been developed. Second, there is no common underlying representation of C^2 data. Such a common representation scheme would make it possible to formally define what measures are possible, ensure comparability of measures in lab, field, live-simulation, and computer simulation data gathering exercises. And third, there is no basis for determining the robustness of these measures and their extensibility to different size groups. Without such a basis the usability, predictability, and meaningfulness of measures is difficult to discern mathematically.

2. Meta-Matrix Representation for C^2 Structures as Typology

In contrast with these previous efforts, what we wish to suggest is a graph theoretic approach to this problem. Specifically, we conceptualize organizational structure, i.e., the C^2 architecture as a set of interlinked graphs. The result is a typology for measuring and monitoring the C^2 structure based on a network approach to organizational units. We illustrate this approach using a simple structure (shown below), data from an A2C2 experiment on C^2 adaptability, and data from a computer-simulation experiment on C^2 adaptability. A graph theoretic approach to organizational measurement is not in itself new. Numerous organizational researchers use network measures to address organizational issues.

Indeed, numerous network measures have been developed [Wasserman and Faust, 1994], some of which were developed particularly to address organizational issues [Krackhardt, 1994; Lin, 1994]. However, a common failing of these measures is that they assume that the organizational structure is adequately described in terms of the personnel and the relations among them. If this were the case, then organizations with identical authority structures should behave identically; but, this is assuredly not the case. In contrast to this personnel only approach, we argue that, at a minimum, personnel, resources and tasks, and the connections within and among each of the sets of components must be considered. Further, we use the term resources broadly to include both physical artifacts or assets and knowledge.

To illustrate our argument we use the hypothetical structure shown in Figure 1. Here there are 5 personnel (the circles), 4 resources (2 aircraft and 2 ships), and 8 tasks. These tasks need to be done to complete the mission. The lines indicate the relations among personnel, resources and tasks. These relations may be directed or not.

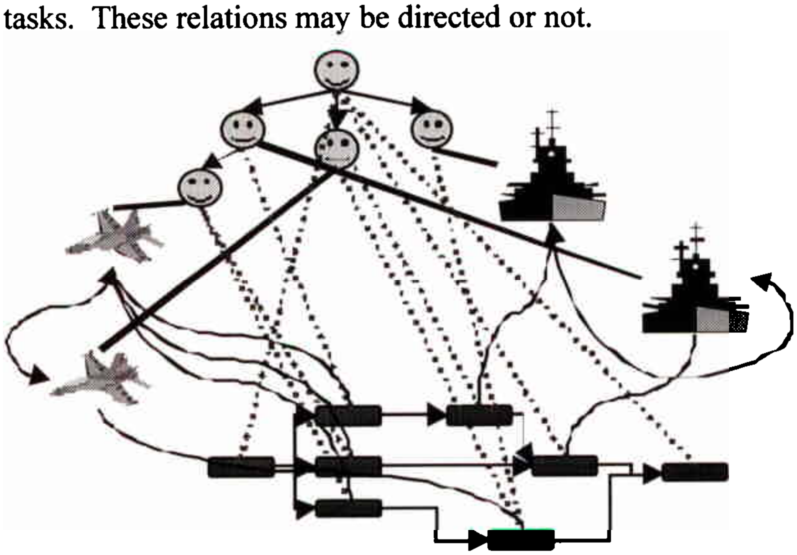

Figure 1. Hypothetical Structure for Illustration

Representing the C^2 architecture as a set of matrices linking personnel, resources, and tasks results in a meta-matrix with 6 sub-matrices. These 6 sub-matrices are shown in table 1: networks, capabilities, assignments, substitutes, needs, precedence. This meta-matrix serves as a typology for classifying all network based measures of organizational structure. This typology, by including substitutes, extends the earlier PCANS framework defined by Krackhardt and Carley [1998]. Known measures of organizational design, such as unity of command, can be categorized by which of these matrices they take into account. An illustrative measure or two for each matrix is listed in each cell. A review of network based measures of organizational structure reveals that most such measures utilize the matrix in only one cell in the meta-matrix. Indeed, most such measures consider only the personnel-personnel cell. Such measures are typically referred to as social network measures. A survey of known measures indicates that few exist which consider substitutes, at least directly. To the extent that social network measures assume that all nodes are of the same type and that the matrix is square, these measures can be applied to either substitutes or precedents, albeit with some need for re-interpretation. For the network sub-matrix measures such as density, hierarchy, and graph connectivity are available for characterizing graphs [Krackhardt, 1994; Wasserman and Faust, 1994]. While most of these measures can be applied to any data that can be represented as graphs, whether or not they are meaningful depends on what data it is. For example, while span of control make sense if the graph represents the command structure it makes less sense if the graph represents the precedence ordering among tasks.

There are a few measures that have been developed for networks with two types of nodes (such as the capabilities, assignments, or needs matrices). However, there are substantially fewer of these and they have been less explored. There are also more detailed measures of process that take multiple sub-matrices into account and most theories of organizational performance, adaptation or change implicitly or explicitly rely on the interactions among two or more sub-matrices. Further, we can compare and contrast the C^2 structures of different organizations by comparing and contrasting their meta-matrices.

	Personnel	Resources	Tasks
Personnel	Networks 5 size 2 span of control	Capabilities 1 coverage	Assignments 1.8 workload
Resources		Substitutes 0 unique	Needs 1.5 usage
Tasks			Precedents 0.25 complexity

Table 1. Meta-Matrix Representation

We can go from an organizational description and data on a unit (such as a team, group, task force, or organization) to a matrix by uniquely identifying each personnel, resource and task and then noting with a 1 that they are connected (i.e., a line occurs in the illustrative structure) and a 0 otherwise. This matrix representation scheme defines a common basis for the comparison of measures. Representing the C^2 architecture in this way enables organizational theories to be contrasted, compared, and given more precise form [Krackhardt and Carley, 1998]. This representation can be used for representing all C^2 structures, irrespective of the source of the data. For example, hypothetical structures, such as the illustrative structure shown in Figure 1 can be represented (see Table 2). We can represent the C^2 structures of organizations that are simulated, such as those simulated using ORGAHEAD, using this framework. We can represent the C^2 structures of organizations used in laboratory experiments using this framework. For example, in the next section we represent the C^2 structures used in the 4th A2C2 experiments at the Naval Post Graduate School and corresponding computer-based simulation experiments on adaptive architectures. In principle, HR records, the organizational chart, the organization's communication network, data from surveys, and so forth can be used as well to fill in this data-structure.

	Personnel	Resources	Tasks
Personnel	01110	0000	10000011
	00001	0010	01000000
	00000	0100	00001100
	00000	0010	00001000
	00000	1000	00110000
	-------	0100	01110000
Resources	-------	1000	00000100
	-------	0001	00001000
	-------	0010	00000010
	-------	-------	01110000
	-------	-------	00001000
Tasks	-------	-------	00000010
	-------	-------	00000100
	-------	-------	00000010
	-------	-------	00000001
	-------	-------	00000001
	-------	-------	00000000

Table 2. Illustrative Structure as Meta-Matrix

When there is more than one type of relation in a cell then multiple matrices exist in that portion of the sub-matrix. These can be combined into a single weighted matrix or treated as multiplex relations. For example, in the case of the networks cell, we can imagine both authority relations (who reports to whom) and communication relations (who can send messages to whom).

3. **Utilizing the Typology**

Measures defined using this representation scheme way were collected in both laboratory and computer-based simulation experiments. The human experiments were conducted at the Naval Post Graduate School as part of the A2C2 project. Portions of the C^2 structures from the 4th experiment are listed in tables 3,4 and 5. Each of these C^2 structures, i.e., their meta-matrix representation, were then used as input to various organizational performance computer models, such as CONSTRUCT [Carley, 1990; 1991] and ORGAHEAD [Carley & Svoboda, 1996; Carley & Lee, 1998]. Using the common representation afforded by the meta-matrix enabled us to compare the predictions of the computer-based simulation model with the human laboratory data.

	Personnel		Resources
	Authority	Communication	
Personnel	111000	111000	111110000000000000000000
	110000	111000	000001110000000000000000
	101111	111111	000000001111111110000000
	001100	001111	000000000000000011111000
A06	001010	001111	000000010000000000000000
	001001	001111	000000000000000000000111
Personnel	1111	1111	100000010000000000000111
	1100	1111	011111101100000000000000
	1010	1111	000000010011000010111000
	1001	1111	000000010000111111100000
A14			
Personnel	111100	111100	000000000110000000000000
	110000	111100	011111110000000000000000
	101011	111111	100000010000000000000111
	100100	111100	000000000011111000000000
A16	001010	001011	000000010000000010111000
	001001	001011	000000010000000011110000

Table 3: Network and Capabilities sub-matrices for 3 C^2 structure for 4th A2C2 Experiment

These 3 structures differ in the networks, capabilities and assignments. In all cases the requirements (what resources are needed to do which tasks, table 4), the precedence (which tasks come before which, not shown), and the substitutes (not shown) are the same. Given these structures the performance and diffusion properties of the structures were examined.

	Resources

Tasks	0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
	0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
	1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
	1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0
	0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0

Table 4. Requirements sub-matrix for 3 C^2 structure for 4th A2C2 Experiment

	Personnel		
	A06	A14	A16
Tasks	1 0 0 0 0 0	0 1 0 0	0 1 0 0 0 0
	0 1 0 0 0 0	0 1 0 0	1 0 0 0 0 0
	1 0 0 0 0 0	0 1 0 0	0 1 0 0 0 0
	0 1 0 0 0 0	0 1 0 0	1 0 0 0 0 0
	1 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	0 0 1 0 0 0	0 1 0 0	1 0 0 0 0 0
	0 0 1 0 0 0	0 1 0 0	1 0 0 0 0 0
	0 0 1 0 0 0	0 1 0 0	1 0 0 0 0 0
	0 0 1 1 1 0	0 0 0 1	0 0 0 0 0 1
	0 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	0 0 1 1 1 0	0 0 1 0	0 0 0 0 1 0
	0 0 1 1 1 0	0 0 0 1	0 0 0 0 0 1
	0 0 1 1 0 0	0 1 0 0	1 0 0 0 0 0
	0 1 0 0 1 0	0 1 0 0	1 0 0 0 0 0
	0 0 1 1 1 0	0 0 0 1	0 0 0 0 0 1
	0 0 1 1 1 0	0 0 1 0	0 0 0 0 1 0
	0 1 0 0 0 0	0 1 0 0	1 0 0 0 0 0
	0 0 0 0 0 1	0 1 0 0	1 0 0 0 0 0

	0 0 1 1 1 0	0 0 0 1	0 0 0 0 0 1
	0 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	1 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	1 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	0 0 0 0 0 1	1 0 0 0	0 0 1 0 0 0
	0 0 0 0 0 0	0 1 0 0	1 0 0 0 0 0
	0 1 1 0 1 0	0 1 0 0	1 0 0 0 0 0
	0 1 0 1 1 0	0 1 0 0	1 0 0 0 0 0
	0 0 1 0 0 0	0 0 1 0	0 0 0 1 0 0
	0 0 1 1 1 0	0 0 0 1	0 0 0 0 0 1
	0 0 1 1 1 0	0 0 1 0	0 0 0 0 1 0

Table 5. Assignment sub-matrices for 3 C^2 structure for 4th A2C2 Experiment

Given the networks and capabilities sub-matrices a measure of expected performance can be calculated. Expected performance given perfect communication and no unexpected events is shown on the right on Figure 2. All else being equal, simulation suggest that the 4 node structure, A14, is expected to be a high performer. However, in point of fact it is not the best performer. Actual performance data is shown on the left in Figure 2. So why is this? Further analysis reveals that in terms of information diffusion, that in A16 information should take the longest to diffuse on average. However, there is a striking difference in terms of whether that information is about the coordinating information or whether that information is about resources. In Figure 3 we see that while resource usage information is slow to diffuse in A16, coordinating information appears to diffuse rapidly. Note, the higher the time-to-diffusion the longer it takes team members to learn the information on average. This suggests that part of the bases for high performance is the robustness of this structure in facilitating the flow of information about what others are doing.

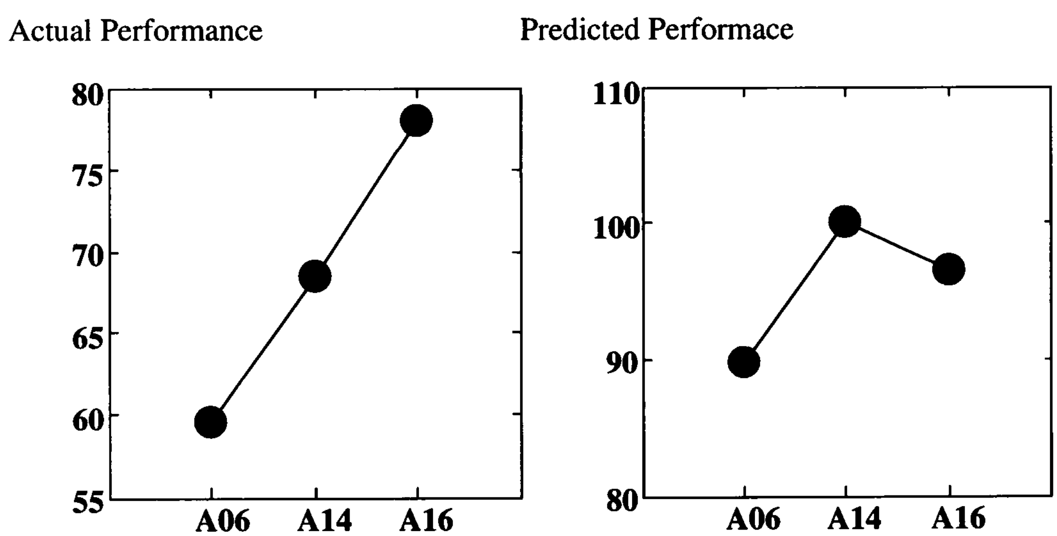

Figure 2. Actual and predicted performance.

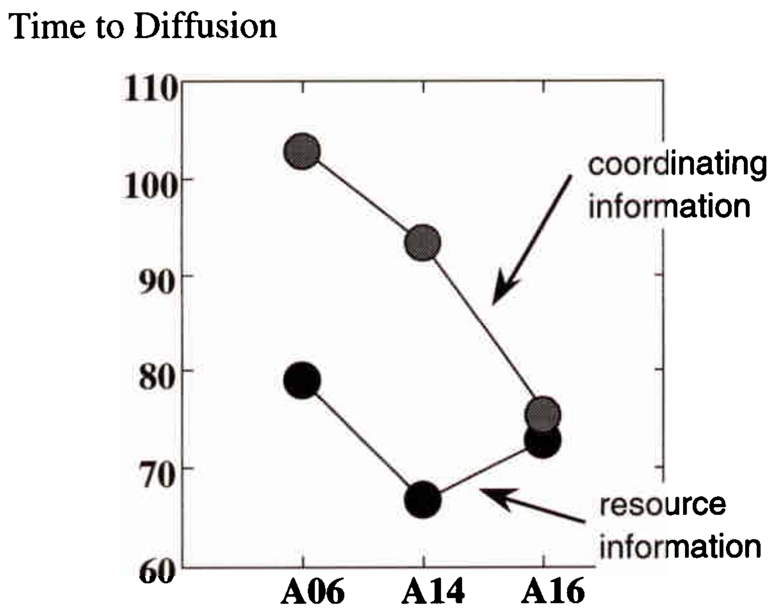

Figure 3. Predicted time to diffusion of coordinating and resource information.

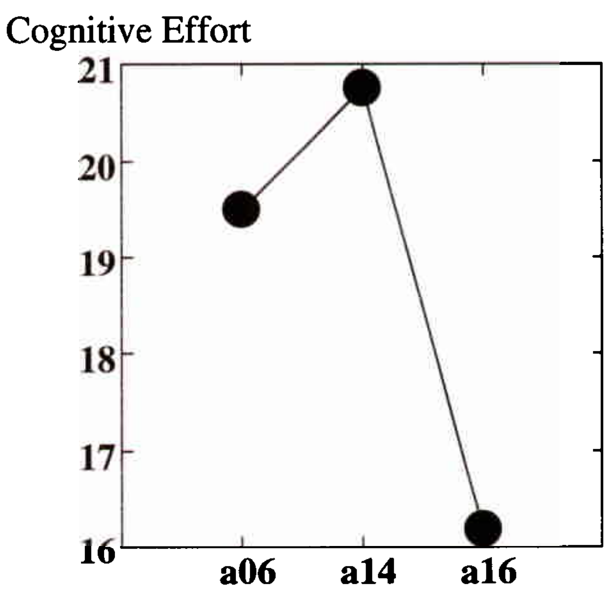

Figure 4. Cognitive effort of C^2 structures

A second, explanation of the relatively high performance of A16 has to do with cognitive effort. Cognitive effort can be measured as the average sum of the number of personnel, tasks and resources that each person in a structure needs to contend with. That is, given the meta-matrix, sum each row in personnel and average by the number of personnel. Doing this provides the information that in A14 and A06 individuals on average need to expend more effort than in A16. The more even spread of cognitive effort in A06 further degrades that structures performance, as the even distribution of cognitive effort drags every one down, rather than allowing a few to shine.

4. **Conclusion**

The proposed typology enables graph-theoretic based measures of C^2 structures to be contrasted and analyzed in a systematic fashion. Results indicate a dearth of measures that link more than one-submatrix. Attempts at predicting performance of organizations based on a single sub-matrix typically fail. Predictions, such as those herein, that are based on multiple sub-matrices at once fare better. Using this typology we defined the C^2 structure of three teams, examined in a laboratory setting. Use of the typology as a representation scheme enabled the three teams to be simulated. These simulations suggested that the reason for differences in performance had to do with the relative ability of information about what others are doing, versus what resources are needed for what through the structure defined by multiple sub-matrices.

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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 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

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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.

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

3.3 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.

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.

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
R2 (adj) = 10.9%, df = 7, 20472, p<0.001		

Table 2. Standardized Regression for Performance.

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.

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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