Structure, Flow, Change: Toward a Social Systems Simulation Methodology[1]

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Abstract

In developing models of social systems, computer simulation methodology is usually limited to simulation languages that carry with them the burden of built in metaphors that must be adapted to social systems, e.g., SWARM (masses of automata), MATHEMATICA (mathematically abstract), STELLA (plumbing), SIMPROCESS (business process), etc. Also, many of these languages call for the researcher's sophisticated programming capability that detracts from social systems model making. Further, each computer program is a prototype making it difficult for the accumulation of knowledge by combining or elaborating existing models.

The metaphor I propose here focuses on the structure of the social system, its elements, and the relevant social relationships among these elements. Elements themselves may be systems and systems may become elements in larger systems. Since these systems deal with the human frames-of-reference, they are limited to causation on the human scale. In this frame-of-reference, time is assumed to be given and is always treated as "running down." The system passes from state to state through social processes that determine the transition probabilities for state changes. When a state change occurs the time for this change is computed. This State/ Process Dynamic (TM) can result in several outcomes. The social system can evolve (become more elaborated and complex). It can remain the same, or it can devolve (become more simple, disintegrate and become extinct).

Preliminary design criteria are discussed for implementing this State/ Process Dynamic (TM) in Java. Java is selected to treat social systems as objects and make the underlying computer program as machine independent as possible. Notions of GUI pallet design are used for implementing social systems models. The final objective of social systems simulation is to be able to use the resulting models for sociological experimentation.

Keywords

systems metaphor, General Systems Theory, open system, structure, system state change, flow, time, change, social system modeling, dynamic social process, conditional transition probability, social systems simulation, computer simulation, simulation methodology, laboratory instrument, sociological experiment, object oriented language, Java, secondary research, innovation diffusion, emergent diffusion process, awareness process, geographic spatial process, social network process, impersonal information process, adoption process

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Introduction

Historically, sociology drew heavily from other sciences to provide frameworks for explanation. Various metaphors that were attempted were borrowed ideas from General Systems Theory (von Bertelanffy, 1968) that came into prominence in the 60's. Discussions then involved the advantage of social systems simulation over deductive theory (Meehan, 1968). More recently other authors have enlarged on the social system as a viable approach to understanding (Bailey, 1994). System notions were easily adapted to social phenomena on a very intuitive level. It was easy to identify and isolate social systems for study (e.g., a dating pair, families, households, small task oriented groups, neighborhoods, communities, cities, and larger and more complex social systems). Social systems are viewed as structural entities that change in time.

One of the goals of a social systems simulation methodology is to expand knowledge in sociology. Simulations that stand alone as prototypes are difficult to understand, difficult to update and change, and difficult to combine with other models. This is counterproductive to the notion of the growth of knowledge. I propose a simulation methodology that has the feature of being easily understood, models are easily built, data are easily introduced into the model in an intuitive appealing manner, and several models using this methodology can be combined either associatively or hierarchically. Various aspects of the model can be modified as more research becomes available for any of its components.[2]

Although the methodology borrows heavily from General Systems Theory, anyone familiar with this metaphor will immediately see that there are many facets of General Systems that are not implemented. They add too much complexity at the current stage of development of this methodology. Further, the growth

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[2] Hundreds of my students have used and continue to use the systems metaphor to organize their secondary research papers. It intuitively identifies the system structure consisting of social elements and social relationships among these elements. They have then also been successful in introducing change into these social systems. It usually takes no more than six hours of instruction on the elements of this methodology for a student to begin model making. Each student is required to read 15 refereed journal articles related to their chosen topic for secondary research. The social systems thus identified and constructed are usually very concise. The choice of topics, the choice of social system, and the State/ Process Dynamic (TM) in many instances are inspired. Success is guaranteed (Werner, 2000). The mantra that summarized this methodology is STRUCTURE/ FLOW/ CHANGE (Capra, 1991, p.328).

of knowledge has been so uneven in social sciences and proceeds in “fits and starts”, that a useful methodology needs to be able to deal with a broad range of knowledge from systems with scarce information to systems with overwhelming amounts of information. This unevenness of the availability of empirical data makes simulation perhaps the only alternative in social systems model making.

Legacy Simulation Languages

Historically, computer simulations of social systems were written in FORTRAN. Today the computer language of choice is object- oriented C++. Although this language can be adapted to any model, it takes a great deal of skill and time to program such a simulation. Some other more general languages based on FORTRAN such as GASP and SIMSCRIPT make this simulation process somewhat easier. Today, one of the higher level languages for this purpose is MIMOSE based on C++ (Gilbert & Troitzsch, 1999, p.100). Even today, a great deal of time and effort are still being spent on computer programming rather than model making.

Over the years many other special purpose simulation languages emerged to solve very specific problems. Since social science had not developed its own generalized simulation language, it borrowed heavily from other disciplines. In each case the social systems model was “shoehorned” into a metaphor that may or may not have been appropriate for the social systems. Some recent examples of the direction of this development are the following:

> SWARM deals with multiple artificial agents that behave individually and their action results in emergent mass behavior. These automata are far removed from the empirical social world and are at times too abstract to have any sociological meaning (Swarm Development Group, 2000).
>
> MATHEMATICA is mathematically highly abstract. The focus is on learning the abstract symbols and computer programming rather than gaining an understanding of the social processes that are being modeled (Gaylord & D’Andria, 1998).
>
> STELLA uses the plumbing metaphor to model flow. The terms used are sources, sinks, leakage and valves, that have little in common with social systems dynamics (Small, Blankenship, Whale, 1997).
>
> SIMPROCESS views the world as a business process model. It also suffers from too much metaphor and not enough social reality (Carpenter, September 1999).

The simulation methodology I am introducing here does not impose such burdensome metaphors on the social system being modeled.

A Minimal Unbiased Modeling Environment

The social system is a key concept in this simulation methodology. This concept seems to introduce the least amount of bias when used to organize social knowledge. The model maker in this systems metaphor must be able to identify the boundary of a social system undergoing change.[3] Next, the various states through which a social system transitions need to be identified. Key to identifying these transitions are the social processes that bring these transitions about. These dynamic processes either occur one after another or in parallel and provide an instant understanding of the direction of flow of the whole social process from state to state. Since very few, if any, social relationships are deterministic, transitions from state to state are all probabilistic. The transition probabilities must be calculated within each process and are usually calculated from values of the variables of system elements.[4] Next, a decision is made whether the element in the social system will transition to another state based on this computed conditional transition probability, or not.

Social System Defined

First, the structural features of a social system must be identified. The social system is easily and intuitively defined as a combination of any two or more interacting social elements. Therefore, social systems are a championship ice-skating pair, a family of adults with minor children, a community of households, a small task oriented work group, or a city of neighborhoods, etc. Clearly the social elements are the pair, family members, small group members, individual households, individual neighborhoods, etc. For modeling purposes, the social system boundaries are clearly and conveniently established around these elements.

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[3] The boundary of a social system is usually identified by geographic social proximity and social network connectivity of the interacting social elements.

[4] Feedback, a traditionally central concept to General Systems Theory, is not modeled directly in this methodology. The conditional transition probabilities are calculated using the values of social process variables. As the social process changes, the values of these variables change. These new values result in newly calculated transition probabilities. Feedback is therefore implicit in the model.

Social systems are open systems. Elements within them are not only influenced by relationships among each other within the system, but are also influenced from outside the system. Identifying the internal relationships among the elements is a little more problematic and is very specific to the subject being modeled. Here the modeler's intuition, ingenuity, serendipity and imagination come into play.

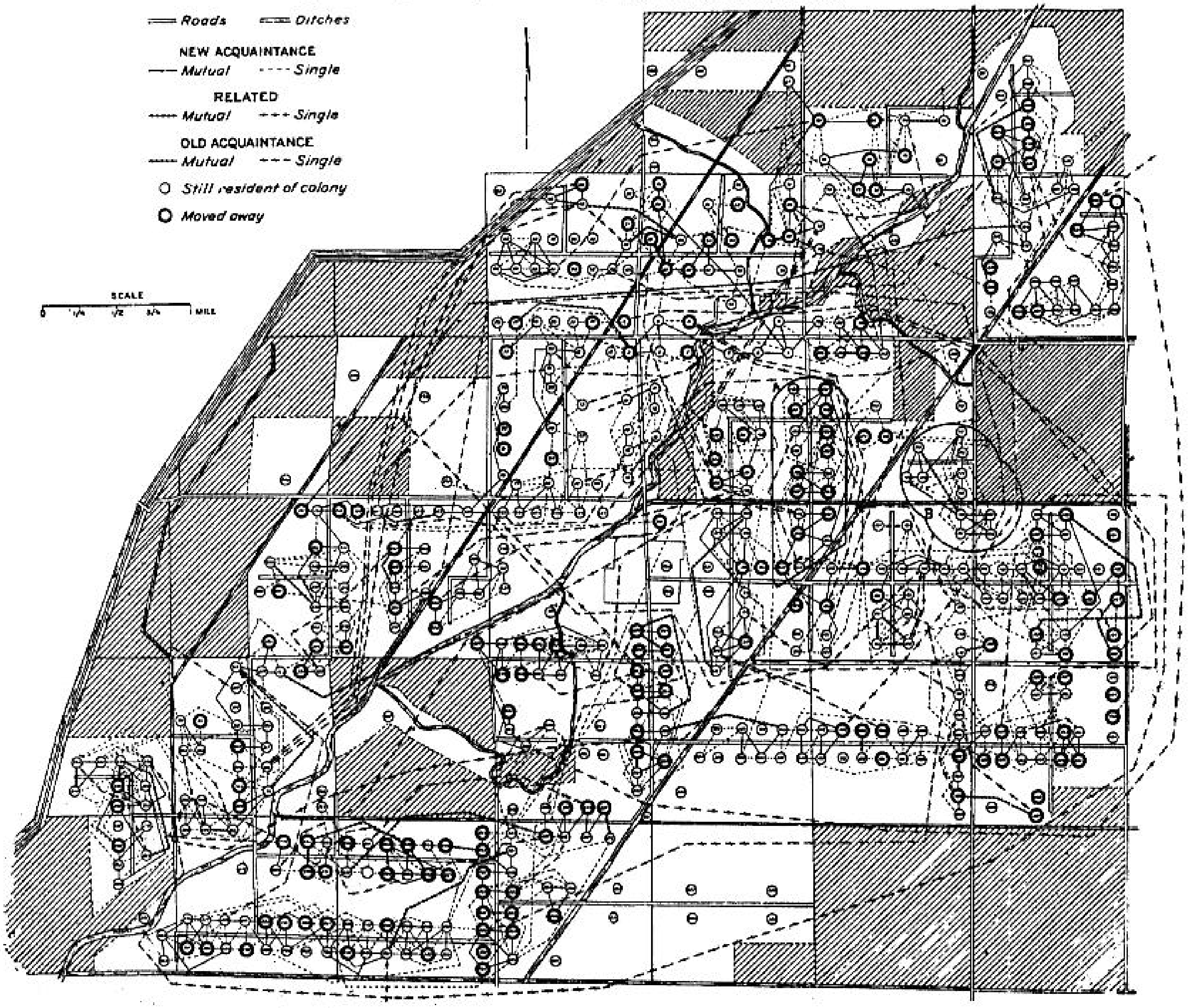
Innovation Diffusion as the Example

Innovation diffusion depends on the spread of information about an innovation through a typical community of 532 households as shown in Figure 1 (Loomis, 1938, pp.394-395). Figure 1 is presented to provide an impression of the simulated community. Three of the primary social relationships among the members of a community are presented here. The households have a geographic spatial relationship to one another, i.e., the community road pattern and location of individual households contribute to non-network social contacts. The social network among these households abstracted from Figure 1 is another social relationship that contributes to the spread of information (The method used for abstracting the social network from this figure is discussed in great detail in Werner, 1971, pp.193-213). I assume the existence of the social network as given. A more detailed example of the reconstructed social network and as it is represented in the simulation is provided in Figure 2. Only the reciprocated links are shown here. (This representation is based on a model provided by Loomis & Davidson, 1939, p.66.) The third relationship is from outside the community. The community receives information about an innovation from a barrage of advertisements from impersonal information sources, e.g., newspapers, billboards, radio.

This example of innovation diffusion is used throughout this paper. The details are available in A model and simulation of the awareness process within innovation diffusion: A synthesis of empirical research.[5] (Werner, 1971). The diffusion process modeled in this example is an emergent process, since every household in the community begins by being unaware of the innovation. Adoption of the innovation occurs after awareness has occurred.

[5] This project was supported in part by an NSF Dissertation Research Grant No. GS-3121.

Figure 1. Visiting Relationships of Families Residing on Dyess Colony, Arkansas, May 1938,



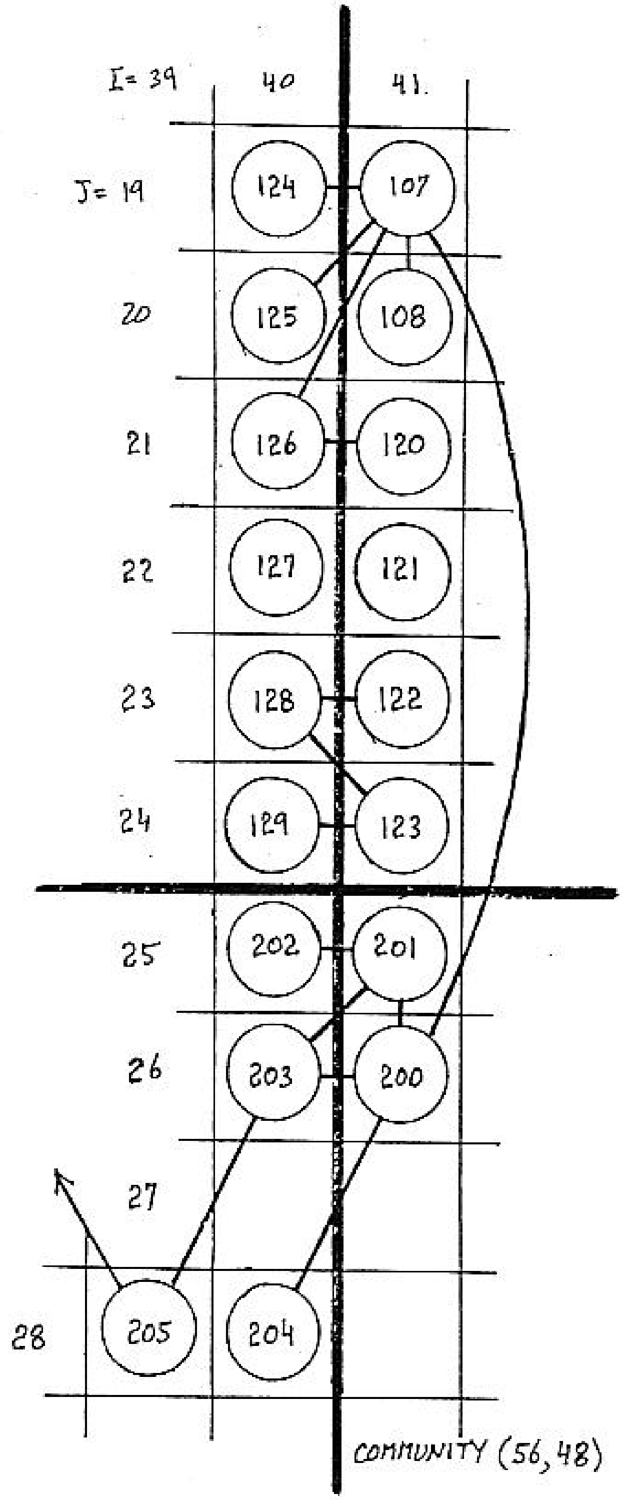


Figure 2. Detailed representation of a few mutual social network choices in the simulated community

State/ Process Dynamic (TM) **Defined**

Next, in the simulation methodology, the dynamic features are added to the social system through the State/ Process Dynamic (TM). This Dynamic is composed of a few essential components and requires few rules for its implementation.

The minimum number of modeling components are:

(1) The social system states are symbolized by circles.
(2) The social processes are symbolized by rectangles.
(3) The direction of flow is symbolized by directional arrows (Refer to Figure 3).

Three rules for social systems model making govern the use of these symbols:

(1) The first rule states that all models begin with a state or a cycle.
(2) The second rule states that all models end with a state or a cycle.
(3) The third rule states that a dynamic process must always intercede between two states.

Using these rules for model making, the innovation diffusion process is modeled as shown in Figure 3.[6]

The details of this model of innovation diffusion are discussed in Werner (1971). Both awareness of an innovation and its eventual adoption are identified as necessary stages in the diffusion processes. Mason (1962, p.115) concluded that "the necessary and sufficient condition for an adoption process is that awareness must occur before adoption." Awareness, after the model plays out, follows a growth curve. In a study by De Fleur the adoption growth curve for newspaper subscriptions concludes in what appears to be a dampened sine wave (1966, p.21). This also occurs for the average weekly attendance of a motion picture (1966, p.41). These observations are interpreted in this model as resulting from a dampened cyclical process that in time approach stability or declines. This process cycles between discontinuation of using the innovation and its future readoption, ad infinitum. Elements of the system can however remain in any state for any length of time. Since the process is probabilistic, a transition due to a small probability may not necessarily occur. Therefore, the lack of adoption is not seen as a "rejection" of an innovation but as its non-adoption (the non transition into another system state).

[6] The innovation diffusion model ends in a cycle. That is, the readoption process can occur following the discontinuation process ad infinitum.

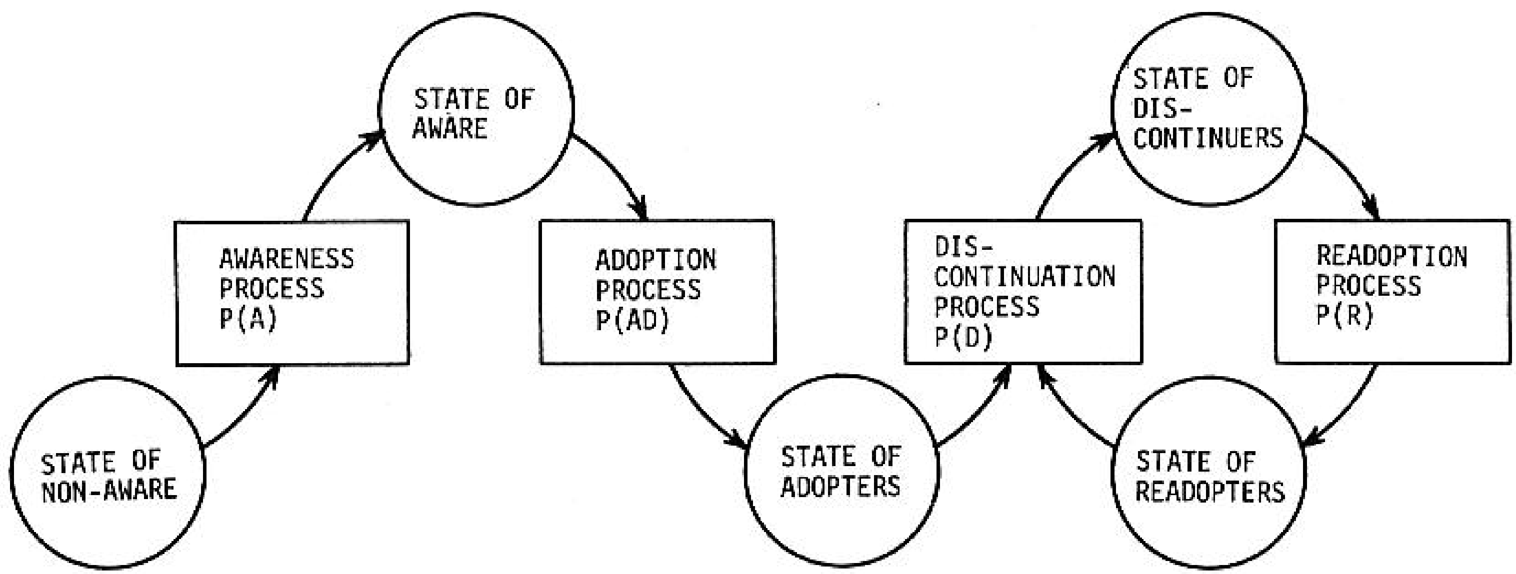


Figure 3. A Technology Innovation Diffusion Model

The three dynamic modeling elements, states, process, and flow of time, are presented in greater detail:

States

Identifying a system state is more a result of good planning than formulation. Ultimately these system states must be observable, replicateable, and somewhat stable conditions of the social system. These states are very much akin to stop action photographs of the system's elements. System elements change in time passing from state to state through processes in which transition probabilities are calculated and transition decisions are made. The outcome of the decision either advances the system elements to the next state or it does not. The length of time that an element remains in a particular state can be very short or quite long. There is a finite probability that a transition will not occur. It is the probabilistic nature of the transition that is central to the process not the time of its occurrence.

Process

The heart of this dynamic methodology is the process. At this point the transition probability for a state change is computed. This computation depends heavily on the variables describing the nature of the elements and on the empirical data supplied to the computation. Since information in the social sciences is unevenly distributed, the modeled processes must be able to function on many levels from very little information about the transition probability on the one hand to very large amounts of detailed information on the other. The details of model making are heavily dependent on the levels of information that are available for each process being modeled.

At a minimum, transition probability is provided by a simple proportion, a ratio or a rate (Figure 4a). Some elements in the system must always be afforded an opportunity to transition into the next state. These minimum data are necessary even if they must be estimated in the absence of any empirical study. This proportion, ratio or rate will remain constant throughout the simulation.

Further improvement of information for computing transition probabilities may provide data that can be represented as a time dependent probability histogram, a frequency polygon or a social indicator (Figure 4b).

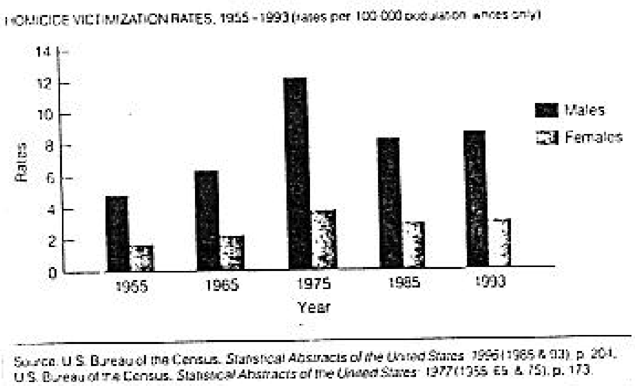
Beyond this point any improvement in information yields more complex relationships that are used to compute transition probabilities. Empirical data such as variables that contribute to the computation of transition probabilities may be introduced into the process. If for example the transition probability is a function of the number of exposures that a household has to impersonal information sources (Figure 4c), the conditional transition probability given these impersonal sources is a function of the number of exposures to that information. It may look like the Weber-Fechner Law (DeFleur & Larson, 1958, p.132).

Still more complex social network data may be introduced and can be used to compute the conditional transition probability given social network sources. Based on the spatial distribution of migrants, telephone communication, marriage, and daily social contacts as surrogate measures Hägerstrand (1967a) postulated that spatial distribution of private communication (non-social network sources) could be described by a distance decay function (the Pareto exponentially decreasing function). This was supported by later work by Morrill & Pitts (1967). This function was spatially generalized over a community into two dimensions. This two dimensional "Mean Information Field" provided a theoretical distribution of the spatial contact probabilities proportion = 75%

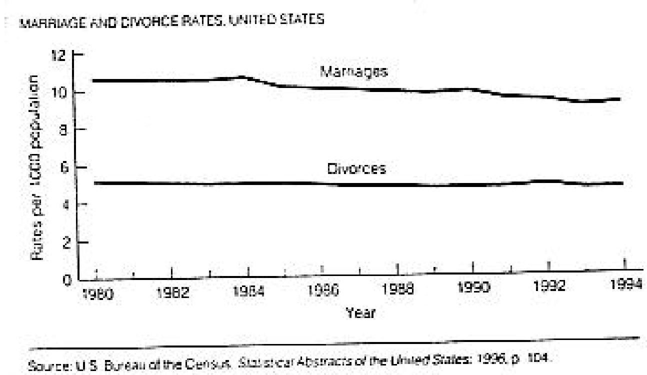
ratio = 0.05

rate is 15 per 100,000

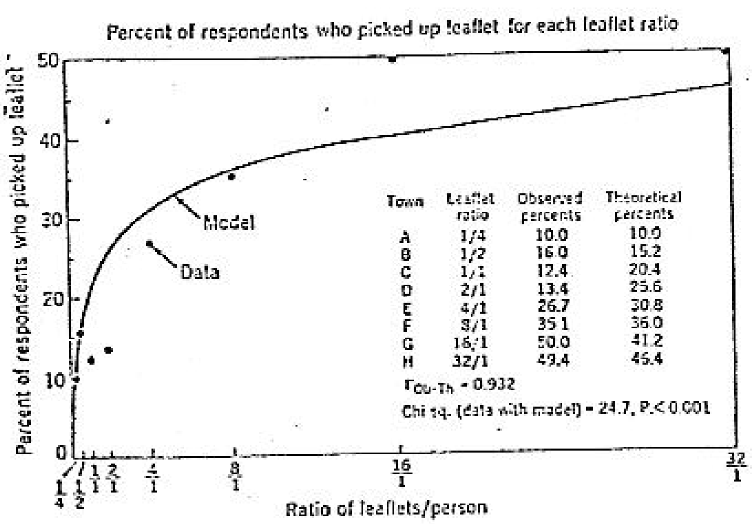
(a) Various rates



(b) Histogram



Social Indicator

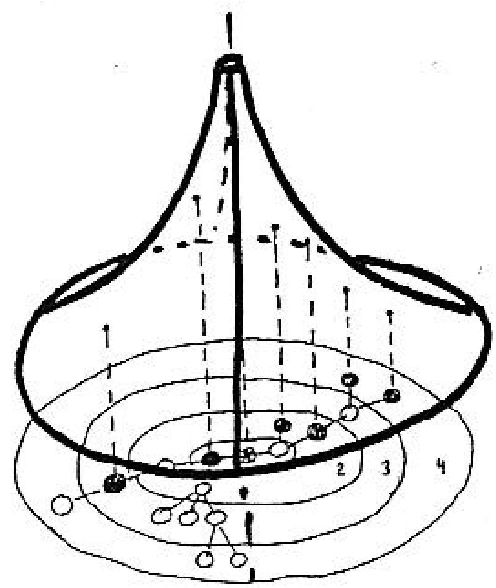


Town	Leaflet ratio	Observed percents	Theoretical percents
A	1/4	10.0	10.0
B	1/2	16.0	15.2
C	1/1	12.4	20.4
D	2/1	13.4	25.6
E	4/1	26.7	30.8
F	8/1	35.1	36.0
G	16/1	50.0	41.2
H	32/1	49.4	46.4

$r_{Ou\text{-}Th} = 0.932$

Chi sq. (data with model) = 24.7, P.< 0.001

(c) Weber- Fechner Law



(d) MIF adapted to Social Network Zones

Figure 4. Various kinds of data input

between unrelated individuals who were aware of the innovation and those individuals they could influence who were not yet aware (Werner, 1971, p.129).

Further generalization by Werner (1971, p.184) of this Mean Information Field to social networks yielded probabilities of becoming aware depending on the ratio of individuals in the social network who knew of the innovation divided by the total number of individuals within a specific zone, at unit "social network distances", removed from an "ego" who is unaware. The total probability is the sum of probabilities computed for several zones (Figure 4d). Each zone relates to the modern idea of "degree of separation". It describes how many individuals from ego at various social network distances know of the innovation when compared to all the individuals in ego's social network at each degree of separation (Guare, 1990; Milgram, 1967).

Finally, a process can involve a very complex relationship among many variables for computing a transition probability as shown in Figure 5. The awareness process within the innovation diffusion model is a very complex computer subroutine for calculating the transition probability that a household will become aware of an innovation given a probabilistic choice among several information sources (Werner, 1971, p.28).

To avoid the necessity for such complex programming, a method must be found to deconstruct this kind of programmed subroutine into a simpler Sate/ Process Dynamic (TM). In doing so it will reduce the need for programming skill and will simplify the data input into the model. This kind of complexity further points to the necessity of being able to hierarchical nest systems within systems. The more sophisticated and comprehensive the data available for computing conditional transitional probabilities, the more detail can be entered into each process. In this modeling methodology, options for accommodating various levels of information based on the complexity of knowledge are provided.

Flow of Time

Time in this metaphor is limited to the scale of human causal experience and is assumed continually to be "running down"; independent variables occur before dependent variables in time. Since all transitions from state to state are probabilistic, the precise time at which any transition will occur is not known. This makes transition time a relative metric.[7] It is not the transition time that is important but the conditional transition probability of a state change. In this metaphor, the transition time is computed as a convenience at the moment that such a transition occurs. The time an element spends in a state, is solely dependent on when and if a transition occurs. It may never occur. Time is treated as being given and as being a relative metric. It is a measure for when transition events occur.

The evolution of the social system toward greater complexity such as a greater division of labor may occur any time. Alternatively, devolution of the social system to greater simplicity, to decline, or to eventual disintegration may also occur any time. A system may also be stagnant and undergo no change. Change in the elements of the social system, changes in the relationships among these elements, and changes in the processes all contribute to changes in the social system.

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[7] Time in human historical terms has no absolute zero. The only thing that it measures is the relative time between events. The measure may be seasons, phases of the moon, years, hours, etc., or any conventional uniform measure with agreed upon duration.

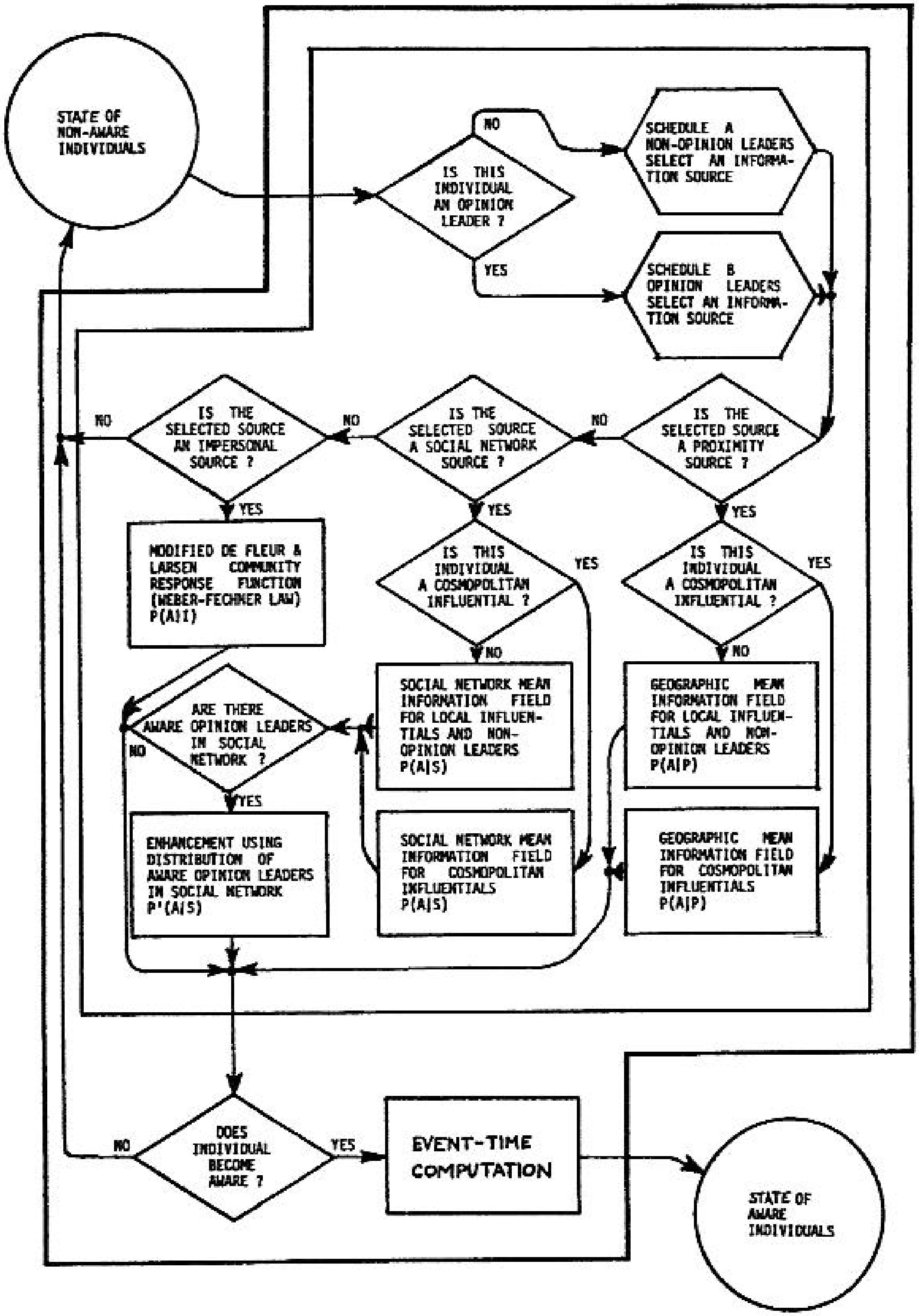

Figure 5. The Awareness Process Flowchart

Simulation as a Tool for Sociological Experiments

The level of abstraction of simulation is somewhere between grounded theory (Strauss & Corbin, 1998) and mathematical modeling (Gaylord & D'Andria, 1998). I am seeking a general methodological tool that can be easily modified and elaborated as more information becomes available through empirical research. Simulation is treated as the laboratory instrument used to test the social systems models through experimentation. Campbell discusses three true experimental designs; the pretest- posttest control group design, the Solomon four- group design, and the posttest- only control group design (Campbell & Stanley, 1963, p.13-34). Of these three experimental designs, the latter is best suited to computer simulation of social systems. When a simulation model is well constructed it is valid, robust, durable, elegant, and parsimonious. It can then be used as an instrument for experimentation. On a modest and most controllable level, simply systematically varying the values of variables assigned to the system elements can yield interesting results. On the most complex level varying the model itself by changing components can provide different unexpected results. Once a baseline is obtained for model stability, the experimental condition can be varied systematically to measure the variations in the outcomes. Since this methodology is easily adapted to a wide variety of social systems models they can be revised, merged, and made into more complex models. This model elaboration contributes to the growth of knowledge.

Increasing the Utility of Analytical Models

Analytical models of social systems quickly become very complex and rich in detail. This is necessary to have a clear understanding of the underlying social processes. On a theoretical basis this kind of detail has great explanatory power. However, on the practical level this makes these models nearly useless for everyday application. For example, in the innovation diffusion model, information about the innovation passes through the social network. Analytically it is important to know the details of a social network for a community of 523 households. On a practical marketing level, this kind of detail is difficult to obtain and difficult to manage. Therefore, it becomes more interesting from a practical point of view if an "information transmissivity" of a social network could be determined and measured using for example an index; $0.0 <= t <= 1.0$. Sampling technology may point the direction to take for determining a representative sample of a very large and complex social network. From these samples, generalizations about the information transmissivity index of the whole social network for a specific community could be made. Such an index would be useful in a marketing variation of this diffusion simulation.

Freeman suggests several ideal measures of centrality for small, complete graphs. These are measurers of centrality in terms of degree, centrality in terms of betweenness, and centrality in terms of closeness (Freeman, 1978/ 79). Could these measures be a point of departure for measuring the information transmissivity of empirically large, complex social networks that are not complete? The innovation diffusion model used here as an example could make use of such an index. Such a systematic simplification of a model would be more practical for computing conditional transition probabilities of awareness for real world application.

Java Implementation

Java is chosen for the implementation of the Social System and of the State/ Process Dynamic (TM). States, flow, and processes are easily visualized in this object oriented language. The polymorphism feature of Java is essential for treating the possible great depth to which a model can grow when its elements can be viewed as a system of systems. This is an essential extension of social systems modeling. The dynamic nature of this language allows it to expand and contract in size during simulation as resources are required for the model within the computer. The near universality of platforms on which Java can reside and its general programming appeal are other essential features for creating the laboratory instrument of a simulation environment. The intuitive nature of the methodology allows the creation of reusable models for a large number of modelers with little programming experience. Every model will no longer be a prototype; models will build upon one another.

The programming environment of this systems metaphor is seen as having two parts; a model building part and a simulation implementation part with “real world data”. The model building part uses a GUI interface to develop a visual model the Social System and a visual model of the State/ Process Dynamic (TM). The simulation implementation part cues the model maker to specific items that are needed for the simulation to work. Such items may include variables identifying characteristics of the elements, general social network characteristics, geographic location identifiers to place elements in a community, etc. Each data component is required to calculate transition probabilities. The system identifies “system states” where minimum information must be provided for simulation to work. The modeler provides more complex data when available. Java allows the manipulation of data structure that are simple or complex. This programming effort begins with the implementation of the GUI interface. This part of the application is programmed using the Swing components of the Java Foundation Classes of the Java 2 Platform.

Conclusion

The purpose of this paper is to present the logic for developing a social systems simulation methodology based on General Systems principles. This simulation methodology is created with the view that models need not always be prototypes. They can be easily modified, elaborated, and combined to form robust experimental platforms for the social science experimental laboratory.

The modeling environment consists of three structural elements:

(1) The social system states are symbolized by circles.
(2) The social processes are symbolized by rectangles.
(3) The direction of flow is symbolized by directional arrows.

The modeling environment consists of three process rules:

(1) The first rule states that all models begin with a state or a cycle.
(2) The second rule states that all models end with a state or a cycle.
(3) The third rule states that a dynamic process must always intercede between two states.

This methodology is implemented in Java that is a reasonably platform independent language that is easily adapted to nested systems objects and has powerful data handling capabilities. The implementation has two aspects. The first, uses GUI interface to visualize both the social system under development and the State/ Process Dynamic (TM) providing for system’s state changes. The other, takes “real world data” at various levels of sophistication and provides the dynamic component consisting of conditional transition probabilities to the experimental simulation environment.

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Linton C. Freeman Festschrift Epilog

Ever since I have known Lin Freeman, http://eclectic.ss.uci.edu/~lin/lin.html , he has been a pioneer in Social Science. One of the first lessons he taught us at the Systems Research Committee at Syracuse University between 1963 and 1966 was that “Things Happen.” It is to Lin’s credit that the universality of this concept has been accepted by the public over the past nearly four decades. The concept *‘Things’* has been popularized by the common four letter *’S’* word. We all know that “S___ Happens”.

Everyone now believes it! Lin anticipated what would capture the public's imagination. “Things Happen” is a particularly profound concept in system dynamics. In the past we usually viewed social systems as having static structures in which components function together. Computer simulation added process and made it possible to provided these static systems with dynamics. The direction of change in social system was always “downhill” and is represented by the flow of time. The change of a social system can be both evolutionary, by increasing in complexity, or devolutionary, in that it can simplify or lead to the decline and destruction of the system. Simply put, the mantra for social systems is STRUCTURE (system structure), FLOW (time) and CHANGE (system dynamics) thanks to Capra and the Tao of Physics (1991, p.328). It is at the systems level of abstraction that I believe the physical sciences and the social sciences share a common intellectual boundary.

In the spring of 1966, Lin, Richard Videbeck and I sat for my Ph.D. research tool defense during which we talked about “blue sky” issues in social systems modeling and simulation. Earlier that year we had had some success in reproducing Hägerstrand’s simulation of spatial diffusion (1967b) using a timesharing hookup between Syracuse University and Duke University. This simulation was a prototype, was completely specific to the model of spatial diffusion and was written in BASIC. Later that year, I provided the work for a small simulation of residential segregation (Freeman & Sunshine, 1970). Nowhere in that experience could we have anticipated the explosion that has since occurred in social systems modeling. Our “blue sky” issues were very modest and not at all revolutionary when compared to the current complex development of social systems simulation.

That we talked “blue sky” issues at all was to Lin’s credit. It demonstrated to me that he is firmly grounded in the empirical social experience, shows brilliance in applying logic to social systems model building, and has the wisdom to apply the conclusion of his research methodology to the prediction and control of social systems. He has instilled in me the desire to seek greater utility in social systems simulation methodology and to link this methodology with continuing, evolving computer technology. Efforts in this direction will allow future model makers greater freedom to concentrate more on creating models of social systems and less on computer programming.