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Computational Organizational Network Modeling: Strategies and an Example

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Abstract

This paper articulates the logic of computational organizational modeling as a strategy for theory construction and testing in the field of organizational communication networks. The paper introduces, *Blanche,* an object-oriented simulation environment that supports quantitative modeling and analysis of the evolution of organizational networks. *Blanche* relies on the conceptual primitives of attributes that describe network nodes and links that connect these nodes. Difference equations are used to model the dynamic properties of the network as it changes over time. This paper describes the design of *Blanche* and how it supports both the process of theory construction, model building and analysis of results. The paper concludes with an empirical example, to test the predictions of a network-based social influence model for the adoption of a new communication technology in the workplace.

Keywords: organizational communication, networks, *Blanche,* adoption, innovation, communication, information technologies

1. Introduction

Computational simulation of organizational structures and activities has been proposed as a viable component in the process of theory construction, specification, and articulation in the social sciences in general (Hanneman 1988), and more specifically in organizational sciences (Carley and Prietula 1994; Morecroft and Sterman 1994; Senge 1990). In the past two decades, several theorists have conceptualized organizations from a networks perspective (e.g., Burt 1982; Rogers and Kincaid 1981; Stohl 1995). In an overview of the field of computation and mathematical organizational theory, Carley (1995) identifies network models as an important framework for theory development. In this paper we argue that there continues to be a loosely coupled relationship between the articulation of theoretical network mechanisms, model-building, simulation, and hypothesis testing. Four important barriers identified in this paper are (i) a lack of emphasis by organizational network researches to categorize the wide variety of theoretical mechanisms that explain organizational behavior (ii) the lack of a general methodology to incorporate simulations into the traditional realm of deducing and testing hypothesis, (iii) the need for model-building and simulation tools that are easily accessible and understood by organizational researchers who are not proficient in object oriented programming, and (iv) the limited effort to combine simulation scenarios with observed empirical data from organizations. This paper addresses these four barriers. First, we articulate a methodology that incorporates computational organizational modeling within the framework of traditional hypothesis testing. Second, we present a computational tool, *Blanche*, that offers researchers who lack programming expertise the ability to articulate theoretical derived computation models of organizational phenomena. Finally, we present an example that uses *Blanche* to make predictions about the adoption of a communication technology based on empirical data collected from a public works department.

2. Theoretical Network Mechanisms

Network researchers have sought to explain organizational behavior in terms of formal organizational structures as well as informal organizational structures such as communication networks, influence networks, advice networks and task networks (Monge and Eisenberg 1987). More recently, there has been a growing interest in examining the underlying logics (Kontopoulos 1993), or generative mechanisms, that explain the manner in which networks enable and constrain organizational and inter-organizational behavior. Monge and Contractor (in press) identify eleven generative mechanisms. These include: (1) exchange and dependency theories (social exchange and resource dependency), (2) contagion theories (social information processing, social learning theory, institutional theory, structural theory of action), (3) cognitive theories (semantic networks, cognitive social structures), (4) consistency theories (balance theory, theory of cognitive dissonance), (5) theories of homophily (social comparison theory, social identity theory), (6) theories of social capital (theory of structural holes, strength of weak ties theory), (7) theories of proximity (physical and electronic proximity), (8) uncertainty reduction theories, (9) social support theories, (10) collective action theories, and (11) theories of network and organizational forms (contingency theory, transaction cost theory, and theories of network organizations).

Monge and Contractor (in press) note that there are at least two implications of reviewing the extant literature on organizational networks in terms of the underlying generative mechanisms. First, most network studies in organizations typically hypothesize and examine organizational behavior only in terms of one of these generative mechanisms. For instance, network explanations for employee job satisfaction have been based on a contagion mechanism (Hartman and Johnson 1989) or a balance mechanism (Kilduff and Krackhardt 1993). Often the predictions based on these two mechanisms are contradictory and not easy to parse out empirically. Second, based on their review, Monge and Contractor (in press) note that the preponderance of research on organizational networks has been inspired by four of the eleven theories reviewed: exchange theories, contagion theories, cognitive theories, and theories of homophily. The few studies based on one of the other seven theories provide ample evidence of their potential explanatory power, and should be actively considered by network researchers. A system to make the simulation of various organizational hypothesis easier would help alleviate the problem by allowing more generative mechanisms to be tested together or against each other, and therefore to help clarify the differences in predictions based these models. The next section describes how computational organizational models offer researchers the ability to articulate and construe the implications of multiple theoretical network mechanisms.

3. Computational Organizational Models

An explicit focus on the generative mechanisms whereby networks enable and constrain organizational behavior has led to an interest in creating formal mathematical and computational models of organizational activities. It has, in effect, led scholars to combine two streams of research, that is conducting organizational simulation based on generative mechanisms, and testing of network theories in organizational contexts (Carley 1995). There are a few promising examples of this integration. Zeggelink (1993) models the evolution of friendship networks based on a set of generative mechanisms derived from social exchange theory (Blau 1964), classical conditioning theory (Lott and Lott 1960), social comparison theory (Festinger 1954), and balance theory (Heider 1958). Leavitt et al. (1994) developed the Virtual Design team (VDT), a computational model of a multidisciplinary engineering design organization based on information processing theory (Galbraith 1977), contingency theory (Thompson 1967), media richness, and social influence theories (Fulk and Steinfield 1990). Lin and Carley (1995) present a computational model for examining organizational performance that draws upon various factors articulated by contingency theories (Scott 1987; Thompson 1967), including task environment, organizational design, and stressors such as crises and time pressures. Corman (1996) offers a cellular automata model, POWERPLAY, to demonstrate the emergence of a dominance hierarchy based on principles inspired by structuration theory (Giddens 1984). Contractor and Grant (1996) describe a computational model to examine the emergence of shared interpretations in organizations based on Burt's (1982) structural theory of action and Heider's (1958) balance theory. All of these studies represent a genre of scholarship that attempt to model explicitly and dynamically the attributes and relationships among a network of agents based on generative mechanisms suggested by one or more social scientific theories. Further, they employ computer simulations to help envision the dynamic implications of their models. The following section describes the traditional use of simulations as well as the adaptation of this approach towards theory construction and testing.

4. Previous and Current Work in Organizational Simulation

Computer simulations have long been used as an effective tool in engineering. Engineers typically use simulations to predict performance of a system that has known dynamic characteristics. These characteristics are typically obtained from theory and are then articulated in the simulation as difference or differential equations. The goal of engineering simulation is then to assess the dynamic performance of a system based on *a priori* knowledge of the dynamic relationships among the various elements of the system.

Forrester (1961,1973) was one of the earliest and most influential advocates of simulation modeling of dynamic social systems. Forrester advocated the use of this approach to model and assess the dynamics of industrial and world phenomena. While this approach has produced a considerable number of studies, it is based on the assumption that the researcher has *a priori* knowledge of the dynamic relationships among elements of the system. Indeed, many of the results of these models have been criticized for specifying relationships that were at best untested, and at worst flawed. In response *to* these criticisms, there has been a more recent interest in redefining the utility of simulations in the social sciences. Rather than using simulations to test the long term dynamics of systems with known inter-relationships, theorists (Carley and Prietula 1994; Contractor 1994; Hanneman 1988) have suggested that simulations can be used to help with social scientific theory construction.

Carley and Prietula (1994) suggest the emergence of a new field, Computational Organizational Theory (COT), to signal the growing interest in the construction of computational models to augment theory building. Most social science theories are richly evocative but highly abbreviated (Poole 1990). That is, they offer explanations that suggest complex inter-relationships, yet the non-mathematical statements of the theory often do not lend themselves to unambiguous and specific descriptions of these relationships. Computer simulations, which require completely unambiguous specifications of the inter-relationships, offer theorists the opportunity to articulate their models with greater precision and rigor. Realistically, this implies that the same theory may lend itself to several alternate models depending upon the interpretation of the theoretical statements. Computer simulations offer the researcher an opportunity to assess the long term implications of these different interpretations of the theory. Hanneman (1988) advocates the use of computer simulations to gain insights into the long-term implications of a dynamic model. It is important to emphasize that the results of a computer simulation are not a surrogate for empirical data. Rather, they indicate the emergent processes implied by the theory. As such, simulation data provide the researcher with an opportunity to deduce hypotheses (that are implicit but not immediately obvious) about differences in the emergent process implied by theories.

Traditional approaches rely on verbal and implicit strategies to articulate hypotheses from the theoretical statement. COT offers the ability to formalize and make explicit the deduction of hypotheses from the theoretical statement. The distinctions between traditional and proposed COT research process are summarized in figure 1 below. In the traditional deductive approach to theory construction, researchers deduce hypotheses by examining the

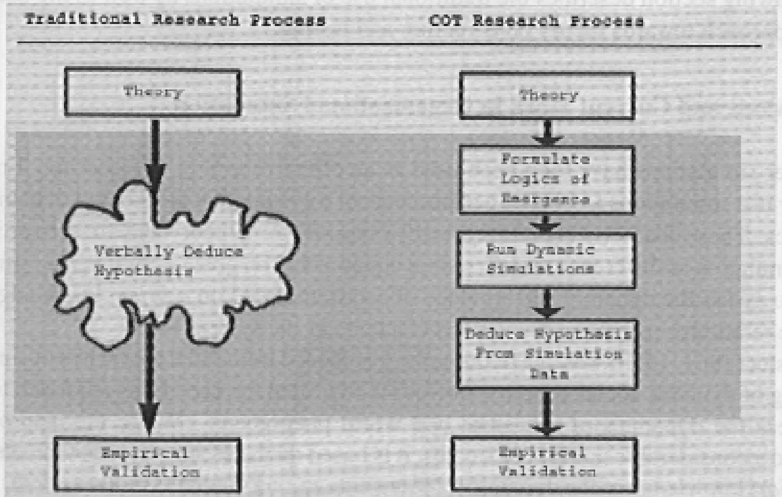

Figure 1. Traditional vs. COT research process.

logical inter-relationships among the verbal statements offered by the theory. These verbally deduced hypotheses are then empirically validated. Empirical rejection of the hypotheses, lead to refinements in the theory. In the proposed computational organizational theory-construction (COT) approach, researchers identify the logics of emergence in the theory, and articulate these logics in a computational model. Given the frequent verbal ambiguities in theoretical statements, the process of identifying the logics is non-trivial. However, the exercise is an important and useful step in adding precision and rigor to the articulation of the theory. Since these logics are potentially non-linear, it is virtually impossible to mentally construe their implications over time and/or for a large number of entities (e.g., individuals, groups, organizations). Hence simulations of the computational model are used to deduce the potentially non-linear, transient and long-term dynamics implied by the logics of emergence for one or more entities. The results of the simulation are then fitted to empirical data. A good fit would imply validation of the theory, while a poor fit would suggest refinements, modifications, or rejection of the theory. A tool to create and simulate COT models is particularly useful in implementing the theory construction outlined above. *Blanche* is such a tool. The following section describes the modeling concepts used in the design of *Blanche*.

5. Modeling Concepts in *Blanche*

In whatever sense a network is modeled, core issues are the articulation of the characteristics of the nodes (or actors) in the network, the interrelationships among the nodes, and the evolution of the attributes and interrelationships over time. *Blanche* is a computational tool to assist in the modeling and execution of computational simulation based on a network conceptualization of organizations. Unlike generic simulation programs such as STELLA (Richmond and Peterson 1990) and MicroSAINT (Micro Analysis 1990), *Blanche* is an object-oriented program that was designed and built to specifically support computational simulation of organizational networks. As such, it provides a flexible and reusable framework for the specification of models and the analysis of results from simulations.

A minimalist framework for computationally modeling network systems is objects or *entities* (actors, people, nodes) characterized by some collection of *attributes* and related by *links* (see Rock-Evans 1989). In addition, a set of generative mechanisms (the logics of emergence) is needed to examine the evolution of networks. A discrete set of generative mechanisms provides flexibility and expressiveness such that dependencies among attributes and links over time are modeled as a function of values at previous time steps (e.g., attribute A at time t is a function of the value of A at time $t-1$ and some links' (L's) values at $t-1$). With the assumption that the values of attributes and links take on real (floating point) values, we propose nonlinear difference equations as a natural and efficient computational approach to representing the evolution of attribute and link values over time. These distinctions are more fully described below.

5.1. *Attributes*

An attribute is simply some measure of any property of a node. If we consider the node as a person, that person can have as many attributes as necessary for the model, where each attribute is represented by a floating point number on an arbitrary scale. Examples of attributes could be a person's expertise, an opinion, an attitude, or workload. State information, such as whether or not a person is engaged in a certain activity, can also be modeled as an attribute.

Attributes can depend on each other. For example, a workload attribute of one person could depend on an attribute that describes the efficiency of the same or other persons. Note that attributes can thus be related to attributes not only of the same node (such as person) but those of other nodes as well. Attributes can also change over time. Time intervals are considered discrete, divided into iterations that could be thought of as seconds, days, or any other consistent length of time. At each new iteration of the simulation, time is incremented, and the attribute's values change. How the attributes change is calculated by its defining nonlinear difference equation.

5.2. *Links*

A link specifies a one-way (directed) channel of variable strength. Links may represent communication, influence, workflow, activation, or any other relationship of interest between two nodes in the network. Strength can be interpreted in a variety of ways. For example, in a communication network, a link from node A to B can represent the volume of communication (say, number of messages) that A receives from B. The link strength is either dichotomous (0 or 1) signifying presence or absence, or continuous. Typically, a higher strength value indicates a stronger linkage. These link values may change depending on the attributes (of the source, destination, or both) as well as other links. For every link variable specified, there will be $n^2 - n$ actual links in the simulation, where n is the number of people in the simulation.

Thus, a model in this framework consists of a list of persons or nodes, each characterized by a set of real-valued attributes; a list of real-valued links relating persons to each other; initial conditions for the values of attributes and links at time $t = 0$; and nonlinear difference equations that model how the attributes and links change over time. In the following section, we articulate a theoretically derived computational organizational model of the adoption of a communication technology in an organization.

6. Modeling the Adoption of A Communication Technology: An Example

The following example is drawn from an ongoing research project examining the information infrastructure at a city's public works department (Jones et al. 1994, 1995). One of the goals of the research project is to examine changes in the work practices following the introduction of CityScape, a communication and collaboration tool. In order to assess existing work practices longitudinal data has been collected over a 18 month period. The data gathered is being used to inform the introduction and deployment of CityScape. Specifically, a computational organizational model, derived from theory, is being used to predict the extent and speed of adoption of CityScape amongst members of the public works department. In this section we describe a proposed computational organizational model in terms of members' attributes and relationships.

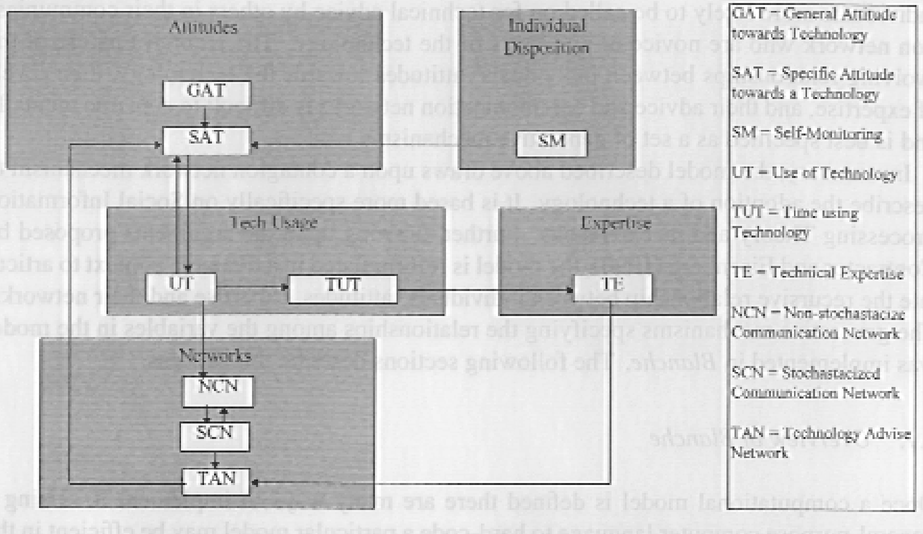

Figure 2. Conceptual computational network model for adoption of technology.

The outcome variable in this model is an individual's usage of the technology. Figure 2 presents the theoretical relationships that serve as antecedents for this outcome variable. The outcome attribute variable for each individual is designated as "Tech Usage" in figure 2.

Our model is derived from Salancik and Pfeffer's (1978) Social Information Processing Theory as well as from a more recent extension to this theory in the domain of technologies, the Social Influence Model of technology use (Fulk, Schmitz and Steinfield 1990). Both of these theories suggest that individuals' attitudes toward a new technology are based on their prior attitudes (indicated as "Attitudes" in figure 2), as well as the attitudes of individuals with whom they communicate (indicated as "Networks" in figure 2). Recent research (e.g., Burkhardt 1994) extending social information processing perspectives, suggest that the extent to which an individual is influenced by the "Network" as opposed to their prior "Attitudes" is in part determined by the individual's disposition towards self-monitoring (indicated as "Individual Disposition" in figure 2). That is, individuals who are high self-monitors are more likely to be influenced by the "Network" than those who are low self-monitors.

In general terms, the theories described above, are based on a contagion network mechanism for the adoption and usage of a technology. That is, an individual is more likely to adopt and use a technology if s/he communicates with others who either use the technology or have a positive attitude towards the technology. However, as Contractor and Eisenberg (1990) note, the adoption of a *communication* technology triggers a recursive relationship between individuals' attributes and their networks. The adoption of a technology, provides the individual with a potential change in their communication network. This in turn provides them with a different set of social influences which may modify their attitudes toward the technology, which in turn may change their use of the technology. Further, ongoing use of the technology by an individual will influence their technical expertise (indicated as "Expertise" in figure 2) in using the technology. This increased expertise will make these individuals more likely to be called on for technical advice by others in their communication network who are novice or non-users of the technology. The recursive nature of the evolving relationships between individuals' attitudes towards the technology, their levels of expertise, and their advice and communication networks is difficult to construe mentally and is best specified as a set of generative mechanisms.

In summary, the model described above draws upon a contagion network mechanism to describe the adoption of a technology. It is based more specifically on Social Information Processing Theory and its extensions. Further, drawing upon the arguments proposed by Contractor and Eisenberg (1990), the model is reformulated in a dynamic context to articulate the recursive relationship between individuals' attitudes, expertise and their networks. The generative mechanisms specifying the relationships among the variables in the model was implemented in *Blanche*. The following sections describe this process.

6.1. *Overview of Blanche*

Once a computational model is defined there are many ways to implement it. Using a general-purpose computer language to hard-code a particular model may be efficient in the short term but does not promote reusability or extensibility. There are simulators in which a user can build these models (such as STELLA), but since they are not designed specifically for network modeling, they can be unwieldy, especially for networks of different sizes and for batch processing of many randomly-generated data sets. Since the models described above have a common framework, an attractive solution is to create a generic, reusable architecture to support the framework and provide the end user with easy-to-use tools to define models (in terms of attributes, links, and equations). *Blanche* is such a system and is designed to be used by network researchers as a tool for building and evaluating quantitative organizational simulations. It is implemented in *Microsoft Visual C++* and runs on Windows 95 and Windows NT. *Blanche* embodies an object-oriented framework in which a network is defined as a collection of Node objects which each have internal attributes and links to other Nodes. Both attribute and links are objects themselves.

6.2. *Implementation of Computational Organizational Model: Blanche ModelBuilder*

Blanche consists of two modules, a part to create a model (*ModelBuilder*) and a part to run the model (*ModelAnalyzer*). In *ModelBuilder*, the user specifies information about the attributes and links; names, equations, file for initial data, and the level (or hierarchy) of the attributes and links. Figure 3 shows the main screen of *ModelBuilder*, while editing our example model. The user creates the model of a single person or node, which will then be used as the model for all persons or nodes in the network. Although in our conceptual framework, it is possible to have heterogeneous nodes in the network (i.e., nodes that have different attributes or use different equations), currently in *Blanche* the representation of nodes is homogeneous. It is possible, however, to model heterogeneous networks by using attributes for classification and if-then statements based upon those attributes. The lack of heterogeneous nodes in this model implies that individuals all have the same attribute variables. It does not imply that they have the same values for these attributes. For instance,

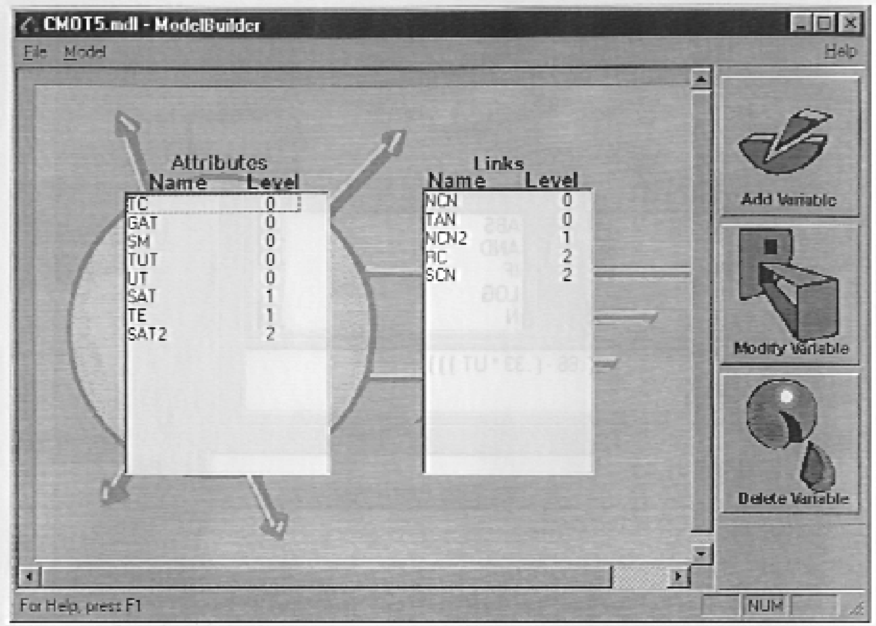

Figure 3. *Blanche* ModelBuilder interface.

in the example being considered here, all individuals were expected to have an attitude towards technology, however their specific attitudes were not assumed to be the same.

To create a variable, the user fills out the dialog box shown in figure 4. This particular one is for variable UT. In this dialog box, all the information needed to define an attribute is filled out: the name, the level of the variable, whether the variable is a link, the equation, the data file, and any comments or description. Currently in *Blanche*, equations must be typed out in text, with standard logical and mathematical operators selectable from the Functions list.

For the model described in the example above, the following nine variables, and two temporary variables, were specified in *ModelBuilder*: Use of the CityScape Technology (UT); Time using CityScape Technology (TUT); General Attitudes towards Technology (GAT); Specific Attitudes towards the CityScape Technology (SAT and SAT2); Self Monitoring (SM); Task Expertise (TE); Stochasticized Communication Network (SCN); Non-stochasticized Communication Network (NCN and NCN2); and Technology Advice Network (TAN). For each of the nine variables, a difference equation was used to describe the dynamic influences on the variable. These nine equations are described below.

The key outcome variable of this computational model was an individual i's Use of the Technology (UT) at time, t. This variable is a dichotomous variable ($1 =$ Used, $0 =$ Not used). It is computed as a non-linear hysteresis function of the individual's level of satisfaction. That is, in order to start using CityScape, an individual's specific attitude towards the technology (SAT) must be 0.66, on a scale of 0 (low) to 1 (high). However, to stop using the technology, the individual's specific attitude towards the technology must

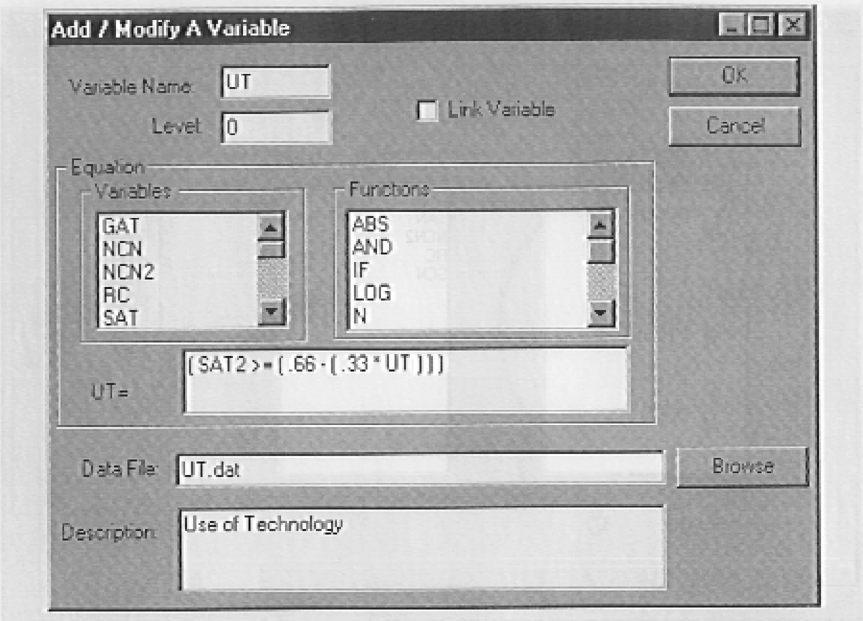

Figure 4. Specifying attributes and links in *Blanche*'s ModelBuilder.

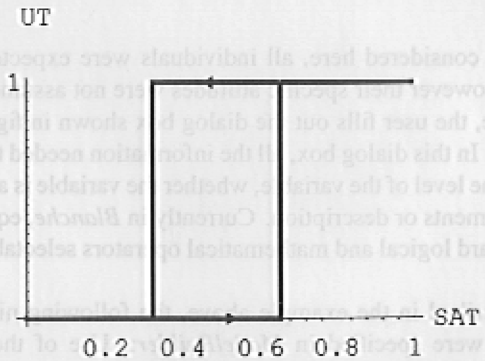

Figure 5. Hysteresis function relating specific attitude towards a technology (SAT) and the use of the technology (UT).

fall below 0.33. This relationship is described in Eq. (1) and depicted in figure 5. Since the technology being introduced was new, each individual starts out with a UT value equal to 0, except for those who were first assigned to use the technology.

$$UT_{i_t} = \begin{cases} 0 & \text{if } SAT_{i_{t-1}} \geq \left(\frac{2}{3} - \frac{1}{3}UT_{i_{t-1}}\right) \\ 1 & \text{if } SAT_{i_{t-1}} < \left(\frac{2}{3} - \frac{1}{3}UT_{i_{t-1}}\right) \end{cases} \tag{1}$$

Time Using Technology (TUT) represents a cumulative measure of the amount of time an individual has used CityScape. Since the technology is newly introduced, each individual

starts with 0. This measure is therefore a direct function of their Use of the Technology (UT). Hence Eq. (2) describes individual i's Time Using Technology at time, $t-1$, thus:

$$TUT_{i_{t-1}} = \begin{cases} TUT_{i_{t-1}} & \text{if } UT_{i_t} = 0, \\ TUT_{i_{t-1}} + 1 & \text{if } UT_{i_t} = 1. \end{cases} \tag{2}$$

An individual i's Specific Attitude towards the Technology (SAT) is specified as a contagion function. That is, it depends on their General Attitudes towards Technology (GAT), their previous Specific Attitudes towards the Technology (SAT), as well as the Specific Attitudes towards Technology of others in their Technical Advice Network (TAN). The extent to which they are influenced by others in their network is moderated by their disposition to be Self Monitoring (SM). If the individual has no one in their technical advice network and if the individual is using the technology ($UT = 1$), then the s/he is assumed to have good or bad experiences based solely on their general attitude toward technology (GAT), with the level of effect the GAT decreasing over the Time the user is Using the Technology (TUT). The value that is calculated must be above one. The variable SAT2 is the bounded value that must be used by other equations. The equation for an individual i's Specific attitude towards the Technology at time t is given by Eq. (3), and the bounding of the value is accomplished in Eq. (4):

$$SAT_{i_t} = \begin{cases} SAT_{i_{t-1}} + UT_{i_{t-1}}\left(NRAND(0, 0.05) + (GAT_i - 0.5)\cdot\frac{0.6}{TUT+1}\right), & \text{if } \sum_{j=1}^{N} TAN_{ij_{t-1}} = 0, \\ (1 - SM_i)SAT_{i_{t-1}} + SM_i \frac{\sum_{j=1}^{N} TAN_{ij_{t-1}} SAT_{j_{t-1}}}{\sum_{j=1}^{N} TAN_{ij_{t-1}}} & \\ \quad + UT_{i_{t-1}}\left(NRAND(0, 0.05) + (GAT_i - 0.5)\cdot\frac{0.6}{TUT+1}\right) & \text{if } \sum_{j=1}^{N} TAN_{ij_{t-1}} > 0. \end{cases} \tag{3}$$

$$SAT2_{i_t} = \begin{cases} SAT_{i_t}, & \text{if } SAT_{i_t} < 1 \\ 1, & \text{if } SAT_{i_t} \geq 1 \end{cases} \tag{4}$$

An individual's Technological Expertise (TE) in using CityScape was specified as a non-linear function of the Time Using the Technology (TUT). In essence, it suggests that there is a learning curve associated with the use of the technology. This equation is described in Eq. (5) and depicted in figure 6.

$$TE_{i_t} = \sqrt{\frac{TUT_{i_{t-1}}}{50}} \tag{5}$$

Individual i's General Attitudes towards Technology (GAT) and disposition towards self-monitoring (SM) at time t were considered as trait variables that are stable. Hence, as indicated in Eqs. (6) and (7), the variables remain unchanged over time:

$$GAT_{i_t} = GAT_{i_{t-1}} \tag{6}$$

$$SM_{i_t} = SM_{i_{t-1}} \tag{7}$$

There are four relational variables in the computational organizational model, although two of the four are "correctional" variables. The first three index task communication among the individuals, and the fourth describes the technical advice network among the

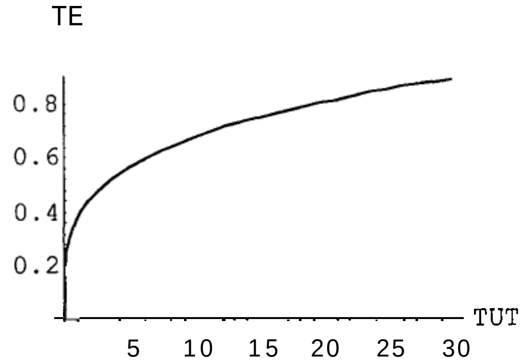

Figure 6. Learning curve function relating technological expertise (TE) and the time using the technology (TUT).

individuals. Calculating the task communication is a multi-step procedure and for each of those steps there is a different equation. First, in Eq. (8), NCN is calculated. NCN describes how a pair of individuals are likely to increase their task communication if they are both using the new technology (UT). There are also random factors represented in this equation. The value obtained in Eq. (8) must be positive, which is ensured in Eq. (9) and assigned to NCN2. This value is then row-normalized in Eq. (10) and is assigned to SCN, which is the variable used by other equations. This final result to the three-step computation represents the proportion of time spent talking to another person.

$$\mathrm{NCN}_{ij_t} = \begin{cases} \mathrm{SCN}_{ij_{t-1}} + N(0, 0.1) & \text{if } \mathrm{UT}_{i_{t-1}} + \mathrm{UT}_{j_{t-1}} \neq 2, \\ \mathrm{SCN}_{ij_{t-1}} + \mathrm{N}(0,0.1) + \frac{1}{\sqrt{N}} & \text{if } \mathrm{UT}_{i_{t-1}} + \mathrm{UT}_{j_{t-1}} = 2. \end{cases} \tag{8}$$

$$\mathrm{NCN2}_{ij_t} = \begin{cases} \mathrm{NCN}_{ij_t}, & \text{if } \mathrm{NCN}_{ij_t} > 0 \\ 0, & \text{if } \mathrm{NCN}_{ij_t} \leq 0 \end{cases} \tag{9}$$

$$\mathrm{SCN}_{ij_t} = \begin{cases} \frac{\mathrm{NCN}_{ij_t}}{\sum_{j=1}^{N} \mathrm{NCN}_{ij_t}} & \text{if } \sum_{j=1}^{N} \mathrm{NCN}_{ij_t} > 0, \\ 0 & \text{if } \sum_{j=1}^{N} \mathrm{NCN}_{ij_t} = 0. \end{cases} \tag{10}$$

Finally, the Technological Advice Network (TAN) describes the network of individuals that a person would go to for advice about adopting the new technology. In order for an Individual i to seek technological advice from Individual j, the former must have considerably lower task expertise (TE) than Individual j, and Individual i must spend at least a modest proportion of time communicating (SCN) with Individual j. This is described in Eq. (11):

$$\mathrm{TAN}_{ij_t} = \begin{cases} 0 & \text{if } (\mathrm{TE}_{j_{t-1}} - \mathrm{TE}_{i_{t-1}})\mathrm{SCN}_{ij_{t-1}} < 1/N, \\ 1 & \text{if } (\mathrm{TE}_{j_{t-1}} - \mathrm{TE}_{i_{t-1}})\mathrm{SCN}_{ij_{t-1}} \geq 1/N. \end{cases} \tag{11}$$

This section has described the implementation of the attribute variables, the relational variables, and the generative mechanisms in the *ModelBuilder*, a module of *Blanche*. The next section describes the execution of the computational organizational model in *ModelAnalyzer*, a second module in ***Blanche.***

6.3. *Execution of Computation Organizational Model: Blanche ModelAnalyzer*

ModelAnalyzer runs the model that has been specified by the *ModelBuilder* program. To run the model, the user specifies the number of nodes (persons, in our example) in the model, the data set(s) that represent initial conditions of the simulation, desired statistics, and the duration of the simulation (specified as the number of iterations or time-steps).

Simulation results output from *ModelAnalyzer* are expressed both statistically and graphically. *ModelAnalyzer* calculates a variety of standard measures such as attribute means and standard deviations, as well as network metrics such as indegrees, outdegrees, closeness, and betweenness. All the results can be viewed via plots and graphs within the program. Data and statistics from the simulation can be saved into an ASCII file that can be imported into various statistical programs for further analysis. In addition, all network data in *ModelAnalyzer* can be directly saved in a format that is readable by KrackPlot (Krackhardt, Blythe and McGrath 1994), a network visualization and plotting program.

For the example at hand, *ModelBuilder* was used to specify a computational organizational model of the use of a new technology, CityScape, by members of the Public Works Department. The goal of this research was to identify the deployment and usage patterns that would be theoretically predicted based on the network contagion mechanisms described earlier in this paper. The model described above was "populated" using data gathered from the Public Works Department (N = 57) for a city in the south-eastern U.S. In particular, attribute data were gathered on individuals' general attitudes towards technologies and their individual disposition towards self-monitoring (Lennox and Wolfe 1984). Relational data were gathered on individuals' task communication networks and their technical advice networks. These data served as initial conditions for the computational organizational model. Since the model was being used to examine the introduction of CityScape, a new technology, individuals' initial technology expertise and technology usage were specified to be zero. Their specific attitudes towards the CityScape technology were specified to be neutral (0.5 on a scale of 0 to 1).

In order to determine the most effective and speedy deployment of CityScape in the Public Works Department, various simulations were executed based on the initial data collected from the organizational members. These simulations were varied on the basis of which individuals were targeted as initial users of the technology. Due to finite training resources, the goal was to identify whether an organizationally broad or focused installment was most likely to help diffuse the adoption of CityScape throughout the organization. Specifically, the question was whether it is better to give the technology to four department heads, or to four people all in one department. Figures 7 below shows the results based on two scenarios. In each of the two scenarios, four individuals were identified as the first users of CityScape. Each of these individuals were assigned a value of 1 for the variable Use of Technology. As mentioned earlier, since a new technology was being introduced into the workplace, the remaining members of the organization were assigned a zero for the variable Use of Technology (UT). The simulations in the two scenarios were run over 50 iterations.

In the first scenario, the four division heads targeted for use of CityScape were the heads of Engineering and Planning Services, Business Management, Environment and Resource Management, and Installation Housing. The four members of the same division

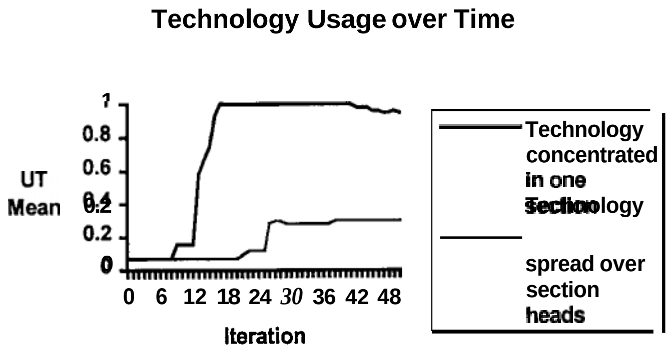

Figure 7. Differences in technology usage under two different scenarios.

(Engineering and Planning Services) targeted in the second scenario were the Group Leader of the General Engineering, the Real Property specialist, a CAD Technician, and an Electrical Engineering Technician.

As is evident from figure 7, the speed and level of deployment varies significantly between the two scenarios, with the more focused deployment (Scenario Two) resulting in faster and much more complete adoption of the technology. Given the non-linear dynamics proposed in the computational organizational model it is impossible to have a priori predicted these differences in deployment patterns. This modeling provides us with hypotheses about the pattern and level of adoption when the technology is actually deployed. Ongoing data collection following the deployment of CityScape will provide us an opportunity to empirically validate the deployment pattern predicted by the selected scenario.

7. Uses and Future Extensions for Computation Organizational Network Modeling

This paper has argued for the intellectual integration of two vibrant research traditions—computation organizational modeling and organizational communication network research. We identified four barriers that must be overcome in order to leverage the benefits of these two traditions. Following an overview of the network mechanisms used to explain organizational behavior, and the logic of computational organization modeling and simulation, we introduced ***Blanche*** as a tool that provides a generic framework for modeling networks and their evolution over time. The researcher specifies nodes in terms of real-valued attribute and link variables. The dynamic interrelationships between nodes, expressed in terms of attributes and links, are modeled as nonlinear difference equations. In this paper we have illustrated how the adoption and use of a new technology can be modeled in this framework. As evidenced by the example, computational organizational network modeling, and tools such as ***Blanche*** offer considerable potential for theory development and testing.

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