Application Of Gerts Network Analysis And Simulation Programming To Problem Areas In Psychology.

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APPLICATION OF GERTS NETWORK ANALYSIS AND SIMULATION PROGRAMMING TO PROBLEM AREAS IN PSYCHOLOGY

by

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Abstract

Lothar R. Schroeder. Application of GERTS Network Analysis and Simulation Programming to Problem Areas in Psychology.

Among the more promising operations research techniques for modeling and analyzing multi-parmeters stochastic systems is GERTS: Graphical Evaluation and Review Technique Simulation. The principle advantage of the network approach is its graphical nature which simplifies the model building process. The intent of the present thesis is to demonstrate the feasibility of applying network modeling and analysis techniques via GERTS computer simulation to a wide range of problems in psychology.

In the first portion of this paper statistics appropriate to three Markov models in psychology are obtained using GERTS. The transition probability matrix of each Markov process is represented in network form and then analyzed. Examples are chosen from the literature in concept identification, choice behavior, and social mobility to demonstrate GERTS versatility in solving absorbing, random walk, and regular Markov processes.

In order to demonstrate the modeling capability of GERTS, a series of five teaching units are developed for psychology courses based on the simulation of behavior in different settings. The five teaching units and the behavior each describes are as follows: Unit I, Imprinting

behavior, predicts following behavior in newly hatched ducklings on the basis of their development of sensory activation and fear during the critical period; Unit II, Spinal Reflex Mechanisms, describes neuromuscular connections involved in simple reflex behavior in network form and simulates the stretch reflex and the flexion reflex; Unit III, The Classical Conditioning Paradigm, has been developed to simulate the typical exponential learning curve and subsequent extinction behavior; Unit IV, Free Recall and the Serial Position Effect, was designed to enable students to study the memory process via a simulation of the serial position effect; and Unit V, Communication Patterns in Groups, incorporates the structural and functional characteristics of communication networks into a GERTS framework. Suggestions are provided as to how students would interact with these units and how instructors might modify them. It is suggested that instructors use one or more of these units as a compliment to the more traditional teaching methods.

A detailed description of a GERTS model of the vertebrate retina is presented next. Predictions made from the response of a simulated ganglion cell to changes in light intensity conform well to analogous empirical data. Finally, GERTS models for manpower allocation and an analysis of inflight refueling serve to demonstrate the usefulness of the network simulation approach in several applied areas.

I.
Introduction

In recent years, there have appeared in the periphery of the psychological discipline a new group of disciplines such as information theory, cybernetics, general systems theory, queuing theory, theory of games, and others. Although they may differ in specific assumptions and methods, they share the common theme that a systems approach can provide a framework for analyzing the complexities and dymanic properties of psychological processes. There is therefore a trend to broaden theoretical concepts to include interactions, non-linearities, feedback and other systems notions. In fact, DeGreene (1970) realized the need to formally relate systems science and psychology, and defined the new interdisiplinary field of systems psychology.

With this current emphasis comes a need to provide psychologists with adequate techniques for analyzing systems. Systems might be represented by differential equations, matrices or some other mathematical procedure. However, much insight into the relationships is lost this way, and in many cases classical mathematics is not efficient in handling large numbers of variables and interactions. Among the most promising alternatives are those derived from operations research and industrial engineering technology. Several authors (Chapanis, 1961; Cogan, 1967) have already suggested incorporation of operations research techniques in the area of engineering psychology, and DeGreen (1970) lists instances where these methods have been utilized in solving human factors problems.

A class of systems analysis techniques which might be of particular value to the psychologist are the network approaches. Gordon (1969) offers the following description of the process of network analysis: "Network analysis represents a formal process by which a transition can be made from a verbal description of a system to the structure of a model." In this graphical precedure, the elements of the system are represented by nodes and the relationships among the elements by arrows (branches) connecting the nodes in question. In addition to the graphical description there is a quantitative analysis of the node and branch characteristics implied in network theory. Among the advantages of network techniques is the ease with which systems can be modeled in network form (Pritsker and Happ, 1966). Other advantages for psychologists (wide applicability, ready translation into programming language, etc.) will become apparent in later discussions.

Two of the most common network analysis procedures are signal flowgraphs and activity networks. The former approach is beneficial in describing systems that require detailed algebraic manipulations, or those that involve probability analyses. In flowgraphs the variables in the system become the nodes, and the functional relations become the branches (transmittances). There are numerous methods for solving the expressions described by flowgraph theory. Whitehouse (1973) presents a review of these methods. Howard (1971) has also demonstrated how numerous Markov models can be solved using flowgraph analysis.

The second approach, activity analysis, is principally designed to solve project scheduling problems occurring in industrial settings. P.E.R.T. (Program Evaluation and Review Technique) and C.P.M. (Critical Path Method) are examples. Generally, the network portrayal consists of branches representing the activities of the project under consideration, and nodes representing the intersection of activities (points in time). In contrast to flowgraphs, activity networks are completely deterministic with the result that all branches must be taken. The most significant result of the analysis is the determination of the distribution of the total time to complete the project.

Pritsker and Happ (1966) have introduced a new graphical analysis procedure which they call G.E.R.T. (Graphical Evaluation and Review Technique). G.E.R.T. uses moment generating functions to transform variables that are additive in nature (e.g. time) so that they may be solved by flowgraph theory (which is a multiplicative system). Multi-parameter stochastic problems can be readily handled by this approach. However, limitations are evident from a computational standpoint when large networks are analyzed, or when "and" logic nodes are required (as in PERT networks). To overcome these inadequacies, Pritsker and Burgess (1970) have developed a computer program, called GERTS, which will solve complex GERT networks via simulation. The GERTS simulation language is a general purpose language written in FORTRAN IV and is relatively easy to use.

Before discussing the specific merits of GERTS for psychology, some general comment on the acceptance of simulation languages by behavioral scientists is in order. First, many psychologists appear reluctant to learn computer programming. For this reason, they often enlist the aid of a programmer who procedes to write a FORTRAN representation of their simulation model. Hilgard and Bower (1966) speak of the impoverished communications between experimental psychologists and computer simulators:

> "Simulation programs are comprised of exceedingly long sequences of instructions, with an almost dumbfounding welter of complex details, and all wrapped up and coded in a

> special programming language adapted to communication to an IBM7090, not to the psychologist who understands nothing of IPL-V. Acquiring facility with one or more list-processing languages is difficult and time-consuming, especially so for older scientists who are very pressed for time by their usual research commitments. In place of a prolonged apprenticeship with a model's program and the computer, the ordinary experimentalist is dependent upon an intermediary to interpret the program for them..."

These difficulties occur, in part, because many simulation languages not only do not provide the user with a simple framework in which he may write simulations to a standard pattern, but are notoriously weak on display. Because the GERTS system is synonomous with a standard network form, the language itself becomes an aid to problem formulation.

Table I lists some of the properties of the GERTS system with corresponding areas of application in psychology. The intent of the present thesis will be to demonstrate the feasibility of applying network modeling and analysis techniques via GERTS simulation to wide range of problems in psychology.

Chapter 2 contains an introduction to the GERTS approach. It outlines the general technique for developing and simulating GERTS network. The next four chapters are concerned with demonstrating GERTS power as a methodological aid in theorizing, in teaching

Table 1

Properties of GERTS and Their Applications to Problem Areas in Psychology

Property	Application
Stochastic & Deterministic Network Descriptors	Math Modeling, Markov processes, Solution of probability problems
Branches having continuous and discrete temporal distributions	Developmental processes, Semi-Markov processes
Availability of network modification	Learning/Adaptation
Q node storage capacity	Memory; attention
Logic node descriptors	Threshold concept; decision making
Counters	Analysis of sub-systems

and in psychological applications.

In chapter 3 the transition probability matrix of a Markov process is represented in network form, and statistics appropriate to several Markov models in psychology are obtained using GERTS.

An investigation of the descriptive qualities of GERTS modeling is undertaken in chapter 4. A series of five teaching units are developed for psychology courses based on the simulation of behavior in different settings. It is suggested that instructors use this package as a compliment to the more traditional teaching methods, or that they expand upon it to meet the demands of their particular institution.

Chapter 5 offers an example of the application of GERTS to a research problem in physiological psychology- the modeling of the vertebrate retina. The power of the GERTS system to model the structure and function of the nervous system is discussed in light of the results of the simulation.

Finally, GERTS models for manpower allocation and an analysis of inflight refueling will serve to demonstrate the usefulness of the network simulation approach in several applied areas. A general discussion of the advantages and the limitations of GERTS takes place in chapter 7 along with a discussion of validation procedures. Future research proposals are suggested.

II.
General Approach to Systems Analysis Using GERTS III

A system can be defined in most general terms as an assembly or set of related elements. The primary concern of the GERTS approach is the analysis of stochastic systems, systems whose elements or states change over time in a probabilistic fashion.

Listed below are five procedural steps which could be employed in analyzing a system using GERTS:

1. Develop a qualitative description of the system in question
2. Convert the qualitative description of the system to a model in stochastic network form (following GERTS format)
3. Determine the system operating characteristics so as to quantitatively describe the network
4. Convert the graphical description to the GERTS programming language
5. Use the computer simulation language as a device to analyze the system.

Step 1 involves specifying the purposes and restrictions under which the model will be formalized (definition of problem). It then becomes necessary to describe the system in the appropriate form (network) which will lead to rapid translation into the GERTS language. Several authors (Pritsker and Burgess, 1970; Whitehouse, 1973) have provided extensive discussions of GERTS III network characteristics and the input requirements for its companion simulation language. This chapter will provide a summary of these techniques and an example of their use.

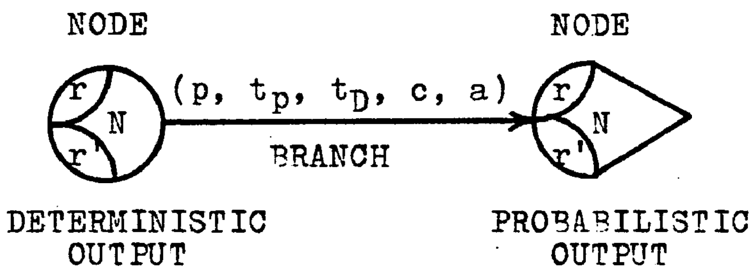
Overview of GERTS III

The purpose of the GERTS network is to provide a graphical description of the activities of a given system. This is accomplished by defining a collection of branches and nodes. The branches represent system activities which take place over a period of time or they may represent instantaneous information transfers. The nodes are events indicating the start and completion of activities, and therefore occur at given points in time. The GERTS computer program performs a simulation of this network by advancing time from event to event (next event simulation) through the branches.

GERTS simulations are initiated with a source node (start event) and terminate with one or more sink nodes. The output characteristics of the source node determines which activities emanating from it will occur. The output type for the source node and for all other nodes may be either deterministic or probabilistic. In the former case, all activities emanating from the node are scheduled to occur, while in the latter case only one of several activities is scheduled to occur (the particular activity determined by a random number generater).

Figure 1 provides an illustration of the node and branch descriptors used in the GERTS system. Nodes

Figure 1. An illustration of node and branch descriptors used with GERTS.



<u>Legend</u>

N = node number

r = number of releases

r'= number of releases to repeat

p = probability of realization

t_p= parameter set for time

t_D= distribution type for time

c = counter type

a = activity number

drawn in the form of a circle have deterministic outputs, whereas nodes having a cone configuration represent probabilistic outputs. Branches are represented by lines connecting nodes. The number of releases, r, associated with a node specifies the number of times activities incident to the node must be completed before the node is realized. If a node is realized, activites emanating from that node are scheduled according to its output type and the simulation continues. At this time the number of releases is set equal to the number of releases required to realize the node after the first time, r'. One simulation ends when a stated number of sink nodes have been realized. However, multiple simulation runs can be performed as specified in the input data.

Each branch in the network has associated with it five parameters (see figure 1):a probability that the activity is scheduled, p; a parameter set for the time to complete an activity, referenced by some arbitrary t_p; a distribution type for the time to complete an activity, t_D; a counter type, C; and an activity number, a, which simply gives a label to each branch. The time parameter set and the distribution type fully describe the time required to complete the activity represented by the branch. There are nine possible time distribution types available and each type specifies the arrangement of the parameters in the parameter set. For example if the time to complete an activity was assumed normally distributed, then t_D would be coded with a 2. The selection of this distribution type insures a parameter set having the following components: the mean value, the minimum value, the maximum value, and the standard deviation of the time to complete the activity. This four valued set is in turn associated with t_p. The counter type may take any value from one to four. The counter enables the analyst to group activities of interest into classes. The GERTS program tallies all branches labeled with specific counters and provides the following summary statistics concerning these activites: the mean, the standard deviation, the minimum, and the maximum number of times these activities were completed prior to the realization of specified nodes. The activity number identifies a branch and consequently permits network modification. Network modification involves replacing the output of a node by the output of a second node based on the completion of a stated activity. This is an important characteristic of GERTS in that it provides flexibility in altering the system while it is in operation. The method for incorporating network modifications is described via the example in this chapter.

Various summary statistics are collected on those nodes which the analyst has indicated as statistics nodes.

Sink nodes are automatically made statistics nodes.

Among these statistics are:

1. The probability that a node is realized
2. The average, standard deviation, minimum, and maximum times to realize a node
3. A histogram of the times to realize a node.

Realization time may be based upon: the time of the first realization of a node; the time of all realizations of node; the time between realizations of a node; the time interval to go between two nodes in the network; and the time delay from first activity completion on the node until the node is realized.

In addition to the printout of the network and the results, there is also a method available for tracing runs.

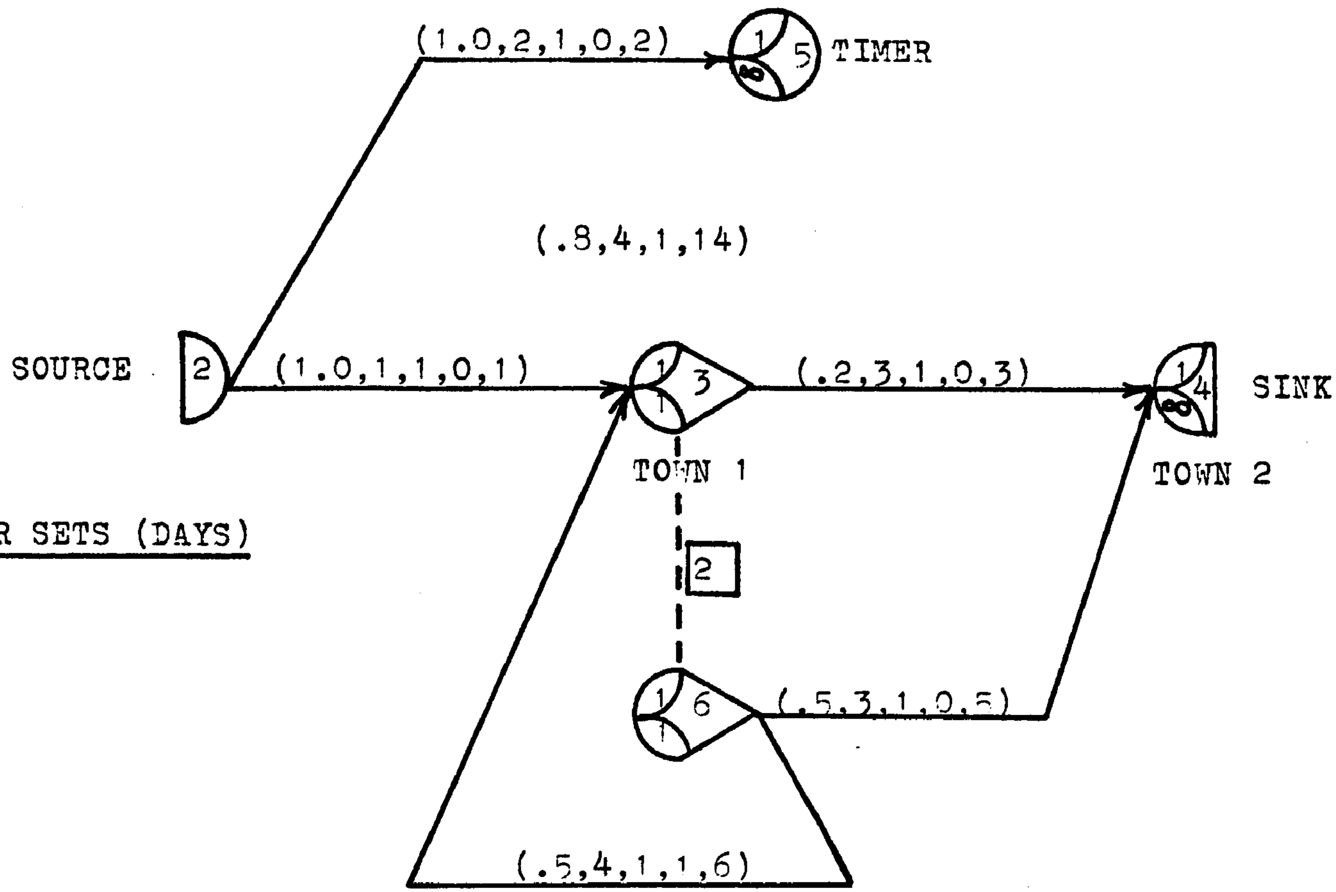
An Example

The example chosen to illustrate some of the characteristics of GERTS III is a modification of the car rental problem described by Howard (1971):

An automobile rental agency rents cars at two locations. The experience of the company shows that when a car is rented in town 1 there is a 0.8 probability that it will re returned to town 1 and a 0.2 probability that it will be returned to town 2. Because of the nature of the trips involved, the length of time a car is rented depends on where it is rented and where it is returned. Cars rented in town 1 and returned to town 1 are rented for 3 days. Cars rented in town 1 and returned to town 2 are rented for 6 days. Assume there are many customers and cars are always rented when they are returned. The first car is rented in town 1. Assume also that if a car is not returned to town 2 in 10 days then management will provide a discount for new customers returning cars to town 2; this will attract 50% of the cars to town 2 and 50% to town 1. Management wishes to determine, on the average, how many cars rented in town 1 will be returned to town 1 before a car is returned to town 2 and how long it will take before a car rented in town 1 is returned to town 2.

Figure 2 shows how this verbal description can be represented in network form. The two events "returns car

Figure 2. A GERTS network for the car rental example.



PARAMETER SETS (DAYS)

1) 0.0
2) 10.0
3) 6.0
4) 3.0

to town 1" and "returns car to town 2" have been graphically described by node 3 (N3) and node 4 (N4) respectively. N3 is a probabilistic node, and N4 is a sink node- its realization will terminate the simulation. N2 is a source node and is required to initiate the simulation at time 0. All of the dynamic activities are represented by the directed branches shown in the figure. The notation P(x,y) is used to represent an activity which begins at node x and terminates at node y.

Since N2 is deterministic both activities, P(2,3) and P(2,5), were scheduled to occur at the initiation of the first simulation run. The values for p therefore were wet equal to 1.0 for both branches emanating from N2. P(2,5) was introduced into the network to record the 10 day interval before management would change its rental policies. This was accomplished by assuming that the time for completion of P(2,5) had a constant distribution (t_D = 1) and that its parameter set (t_p = 2) took on the value of 10.0 days (see inset in figure 2 for parameter set #2). No counts were taken of this branch (c = 0), and the activity number was arbitrarily set equal to 2.

The first rental in town 1 was simulated at time 0.0; therefore P(2,3) also had associated with it a t_D = 1, but in this case, the parameter set (t_p = 1) represented an activity requiring 0.0 time for completion. No counts were taken of this branch and "a" was given the value of 1.

The value of $p = .2$ for P(3,4) suggests that there was a 20% probability that this branch was taken (scheduled) once a car was rented in town 1. It then took 6 days to complete P(3,4) as indicated by $t_p = 3$ and $t_D = 1$. Again no counts were taken and the branch was arbitrarily labeled #3. Eighty percent of the cars rented in town 1 were returned to town 1. The branch, P(3,3), describes this activity. The time to complete p(3,3) was 3 days ($t_p = 4$, $t_D = 1$). Since management wished to be informed of how many cars would be returned to town 1 before a car was returned to town 2, P(3,3) was tagged with a counter (C = 1).

The dashed line between N3 and N6 indicates that after P(2,5) is realized (10 days) a network modification will occur whereby N3 will be replaced by N6. This will have the effect of altering the output probabilities. The .2 in the square adjacent to the dashed line indicates that the network modification is contingent upon the completion of activity #2.

Once the system has been modeled in network form and all parameters have been identified, it is a relatively simple matter to simulate the network using the GERTS III computer program. The input requirements consist of, at the most, seven different types of data cards. Table 2 provides a general description of each

Table 2

Network and Control Information Required for Performing the Simulation from Pritsker & Burgess (1970)

Data Card Type	General Description
1	Identification information, number of times simulation is to be performed, and an initial random number seed (card one)
2	General node, counter, and network modification data (one card)
3	Description of each node (one card for each node)
4	Parameters of time variables associated with activities (one card for each parameter set)
5	Description of each activity (one card for each activity)
6	Network modifications desired (one card for each activity that modifies network. If none, no data card 6 required).
7	Run numbers to be traced (one card only if tracing is requested by using a negative project number)

card.

The modified car rental problem is as a simple example of a discrete-time semi-Markov process. Although such models can be solved analytically (see Chapter 3) this is often a difficult procedure. The output of the GERTS III solution is presented in table 3 for 400 simulations of the network.

The statistics calculated for the sink node, N4, represent the values associated with the time of completion of the network. From table 3, it can be seen that N4 occurs with a probability equal to 1.0 and the network has a mean realization time of 14.50 days (time for first car to be returned to town 2) with a standard deviation of 6.62 days. The range varied from 6 to 51 days. Node type "F" signifies that statistics were collected from the first realization of the node. The second row in the printout summarizes the statistics concerning the number of activities tagged with a counter #1, which were completed prior to network realization. In the car rental example, an average of 2.83 cars were returned to town 1 (N3) prior to the return of a car to town 2 (N4).

A histogram for N4 is also presented in Table 3. Since the lower limit is 3 and the cell width is also 3, it can be seen that no cars were returned to town 2 for 6 days and in 77 of the 400 simulation runs a car was

Table 3

An Example of the GERTS III Summary Report: Car Rental Problem

Final Results for 400 Simulations

Node	Prob./Count	Mean	Std.Dev.	# of Obs.	Min.	Max.	Node Type
4	1.0000	14.5050	6.6170	400	6.0000	51.0000	F
4	1	2.8350	2.2057	400	0.0000	15.0000	

Histograms

Node	Lower Limit	Cell Width	Frequencies										
4	3.00	3.00	0	0	77	50	55	59	78	42	19	11	6
			1	0	0	1	0	0	1	0	0	0	0
			0	0	0	0	0	0	0	0	0	0	0

returned to town 2 (network was realized) between the 6th and 9th day. The last car to be returned fell in the interval between the 51st and 54th days. Other values can be read directly from table 3.

GERTS III Q

The GERTS III Q program is an extension of GERTS III which includes the capability to model systems requiring information storage (Pritsker and Burgess, 1970). The Q-node is the only new feature of GERTS III Q. When an activity incident to a Q node is completed an item (customer, transaction, etc.) is said to have arrived at the queue. The activity emanting from a Q node represents a service activity requiring some time to complete.

It is assumed that only one item can be served at a time. Therefore, when an item enters a queue it will be immediately served (the service activity is scheduled to occur), or, if an item is currently being served, the item will remain in the queue and the GERTS program will update the number of items waiting to be served by 1. Items in a queue waiting to be served may eventually be served on a first-in-first-out (FIFO) or last-in-first-out (LIFO) basis. The programmer can initiate the simulation with items already in a queue and can also specify a maximum number of items permitted in a queue. When this maximum is surpassed during the course of a simulation and a new item arrives, the item will leave the system or be sent to a given node (balk).

The input format for GERTS III Q is identical to GERTS III except that data card type 3 (see table 2) is modified to include Q node information.

III
Analyzing Markov Chain Processes with GERTS

A review of the more recent literature on mathematical psychology will demonstrate a prevalence of Markov chain models (Atkinson, Bower, & Crothers, 1965; Coombs, Dawes, & Tversky, 1970; Levine & Burke, 1972; Greeno, 1973). Since many Markov processes can be solved with flowgraph techniques (Howard, 1971), it is reasonable to expect that G.E.R.T. network analysis would also be useful in this context. Whitehouse (1965) in investigating this relationship has found G.E.R.T. quite applicable to discrete, continuous, and semi-Markov representations. The transition probability matrix of a Markov process, and hence the process itself, can be graphically represented by a G.E.R.T. network; the nodes became the states through which the system can pass, and branches take on the values of transition probabilities. For Markov chains the transitions occur at every time unit and the probability of making a transition to each state depends only on the current state of the process. A semi-Markov process permits the time between transitions to have any distribution, and to depend upon the present state and the next future state.

Although analytical methods, and in particular G.E.R.T., can be used successfully to evaluate certain Markov processes, the same might be determined using the GERTS simulation program. Sinulation is especially useful if a computationally unmanageable mumber of states evolves or if the system is semi-Markov in nature. Since GERTS permits tagging an activity with a counter, it becomes a simple matter to investigate the frequency with which an activity is performed. This same question would be difficult to answer using standard Markov procedures (Whitehouse, 1965). Finally, it is possible to demonstrate that GERTS is successful in providing estimates of transient as well as steady state probabilities, and also in calculating sequential statistics relevant to certain Markov Models.

In this chapter, statistics of interest are determined for several Markov-type models using the GERTS simulation analysis. Examples are chosen from the literature in concept identification, choice behavior, and social mobility theory to demonstrate GERTS versatility in solving absorbing, random walk, and regular Markov processes. In addition, an analysis is performed concerning the size of the runs necessary to obtain results within given tolerances.

Simulating an Absorbing Markov Process: Concept Identification

An absorbing Markov chain is a chain that has one or more states which will terminate the transition process once they are entered. In other words, at least one transition probability has a value equal to one. Since the GERTS network is defined as having at least one absorbing state (sink node), it is likely that the GERTS approach is well suited for this type of problem. Whitehouse (1965) has shown this to be the case for G.E.R.T. network analysis.

The model chosen to illustrate GERTS capability in analyzing absorbing Markov processes is based upon Bower and Trabasso's (1964) extension of a simple model of problem solving in concept identification given by Restle (1962). First, a review of the concpt identification paradigm is in order.

An experiment in concept identification is usually conducted using a set of stimuli generated by varying the values of certain dimensions such as shape, size, and color. The experimenter decides on a rule for classifying the stimuli (usually into two categories) and the subject's task is to identify this classification schema. In the experiment, stimuli are shown to the subject one at a time, and the subject indicates which category he thinks the stimulus belongs in.

Feedback is given after each trial. The experimenter infers that the correct rule has been identified when the subject has given a long series of correct responses.

According to the model proposed by Restle (1962) the subject has a set of hypothese about what might be the correct rule. If the classification hypothesis he is using is inconsistent with the information he receives he rejects the hypothesis and samples a new hypothesis. Atkinson, Bower, and Crothers (1965) have provided a simple representation of the subject's state of knowledge in this situation: a presolution state, $\overline{S}$, and a solution state, S. When in S, the subject attends to the relevant attribute and always responds correctly. In state $\overline{S}$ he is attending to irrelevant attributes. It is assumed that the subject begins in $\overline{S}$ and makes a response. If he is correct (with a probability, p) he assumes that he has chosen the proper hypothesis. If he makes an error (with a probability, $q = 1-p$) he randomly samples another hypothesis from the total pool of possible hypotheses. He has a probability, c, of sampling the correct hypothesis. The model implies that while in pre-solution the response on a given trial is independent of the outcomes of the preceding trials, and therefore constitutes a Bernoulli series of observations. The theory also implies that the transition to S can only occur when the subject makes an error while in $\overline{S}$ and then samples the correct hypothesis. In this system once a problem solver samples the correct hypothesis he will be absorbed in S.

The transition matrix corresponding to the two-state concept identification model is as follows:

$$\begin{array}{c} \\ \bar{S}_n \\ S_n \end{array} \begin{array}{c} \begin{array}{cc} \bar{S}_{n+1} & S_{n+1} \end{array} \\ \begin{bmatrix} 1-qc & qc \\ 0 & 1 \end{bmatrix} \end{array}$$

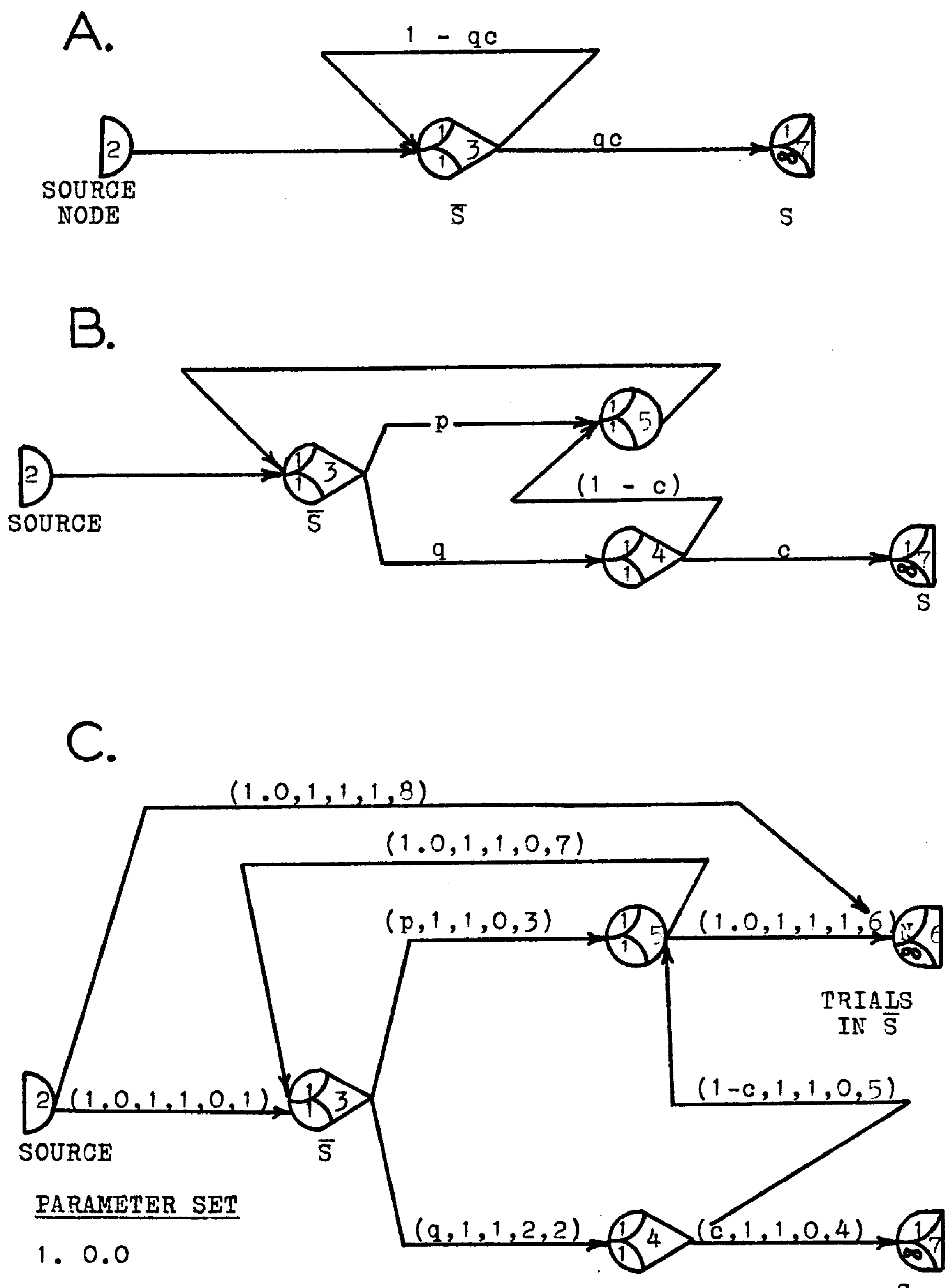
where the state on trial n is denoted $\bar{S}n$ or Sn.

The simplest GERTS network description of this model is shown in figure 3A. Here states $\bar{S}$ and S are represented by N3 and N7 respectively. By assumption the process begins in $\bar{S}$ on trial 1; therefore, the source node (N2) feeds directly into $\bar{S}$. The transition probability of moving from pre-solution to solution, qc, is shown on P(3,7). The probability of remaining in pre-solution, 1 - qc, is represented by the feedback loop.

Since the parameters p, q, and c are to be considered separately, an expansion of the network is required (see figure 3B). This revision includes two additional states: the probability of being in $\bar{S}$ following an error, N4, and the probability of being in $\bar{S}$ following a correct response or an incorrect hypothesis selection, N5. It is easy to demonstrate that the input into N3 in figure 3B is equivalent to the feedback loop in figure 3A:

$$\begin{aligned} P(\bar{S}) &= p + q(1-c) \\ &= p + q - qc \\ &= 1 - qc \end{aligned}$$

Figure 3. Three stages in the development of a GERTS network representation of the concept identification model.


A.
1 - qc
2
3
qc
7
SOURCE
NODE
$\bar{S}$
S
B.
p
5
2
3
(1 - c)
4
q
c
7
SOURCE
$\bar{S}$
S
C.
(1.0,1,1,1,8)
(1.0,1,1,0,7)
(p,1,1,0,3)
(1.0,1,1,1,6)
6
TRIALS
IN $\bar{S}$
(1-c,1,1,0,5)
2
(1.0,1,1,0,1)
3
SOURCE
$\bar{S}$
PARAMETER SET
1. 0.0
(q,1,1,2,2)
4
(c,1,1,0,4)
7
S

whereas P(S) remains equal to qc.

One final node is required. In order to determine statistics following a given number of trials in pre-solution, N, node 6 will be used as a trial counter and possible sink node. The final GERTS network with appropriate notation is shown in figure 3C.

The subject is in $\bar{S}$ before making his first response. This is simulated in figure 3C when N2 schedules an activity imputing directly into N3. N2 also schedules an activity leading into N6, the trial counter. Should the hypothetical subject make a correct response on trial #1 [P(3,5) scheduled], then he will remain in $\bar{S}$ [P(5,3) will be scheduled] at the start of trial #2 [P(5,6) will be scheduled]. If he should proceed to make an error on trial #2 [the activity represented by P(3,4) would be realized], he would then sample a new hypothesis and either P(4,5) or P(4,7) would be scheduled depending upon whether he had sampled an incorrect or a correct hypothesis. P(4,5) serves to retain the subject in $\bar{S}$ at the start of the next trial. The transition into the absorbing state, S, is made when the activity associated with P(4,7) has been completed. The mean number of trials, in $\bar{S}$ was determined by first placing a counter (#1) on P(2,6) to record trial #1 and by also placing counter #1 on P(5,6) to enable subsequent pre-solution trials to be tallied. P(3,4) was tagged with counter #2 so that simulated error responses could be tallied.

The analytical solutions to the statistics of interest concerning the concept identification model were derived by Bower and Trabasso (1964) using linear operators. Simulated results will be compared directly to these predictions and, whenever possible, to observed data. In each of Bower and Trabasso's analyses p was assumed equal to .5 (therefore q also equals .5). This was because the experimental situation dictates that a subject make one out of two possible responses based on an irrelevant cue, and it is assumed that he is operating near the chance level in $\overline{S}$. The value of c can be estimated analytically as the reciprocal of the observed mean total errors, and equals .0873 for the data collected by Bower and Trabasso. These same values for p, q, and c were used in the GERTS analysis, although an experimenter could run a simulation of the network in figure 3C and choose that value for c which provides an accurate estimate of the observed mean total errors. The value for c would then be used in further simulation analyses to predict other important summary statistics concerning concept identification.

The initial statistics analyzed with the GERTS approach were the mean and standard deviation of the number of trials in $\bar{S}$. In this analysis the solution node, N7, was made the sink node. Table 4 presents the summary of 500 simulation runs of the network shown in figure 3C. The results indicate that node 7 was realized with a probability equal to 1, and that no time elapsed in performing activities leading to network realization. The statistics associated with counter #1 indicate that the average number of trials before the realization of N7 (solution) was simulated as 22.15 while the standard deviation of trials was simulated as 23.89. This compares with 22.90 and 22.40 for the mean and standard deviation determined analytically, and an observed mean and standard deviation of 22.89 and 22.39. The statistics associated with counter #2 predict the mean and standard deviation of the total number of errors made in $\bar{S}$. Referring once again to table 4, the results obtained from the GERTS simulation of the concept identification model yielded a mean of 11.12 errors and a standard deviation of 11.59 errors. This compares with an observed mean number of errors equal to 11.45 and an observed standard deviation of 11.02 errors. The corresponding predicted mean number of errors also should equal 11.45, since the parameter used to calculate the mean number of errors (c) was directly estimated from the observed mean number of errors. The predicted standard deviation of the number of errors equalled 10.96.

Table 4

GERTS Summary Report for the Network Shown in Figure 3c

Final Results of 500 Simulations

Node	Prob./Count	Mean	Std.Dev.	# of Obs.	Min.	Max.	Type
7	1.0000	0.0000	0.0000	500	0.0000	0.0000	F
7	1	22.1480	23.8865	500	1.0000	172.0000	
7	2	11.1220	11.5876	500	1.0000	92.0000	

The probability of being in solution after n trials, P(Sn), was then determined. The only necessary alteration of the network was to set the number of releases on N6 equal to the value of n and to assigm N6 the status of a sink node. The realization of either N6 or N7 halted the simulation. Simulated probabilities of solution were calculated for various values of n. Table 5 shows these values for 500 simulations and the corresponding analytical solutions. Bower and Trabasso (1964) offer no empirical data concerning P(Sn), but such data could be readily obtained.

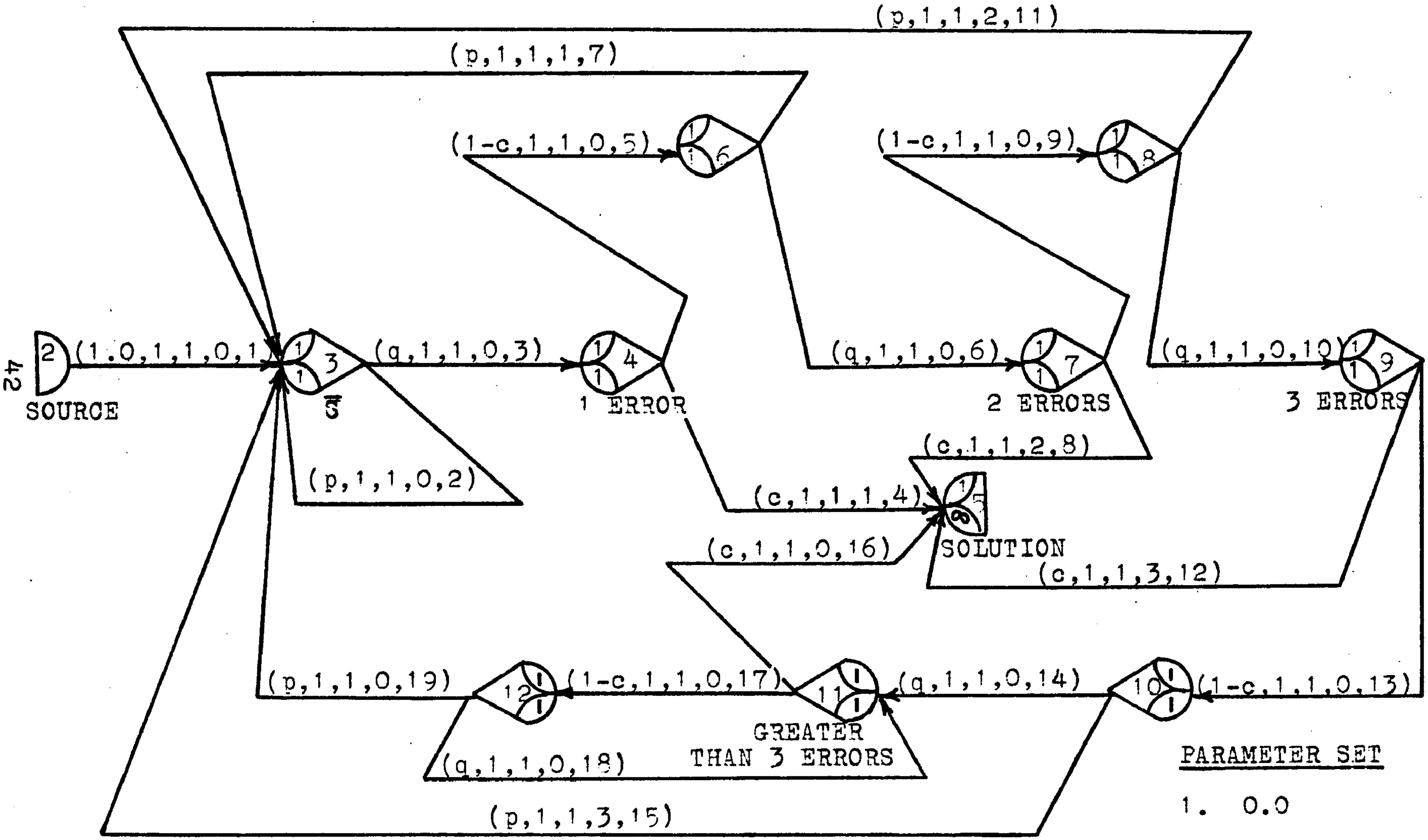
Error runs were simulated to demonstrate the utility of GERTS in solving sequential statistics. In the concept identificaton paradigm, an error run (rn) is defined as any number of consecutive errors preceded and followed by a correct response (the subscript n refers to the length of the error run). Figure 4 is the GERTS representation of the network required to simulate the average number of error runs for n = 1, 2, and 3. In the present model a correct response can result from either the subject selecting the correct hypothesis and moving into S or selecting the incorrect hypothesis but still guessing correctly on a given trial (remains in $\overline{S}$). Consequently both P(4,5) and P(6,3) were tagged with counter #1 which in turn permitted r_1 to be tallied. Counter #2 on P(7,5) and P(8,3) and counter #3 on P(9,5) and P(10,3) simulated

Table 5

Simulated Values of P (Sn) Based on 500 Computer Runs Along With Analytical Values

N	Simulated	Predicted
5	.154	.163
10	.328	.330
20	.562	.570
40	.796	.824

Figure 4. A GERTS network for analyzing error run statistics in the concept identification model.



PARAMETER SET

1. 0.0

r_2 and r_3 respectively. Runs greater in length than r_3 eventually moved the system to N11 where subjects could: continue making errors, move into the solution state, or start the run count again. When the solution node (N5) was realized the network was realized.

Table 6 lists the mean values for r_1, r_2, and r_3, derived from the GERTS simulation of the network in figure 4, predicted analytically, and observed in a concept identification experiment. An inspection of the results tabulated suggests that the generation of the simulated data is consistent with the analytical solution and actual empirical data.

Table 6

Comparison of GERTS Solution and the Predicted and Observed Values for Mean Error Runs of Length n = 1, 2, and 3.

	Simulation (500 runs)	*Analytical Solution	*Observation
r_1	3.28	3.34	3.11
r_2	1.58	1.55	1.72
r_3	.71	.71	.76

*Taken from Bower and Trabasso (1964)

Simulating a Random Walk Process: Choice Behavior

Consider a process such that if it is at state j, at all instants of time the process moves to the right to state $j + 1$ with a probability, p, or to the left to state $j - 1$ with a probability, $q = 1-p$. Such a situation defines a one-dimensional random walk process. One special type of random walk chain defines the two end states as absorbing states. This process will be considered next in the context of a model designed to describe choice behavior.

The random walk models offered by Bower (1959) attempt to analyze the behavior of a subject when he is given the opportunity to select one discriminative stimulus from a set of alternatives. Choice behavior of a rat in a T-maze serves as a useful example. In this situation when the animal reaches the choice point it spends a great deal of time orienting first toward one goal box then towards the other until it eventually makes the choice response. The particular behavior of orienting back and forth between alternatives is known as "vicarious trial and error" (VTE) behavior.

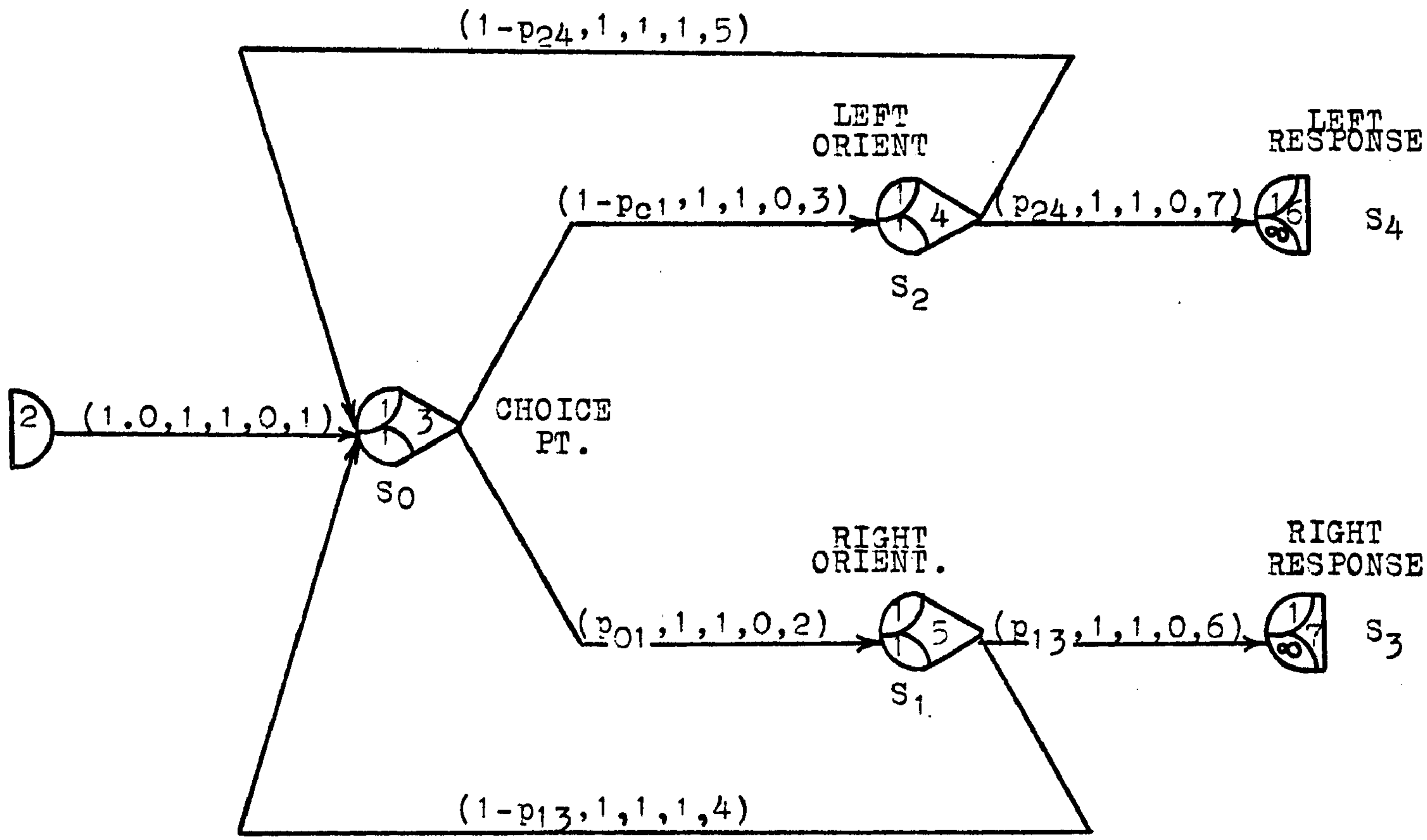
One of Bower's models of choice behavior in a T-maze, model A, defines five states: when the subject is at the choice point and orienting straight ahead he is in state S_0. At this time the subject leaves S_0 and may either orient his body towards the right goal, state S_1, or orient his body towards the left goal, state S_2. When the subject is in state S_1 he either approaches the right goal, state S_3, or reorients away from S_1 and reverts to the neutral state S_0. When the subject is in state S_2 he may either approach the left goal, state S_4, or reorient to S_0. States S_3 and S_4 are absorbing states since a particular experimental trial is terminated when the animal approaches either side of the maze.

It is possible to empirically estimate the state to state transition probabilities from the sequence of orienting responses that occur on individual trials of an experiment. The transition matrix takes the following form:

		NEXT STATE				
		S_0	S_1	S_2	S_3	S_4
	S_0	0	p_{01}	$1-p_{01}$	0	0
CURRENT	S_1	$1-p_{13}$	0	0	p_{13}	0
STATE	S_2	$1-p_{24}$	0	0	0	p_{24}
	S_3	0	0	0	1	0
	S_4	0	0	0	0	1

The GERTS network diagram representing the random walk process is shown in figure 5. The definition of a trial in a T-maze ensures that the subject begins every trial in S_0. Therefore the source node, N2, directly inputs into N3. Since choice time is not of concern in this model, transitions are assumed to occur instantaneously. Consequently all branches have $t_p = 1$

Figure 5. The GERTS representation of the random walk model for choice behavior in a T-maze.



PARAMETER SET

1) 0.0

and $t_D = 1$ (0.0 time to complete the activity and a constant time distribution). Once a subject enters S_0, he may proceed to S_1 with a probability equal to p_{01} [represented on branch P(3,5)] or he may orient to S_2 with a probability equal to $1 - p_{01}$ [see branch P(3,4)]. The probability of reorienting to S_0 from S_1 or S_2 is represented by the feedback loops P(5,3) and P(4,3) respectively. Finally, P(5,7) designates the transition probability of approaching the right goal from S_1 while P(4,6) represents the transition probability of approaching the left goal from S_2. Realization of either N6 or N7 serves to halt the simulation of this network.

One of the most interesting statistics to be predicted by this model concerns the mean number of VTE's within the sequence of orienting responses that constitutes one trial. VTE behavior is represented on the GERTS network by P(5,3) and P(4,3); therefore, these branches have counters associated with them ($C = 1$). All other branches have C equal to 0.

An experiment was performed (Bower, 1959) in order to provide estimates of the transition probabilities on each of 11 trials in the T-maze paradigm. In this study, rats were rewarded with 5 food pellets when entering the right goal box and 1 pellet when a left response was made. It was observed that the $p_{01} = .5$,

$p_{13} = .55$, and $p_{24} = .37$ for trial #1. Given these transition probabilities, the calculted mean number of VTE's on trial #1 is equal to 1.17, while the calculated probability of a right response is .60 on trial 1.

The final results for 900 simulations of trial #1 are provided in table 7. It is evident that the realization of either N6 or N7 required 0.0 time. The probability of making a right response (being absorbed in S_3) was approximately .59. This compares favorably to the predicted results. The mean number of VTE's was summarized separately prior to the realization of N6 and N7. The two results, 1.17 prior to N6 and 1.22 prior to N7, are almost equal. This is also a reasonable finding since Atkinson, Bower, and Crothers (1965) have proven that the average amount of VTE-ing should be equivalent regardless of whether the subject terminates a trial in S_3 or S_4.

It is possible to use GERTS to test other assumptions of the choice behavior model by making a few modifications to the network in figure 5. For instance, Bower (1959) has suggested that perhaps subjects orient back and forth between S_1 and S_2 and use S_0 only to determine the starting point of the cycles of reorientation. He calls this model B. A revision could be accomplished, reflecting these new assumptions, by requiring that P(5,3) input into N4 rather than N3 and by having P(4,3) input into

Table 7

GERTS Summary Report for the Choice Behavior Model

Final Results of 900 Simulations

Node	Prob./Count	Mean	Std.Dev.	# of Obs.	Min.	Max.	Type
6	.4122	0.0000	0.0000	371	0.0000	0.0000	F
6	1	1.1752	1.5331	371	0.0000	9.0000	
7	.5878	0.0000	0.0000	529	0.0000	0.0000	F
7	1	1.2155	1.6140	529	0.0000	12.0000	

N5 as opposed to N3.

Another efficient use of the GERTS approach would involve expanding the random walk model of choice behavior to include data regarding decision times. The process then becomes semi-Markov in nature and analytical solutions become exceedingly difficult. This is especially true if the steps between any two adjacent states require different average times of completion- even if the distributions can be assumed to take the same form.

Simulating A Regular Markov Process: Social Mobility Theory

A Markov chain is considered regular if and only if it is possible to be in any state after some number (N) of steps. The long range prediction of being in any state, known as the steady-state probability victor (α), is independent of the initial state of entry. It has also been demonstrated (Kemeny & Snell, 1960) that α is approach very rapidly and can be approximated even for moderately large values of N.

Kemeny and Snell (1960) have analyzed a problem in occupational mobility using a regular Markov chain. The problem is really two-fold and may be stated as follows. First, given that the total population is presently separated into occupational classes and that there is a degree of movement among the classes each generation, what is the fraction of the population which will be in each of the classes after N generations? This can be called the transient probability vector, β, which approaches α as N approaches infinity. The second question concerns the calculation of the mean first passage time-in this case the average number of generations required to move to each class given the individual begins in a particular class.

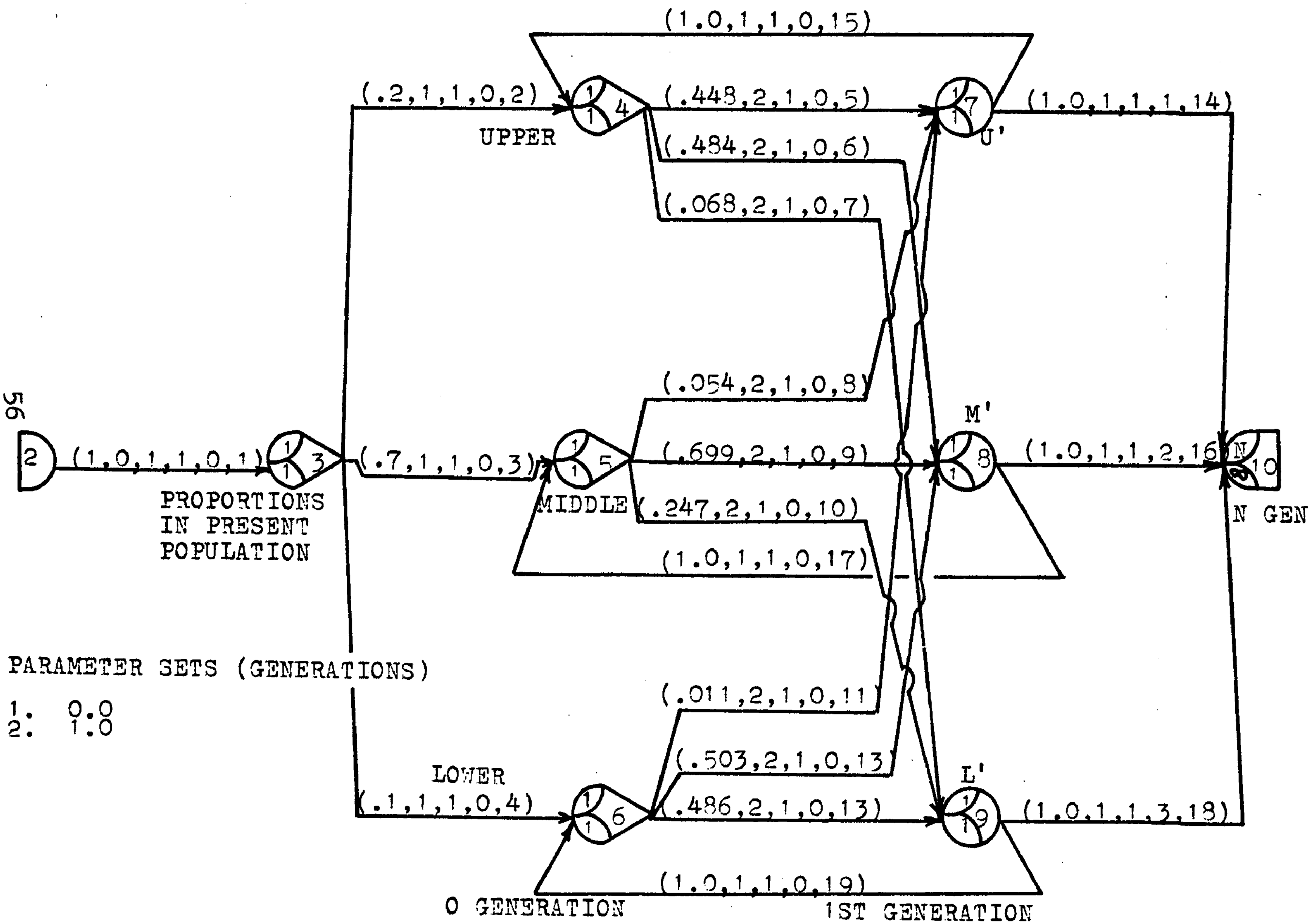
A transition matrix is first constructed which designates for each class the fraction of the decendents that would be expected to go into each of the occupations. Assume that occupations are classified as upper, middle, and lower. The matrix below summarizes the transition probabilities constructed from data collected in England and Wales (Glass & Hall, 1954):

$$
\begin{array}{ll}
 & \text{NEXT GENERATION} \\
 & \begin{array}{ccc} \text{Upper} & \text{Middle} & \text{Lower} \end{array} \\
\begin{array}{r} \text{PRESENT Upper} \\ \text{Middle} \\ \text{GENERATION Lower} \end{array} &
\begin{bmatrix} .448 & .484 & .068 \\ .054 & .699 & .247 \\ .011 & .503 & .486 \end{bmatrix}
\end{array}
$$

In this example, also assume that initially 20% of the population is in the upper class, 70% in the middle class, and 10% in the lower class.

The GERTS diagram for the social mobility model is represented in figure 6. N2 initiates the simulation by hypothetically sending one individual into the system. N3 randomly schedules one of three branches that determines which occupational class the individual presently resides: with a .2 probability the individual is currently a member of the upper class, with a .7 probability he is a member of the middle class, and with a .1 probability he is in the lower class. Up to this point in the network no time has elasped and all branches have been designated with parameter set 1 and a constant time distribution. Movement from the states in one generation to the states in the next generation was accomplished with 3 new sets of deterministic nodes- N7, N8, and N9 each representing the upper, middle, and lower classes

Figure 6. A GERTS network of the regular Markov process for social mobility.


(1.0,1,1,0,1)
PROPORTIONS
IN PRESENT
POPULATION
(.2,1,1,0,2)
UPPER
(.7,1,1,0,3)
MIDDLE
(.1,1,1,0,4)
LOWER
(1.0,1,1,0,15)
(.448,2,1,0,5)
(.484,2,1,0,6)
(.068,2,1,0,7)
(.054,2,1,0,8)
(.699,2,1,0,9)
(.247,2,1,0,10)
(1.0,1,1,0,17)
(.011,2,1,0,11)
(.503,2,1,0,13)
(.486,2,1,0,13)
(1.0,1,1,0,19)
O GENERATION
1ST GENERATION
U'
M'
L'
(1.0,1,1,1,14)
(1.0,1,1,2,16)
(1.0,1,1,3,18)
N GEN.
PARAMETER SETS (GENERATIONS)
1. 0.0
2. 1.0

respectively. Recall that a regular Markov chain has no absorbing states. The use of these extra nodes enabled the system to eventually terminate with the realization of sink node, N10, after N generations.

In following the hypothetical individual who is in the system in the current generation, assume that he is a member of the middle class [P(3,5) has been completed]. The 3 branches emanting from N5 represent that the probability that his decendent will move from the middle class to the upper class [P(5,7)], remain in the middle class [P(5,8)], or move from the middle class to the lower class [P(5,9)]. Each of these paths has associated with it the time parameters $t_p = 2$ (1 generation) and $t_D = 1$ (constant time distribution). For example, assume that the first descendent moves into the lower occupational class [Completes P(5,9)]. Since N9 is deterministic two activities are scheduled to occur with a probability of 1.0. P(9,10) inputs into the sink node and registers the fact that one generation has elapsed. P(9, 10) requires 0.0 time and is tagged with a counter (c = 3). P(9,6) resets the system such that another transition can occur in the second generation. This process continues until N10 is realized, ending one simulation run. The succeeding runs simulate the occupational mobility of the descendents of additional individuals.

Table 8 offers the results of 500 simulations of 50 generations of social mobility. N10 has been realized on each run with a time to realization of 50 generations. Counter #1 states the mean number of individuals making transitions to the upper class (3.53), counter #2 provides the mean number of occurrences of movement to the middle class (31.07), while counter 3 indicates mean movement to the lower class (15.40). Simply divide by 50 to obtain the fraction of individuals in each of the classes after 50 generations (B_{50}). B_{50} = .071, .622, .308 for the upper, middle, and lower classes respectively. This compares favorably with α = .069, .624, .309 given by Kemeny and Snell (1960) for the steady state probabilities in this sample. A second analysis of the regular Markov process was performed simulating only 10 generations. B_{10} resulted in simulated values of .080, .635, and .285- all approaching the steady state predictions.

A few minor revisions in the network in figure 6 were performed in order to calculate the mean first passage time. For example, in analyzing the average number of generations required to move to each class given the individual was a member of the lower class (N6) in the present generation, it was necessary to delete P(2,3), P(3,4), P(3,5), and P(3,6). A branch from N2 to N6 initiated the simulation. N7, N8, N9, and

Table 8

GERTS Summary Report for the Social Mobility Problem

Final Results for 500 Simulations

Node	Prob./Count	Mean	Std.Dev.	# of Obs.	Min.	Max.	Type
10	1.0000	50.0000	0.0000	500	50.0000	50.0000	F
10	1	3.5340	2.8328	500	.0000	15.0000	
10	2	31.0660	4.1250	500	20.0000	43.0000	
10	3	15.4000	4.2779	500	3.0000	28.0000	

N10 were made sink nodes and all of these nodes had to be realized before the network was realized. The value of N was set equal to 1 for N10. The average time to realize N7, N8, and N9 corresponded to the mean first passage time to the upper, middle, and lower classes respectivly. The simulated data is listed in table 9 for 400 simulations, with the corresponding predicted mean passage times calculated by Kemeny and Snell (1960). For instance, the GERTS solution indicates that it requires an average of 24.2 generations to move from the lower occupational class to the upper occupational class. It is apparent that the simulated data is similar to the analytical predictions.

Table 9

A Comparison of Simulated and Predicted Mean First Passage Times for the Social Mobility Model

	Upper	Middle	Lower
Simulated	24.2	1.8	3.2
Analytical Solution	26.5	1.9	3.2

Runs Analysis for Simulated Markov Chains

One determination of the degree of success of simulated Markov chains can be achieved through an analysis of the number of runs necessary to obtain results within given tolerances. If k equals the magnitude of the error following a simulation, then the probability that the simulated mean will fall between $\pm$ k of the predicted mean 95% of the time is:

$$P(u - k \leq \bar{x} \leq u + k) = .95$$

Subtracting u:

$$P(-k \leq \bar{x} - u \leq +k)$$

Dividing by the standard deviation of the sample:

$$P\left(\frac{-k\sqrt{N}}{S_x} \leq Z \leq \frac{+k\sqrt{N}}{S_x}\right)$$

Since a Z score greater than or equal to 1.96 occurs less than 5% of the time then,

$$\frac{k\sqrt{N}}{Sx} = 1.96$$

and $$k = \frac{1.96\ Sx}{\sqrt{N}}$$

The percentage error achieved 95% of the time is calculated by dividing k by the predicted value, u. Therefore,

$$\text{Percentage Error} = \frac{1.96\ Sx}{\sqrt{N}\ u}$$

Each of the analysis in this chapter was performed for 100, 200, 300, 500, and 900 simulation runs. The percentage error was then calculated for each result. Table 10 lists the percentage error as a function of the number of simulation runs for 5 simulation analyses of Markov processes. As might be expected, the percentage

Table 10

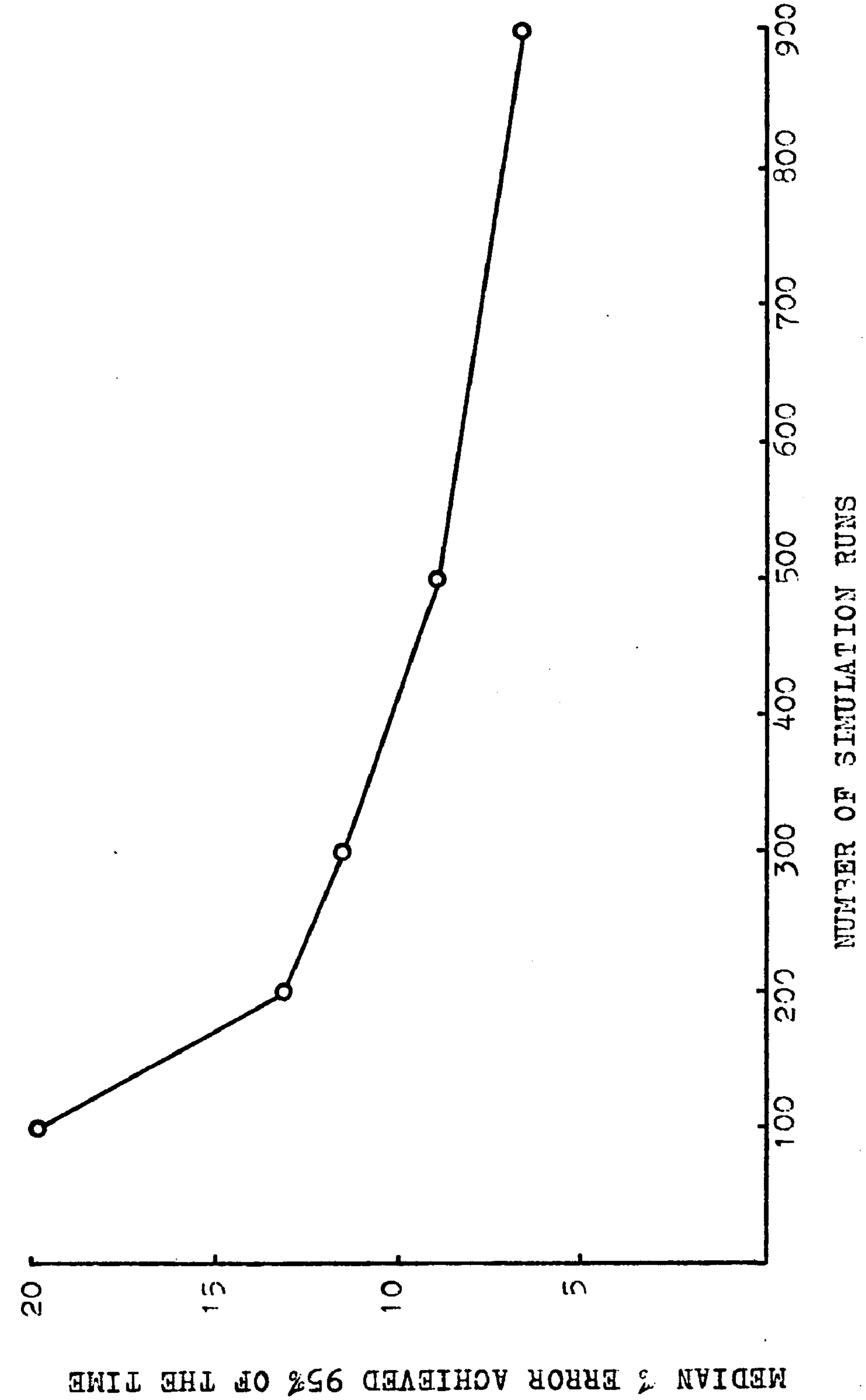
The Percentage Error in Simulated Results Achieved 95% of the Time

		Markov Analysis Performed				
		Mean Trials in concept Identification	Mean Errors in concept Identification	Mean r_1 in concept Identification	Mean VTE's in Choice Behavior	Mean First Passage Time
	100	19.8	18.5	23.4	32.0	14.8
Number	200	13.0	12.8	16.8	13.9	13.1
of	300	11.8	11.4	10.1	17.0	11.1
Runs	500	9.2	8.9	8.6	13.2	8.5
	900	6.7	6.6	6.8	8.5	6.3

error decreases as the number of runs increases. It should also be noted that the accuracy of simulated results depends, to a large extent, on the type of analysis performed.

Figure 7 is a graph of the median percentage error achieved 95% of the time as a function of the number of simulation runs. For the problems discussed in this chapter, a reasonable degree of accuracy ($<$ 10% error 95% of the time) can be achieved with 400 simulation runs.

Figure 7. The median percentage error as achieved 95% of the time as a function of the number of simulation runs. Each point is based on five Markov analyses.


NUMBER OF SIMULATION RUNS
100
200
300
400
500
600
700
800
900
MEDIAN % ERROR ACHIEVED 95% OF THE TIME
20
15
10
5

IV

A GERTS Simulation Approach to Teaching Psychology

The use of computer simulation as an aid to learning has grown rapidly in the last few years at all levels of education. Probably the most interesting application of simulation techniques in education exists in computer-based games. The Sumerian game devised by Moncrieff (1965) is one of the better known simulation games and may serve as an example. In this game sixth grade history students are presented with information related to an ancient city for which they are playing the role of king. The students make certain decisions regarding their city-state and a computer returns a progress report on the effects of these decisions. Unanticipated natural events can be cycled in randomly by the computer. Not all computer games follow this format. Where they do differ, it usually is with regards to the preciseness of their rules and goals. For instance, although it is common to determine winners at the end of these games, some simulations are only loosely evaluated and are scored as exercises not contests.

There are many virtues in using computer simulation as a medium for instruction. First the computer is very flexible and responsive. Most students tend to focus on only one aspect of a phenomenon at a time, greatly limiting their ability to understand phenomena with even a few interactions among elements. Through simulations the learner experiences these complexities in trial form, and consequently acquires a belief in the predictability and responsiveness of his environment. It is interesting to note that Coleman and Campbell, et.al. (1966) have shown that such a belief (efficacy) is the most important predictor of achievement in school.

That models developed for the classroom often use probabilistic mechanisms to simulate environments has certain advantages. The natural interest of the student participating in such schemes may lead to the learning of simple probability from a series of direct experiences.

The greatest virtue of the computer-based approach is its ability to provide individualized instruction. Variation in the sequence and difficulty of the problems can be made in accordance with individual differences.

Do the procedures inherent in the digital simulation approach meet the goals of contempary education? Bruner (1960), in summarizing the conclusion of a national conference on education, emphasized that the proper content of education was the fundamental structure of the material- as opposed to the factual detail of the subject matter. Structure is related to the ideas and themes which lie at the heart of each subject. The conference also pointed out the important role of intuitive thinking in the process of learning; particularly the advantages of the shrewd guess, the tenative hypothesis, and in general, inductive thinking as a way of discovering structure. Similarly, digital simulation approaches are highly dependent upon the manner in which the activity of learning is structured; i.e., the kinds of actions the learners take and the kinds of feedback they get in return. The very process of formulating the model forces attention of these problems.

Theoretically, one cannot help but get enthusiastic over digital simulation exercises and games as aids to learning. However, some researchers have attempted to validate these approaches in controlled experiments-often with mixed results. Probably the most important study was the evaluation of the Northwestern Internation Simulation (INS) (Robinson, 1965). This study compared college students who played INS with a control class which had the material introduced via case studies. Robinson found few significant differences on a number of measures of achievement and interest. Cherryholmes (1966) concludes that games do motivate, but there is no substantial evidence that they teach facts or problem-solving skills, or that they induce critical thinking any more effectively than other methods of learning. Wing (1968) got results which were more encouraging. His study demonstrated that although there was no appreciable gain in measured learning effectiveness, there was a decrease in the time invested per pupil under game-study conditions. These contradictory findings point to the extreme complexity of evaluating these procedures.

Because of their limitations, simulation games and exercises should probably be used as an adjunct to the regular curriculum with extensive classroom discussion following. Sprague (1966) conveys this idea nicely in the following three suggested strategies:

> a)We should design and try packaged units of study built around simulations with suggested readings, guides for incorporating the units into existing standard courses, and suggestions for ways in which simulations can be varied in form and content to meet demands of different settings.
> b)Whole courses should be constructed around one or more simulations and tried in a variety of situations.
> c)Taking an even broader look, we might envision a whole series of, for example, international relations simulations, the simplest of which could be tried by first graders, slightly more complex varieties by more advanced students, and so on. By the time a student reached his senior year in high school, he might be taking part in simulations far more elaborate and demanding, having had 10 years of simulation experience.

Main (1972) at the University of Michigan has begun the development of "EXPER SIM" (Experiment Simulation), a course designed to develop predictive skills in the student. In this program, graduate students construct models using a general purpose computer language written in Fortran IV. The undergraduate experimenter then generates hypotheses within a given problem area, designs experiments, and uses the developed simulation models to generate hypothetical data which is consequently compared to predicted results. A pilot study (Main, 1971) has demonstrated that the computer experience tends to affect certain student biases towards research design- not always in the preferred direction. Students who experience classroom demonstrations, on the other hand, show relatively stable attitudes when comparing pre-course and post-course surveys. Much more work is obviously needed in this area.

The following sections will serve to demonstrate the feasibility of using GERTS to describe and simulate empirical data in five areas of psychology. One or more of these units could serve as a supplement to traditional undergraduate and graduate laboratory experience. Instructors would spend perhaps one class period teaching students the mechanics of GERTS. Students would then be introduced to current literature in the area represented by a given unit. Selected variables within that well-defined problem area would be described. A student would then be asked to systematically alter some of the independent variables or elements modeled, and to predict their effects on the performance of a given teaching unit. He keypunches the appropriate information concerning the state of a particular unit on I.B.M. cards and in a reasonably brief period, he receives output concerning the simulated behavioral response. It is also possible for more advanced students to develop their own simulation models or to make revisions in the present units. Proposed modifications will be suggested in conjunction with each unit described in this chapter.

Unit I
Imprinting Behavior

The initial simulation exercise concerns variables believed to influence imprinting behavior. The term imprinting refers to the attachment of a complex behavior pattern to a stimulus which happens to be present at optimal times in the development of an organism. Attention was first drawn to imprinting by the European naturalist, Lorenz (1935), who argued that this behavior differs markedly from other learning processes. Bateson (1966) and Sluckin (1964) offer excellent discussions of the characteristics of imprinting behavior.

One principle characteristic that distinguishes imprinting from learning is the existence of a critical period- the time during which the animal may develop a preference to a wide variety of objects and eventually reject others. Hess (1959) carried out a series of controlled experiments with ducklings from one to 32 hours after hatching. He found that animals who were shown a male decoy 13 to 16 hours after hatching demonstrated the strongest preference for this model, as opposed to a real female mallard. There was a dramatic drop in the effectiveness of the imprinting procedure when given earlier or later in the animal's development. The present model attempts to simulate this finding.

Most theories which speculate on the nature of the development of imprinting behavior during the critical period hypothesize two factors: one causing an increase in readiness to accept the training stimulus and one causing the subsequent decline in imprinting behavior during the end of the critical period.

Two popular explanations for the onset of the critical period involve either a hypothetical increase in locomotor ability (Hess, 1959), or an increase in arousal (Tolman, 1963). There is considerable evidence to support the arousal theory since shock (Hess, 1964), handling (Thompson & Dubanowski, 1964) and certain stimulants (Kovach, 1964) facilitate imprinting up to 18 hours after hatching. On the other hand, Collins (1965) has demonstrated that chicks which had been restrained from following the training object, followed it just as strongly when tested as did chicks that had been given the opportunity to follow during training. This evidence appears to undermine the importance of locomotion during the early stages of the critical period.

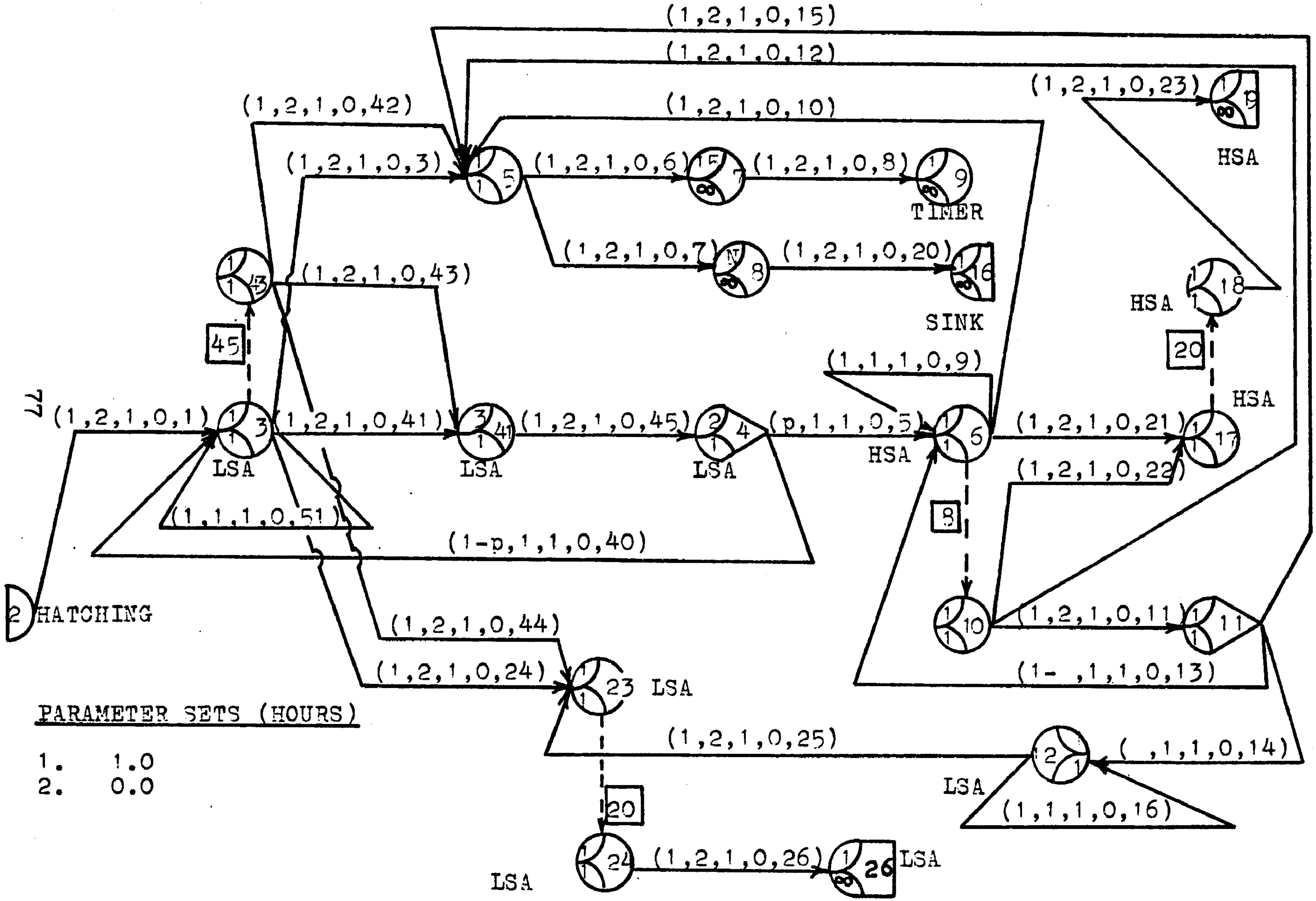
The most influential theory concerning the cause of the decline in imprinting behavior postulates an increase in fear (Hess, 1959). A second explanation posits a decrease in the internal motivation of the following reaction in addition to the increase in fear. The first hypothesis has received considerable experimental support, while the second explanation must await confirmation (Bateson, 1966).

The present model assumes there are two factors chiefly responsible for imprinting behavior- a change in sensory activation and a change in the fear state. It is further assumed that a developing organism can be in one of two sensory activation states- low sensory activation (LSA) or high sensory activation (HSA); additionally he may be in one of two fear states-low fear (LF) or high fear (HF). Following behavior occurs if and only if the animal is in a condition of HSA and LF. Sensory activation is considered first.

Tolman (1963) has found that as a function of hours following hatching, the probability that a duck will be active increases for 13-16 hours and then decreases again for the remainder of the first day. The present model assumes that the probability of being in HSA mirrors Tolman's data. An organism begins in LSA and after several hours of its development has a certain probability, p, of passing into HSA. Fifteen hours after hatching, animals which are in a HSA state will return to LSA with a probability, γ .

Figure 8 represents the GERTS network designed to simulate increases and decreases in sensory activation. At the simulated time of hatching, N2 initiates the network by placing the organism in LSA (N3). Node 3

Figure 8. A GERTS network designed to simulate changes in sensory activation for the imprinting model.



PARAMETER SETS (HOURS)

1. 1.0
2. 0.0

is deterministic and schedules 4 activities. The first output from N3 [P(3,5)] initiates a series of nodes which function as timers. For instance, N7 will only be realized after 15 hours have elapsed corresponding to 15 completions of P(5,7) , while N8 can be set at any value of N and will terminate the simulation after N hours. The path, P(3,41), takes o.o time and serves to retain the organism in LSA. P(3,23) requires 0.0 time and indicates that the subject is in LSA after a given time period. For example, when P(8,16) is completed then a network modification will occur whereby N23 is replaced by N24 and if the organism is still in LSA [P(3,23) or P(43,23) completed] then the network will terminate in LSA (N26 will be realized). The activity represented by the final branch emanating from N3, P(3,3), requires one hour to complete. This branch insures that N3 will schedule events every hour.

After two hours, 3 inputs will have arrived at N41 and this node will be realized. P(41,4) will then be scheduled (branch #45) and a network modification will result (the output of N3 will be replaced by the output of N43). The next input into N3, occurring after three hours, will schedule P(43,41) to be completed. N41 will then be realized and P(41,4) will be taken again. Thus the effect of setting the number of releases, r, equal to 3 on N41 will be to retain the subject in the LSA state until three hours after hatching. This is reasonable since Tolman (1963) has demonstrated that ducklings remain inactive for several hours.

N4 is a probabilistic node and determines whether the subject moves into the HSA state with a probability, p, or remains in the LSA state with a probability, 1 - p. Each of the activities represented by the branches emanating from N4 requires one hour to complete.

An animal which has moved into a HSA condition may return to LSA after 15 hours. This is simulated in the following manner. Recall that P(7,9) will be taken after 15 hours, and this in turn will insure that N6 is replaced by N10. Therefore, additional inputs entering N6 after 15 hours will cause N10 to schedule 3 branches to be completed. The first path, P(10,17) indicates that the subject is in HSA after a given time period. The second output, P(10,5) keeps adding the hours of development, while the 3rd path, P(10,11), inputs into another decision node (N11). With a probability, γ , the subject will now return to a LSA state for the remainder of the simulation; with a probability, $1 - \gamma$, the subject will remain in HSA for another hour. After N hours, N17 will be replaced by N18 and if the organism is still in HSA he will terminate in that condition (N19 will be realized).

The network has 3 sink nodes (N16, N19, and N26). Only two of these 3 nodes must be realized before the entire network is realized. N16 will be realized on every run since it is directly controlled by the value given for N in N8. Therefore, the probability of being in HSA or LSA can be taken as the probability of N19 or N26 being realized, respectively.

Figure 9 shows the actual percentage of ducklings awake and active as a function of the number of hours after hatching (Tolman, 1963). The simulated probability of being in HSA is also shown on this same graph for 100 runs of the GERTS network in figure 8. Values of $p = .044$ and $\gamma = .500$ were used in the analysis. For simplicity, both parameters were estimated by a trial and error procedure designed to yield a reasonable fit to the empirical data, in figure 11. The analytical expression for predicting the initial portion of the simulated curve, from hour 3 to hour 15, can be determined in the following manner: by assumption, an organism is in LSA for the first 3 hours, so $P(LSA)_3 = 1$. The likelihood that he remains in LSA at the beginning of hour 4 is $1 - p$; therefore

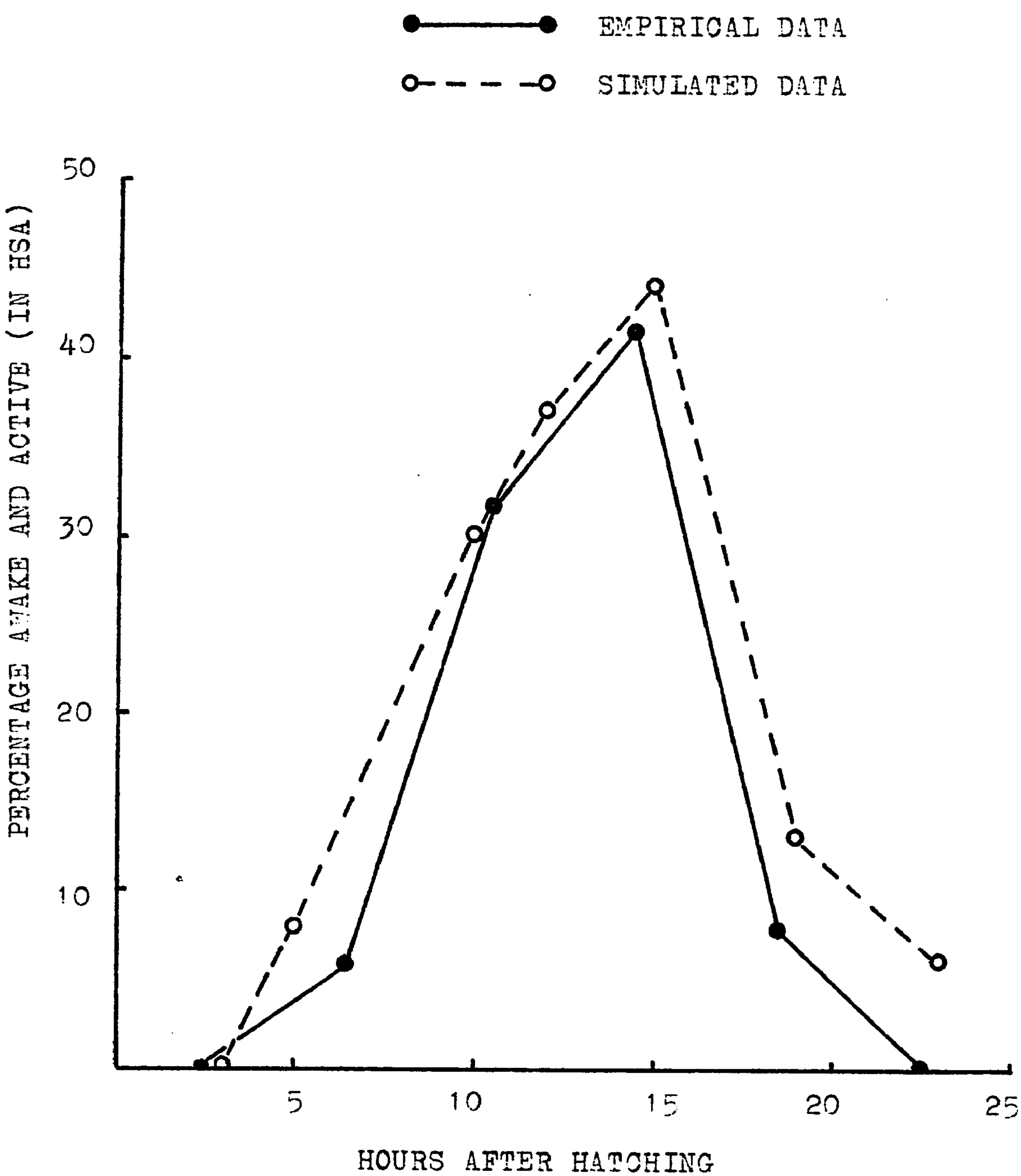
$$P(LSA)_4 = 1 - p$$

The probability that the subject is in state LSA at the beginning of hour 5 is

$$P(LSA)_5 = P(LSA)_4\ (1-p) = (1-p)^2$$

Successive values of P(LSA) are generated in a similar fashion- multiply the previous trial value of P(LSA) by

Figure 9. A comparison of the GERTS simulation of the activation process during the critical period with empirical data collected by Tolman (1963). Simulations are based on 100 runs with $p = .044$, $\gamma = .5$.


EMPIRICAL DATA
SIMULATED DATA
PERCENTAGE AWAKE AND ACTIVE (IN HSA)
50
40
30
20
10
5
10
15
20
25
HOURS AFTER HATCHING

$(1-p)$ which results in an increment in the value of the exponent of the $(1-p)$ term. The general result then becomes, $P(LSA)_N = (1-p)^{N-3}$

Therefore, P(HSA) becomes

$$P(HSA)_N = 1 - (1-p)^{N-3}$$

No formula was derived to predict the subsequent decline in activation.

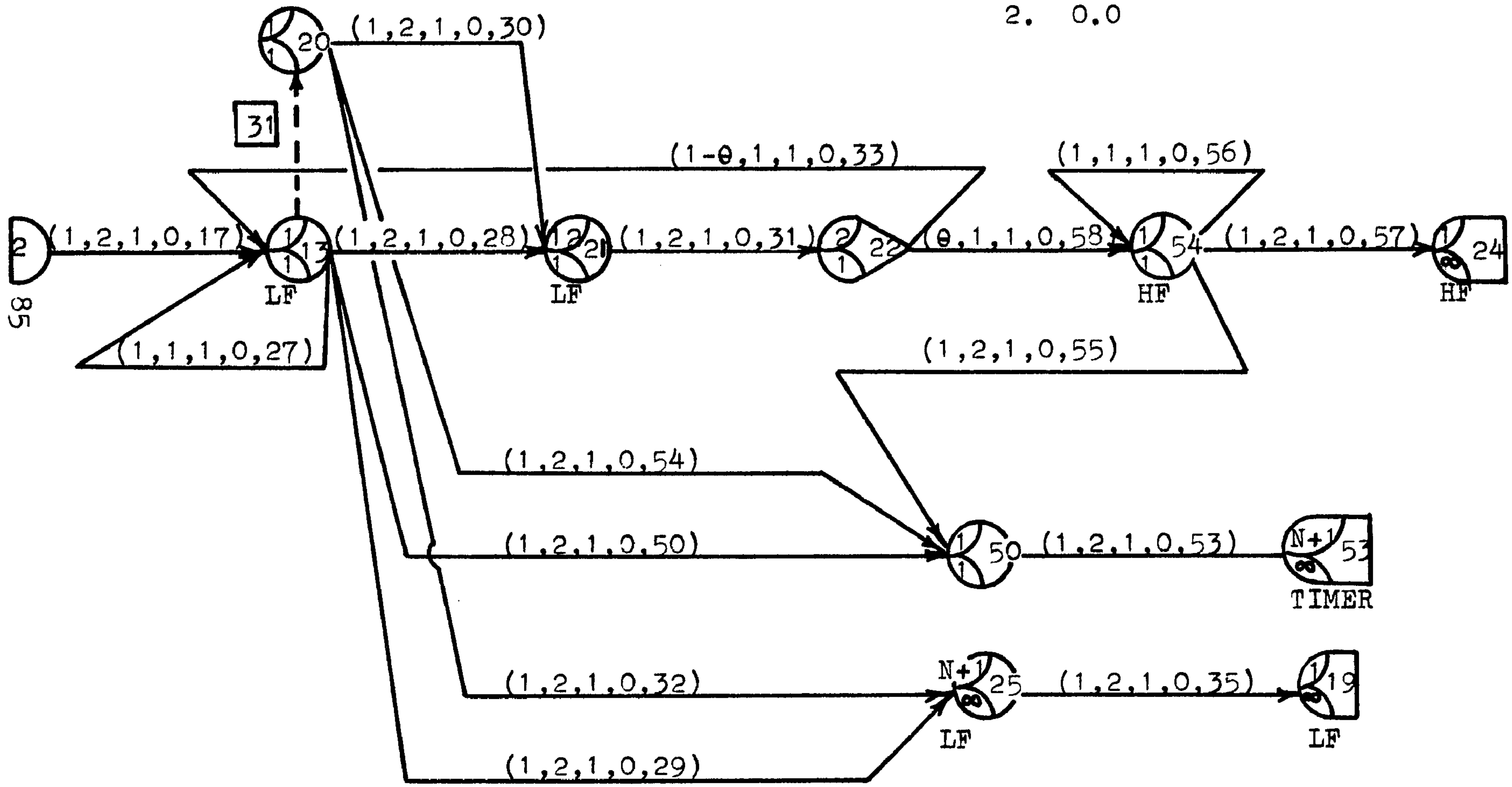
The present model assumes that the decline in the effectiveness of the training stimulus is due to a return to a state of low activity (LSA) and a gradual development of fear. Evidence suggests that newly hatched ducklings will begin to emit distress calls and move away from a training stimulus 9 to 12 hours after hatching (Hess, 1959); they will also begin to escape shock 15 hours after hatching (James & Binks, 1963). It is therefore assumed that an animal remains in an LF condition for 12 hours. At this time he has a probability, θ, of moving into a HF condition. An organism never returns to LF once he has entered HF.

Figure 10 shows the GERTS network designed to simulate movement from a LF state to a HF state. This simulation begins with an input into N13. N13 operates much as N3 did in the previous network diagram (Figure 8). It schedules activities designed to keep the system in a LF condition, P(13,13), P(13,21), and P(13,25), and to keep a count of the number of hours that have passed,

Figure 10. A GERTS network designed to simulate changes in fear for the imprinting model.

PARAMETER SETS (HRS.)

1. 1.0
2. 0.0

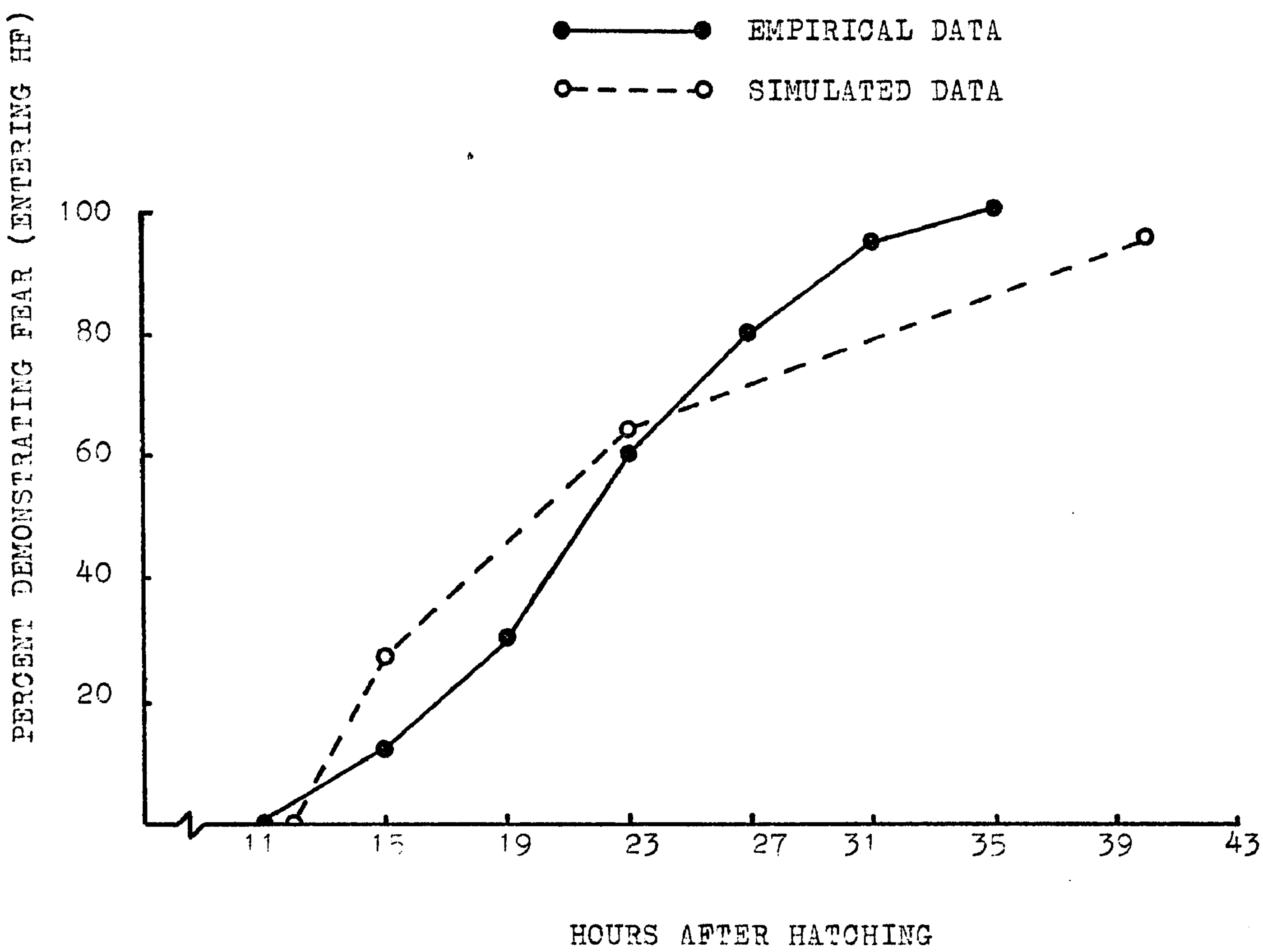


P(13,50). Once 12 hours have elapsed N21 is realized and the activity represented by branch, P(21,22), is completed in 0.0 time. N22 does not become realized since r is set for 2 releases. Instead, a network modification occurs whereby N13 is replaced by N20. The next output from N20 will eventually result in N22 being realized. N22 is aprobabilistic node and at this point P(22,54) will be scheduled with a probability, θ, and P(22,13) will be scheduled with a probability, 1 - θ. If HF state (N54) is realized, this information passes to sink node, N26 in 0.0 time. Feedback loop, P(54,54) is also scheduled so that at every hour P(54, 50) will input into the timer N50 to N53). If after 12 hours an organism remains in LF [P(22,13) is taken each hour after 12 hours], then outputs will continue to emanate from N20.

There are three defined sink nodes: N26, N53, and N19. The simulation will cease after N hours. At this time N53 will be realized. Only one other sink node must be realized before the network is realized. If the organism had passed into a HF condition then N26 will end the simulation. If the organism had remained inLF, then N19 will terminate the simulation. The GERTS summary report tabulates the probability that either of these events occurred after N hours.

Figure 11 is a graph or the development of fear as obtained by Hess(1959) and the development of fear as

Figure 11. A comparison of the GERTS simulation of fear generation during the critical period with empirical data collected by Hess (1959). Simulations are based on 100 runs with $\theta = .08$.


EMPIRICAL DATA
SIMULATED DATA
PERCENT DEMONSTRATING FEAR (ENTERING HF)
100
80
60
40
20
11
15
19
23
27
31
35
39
43
HOURS AFTER HATCHING

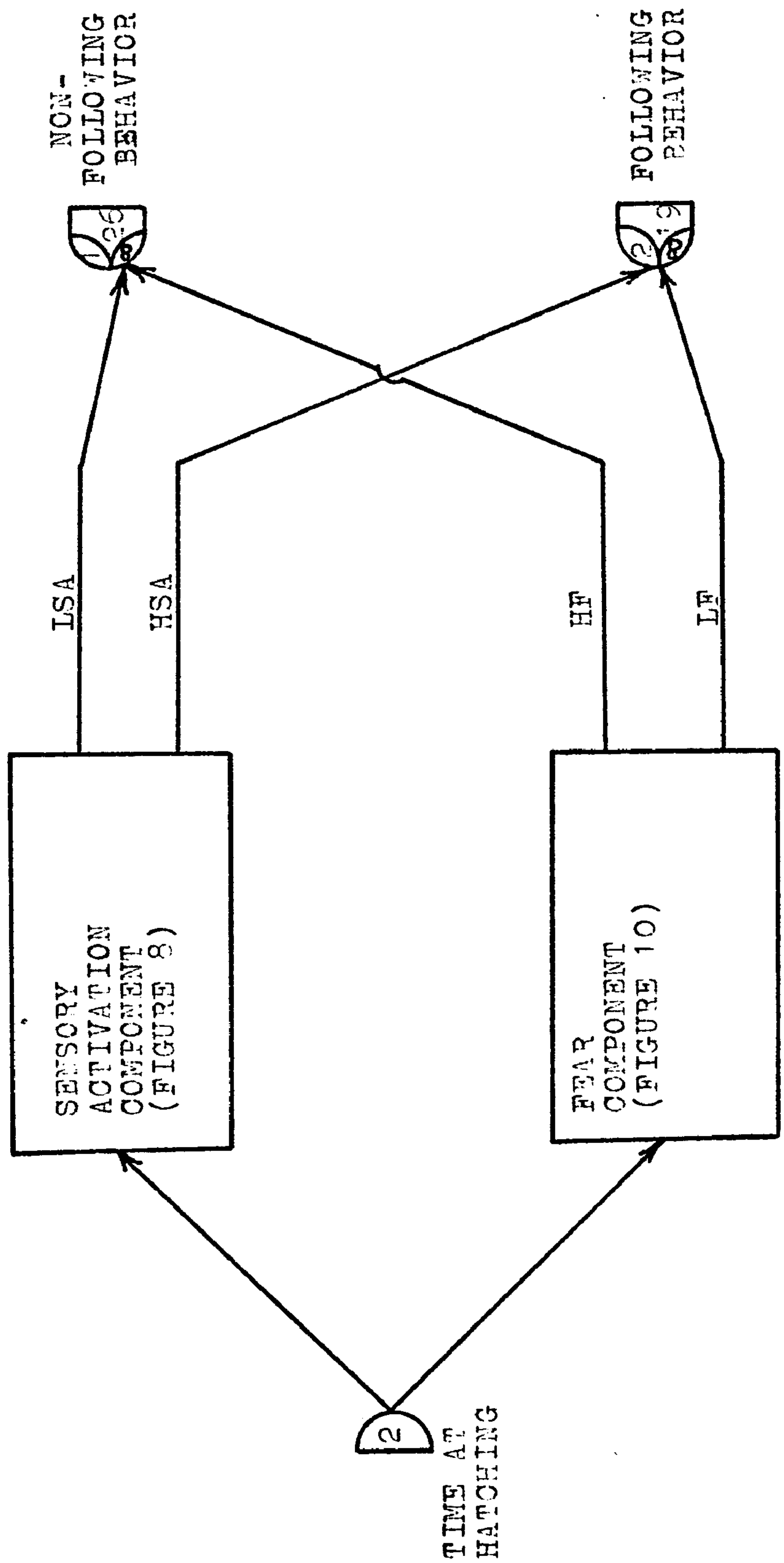
simulated by the GERTS analysis. The parameter, θ, was estimated by trial and error to be .08. The resulting simulated data provided an approximation of the empirical data, although the shape of the empirical curve is sigmoidal, whereas the simulated plot has a slope which is continuously decreasing. More simulated data points at the upper limits of the curve might provide a more complete comparison.

The next stage in the development of the imprinting model involves testing a combination of the two networks to determine whether both factors (sensory activation and fear) will operate simultaneously to generate the expected following behavior.

Figure 12 illustrates schematically how the sensory activation process (diagrammed in figure 8) and the development of fear (diagrammed in figure 10) are combined in the present imprinting model. This figure also demonstrates the modular capability inherent in the GERTS network. Non-following behavior occurs after N hours when either of two events have been simulated: an organism is in a LSA state <u>or</u> he is in a HF state. This condition is achieved by setting r = 1 on N26. On the other hand, r is set for 2 releases on N19. Consequently, following behavior results only after an organism has reached a HSA state <u>and</u> has remained in a LF condition.

The number of hours of development, N, can be

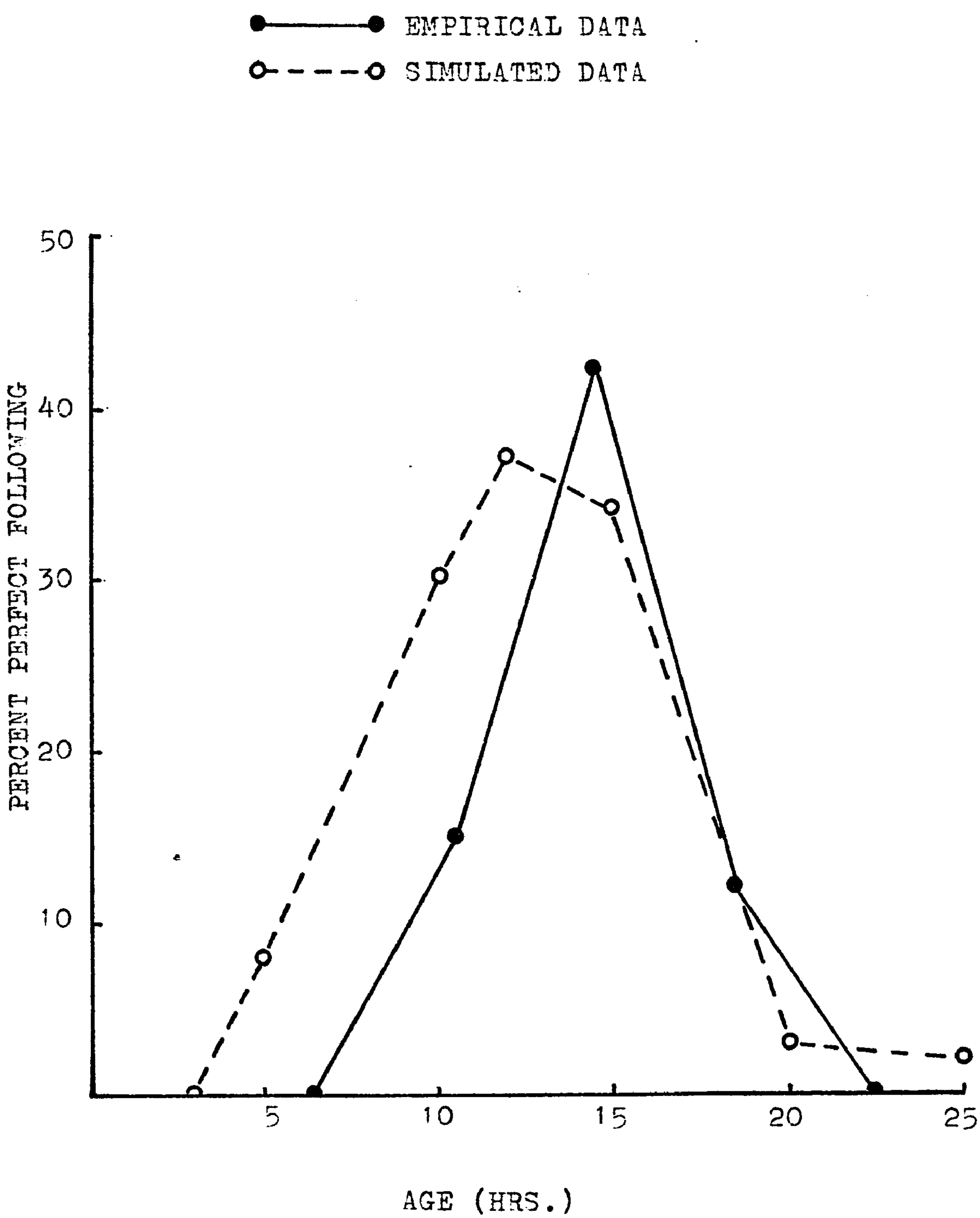
Figure 12. A schematic diagram of Unit I: Imprinting Behavior. The diagram illustrates how the sensory activation component combines with the fear component to simulate following behavior.


NON-FOLLOWING BEHAVIOR
FOLLOWING BEHAVIOR
LSA
HSA
HF
LF
SENSORY ACTIVATION COMPONENT (FIGURE 8)
FEAR COMPONENT (FIGURE 10)
TIME AT HATCHING

controlled by setting the value of r = N for node 8 in the sensory activation component. If this approach is taken, there is no need to retain the timer (N50 and N53) from the fear component since it was designed to achieve the same purpose. The simulation will terminate when N16 (from figure 8) is realized and either N19 or N26 is realized. Simulations were performed at seven different values of N for the imprinting model. Figure 13 compares the degree of simulated following behavior with empirical data collected by Hess (1959). The values for the parameters p, γ, and θ were set equal to those previously used in predicting sensory activation and the development of fear. It appears that the simulation model does quite well in predicting the eventual decline in following behavior, but is 3 to 4 hours early in its generation of the initial rise in the curve. This latter prediction, however, receives some support from Gottlieb (1961). He found that if incubation time is carefully controlled, then maximum following behavior is ellicited 10 hours after hatching.

Instructors have several options available in using Unit I in the classroom setting. One approach would have more advanced students spend several hours learning the mechanics of GERTS programming. Students could then study some of the characteristics of imprinting behavior and could also become familiar with the present simulation

Figure 13. A comparison of the GERTS simulation of imprinting behavior during the critical period with that of Hess, 1959. Simulations are based on 100 runs; $p = .044$, $\theta = .08$, $\gamma = .05$.


EMPIRICAL DATA
SIMULATED DATA
50
40
30
20
10
PERCENT PERFECT FOLLOWING
5
10
15
20
25
AGE (HRS.)

simulation model. At this point they would be ready to either test the effects of minor revisions in the present network or go develop new networks based upon their own theories or theories originating in the literature. For example, a student might simulate the effects of assuming HSA is an absorbing condition. This would eliminate one parameter from the model.

Since Unit I is modular, students have the ability to first study components in isolation, and then study them as they interact. For instance, a student might remove the sensory activation component and replace it with a component which predicts an increase in locomotor ability as suggested by Hess (1959). Hess has shown that as chicks grow older they are able to rejoin their siblings at greater and greater speeds. Do the parameters which predict changes in locomotion ability and fear also generate changes in following behavior?

Students might also attempt to test some one of their own hypotheses- e.g. does the initial increase in following behavior correspond to an increase in the ability make visual discriminations? If data can not be found in the literature concerning such a problem, and if time permits, then students might design a small experiment to collect such data. The end result of such a process would be a revised simulation model of imprinting behavior.

A second possibility is for the instructor to have principle responsibility in revising the present model. Using this approach, students would learn a few of the more basic characteristics of imprinting (experimental paradigm used to train and test birds, definition of the critical period, factors used in development of present model) and then would be required to predict changes in following behavior as function of additional variables. For example a student might be asked to predict the effects of the administration of a tranquilizer at various ages following hatching. Some of these drugs either prevent imprinting from occurring (presumably by reducing sensory activation) or prolong the period during which imprinting can occur (presumably by reducing the fear response) (Hess, 1959). The instructor would decrease the value of p in the former case, and increase δ while decreasing θ in the latter case. Students would receive almost immediate feedback concerning their predictions. Other variables whose effects on imprinting behavior are known and which might be considered are: shock presentation, auditory stimulation, temperature changes, novelty of the training stimulus, presentation of stimulants (see Bateson, 1966 for a review of findings).

The following is a list of some of the benefits a student might derive from the use of Unit I:

a)An understanding of the variables which influence imprinting behavior

b) An understanding of the experimental paradigm necessary to demonstrate imprinting behavior
c) Knowledge of independent vs. dependent variables
d) A consideration of behavior as a probabilistic phenomenon
e) Experience generating and testing hypotheses with a computer
f) Experience in model building
g) An understanding of the use of simulation as a method
h) Experience in designing experiments to test theories
i) An increased understanding of GERTS.

It seems that instructors would receive similar benefits. Unit I and the additional units to be described should be particularly attractive to an instructor in psychology when: he lacks experimental facilities, he has insufficient funds to purchase animals or acquire subjects, he has insufficient funds to maintain present equipment, there is too little time to run an entire study, or it is unethical to perform the actual experiment. Cost considerations are discussed further in Chapter 7.

Unit II
Spinal Reflex Mechanisms

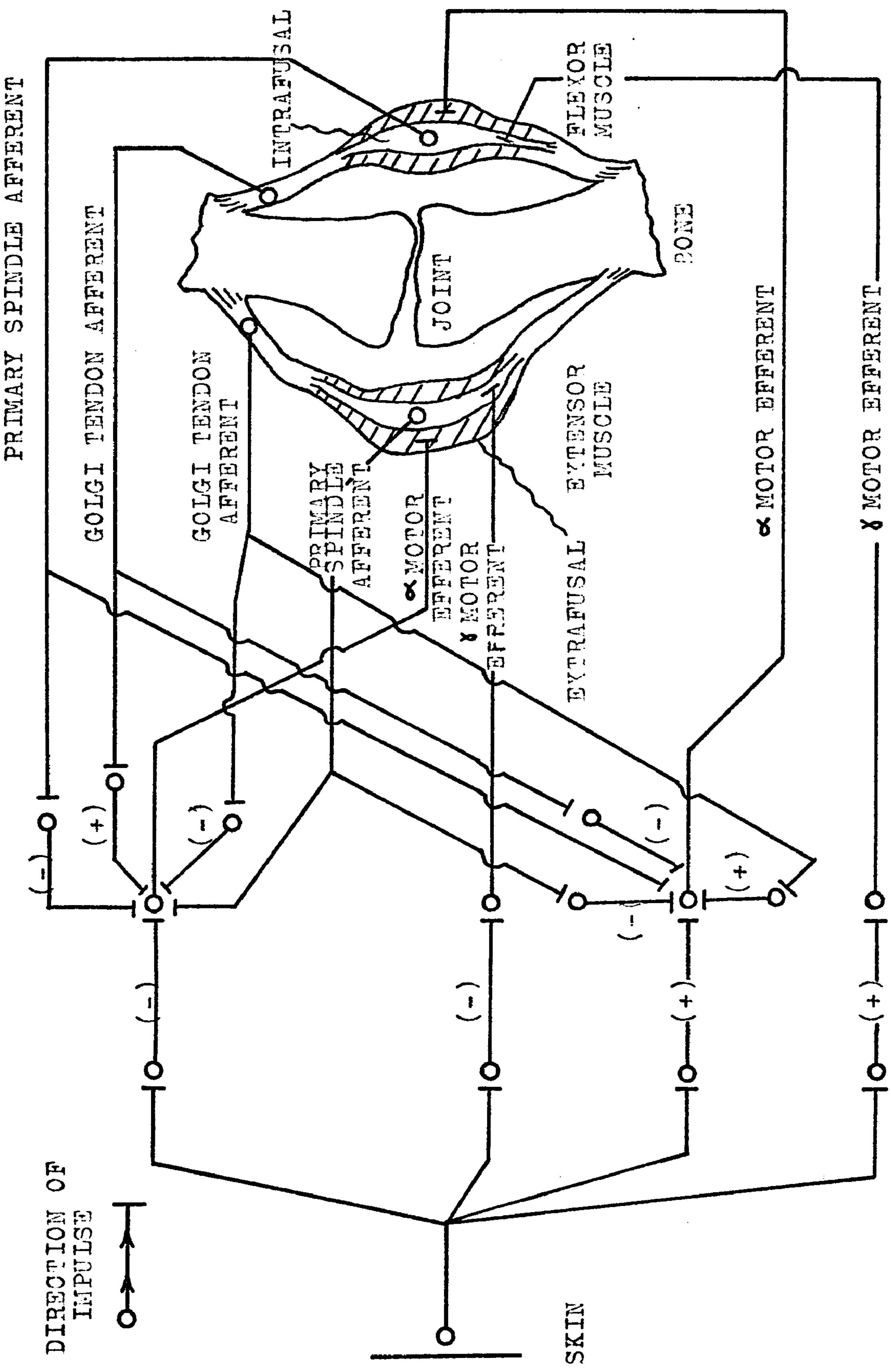
Spinal reflexes are movements in response to stimulation mediated by the spinal cord after the cord has been severed from the brain (Thompson, 1967). The interest in this behavior stems from the proposition that the functioning of these reflexes may serve as a prototype for more complex behavior in intact animals. The relative functional simplicity of this system is deceiving; in actuality spinal reflexes are the result of numerous complex feedback processes. Agarwal, et.al. (1970) has argued that the complexity of the system is such that it can not be analyzed by traditional analytical methods but must be simulated on a computer. It is hoped that the GERTS network model described in this unit will benefit the student in several ways: it will enable him to visualize some of the anatomical relations between muscles and the nerve fibers which innervate them; it will enable him to gain an understanding of the human body as an open system (i.e. interacting with the environment on the input side and the output side). The functioning of muscles at joints, and their neural connections in the spinal cord will be considered first.

All reflexive joint movements are essentially controlled by two kinds of antagonistic muscles- extensors and flexors. Extensors are connected across the larger angle of a joint in such a way that their contraction results in an extension of the limb. Flexors work in opposition to extensors and are connected across the smaller angle of the joint so that their contraction yields a flexion (bending) response. Other muscles may have some control over lateral movements but they will not be considered in the present model.

The internal workings of extensors and flexors are schematically represented in figure 14 summarized from Thompson (1967) along with their principle neural connections to the spinal cord. The bulk of the work of either muscle is accomplished with extrafusal muscle fibers which shorten in response to stimulation. Intrafusal fibers, on the other hand, serve a sensroy function and signal the state of contraction of the extrafusal muscle fibers as well as any change in their tension (Grossman, 1973). Extrafusal fibers are innervated by fast conducting alpha (α) motor efferents (efferents transmit information away from the central nervous system), while intrafusal fibers are innervated by gamma (γ) motor efferents.

Muscles have a variety of sensory receptors that transmit information to the central nervous system via afferent neurons. Two main receptors are the spindle organs lying within the intrafusal fibers and the Golgi tendon organs which reside in the tendons connecting

Figure 14. A summary diagram showing ipsalateral connections to antagonistic muscles at a joint. Interneurons are either excitatory (+) or inhibitory (-).


PRIMARY SPINDLE AFFERENT
GOLGI TENDON AFFERENT
INTRAFUSAL
FLEXOR MUSCLE
JOINT
BONE
GOLGI TENDON AFFERENT
PRIMARY SPINDLE AFFERENT
EXTENSOR MUSCLE
α MOTOR EFFERENT
γ MOTOR EFFERENT
EXTRAFUSAL
α MOTOR EFFERENT
γ MOTOR EFFERENT
(+)
(−)
DIRECTION OF IMPULSE
SKIN

muscle to bone. Muscle spindles and their end organs are arranged in the intrafusal fibers in a parallel fashion to the extrafusal fibers so that they stretch when the muscle stretches and contract when the muscle contracts. The stimulus that normally excites the muscle spindle is stretch of the extrafusal fibers, or contraction of the intrafusal fibers by mean of γ efferents. The resulting discharge of the spindle endings is approximately proportional to the amount of stretch in the muscle. The information is transmitted to the central nervous system via the primary afferent fibers (Type Ia), which are among the largest. These spindle afferents have monosynaptic excitatory connections with α motor efferents that innervate related extrafusual muscle fibers; they also exert disynaptic inhibitory control over anatagonistic muscles (see figure 14)(Eccles & Lundberg, 1958). The muscle spindle fibers comprise a negative feedback system whereby an increase in activation of the spindle end organs results in a contraction of the neighboring extrafusal fibers and a subsequent reduction in the tension of the muscle spindle.

The second receptor found in the extensors and flexors is the Golgi tendon organ. It lies in series with the muscle and therefore stretches when the muscle (extrafusal) contracts as well as when the muscle is stretched by the action of an antagonist. Golgi tendons respond to stretch with a brief burst of activity followed by a quick return to a slow steady state discharge (Grossman, 1973). Golgi tendon organs initiate activity in afferents that are linked with motor neurons via a single interneuron. They tend to inhibit motor neurons connected to the stimulated extensor muscles, and tend to excite antagonistic muscles.

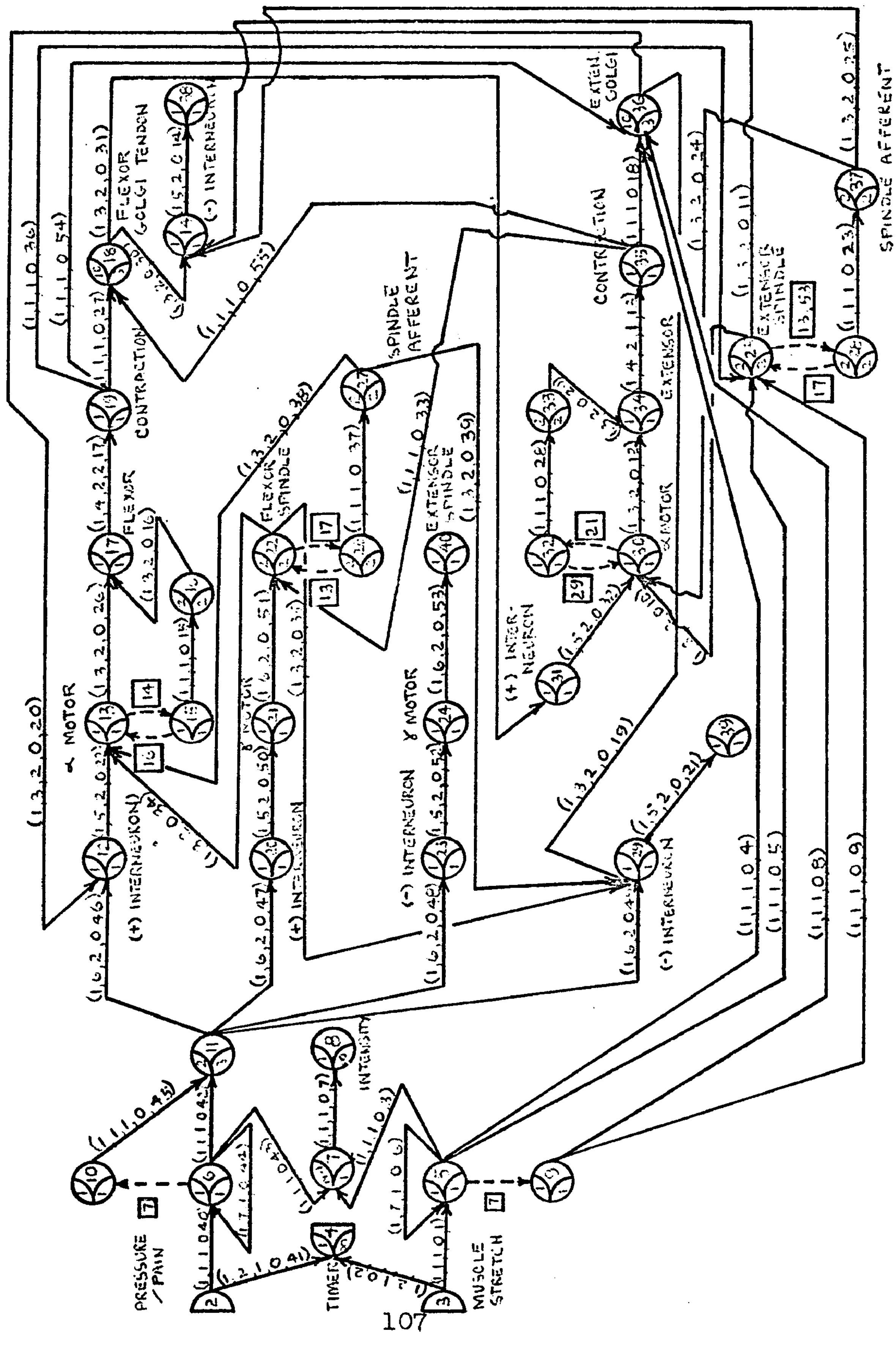
The basic feedback system is further complicated by activity of γ motor efferents which stimulate contraction in the intrafusal muscle fibers. The γ motor neurons do not generate direct changes in muscle tension, but instead alter the extent of activity of the muscle spindle organs. Their primary function is to prevent muscle spindles from becoming flaccid during muscular contraction. For instance, when a contracting flexor muscle shortens, spindle activity would normally decrease. However, it is maintained by the γ activity of the spindle muscle fibers. Light touch, pressure, and pain from skin receptors are the most effective stimuli altering motor neuron firing. As noted in figure 14, such stimuli generally increase γ activity to flexors of the same limb (ipsilateral) and decrease it to extensors. Just the opposite occurs for γ activity to muscles of the opposite limb (not diagrammed). The shortest possible circuit here is three or four neurons (Gayton, 1972); however, the present model assumes one interneuron between the skin afferents and the γ motor efferent.

How does the system diagrammed in figure 14 operate to produce reflexive behavior? First consider the stretch reflex. This is the simplest of all spinal reflexes. It is evoked by pulling on the tendon of a muscle or, in the intact animal, by pushing against a limb. It serves to compensate for changes in external load on the limbs, particularly those due to the force of gravity. The afferent impulses which trigger the reflex (contraction of the extensor) arise in the muscle spindle receptors and travel to the spinal cord via primary spindle afferents. These fibers synapse directly with motor neurons of the extensors, and have disynaptic inhibitory connections with α efferents to flexors. The knee jerk offers an example of a stretch reflex in man. It is a rapid and vigorous extension of the limb when the tendon below the knee cap is tapped. The Golgi tendon organ activity tends to return the system to its initial condition.

The flexion reflex, a defensive reflex, is the most common type of response to a strong or painful stimulation of the skin. Sensory information is transmitted via efferents causing a contraction of the flexion muscles ipsilateral to the cutaneous stimulation. Another connection provides concurrent inhibitory influences to antagonistic extensor muscles. Extension of the opposite limb often accompanies flexion of the stimulated limb. The stretch reflex and the flexion reflex are the principle behaviors simulated in Unit II.

The GERTS network for the spinal reflex model was developed to contain all of the information diagrammed in figure 14. The resulting GERTS network description is presented in figure 15. In this network initiation of source node, N2, will begin a simulation of the flexion reflex, while initiation of N3 will generate stretch reflex behavior. The timer node, N4, is the only sink node in the network and will terminate either simulation upon the completion of P(2,4) or P(3,4). In most cases the time for completion of these branches (t) was set at a constant value of 500 msec. The number of inputs into the system was modeled to be directly proportional to the intensity of the stimulus. For a flexion reflex, stimulus intensity might be analogous to the extent of the force on a given surface area of skin. For the stretch reflex simulated intensity might correspond to the degree of stretch achieved in a given tendon. A feedback loop around N6 transmits one impulse into the system every one msec. until N7 is realized. At this time N6 is replaced by N10 and the last input enters the system. The number of releases, r, on N7 can be varied giving the analyst control over the intensity of a hypothetical stimulus lending to the flexion response. N7 functions

Figure 15. The GERTS network description for unit II: Spinal reflex mechanisms.


PRESSURE / PAIN
TIMER
MUSCLE STRETCH
INTENSITY
(+) INTERNEURON
α MOTOR
γ MOTOR
(-) INTERNEURON
FLEXOR
CONTRACTION
FLEXOR GOLGI TENDON
FLEXOR SPINDLE
SPINDLE AFFERENT
EXTENSOR SPINDLE
EXTENSOR
EXTEN. GOLGI
SPINDLE AFFERENT

in an analogous fashion for the simulation of the stretch reflex.

A consideration of the simulation of the stretch reflex will be made first. Recall that this reflex is initiated by stretching the tendon of a muscle. In the present model the tendon of an extensor muscle was stretched (as in tapping knee). The stretching of the tendon will affect both the Golgi tendon organs on the extrafusal fibers of the extensor and also the muscle spindle receptors within the intrafusal fibers of the stimulated muscle. P(5,36) and P(5,25) reflect these considerations. N36 represents a hypothetical Golgi tendon organ of the stimulated extensor muscle. The values of r and r' (10 and 3 respectively) on N36 are analogous to thresholds on a receptor. In other words, an intensity of 10 inputs is required to realize N36 the first time. In the present model, node realization (for nodes representing neurons) is analogous to the generation of an action potential. After this first realization, N36 will be realized every time 3 inputs arrive. The values 10 and 3 are arbitrary. An analysis of the effects of raising and lowering these r values was made and will be described later.

Upon realization of N36, activities are scheduled for P(36,12) and P(36,29). These branches represent the time required for the neural impulse to traverse the afferents from the muscle to the interneurons in the dorsal segment of the spinal cord (see time parameter 3 in figure 15). All data related to neural conductiontime was obtained from a summary prepared by Thompson (1967). Consider inputs into N12 first. N12 represents an excitatory interneuron. Each time it receives an input from N36, it will schedule the activity represented by P(12,13) to occur. All interneurons are assumed to have a conduction time of $t_p = 5$ and $t_D = 2$ (normal distribution). Conduction velocity is directly related to fiber diameter; there is evidence that the distribution of sizes is bell shaped with its mean and variance a function of the fiber group in question (Erlanger & Gasser, 1937). N13, the motor efferent, requires only one input before it is realized. It directly stimulates the hypothetical flexor muscle. The time required before P(13,17) is completed represents the conduction time of the α motor efferent. The flexor muscle, N17 will contract with each input from the α motor efferent. P(17, 19) represents the activity of contraction, taking 24 msec. on the average ($t_p = 4$, $t_D = 2$).

The other output from the extensor Golgi tendon [P(36,29)] has an inhibitory effect on the extensor muscle. P(36,29) leads to an interneuron, but in this case N29 schedules P(29, 39) to occur, whose completion consequently causes N30 to be replaced by N32. The net effect of this modification is to raise the threshold of the α motor efferent leading into the extensor muscle (N30 has a threshold value of r = 2, r' = 2), and to decrease the probability of the extensor muscle contracting (N35 being realized).

Recall that the initial external stimulus was to affect both N36 and N25. N25 simulates an extensor spindle. The value of 2 is given for both r and r' on this node. This is consistent with the finding that spindle receptors are more sensitive to stretch than Golgi tendon organs and therefore have lower thresholds (Mountcastle, 1956). The extensor spindle has a mono-synaptic excitatory influence on the α motor efferent to the extensor muscle of the stimulated limb [P(25,30)]. It also has a disynaptic inhibitory influence on the α motor efferents innervating the flexor muscles. The latter effect was accomplished when P(25,14) was traversed (spindle afferent to spinal cord). This led to the scheduling of P(14,38). Finally, upon the completion of P(14,38)(transmission of an impulse along the inhibitory interneuron), N13 was replaced by N15 and the threshold of the α motor efferent to the flexor was raised (N16 has a higher value of r and r'). The threshold returns to normal when the activity represented by P(16,17) is completed.

Since the threshold for N25 is lower than that for N36, N25 will probably have an effect on the network prior to N36- especially for low stimulus intensities. If we assume that this is the case, one of the first responses recorded by the model will be a contraction of the extensor muscle resulting from the direct monosymaptic excitatory input into N30. The counter on P(34, 35) will enable this event to be noted and tabulated. The simulation will not end at this point. Contraction of the extensor muscle will eventually have 3 effects: first it will serve as an added input into the Golgi tendon organ of the extensor [P(34, 35)] which may or may not fire at this time. If it does fire it will eventually serve to excite the α motor efferent [P(36,12)] helping to implement contraction of the flexor muscle, and will also tend to inhibit a further contraction of the extensor by raising the threshold of the α motor efferent. Contraction of the extensor muscle will have a second main effect. It will aid in stimulation of Golgi tendon organs of antagonistic flexor muscles [P(35,18)]. Finally, it will contribute to the stimulation of spindle receptors in flexor muscles [P(35,22)]. Each simullated contraction of the flexor muscle is tallied with counter #2 on P(17,19).

It is clear from the complexity of the interactions that it is difficult to predict the performance of the stretch reflex model. A simulation of the model was initially performed at a low degree of tendon stretch

(N = 5) for a period of 500 msec. All network parameters were given the values that are shown in figure 15. A trace of the activity completions was made of the first run and appears in figure 16. The trace offers the GERTS programmer information concerning the time of completion of each branch in the network for as many simulation runs as is desired. For instance, it took 0.0 time for the first branch to node 5 to be completed on run #1. Specification of 4 of the attributes associated with a branch is also shown; t_p, t_D, c, and "a" respectively. Primary interest centers on the time of completion of P(34,35) (activity #13) and P(17,19) (activity #17), which are associated with extensor and flexor contraction respectively. Activity #13 was completed for the first time 36.73 msec. after stimulus onset. A second contraction of the extensor muscle occurred 46.05 msec. after stimulus onset. There were no simulated contractions of the flexor muscle during the 500 msec. period.

Simulations were performed for other values of N. An analysis of the traces for these runs provided data concerning extensor contractions and flexor contractions. Figure 17 shows the difference between the number of extensor contractions and flexor contractions for each 20 msec. interval following the initiation of a given stretch reflex simulation. Each curve provides the results for a different stimulus intensity. For all

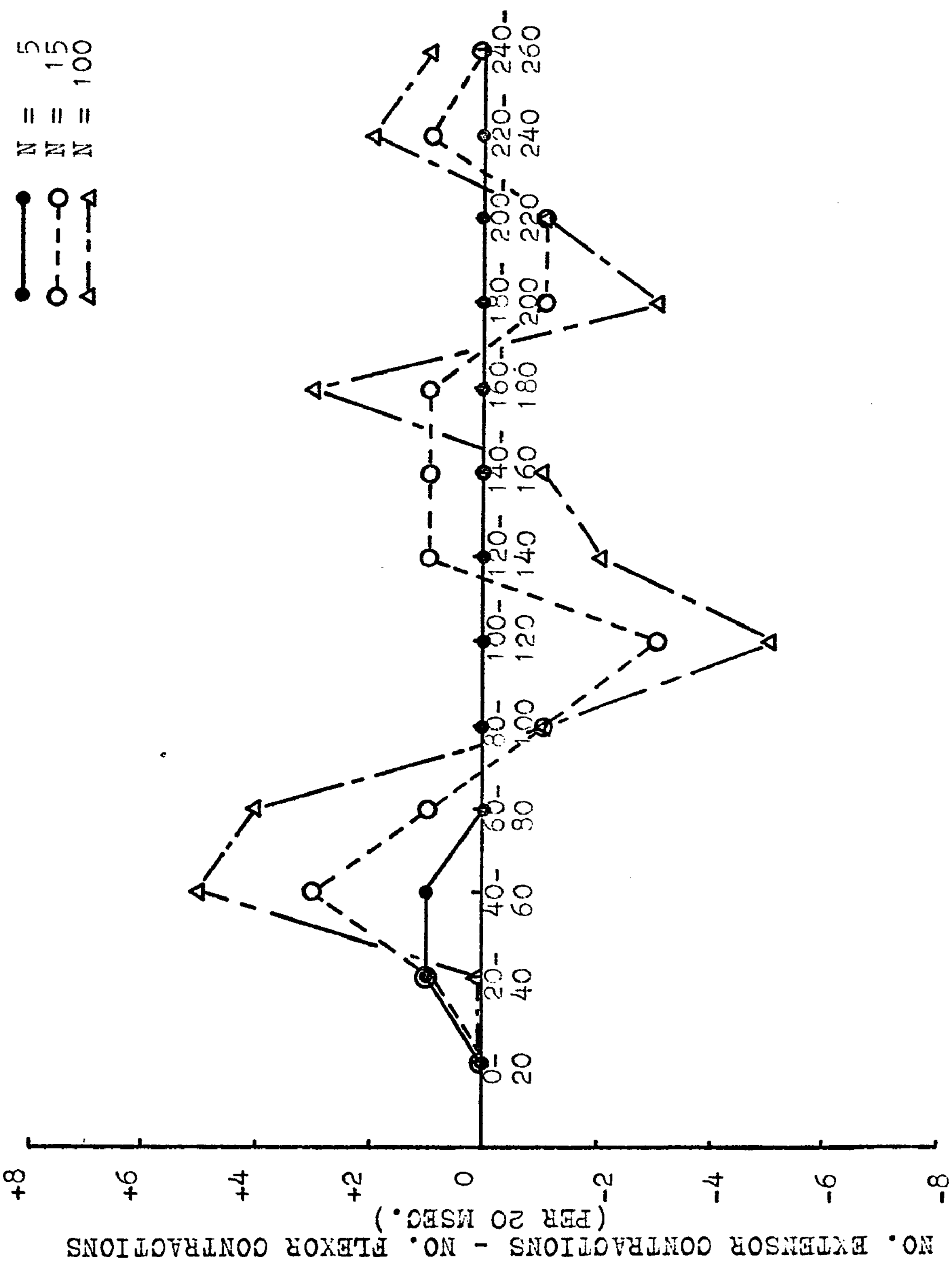
Figure 16. A trace of the activity completions for the simulation of the stretch reflex.

```
AT TIME   0.00 ACTIV. ON NODE  5 WITH ATTRIB.  1  1  0   1 WAS REAL. ON RUN  1
AT TIME   0.00 ACTIV. ON NODE  7 WITH ATTRIB.  1  1  0   3 WAS REAL. ON RUN  1
AT TIME   0.00 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0   4 WAS REAL. ON RUN  1
AT TIME   0.00 ACTIV. ON NODE 25 WITH ATTRIB.  1  1  0   5 WAS REAL. ON RUN  1
AT TIME   1.00 ACTIV. ON NODE  5 WITH ATTRIB.  7  1  0   6 WAS REAL. ON RUN  1
AT TIME   1.00 ACTIV. ON NODE  7 WITH ATTRIB.  1  1  0   3 WAS REAL. ON RUN  1
AT TIME   1.00 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0   4 WAS REAL. ON RUN  1
AT TIME   1.00 ACTIV. ON NODE 25 WITH ATTRIB.  1  1  0   5 WAS REAL. ON RUN  1
AT TIME   2.00 ACTIV. ON NODE  5 WITH ATTRIB.  7  1  0   6 WAS REAL. ON RUN  1
AT TIME   2.00 ACTIV. ON NODE  7 WITH ATTRIB.  1  1  0   3 WAS REAL. ON RUN  1
AT TIME   2.00 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0   4 WAS REAL. ON RUN  1
AT TIME   2.00 ACTIV. ON NODE 25 WITH ATTRIB.  1  1  0   5 WAS REAL. ON RUN  1
AT TIME   3.00 ACTIV. ON NODE  5 WITH ATTRIB.  7  1  0   6 WAS REAL. ON RUN  1
AT TIME   3.00 ACTIV. ON NODE  7 WITH ATTRIB.  1  1  0   3 WAS REAL. ON RUN  1
AT TIME   3.00 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0   4 WAS REAL. ON RUN  1
AT TIME   3.00 ACTIV. ON NODE 25 WITH ATTRIB.  1  1  0   5 WAS REAL. ON RUN  1
AT TIME   3.00 ACTIV. ON NODE  8 WITH ATTRIB.  1  1  0   7 WAS REAL. ON RUN  1
AT TIME   4.00 ACTIV. ON NODE  5 WITH ATTRIB.  7  1  0   6 WAS REAL. ON RUN  1
AT TIME   4.00 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0   8 WAS REAL. ON RUN  1
AT TIME   4.00 ACTIV. ON NODE 25 WITH ATTRIB.  1  1  0   9 WAS REAL. ON RUN  1
AT TIME   6.83 ACTIV. ON NODE 30 WITH ATTRIB.  3  2  0  10 WAS REAL. ON RUN  1
AT TIME  11.94 ACTIV. ON NODE 30 WITH ATTRIB.  3  2  0  10 WAS REAL. ON RUN  1
AT TIME  12.06 ACTIV. ON NODE 14 WITH ATTRIB.  3  2  0  11 WAS REAL. ON RUN  1
AT TIME  13.07 ACTIV. ON NODE 14 WITH ATTRIB.  3  2  0  11 WAS REAL. ON RUN  1
AT TIME  16.34 ACTIV. ON NODE 34 WITH ATTRIB.  3  2  0  12 WAS REAL. ON RUN  1
AT TIME  17.93 ACTIV. ON NODE 38 WITH ATTRIB.  5  2  0  14 WAS REAL. ON RUN  1
AT TIME  17.95 ACTIV. ON NODE 38 WITH ATTRIB.  5  2  0  14 WAS REAL. ON RUN  1
AT TIME  18.64 ACTIV. ON NODE 34 WITH ATTRIB.  3  2  0  12 WAS REAL. ON RUN  1
AT TIME  36.73 ACTIV. ON NODE 35 WITH ATTRIB.  4  2  1  13 WAS REAL. ON RUN  1
AT TIME  36.73 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0  18 WAS REAL. ON RUN  1
AT TIME  36.73 ACTIV. ON NODE 22 WITH ATTRIB.  1  1  0  33 WAS REAL. ON RUN  1
AT TIME  36.73 ACTIV. ON NODE 18 WITH ATTRIB.  1  1  0  55 WAS REAL. ON RUN  1
AT TIME  46.05 ACTIV. ON NODE 35 WITH ATTRIB.  4  2  1  13 WAS REAL. ON RUN  1
AT TIME  46.05 ACTIV. ON NODE 36 WITH ATTRIB.  1  1  0  18 WAS REAL. ON RUN  1
AT TIME  46.05 ACTIV. ON NODE 22 WITH ATTRIB.  1  1  0  33 WAS REAL. ON RUN  1
```

Figure 16 (con't)

```
AT TIME  46.05 ACTIV. ON NODE  18 WITH ATTRIB.   1   1   0   55 WAS REAL. ON RUN   1
AT TIME  53.76 ACTIV. ON NODE  29 WITH ATTRIB.   3   2   0   35 WAS REAL. ON RUN   1
AT TIME  54.86 ACTIV. ON NODE  13 WITH ATTRIB.   3   2   0   34 WAS REAL. ON RUN   1
AT TIME  54.86 ACTIV. ON NODE  16 WITH ATTRIB.   1   1   0   15 WAS REAL. ON RUN   1
AT TIME  57.59 ACTIV. ON NODE  39 WITH ATTRIB.   5   2   0   21 WAS REAL. ON RUN   1
AT TIME 500.00 ACTIV. ON NODE   4 WITH ATTRIB.   2   1   0    2 WAS REAL. ON RUN   1
```

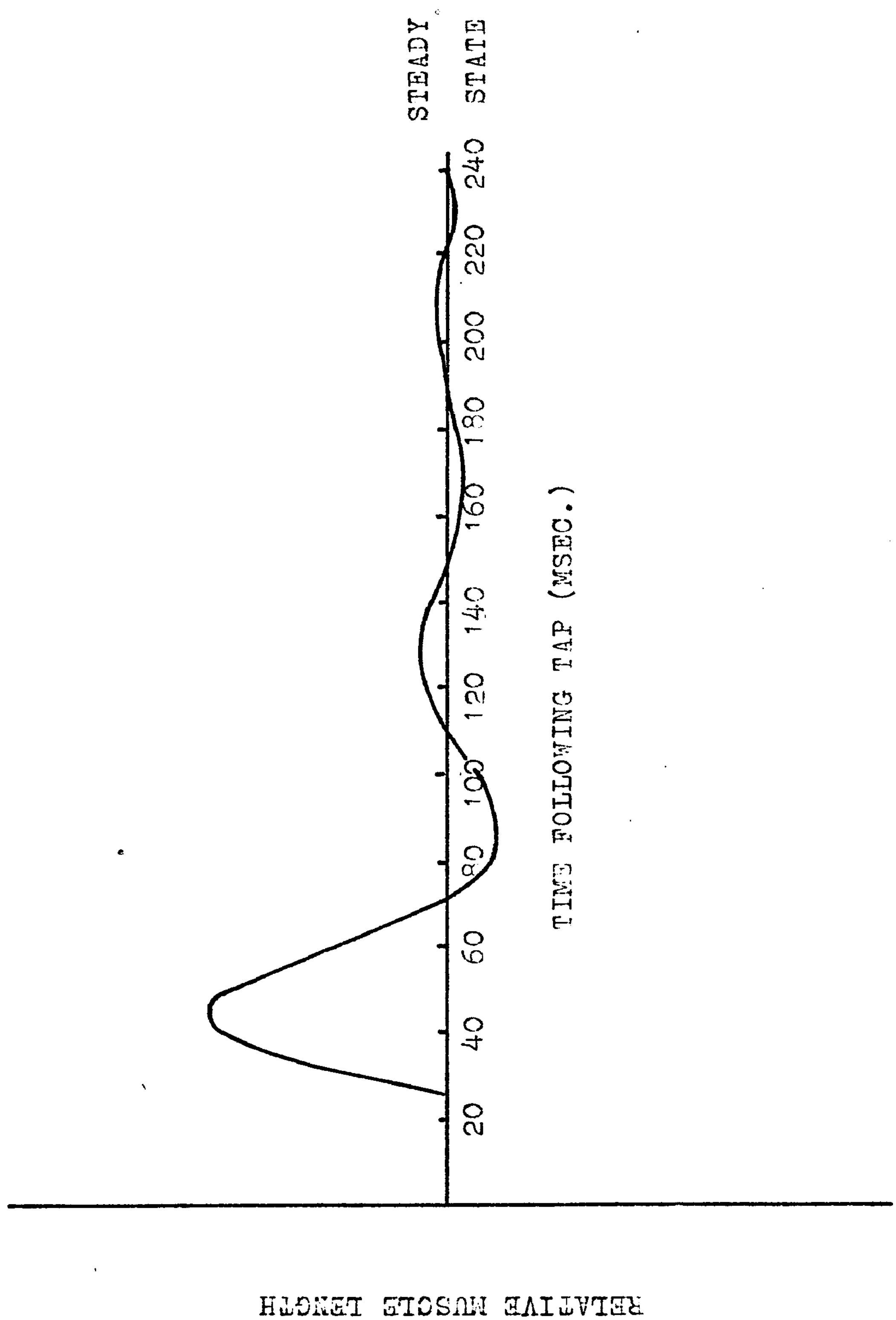
Figure 17. Performance of the stretch reflex simulation model under three intensities of tendon stretch. Each curve was derived from the analysis of a single trace. Node values of r/r were 2/2 for spindle organs and 10/3 for Golgi tendon organs (those shown in figure 15).


N = 5
N = 15
N = 100
0- 20
20- 40
40- 60
60- 80
80- 100
100- 120
120- 140
140- 160
160- 180
180- 200
200- 220
220- 240
240- 260
+8
+6
+4
+2
0
-2
-4
-6
-8
NO. EXTENSOR CONTRACTIONS - NO. FLEXOR CONTRACTIONS
(PER 20 MSEC.)

values of N, the model predicts an initial increment of extensor contractions over flexor contractions. This finding is analogous to the rapid knee jerk response elicited by the patellar tendon (Guyton, 1972). For N = 15 and N = 100 the curves become cyclical with decreasing amplitudes as the time following stimulation increases. It is also apparent that the greatest response amplitudes, on either side of a base line condition (pre-stimulus load), occur with the largest stimulus intensity (N = 100). This is consistent with early studies (Lombard, 1887; Dodge, 1911) demonstrating that in general the amplitude of the tendon jerk varies directly with the force of the blow.

Figure 18 is an example of a typical human myogram recorded from the quadriceps muscle during elicitation of the knee jerk (Guyton, 1972). The initial peak extensor response occurs approximately 40 msec. after the patellar tendon is struck. This compares quite favorably with the initial peak responses shown in figure 17. It is also apparent that there is an analogous cyclical change in the length of the quadriceps muscle. For example the inital peak flexor response occurs approximately 60 msec. after the peak extensor response. This idea receives support from Dodge (1911) who observed that the flexors contract 10-60 msec. later then the extensor in a knee jerk. The greateat discrepancy

Figure 18. A myogram recorded from the quandriceps muscle during elicitation of the knee jerk (from Guyton, 1972).

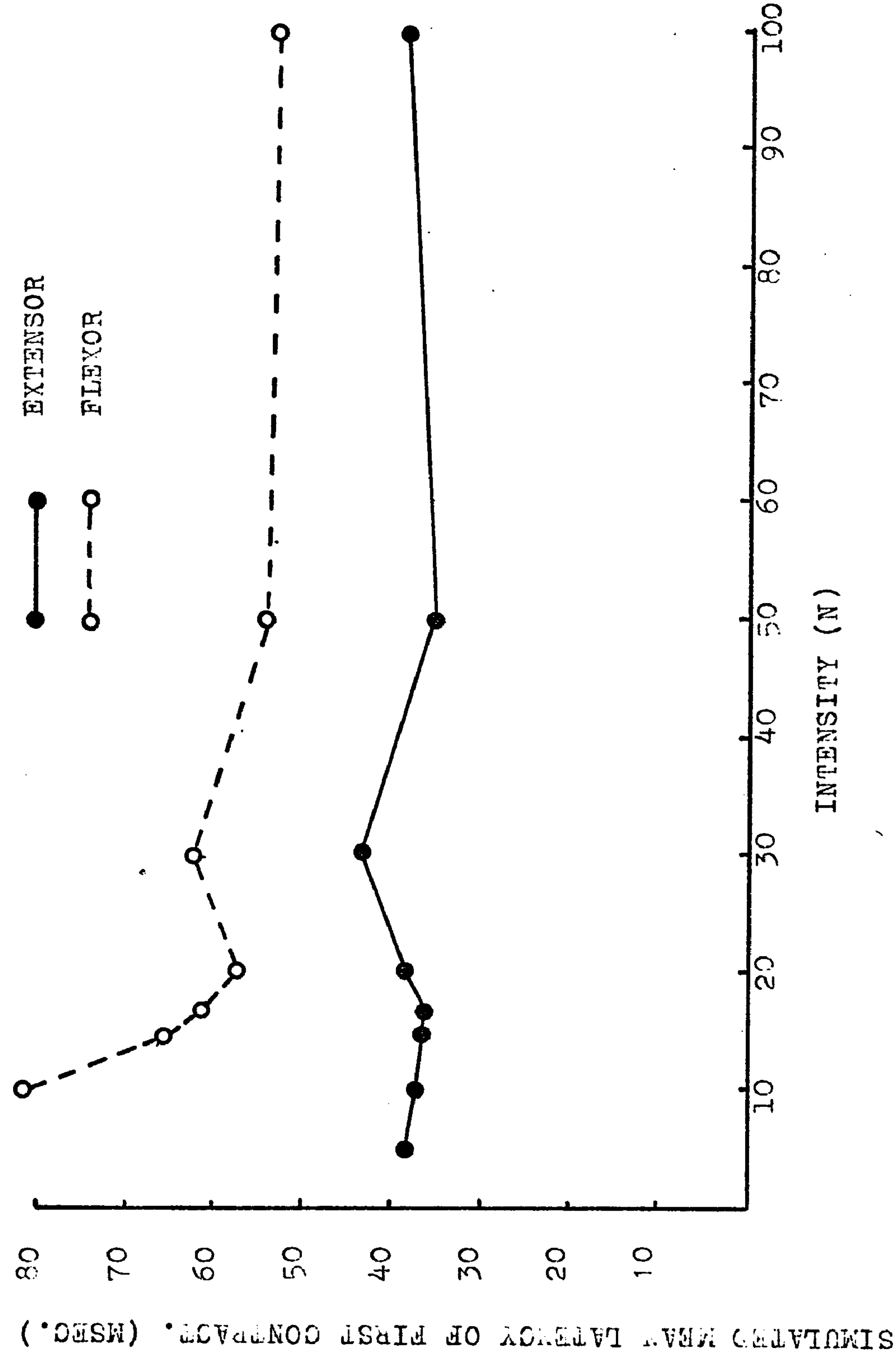

STEADY STATE
20
40
60
80
100
120
140
160
180
200
220
240
TIME FOLLOWING TAP (MSEC.)
RELATIVE MUSCLE LENGTH

between the simulated response curves of figure 17 and the empirical muscle response lies in the greater amplitude of the first flexor response and the succeeding cyclical responses for the simulation model. This discrepancy will be discussed later in this section.

Additional simulations were performed at N = 10, 17, 20, 30, and 50. Figure 19 demonstrates how the latency to the first extensor contraction and first flexor contraction varies as the simulated stimulus intensity increases. Mean latency to the first extensor response appears to be a constant value. Agarwal, et.al. (1970) found this to be the case when they varied the hammer force necessary to generate the stretch reflex in humans. This is probably because the spindle organ, which directly initiates the stretch reflex, operates at a low threshold. On the other hand, the simulated mean latency to the first flexor contraction decreases with increasing intensity. This finding apparently stems from the increased influence of the Golgi tendon organ at higher stimulus intensities. No experimental evidence has been found to support or contradict this prediction.

For pėdagogical purposes, it is of some interest to investigate the performance of the stretch reflex model: 1) without the influence of the Golgi tendon organs; and 2) without the influence of the spindle receptors. The first objective was accomplished by setting r equal to

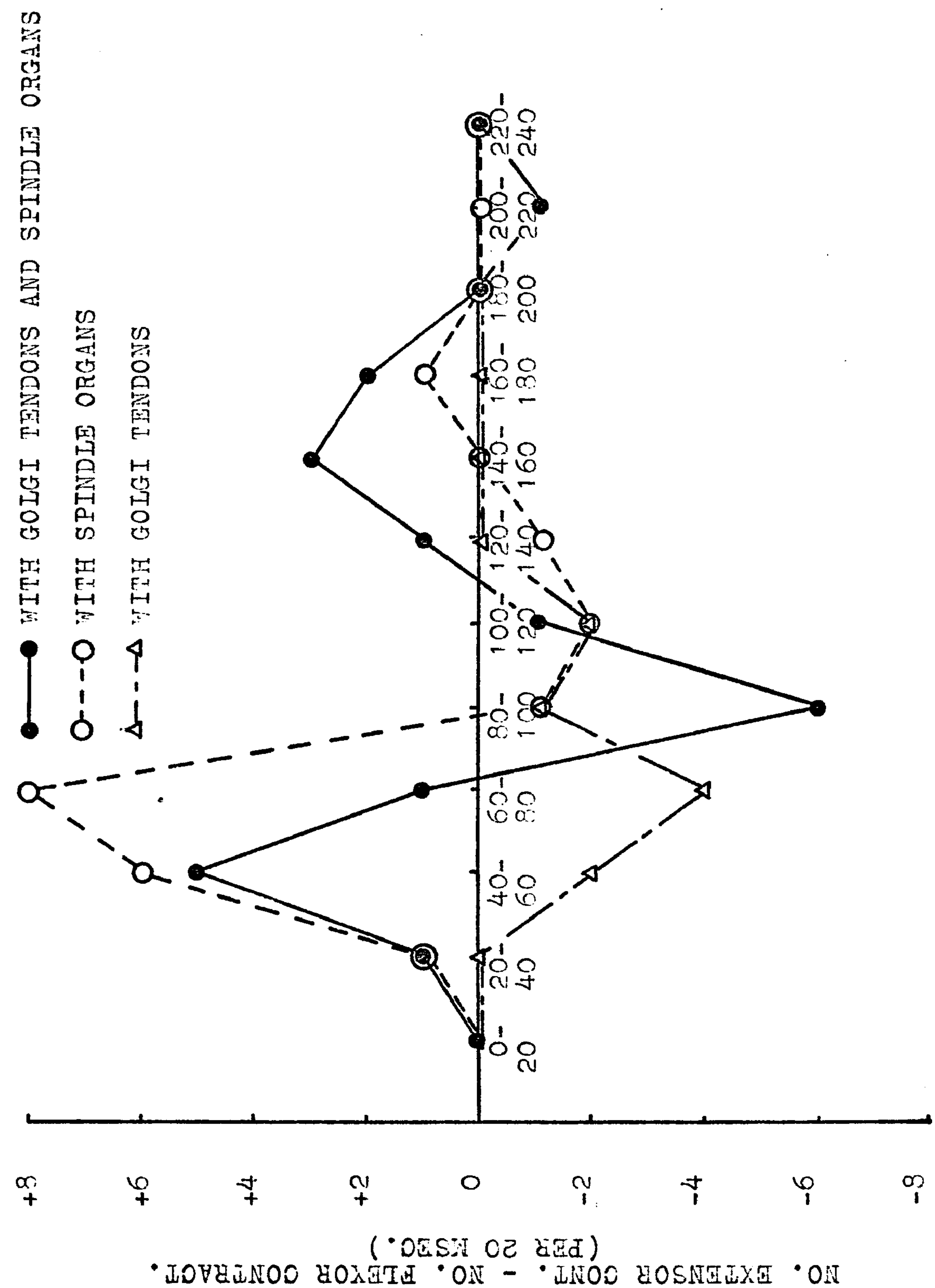
Figure 19. Mean latencies to the initial extensor contraction and flexor contraction for the stretch reflex model as a function of intensity. Each point is based on five simulation runs.


EXTENSOR
FLEXOR
INTENSITY (N)
10
20
30
40
50
60
70
80
90
100
SIMULATED MEAN LATENCY OF FIRST CONTRACT. (MSEC.)
80
70
60
50
40
30
20
10

999 for N36 and N18. In a similar fashion, the influence of spindle receptors (N22, N25, N26, and N28) could be elinated by raising their r values to 999. Figure 20 presents the consequences of removing either the Golgi tendon organs or the spindle organs on simulated stretch reflex behavior. It is apparent that when Golgi tendon organs are removed from the network, the initial extensor response is potentiated and subsequent changes in simulated muscle length are minimized. Interestingly, the curve just described more nearly mirrors the actual stretch reflex shown in figure 19. This would suggest that in any revisions of the spinal reflex model, either the threshold of the Golgi tendon organs be raised, or perhaps their excitatory influence on flexor muscles should be lessoned independent of their inhibitory actions on extensor muscles. In either case the effects of such network changes should also be determined on simulated flexion reflexes (to be considered next). Finally, it should be noticed in figure 20 that elimination of spindle organs from the network results in complete negation of the extensor response.

In the spinal animal, almost any sensory stimulus applied to the limb will cause the flexor muscles of the limb to contract strongly, thereby withdrawing the limb from the stimulus (Guyton, 1972). The initial stimulus condition necessary to simulate the flexor reflex begins with source node number 2 in figure 15.

Figure 20. The performance of the stretch reflex model under ine influence of both Golgi tendon organs and spindle organs, of only spindle organs, and of only Golgi tendon organs. N = 30 for all simulations.


WITH GOLGI TENDONS AND SPINDLE ORGANS
WITH SPINDLE ORGANS
WITH GOLGI TENDONS
0-20
20-40
40-60
60-80
80-100
100-120
120-140
140-160
160-180
180-200
200-220
220-240
+8
+6
+4
+2
0
-2
-4
-6
-8
NO. EXTENSOR CONT. - NO. FLEXOR CONTRACT.
(PER 20 MSEC.)

The run timer node, N4, and the stimulus intensity control P(7,8) operate in the same fashion as described for the simulation of the stretch reflex. Information concerning the strength of the stimulus is received by a hypothetical skin receptor, N11, which transmits this information if its threshold is surpassed. In this model, 2 activities incident to N11 must be completed before N11 causes more activities to be scheduled. After the first realization of N11, 3 activities are required to realize N11 (r' = 3). This condition has a neural analog in the receptor adaptation process, whereby the sensitivity of the cell decreases upon activation. Since N11 is deterministic all activities emanating from it will be scheduled.

P(11,12), P(11,20), P(11,23) and P(11,29) represent afferent connections from the skin receptor to various interneurons in the dorsal segment of the spinal cord. N12 is an excitatory interneuron which terminates at an α motor efferent (N13) in the ventral segment of the spinal cord. The α motor neuron in turn innervates the flexor muscle and its subsequent contraction (N17 and N19).

A second excitory interneuron, N20, synapses directly on the γ motor efferent which in turn innervates the flexor spindle receptor (N22). As long as the flexor muscle has not contracted [the activity represented by P(17,19) has not been completed], then only 2 activities into N22 must be completed before N22 will be realized. Completion of flexor contraction prior to this event results in a network modification whereby N22 is replaced by N26 and the flexor spindle threshold is consequently raised. When the flexor spindle is in fact stretched beyond its threshold, then it will have an inhibitory effect on the α motor neuron innervating the extensor muscle [P(22,29)] and a monosynaptic excitory effect on the α motor neuron innervating the flexor muscle [P(22,13)].

The interneuron represented by N23 is inhibitory and synapses on the γ motor efferent innervating the extensor spindle organs. When P(24,40) has been completed, N25 is replaced by N28 and the threshold for the extensor spindle is raised.

Finally, N29 represents a second inhibitory interneuron. When the activity emanating from this node is completed [P(29,39)], the threshold of the α motor efferent to the extensor muscle is raised by having N30 replaced by N32. This process will delay contraction of the extensor muscle. The subsequent effect on the network of either the contraction of the extensor muscle or the contraction of the flexor muscle will be identical to what has already been described for the simulation of the stretch reflex.

In generating the flexor reflex response from the spinal reflex model all GERTS network parameters were again set equal to those shown in figure 15. Three analyses were performed on traces following simulations having N = 10, 50, and 100. The resulting difference between the number of extensor and flexor contractions are graphed in figure 21 for each 20 msec. interval following stimulation. The simulated data provide almost a mirror image of the results predicted by the stretch reflex simulation; that is, a flexor reflex occurs prior to the cyclic behavior of the muscle. This is true for intermediate and high stimulus intensities. It is also apparent that the duration of the initial flexor response increases markedly when N = 100. Although there is no direct evidence concerning stimulus intensity, Guyton (1970) has shown that the flexor reflex may last as long as several seconds provided the stimulus is of long duration.

Figure 22 shows an analogous flexor reflex generated by the administration of shock to the limb of a sheep (Liddel, 1934). It is noteworthy that the empirical latency to peak flexor response and the computer generated latency to peak flexor response for N = 50 and N = 100 compare quite favorably (approximately 100 msec.). Some discrepancies between simulated findings and empirical data occur in relation to the amplitude of the subsequent cyclic responses and the speed with which the muscle response dampens (reaches a steady state).

Although the spinal reflex model does well in

Figure 21. Performance of the spinal reflex model under conditions instituted to simulate flexor reflex behavior. Curves represent the degree of extensor activity and flexor activity at three simulated intensities and were derived from analyses of simulation traces.

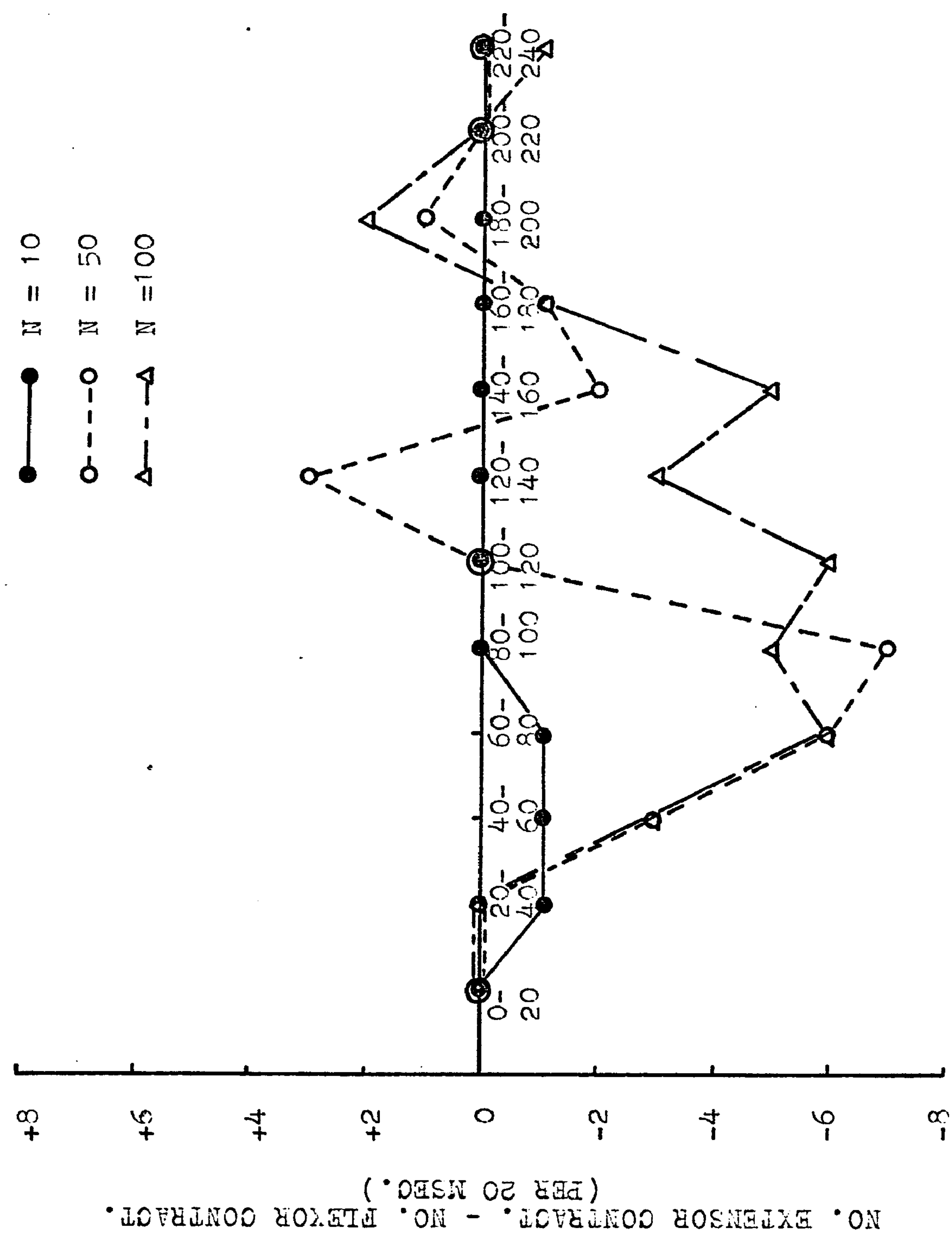
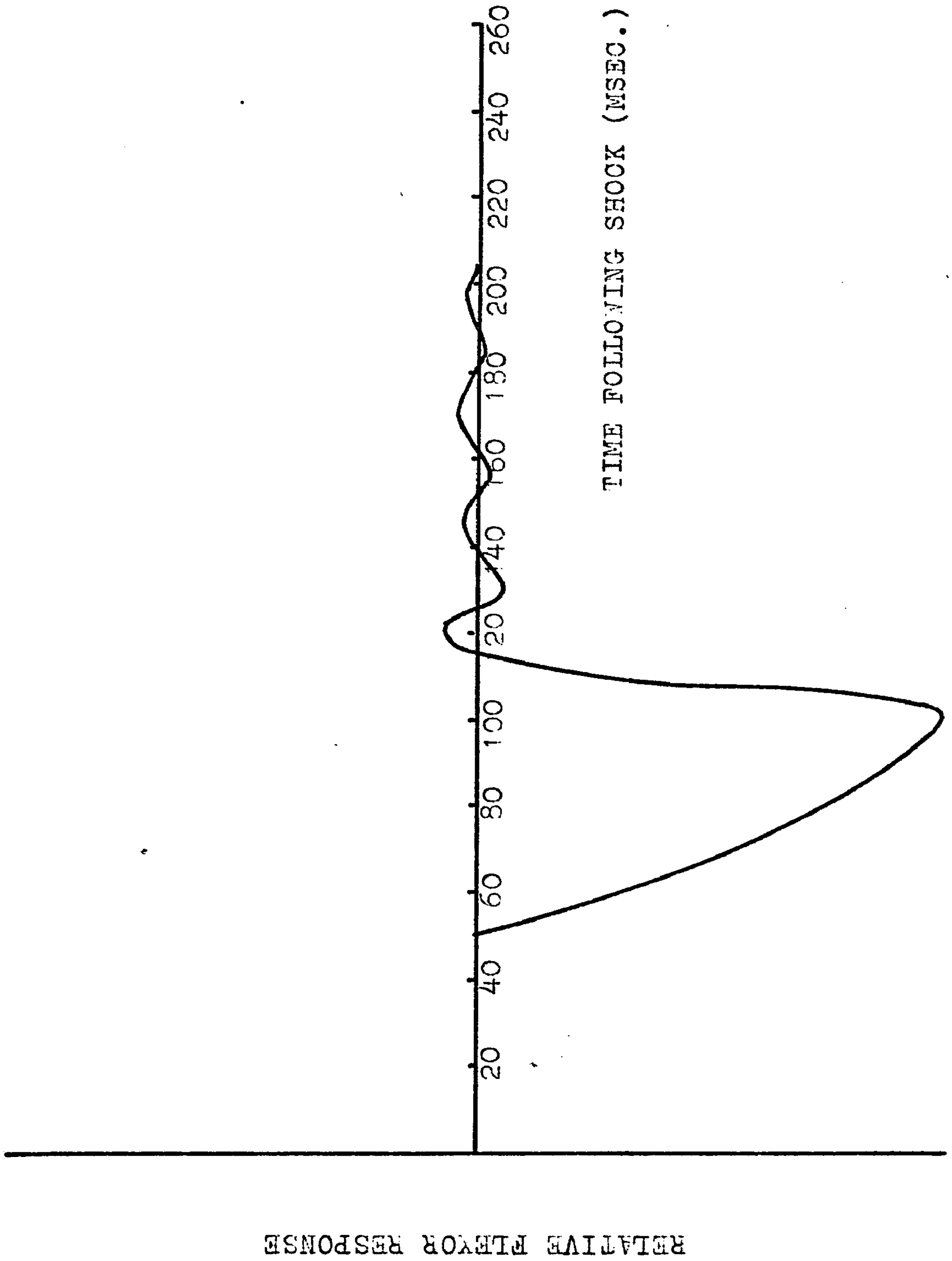

N = 10
N = 50
N =100
0- 20
20- 40
40- 60
60- 80
80- 100
100- 120
120- 140
140- 160
160- 180
180- 200
200- 220
220- 240
+8
+6
+4
+2
0
-2
-4
-6
-8
NO. EXTENSOR CONTRACT. - NO. FLEXOR CONTRACT.
(PER 20 MSEC.)

Figure 22. Unconditional response to shock by sheep (from Liddel, 1934).

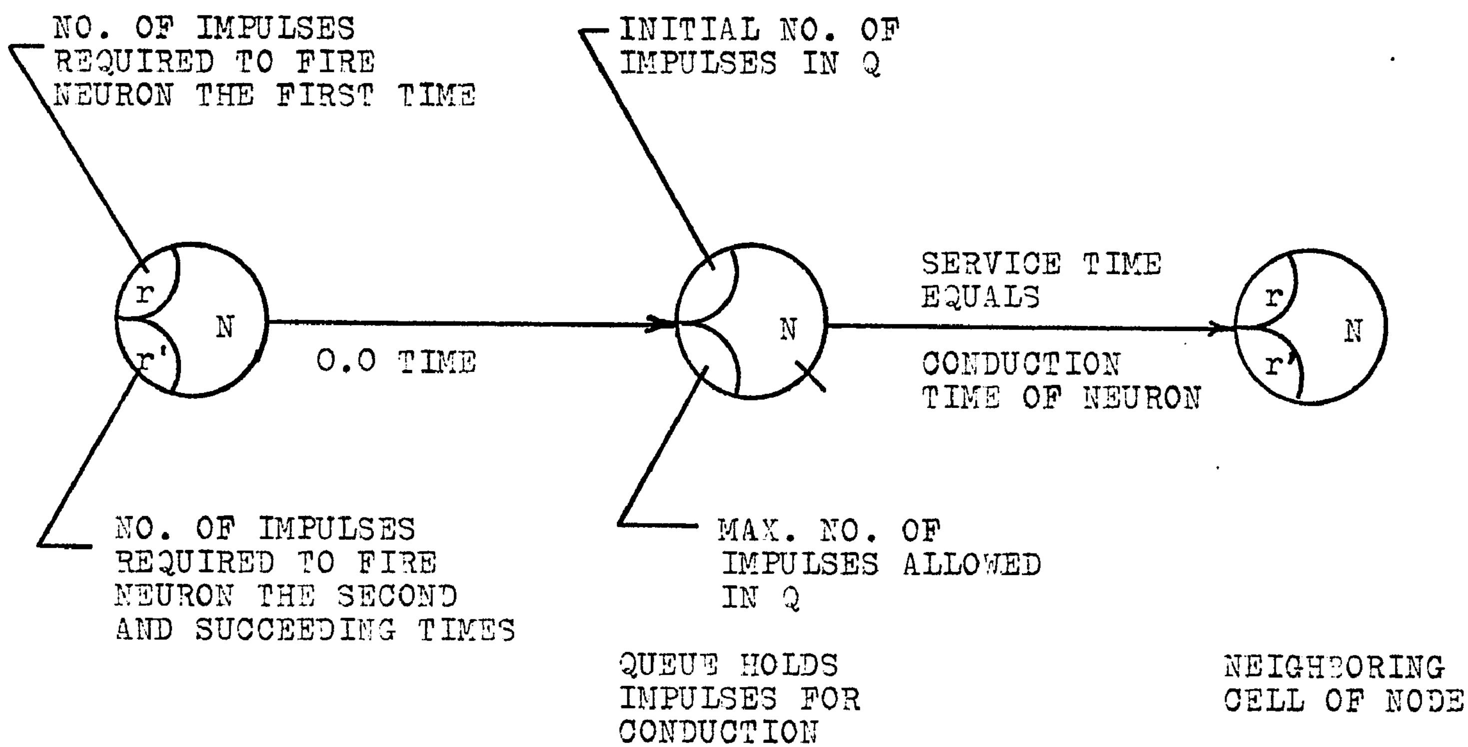

20
40
60
80
100
120
140
160
180
200
220
240
260
TIME FOLLOWING SHOCK (MSEC.)
RELATIVE FLEXOR RESPONSE

predicting most aspects of reflex behavior, it has an apparent shortcoming with regard to accurately genera-timg the inter-response times of these muscle contractions. For example, when N is large, then as many as 20 contractions may be simulated within a 20 msec. interval. This rate of contraction is even too rapid for fast muscles which have contraction times ranging from 7.5 to 40 msec. (Thompson, 1967). The difficulty arises because each node has limited memory and if too many activities incident on a node are completed, then node realization may occur prior to the completion of activities emanating from the node. The end result is a scheduling problem for the GERTS program, and an overall decrease in the time required to complete certain activities in the network. To circumvent this situation the network comprising unit II should be revised to include the storage capabilities of the Q node. Recall that if an activity emanating from a Q node is taking place (an item is being served) then items arriving at the Q node will be stored (put in queue) until they can be scheduled. Each neural conduction time and each muscle contraction time could represent the service time associated with a given Q. The initial number of items in each Q would be 0. The maximum number of items allowed in each Q would be set at some large magnitude. No items would balk from the Q nodes. Items would be served on FIFO (first in first out) basis.

Neural threshold information could not be designated on the Q node since there is no provision for r and r' considerations. Therefore, a separate node should be established to accomplish this function. A proposed representation of a neuron using GERTS network descriptors is shown in figure 23. Several important GERTS III Q program restrictions should be considered when attempting to use this neural representation. First, the neuron requires an additional branch to establish a count of the number of times items were serviced (e.g. if you wanted to determine the number of neural firings or muscle contractions). Also, only one service activity can be associated with a given Q-node. Therefore, each afferent and efferent neuron requires a separate Q-node. Finally, as will be demonstrated in conjunction with unit IV, network modifications can not be performed when they involve replacing one Q-node with a second Q-node.

How would unit II be utilized in the classroom setting? A student would initially be required to study the basic physiology of spinal reflexes. The instructor might then ask him to predict the effects of selectively removing Golgi tendon organs and spindle organs on stretch reflex behavior and flexor reflexes. This should help the student understand the function of each receptor and also clarify the idea of a feedback loop.

Figure 23. A possible functional description of a neuron in GERTS network terminology.


NO. OF IMPULSES REQUIRED TO FIRE NEURON THE FIRST TIME
r
r'
N
0.0 TIME
NO. OF IMPULSES REQUIRED TO FIRE NEURON THE SECOND AND SUCCEEDING TIMES
INITIAL NO. OF IMPULSES IN Q
N
MAX. NO. OF IMPULSES ALLOWED IN Q
QUEUE HOLDS IMPULSES FOR CONDUCTION
SERVICE TIME EQUALS
CONDUCTION TIME OF NEURON
r
r'
N
NEIGHBORING CELL OF NODE

The effect of varying the intensity of the stimulus could be studied with the simulation model in much the same fashion as was described in this chapter. The functional nature of interneurons could also be altered such that they would have a greater inhibitory or excitatory impact on the system.

There are additional revisions which the advanced student might contemplate. For example, muscle fatigue and drugs are known to modify the strength of the contraction of muscle fibers even though the nerve impulses remain constant (Merton, 1956). Their effects on the model should be considered. An additional sensory receptor, the flower-spray ending, could be introduced into the muscle spindle. Its known function is to excite flexor motor neurons (Thompson, 1967).

Alpha motor neurons have branches called recurrent collaterals which run back into the spinal cord where they generally cause inhibition (Renshaw, 1941). These might be introduced into the network to provide a greater net inhibition of muscular activity. Finally, intersegmental spinal influences or even cortical influences could be introduced, although such considerations are extremely complex.

Unit III
The Classical Conditioning Paradigm

Unit III is designed to provide students with an understanding of the classical conditioning paradigm. A GERTS model has been developed which generates the typical exponential learning curve and simulates the subsequent extinction process.

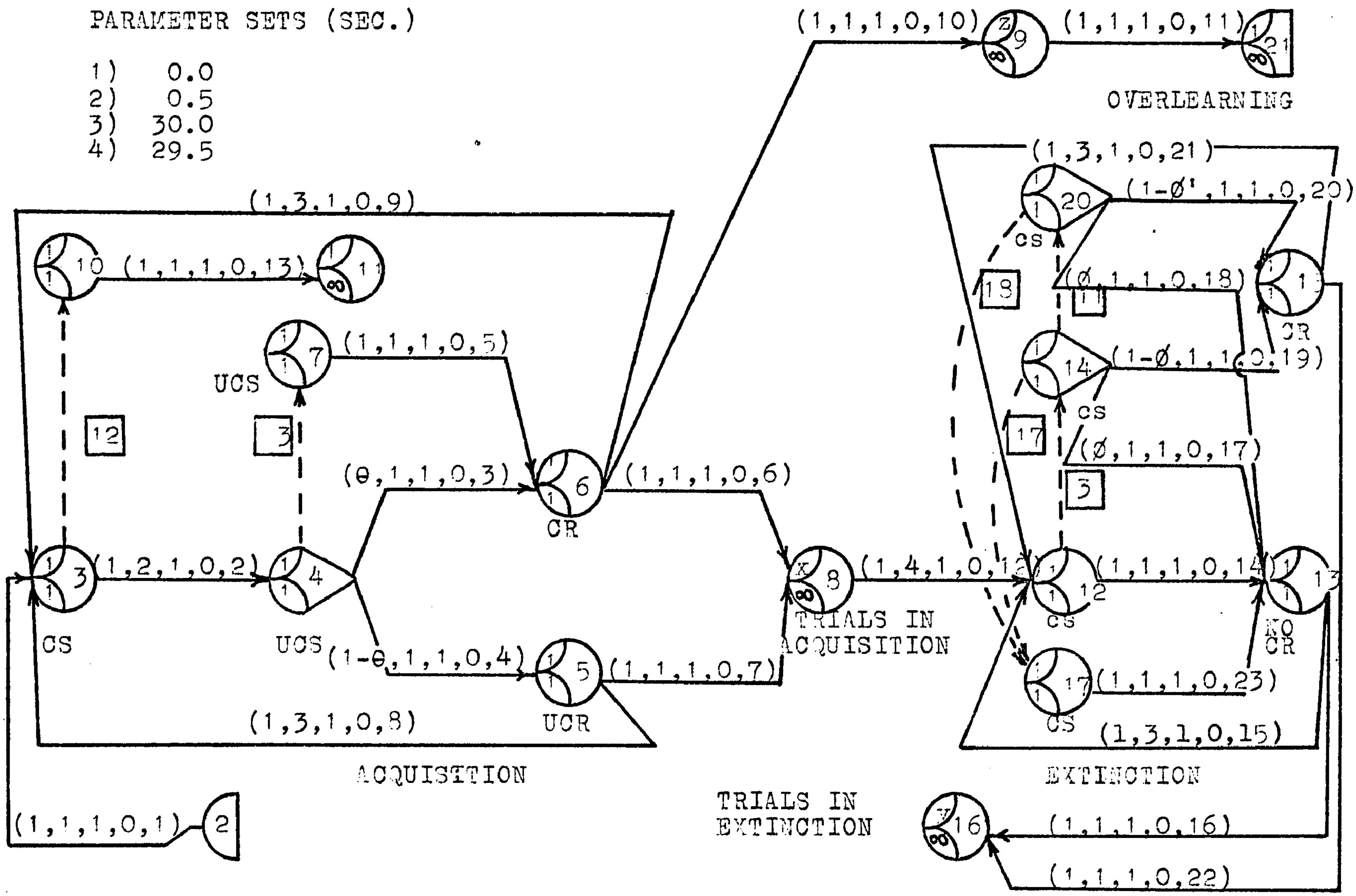
Classical conditioning refers to the learning paradigm in which one stimulus, as the result of being paired with a second stimulus, comes to elict a response it did not elicit just previously (Mikulus, 1974). In this situation the first stimulus is known as the conditioned stimulus (CS) and the response it comes to elicit is called the conditioned response (CR). The second stimulus, the unconditioned stimulus (UCS), had been eliciting an unconditioned response (UCR) at the time of the pairing of the CS and UCS.

Pavlov (1927), the Russian physiologist, initiated a series of investigations to study this phenomenon. He originally observed that dogs salivated when they heard the footsteps of the individual who normally fed them. The anticipatory nature of the salivation response led Pavlov to believe that it was psychical and was the product of previous experience. An extensive body of literature followed Pavlov's early investigations. These studies were concerned with variables that effect the generation of the conditioned response and the theorical foundation of the response. Kimble (1961), Gormezano (1966), and Stolurow (1973) present excellent reviews of this literature.

Varieties of classical conditioning procedure are designated in terms of the relationship between the CS and the UCS. Typically the CS begins a half sec. prior to the onset of the UCS. Repeated pairings of the CS and UCS ideally produce a change in some aspect of the strength of the CR. Indices of response strength fall into two broad categories: the first class of indices refers to some measureable feature of the individual responses themselves. Examples of this type would include the amplitude of the response, the latency of the response, and the duration of the response. The second class of indices is based on whether CR's occur or fail to occur. That is, a response may be considered to be a CR if, during CS-UCS pairings, the response occurs prior to the onset of the UCS. A response may also be designated a CR if, during test trials interspersed throughout training, a response occurs to CS alone. Thus the response strength will be great if there is a high probability that a response will occur in a given unit of time or if a given stimulus appears. Response probability will be the principle dependent variable in unit III.

The network diagramed in figure 24 is designed to permit the student to study the development of the CR

Figure 24. A network description of unit III: the classical conditioning paradigm. The network is designed to simulate acquisition, extinction, and overlearning.



PARAMETER SETS (SEC.)
1) 0.0
2) 0.5
3) 30.0
4) 29.5
(1,1,1,0,1)
CS
(1,2,1,0,2)
UCS
(1,3,1,0,8)
(1,3,1,0,9)
(1,1,1,0,13)
12
3
UCS
(1,1,1,0,5)
(θ,1,1,0,3)
(1-θ,1,1,0,4)
CR
UCR
(1,1,1,0,6)
(1,1,1,0,7)
ACQUISITION
(1,1,1,0,10)
(1,1,1,0,11)
OVERLEARNING
TRIALS IN ACQUISITION
(1,4,1,0,12)
(1,3,1,0,21)
(1-Ø',1,1,0,20)
(Ø,1,1,0,18)
(1-Ø,1,1,0,19)
(Ø,1,1,0,17)
(1,1,1,0,14)
(1,1,1,0,23)
(1,3,1,0,15)
18
17
5
11
CS
CR
NO CR
EXTINCTION
TRIALS IN EXTINCTION
(1,1,1,0,16)
(1,1,1,0,22)

under three conditions: during acquisition when the CS is paired with the UCS; during extinction when the CS is presented alone; and during extinction following a number of trials of overlearning.

The simulation is initiated when N2 schedules the first activity incident on N3. N3 represents the presentation of the CS during acquisition in the classical conditioning paradigm. The branch from N3 to N4 simulates the inter-stimulus interval (ISI) between the CS and the UCS. Most studies have demonstrated that the optimal ISI is in the neighborhood of .5 sec. (Kimble, 1961); therefore P(3,4) has associated with it $t_p = 2$ (.5 sec.) and $t_D = 1$ (constant distribution). Following the first pairing of the CS and the UCS (the completion of the activity represented by P(3,4), there will be a probability, θ, that the subject will generate a CR and a probability, $1 - \theta$, that the subject will generate a UCR. Thus, an individual subject can demonstrate complete learning in one trial (a consideration of the appropriateness of this assumption will be made at the end of this section). Once N6 is realized, a subject will continue to produce conditioned responses for the remainder of the acquisition trials. This is accomplished by replacing the probabilistic node, N4, with the deterministic node, N7, upon the completion of P(4,6).

Both N5 and N6 have feedback loops returning to N3.

Either of these activities, when completed, represent the duration of the inter-trial-interval (ITI). In this network the ITI equals 30 sec. the realization of N3 simulates the start of the next acquisition trial. N5 and N6 also have branches leading to N8. The value of r for N8 determines the number of CS-UCS pairings which will be simulated. Upon the realization of N8, P(8,12) will be scheduled. The completion of P(8,12) will halt the acquisition phase of the simulation since N3 will consequently be replaced by N10 and no further trials will be initiated. If N12 is designated a sink node then one simulation run will cease after a specified number of trials. Additional simulation runs indicate that different subjects generate the conditioned response on different trials. The probability that N6 will be realized prior to network realization will provide an index of the probability of the CR, Pr(CR), for a group of subjects (a large number of runs) on any given trial. Pr(CR) can also be determined analytically in the following manner for n CS - UCS pairings: the probability that a subject will make a UCR after 1 trial is

$$Pr(UCR)_1 = (1 - \theta)$$

The likelihood that he makes an UCR after a second CS-US pairing is $Pr(UCR)_2 = Pr(UCR)_1 \ (1 - \theta) = (1 - \theta)^2$ Successive values of Pr(UCR) are generated in a similar fashion. The general result then becomes

$$Pr(UCR)n = (1 - \theta)^n$$

Therefore, Pr(CR)n becomes

$$Pr(CR)n = 1 - (1 - \theta)^n$$

The latency for the CR and the UCR has not been considered in the acquisition phase of the present network description- both P(4,6 and P(4,5) have 0.0 times associated with their activities. Different time parameters for P(4,5) could be estimated on the basis of the type of UCR being simulated. On the other hand, the latency associated with the CR can only be considered when its value is less than the ISI (by the definition of an anticipatory response). If the typical CR latency is longer than the selected optimal interval, it is necessary to obtain empirical measures of the CR on trials other than the acquisition trials (Gormezano, 1966). Short latency skeletal responses (.2 to .5 sec.) could be simulated, but a revision of the network would be necessary. For example, a new CS node could be defined to replace N3 upon the completion of P(4,6). This new node would lead directly into a CR node and the branch connecting these additional nodes would represent the latency of the CR. Finally, the new CR node could input into the UCS node, N4, after a brief interval (equal to the difference between the ISI and the latency of the CR).

If a student desires to study the extinction phase of classical conditioning in conjunction with the acquisition phase, then N12 is not designated as a sink node. Extinction trials will begin when N12 is realized for the first time. This process simulates the experimental presentation of the CS alone. If a subject has not produced a CR during acquisition, then he has not learned an association between the CS and UCS and will fail to generate a CR during extinction. N13 represents the event "no CR". Normally, the realization of N12 will directly lead to the realization of N13. However; if learning has occurred during acquisition, then the activity associated with P(4,6) will have been completed. This in turn will effect the extinction portion of the network by causing N12 to be replaced by N14. How a subject is assumed to be in the CR state and will extinguish the CR response with a probability, Ø, represented on P(14,13). On the other hand, a subject has a probability, 1 - Ø, of resisting extinction (producing a CR). This is represented by P(14,15). If P(14,13) is taken, then an additional network modification causes N14 to be replaced by N17. The net effect of this modification is to retain the subject in the extinction condition following the realization of N13.

Both N15 and N13 have branches feeding back to N12. These branches represent the ITI during extinction and the completion of either activity will eventually cause another CS to be presented (N12 realized). The number of trials during extinction, y, can be manipulated by varying the value of r on N16.

If is possible to calculate the probability of a subject producing a CR during the extinction phase $\left[P(CR)n,y\right]$ given a specified number of trials of CS-UCS, pairings and a specified number of trials of CS alone:

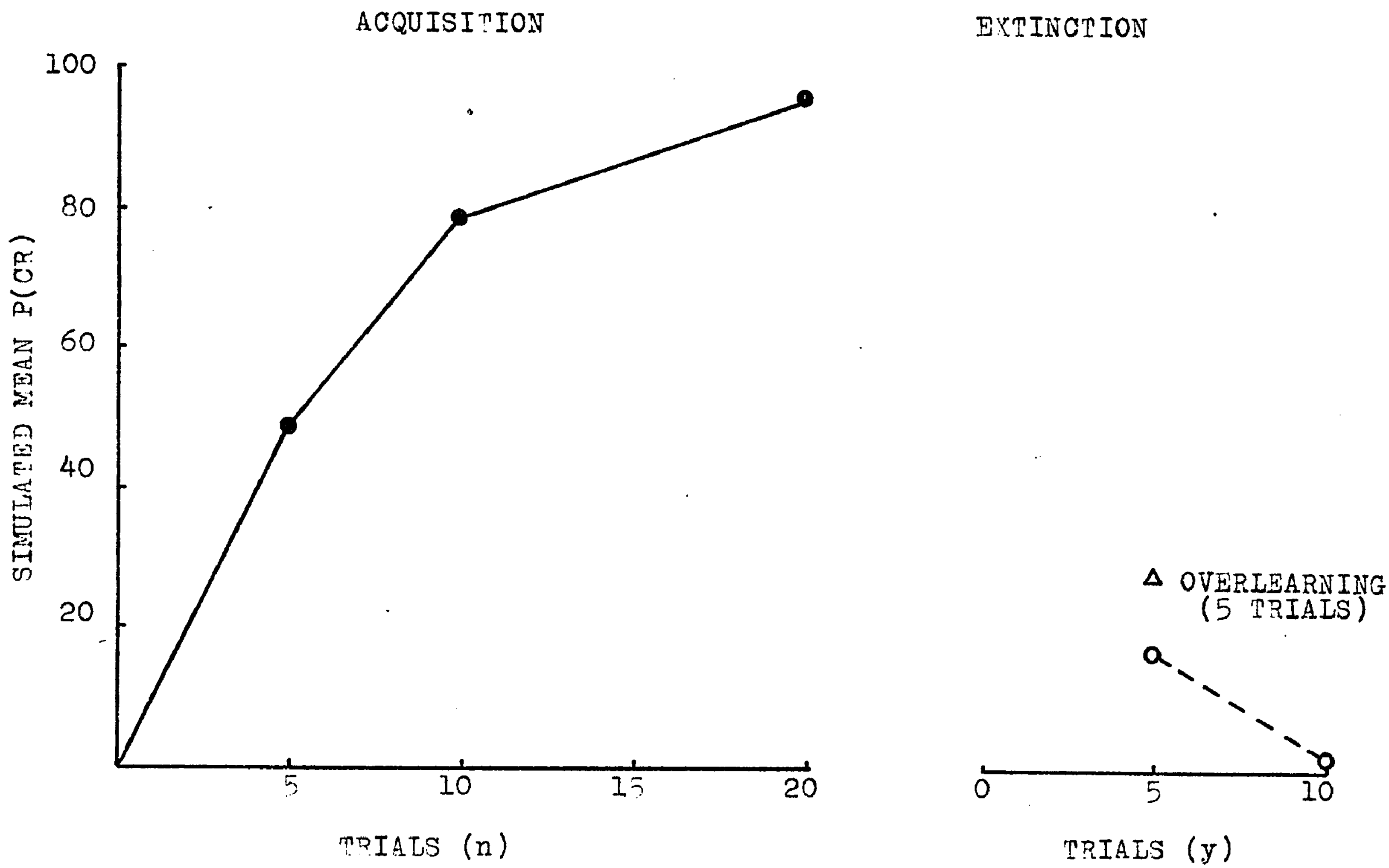
$$P(CR)n,y = P(CR)n \times P(CR)y$$
$$= \left[1 - (1-\theta)^n\right](1-\emptyset)^y$$

The consequences of overlearning have also been considered in the model shown in figure 24. Mackintosh (1963) has demonstrated that some degree of overtraining, produced by continuing reinforcement beyond the point at which the subjects meet the criterion of learning, results in an increase in resistence to extinction. Since the present model views learning as an all-or-none process, any acquisition trials following the realization of N6 simulate overlearning. These trials are counted via the r parameter on N9. P(9,21) emanates from N9 and will be scheduled upon the realization of N9. The completion of P(9,21) causes N14 to be replaced by N20. The immediate effect of this network modification is make possible a change in the value of $\emptyset$. If a student wishes to simulate an increase in resistence to extinction following a specified number of trials of overlearning then $\emptyset$ should be lowered [this new probability is designated ϕ' on P(20,13)]. If overtraining is extended still further (set r on N9 to some higher value), then there is some evidence for a decrease in resistence to extinction (Hulse, Deése, & Egeth, 1975; Logan, 1970). In this case the programmer should designate the value of ϕ' as greater then ϕ.

Simulations of the network in figure 24 were performed with θ arbitrarily set at .13 and ϕ set at .3. Figure 25 presents the simulated learning curve generated with three values of n and the simulated extinction curve for $n = 20$ and $y = 5$ and $y = 10$. Each point represents the mean P(CR) and is based on 100 simulation runs. Also shown in figure 25 is the effect of 5 trials of overlearning on extinction behavior. ϕ' was set at .2 for this analysis. An inspection of the simulated acquisition curve indicates that it takes the form of a "growth curve" as would be predicted from the all-or-none model (Estes, 1959). The simulated extinction curve is based upon only two points but it is consistent with empirical data demonstrating an abrupt reduction in the percentage of CR's when the CS is presented alone (Hartman & Grant, 1960). Finally, the expected increase in resistence to extinction was achieved with 5 trials of overlearning.

It is hoped that students working with this model can gain an understanding of the nature of the relationships

Figure 25. The simulated learning and extinction curves for unit III: the classical conditioning paradigm. Each point is based upon 100 runs. $\dot{\theta} = .13$, $\emptyset = .3$, $\emptyset' = .2$. Extinction data follows 20 trials of acquisition.


ACQUISITION
EXTINCTION
SIMULATED MEAN P(CR)
100
80
60
40
20
5
10
15
20
TRIALS (n)
OVERLEARNING (5 TRIALS)
0
5
10
TRIALS (y)

between the stimuli presented and the responses recorded in the classical conditioning experiment. It is apparent that he or she will also get to understand the importance of various underlying assumptions. For instance, students will gain some insight into the way in which a model which predicts all-or-none learning on an individual basis can generate a continuous curve when subject data is pooled. The all-or-none vs. incremental learning controversy is still an important theoretical issue (Mikulas, 1974) and could be discussed by students in conjunction with unit III.

A critical assumption of the two-state model is that the probability of remaining in a UCR state is constant over the sequence of precriterion responses (stationarity). A test of this property was made by Estes (1964) on data from a series of eyelid conditioning experiments with human subjects. He found that the proportion of CR's per trial is relatively stationary between the first CR and the last non-CR trial (eyelid closures of at least 1 mm. deflection from a baseline were considered to be CR's). In light of this data, Estes (1964) has suggested that a 3 state model would provide a more accurate description of classical conditioning. Students could modify Unit III to reflect this suggestion. Here learning occurs by discrete jumps, but subjects may go to an intermediate level before going to the terminal state of perfect performance. Bower and Theios (1963) have also developed a 3-state model to account for eyelid conditioning data.

An additional revision of the present network has already been described and concerns simulation the latency of the CR. Students might also attempt to add a segment of to unit III in order to incorporate findings related to spontaneous recovery. The effect of changing variables such as the ISI and ITI could be studied on the probability of generating the CR. This would be accomplished through the use of network modifications much as was done with the consideration of overlearning.

Unit IV
Free Recall and the Serial Position Effect

The usual procedure during a free recall memory experiment if for the experimenter to present first a list of unrelated items, one item every second or two. The subject then is required to recall as many items on the list that he can, in any order. One of the most important characteristics of free recall concerns the variation in the probability of recall of individual items as a function of their position in the list. A graph of this relationship is known as the serial position curve. Murdock(1962) presented lists of common unrelated English words to subjects at different rates. He found that for relatively long lists the serial position curves have three distinct segments. The probability of recall is greatest for items at the end of the list, next greatest for items in the beginning, and least in the middle.

The enhanced accuracy of the first few serial positions is thought to represent a primacy effect and of the last seven or so a recency effect. The low middle portion of the curve is often referred to as the asymptote. Theorists who believe in the existence of two separate memory systems argue that the recency effect appears to be independent of factors that influence other segments of the serial position curve. For these theorists improved recall in the final portion of the curve is the result of the ability of subjects to select items from short term memory (STM). Recall of the early and middle list positions is thought to reflect the long term storage (LTM) of items in direct proportion to the amount of rehersal given then (Peterson, 1975).

Although serial position curves will vary somewhat with the type of the material and the nature of the practice (Hulse, Diese, & Egeth, 1974), the effect is one of the most pervasive phenomena of human memory. Even a partial list of theorists who have attempted to incorporate these findings into their formulations is long (Broadbent, 1958; Waugh & Norman, 1965; Atkinson & Shiffrin, 1968). Norman (1970) reviews some of the more prominent models of human memory. More recent theories (Laughery, 1970; Frijda, 1972; Morimoto, 1972) have used simulation as a methodological tool in the study of memory.

The present unit was designed to enable students to study the memory process via a simulation of the serial position effect. The outstanding features of this particular unit are its modular nature and use of the Q-node as a means for temporarily storing information.

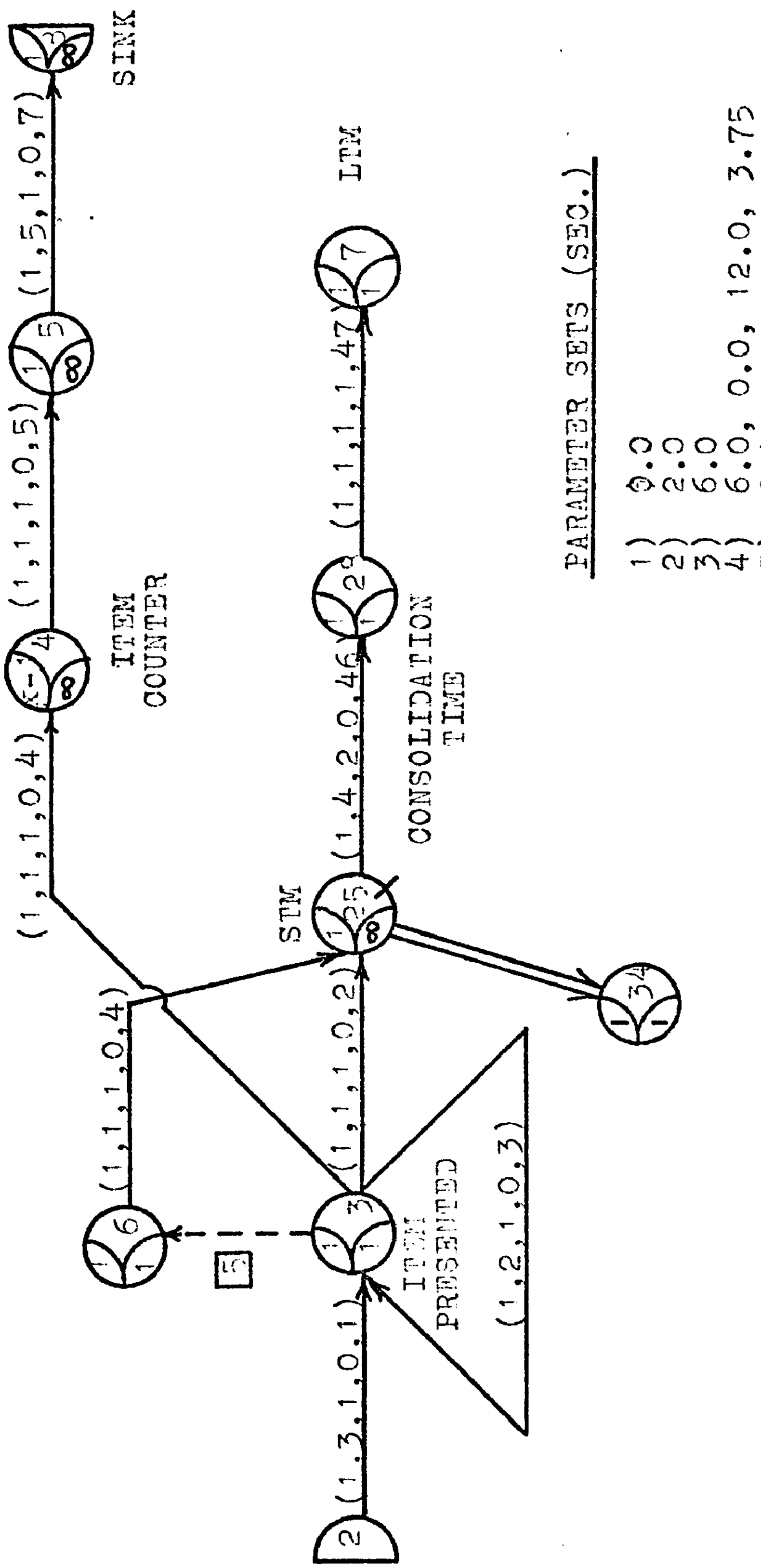
The model described in this unit considers memory to be a two-stage process comprised of a STM and a LTM. Each stage is functionally represented by a Q-node. Just prior to the presentation of the list of items, it is assumed that a subject is able to remove all but one item of previous information from his STM. The clearning of most of the recent memories could conceivably operate through an attention mechanism. All list items pass initially into STM. Here items are consolidated (serviced by the Q node) on a L.I.F.O. basis and, if consolidated, enter LTM. Rehearsal is seen as a way to facilitate the entry of information into LTM, and not as means for retaining information in STM. The consolidation time per item is normally distributed (the rationale for this assumption will be discussed shortly).

As soon as the final item on the list enters STM, a subject attempts to recall all items by first searching his STM and then searching his LTM; however, retrieval is hindered by interference. Distracting stimuli, present in the environment operate much as new items would and "push down" relevant list items from their positions in the STM queue. Other investigators (Waugh & Norman, 1965; Reitman, 1971; Shiffrin, 1973) have also concluded that interpolated information can interfere with material being held in STM. The arrival time for interfering information was estimated from the data. It is assumed that a subject utilizes the first 15 sec. following list presentation to retrieve items from STM, and the remaining 75 sec. to retrieve items from LTM. The model also assumes a differential rate of retrieval from STM and LTM, with items from LTM being recalled at a significantly slower rate. Subjects retrieve information from both memory stores on a L.I.F.O. basis.

From a programming standpoint, the model is divided into three modules: the consolidation process, retrieval from STM, and retrieval from LTM. Discussion will begin with a consideration of the consolidation process.

Figure 26 is a GERTS graphical representation of the consolidation process. The simulation of the network is initiated with N2. The activity represented by P(2,3) requires 6 seconds to complete. Therefore, the hypothetical free recall experiment does not begin until 6 seconds after the simulation begins. This was done to insure that other aspects of the model would be functioning when the first simulated item was presented to the subject. Once an item has been presented and N3 has been realized, the item passes directly into STM via P(3,25). Additional items in the list are generated by means of the feedback loop, P(3,3), whose completion time is a constant and represents the rate of presentation. Items continue to enter STM (N25) until the item counter, N4, is realized. The realization of N4 leads to the completion of P(4,5) and the eventual replacement of N3 with N6. This, in turn, insures that only one additional item will input into STM. The x value associated with the number of releases on N4 corresponds to the list length simulated

Figure 26. The GERTS network description of the consolidation process for Unit IV: free recall and the serial position effect.


SINK
(1,5,1,0,7)
(1,1,1,0,5)
ITEM COUNTER
(1,1,1,0,4)
LTM
(1,1,1,1,47)
CONSOLIDATION TIME
(1,4,2,0,46)
STM
(1,1,1,0,4)
(1,1,1,0,2)
ITEM PRESENTED
(1,2,1,0,3)
(1,3,1,0,1)
PARAMETER SETS (SEC.)
1) 0.0
2) 2.0
3) 6.0
4) 6.0, 0.0, 12.0, 3.75
5) 2.1

in the free recall experiment.

All parameters associated with the Q node (node 25) in figure 26 are extremely critical for the eventual functioning of the model. One item of information is assumed to be in the A node at the start of the simulation. The presence of this item simulates the influence of proactive interference on STM. Peterson (1975) has concluded that proactive effects can have a significant impact upon the immediate recall of test items. The maximum number of items allowable in N25 is infinite, and items are processed on a LIFO basis. The service time for N25 represents the consolidation time of one item from STM to LTM. The time parameter (set) associated with P(25,28) remains a constant for all experimental simulations. It was derived in the following manner. An inspection of the serial position curves formulated by Murdock (1962) indicates that for long lists (greater than 20 items) the asymptate appears to be a function of the presentation rate. For instance the asymptote for lists 20 items long with each item presented every 2 seconds (designated 20-2) falls in the neighborhood of 30% probability of recall. Since one item is arriving every 2 sec., then if the model requires an average of 6 sec. before an item can enter LTM, only 33% of the total number of items would be consolidated after all items have been presented. The utilization of 6 sec. as the mean consolidation time would result in approximately 17% of the items entering LTM if items were arriving one every second. This result is also similar to the empirical finding made by Murdock (1963). The consolidation time is thus assumed to be normally distributed with a mean of 6 sec. The value may be somewhat low since empirical estimates of the consolidation time have ranged from 10 sec. to a week (Mikulas, 1974).

The standard deviation of this distribution was derived from a consideration of the probability that the first item on the list will enter LTM. Recall that the simulation begins with an item already in STM. The computer will initiate the program by servicing this item on P(25,28). After 6 sec. the first item on the list arrives in STM. If the server is busy (the interfering item is still being consolidated) then item #1 will wait in the queue until the consolidation of the interfering item is complete. Assume the second item on the list arrives 2 sec. later. Then if the second item arrives before the first item has been served, then the second item will be served next. This is because service is on a LIFO basis. It is therefore apparent that the necessary conditions for item #1 <u>not</u> to be consolidated are: 1.the interfering item in memory has a consolidation time greater than 8 sec.; 2.the second item entering STM will then be processed and it must have a consolidation time greater than 2 sec.; 3. the third, and each succeeding item may require processing times greater than 2 sec. but this is conditional upon the consolidation times for previous items. The probabilities for the first two events listed above can be determined by calculating the appropriate area under the normal distribution defined by the mean and standard deviation of the consolidation time. The third event will be assumed to have a negligible effect on the probability of the first item entering LTM. Now if the mean of the distribution is 6 sec. and the standard deviation is 3.75 sec., and if new items are arriving every 2 sec. then,

P (item #1 not being consolidated) $\approx$
P (interfering item has consolid. time > 8 sec.) x
P (item #2 has a consolid. time > 2 sec.)

$\approx$ P (Z score > .53) x P (Z > - 1.07)

$\approx$ (.30) (.86)

$\approx$ .26

The probability of item #1 entering LTM is one minus this value- or approximately .74. This result does not insure that item #1 will be recalled with a probability of .74 since retrieval processes have yet to be considered. It does however, insure that item #1 will have a greater probability of entering LTM than succedding item (which enter with a probability of .33). The primacy effect is therefore assumed to be principally due to the fact that STM is relatively empty at the beginning of a list and so material encountered early has a greater chance of being consolidated.

Each item which has been consolidated causes N28 to be realized. This in turn schedules P(28,7) to be completed. P(28,7) is tagged with c = 1 which enables the mean number of items entering LTM to be tallied. Simulations were performed on the network described in figure 26 for experiments involving 10-2, 20-1, 20-2, and 40-1 item presentations. The probability of a given item being consolidated into LTM was determined by a direct analysis of between 50 and 100 traces for each experimental condition. In all simulations the consolidation time was normally distributed with a mean of 6 sec. and a standard deviation of 3.75 sec. The results of simulated experiments involving 20-1 and 20-2 items are shown in figures 27 and 28 respectively. The simulated asymptotic proportion of items entering LTM appears to be consistent with the values predicted for each rate of presentation. It is also apparent that the first item enters LTM with a much greater frequency. The last item presented to the subject in all cases fails to be consolidationed, the reason being that as soon as the last item enters STM, this particular aspect of the free recall simulation ends. At this point the subject is requested to recall as many items as he can. The next module considers how the subjects' search strategy and how interference both

Figure 27. The simulated probability of an item being consolidated into LTM as a function of its serial poxition in a list 20 items long. Items presented one every second. The consolidation time was normally distributed with a mean of six sec. and a standard deviation of 3.75 sec.

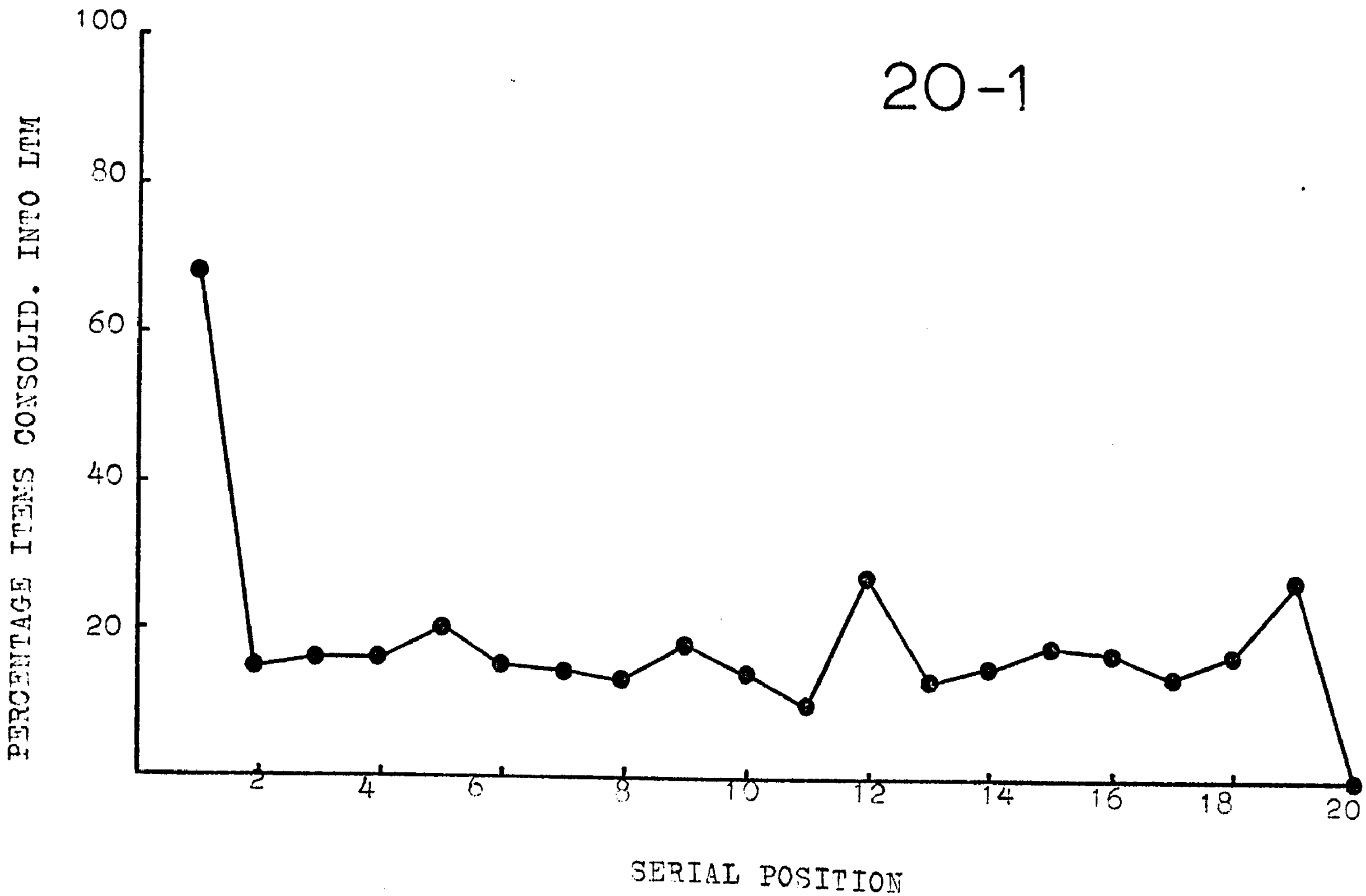
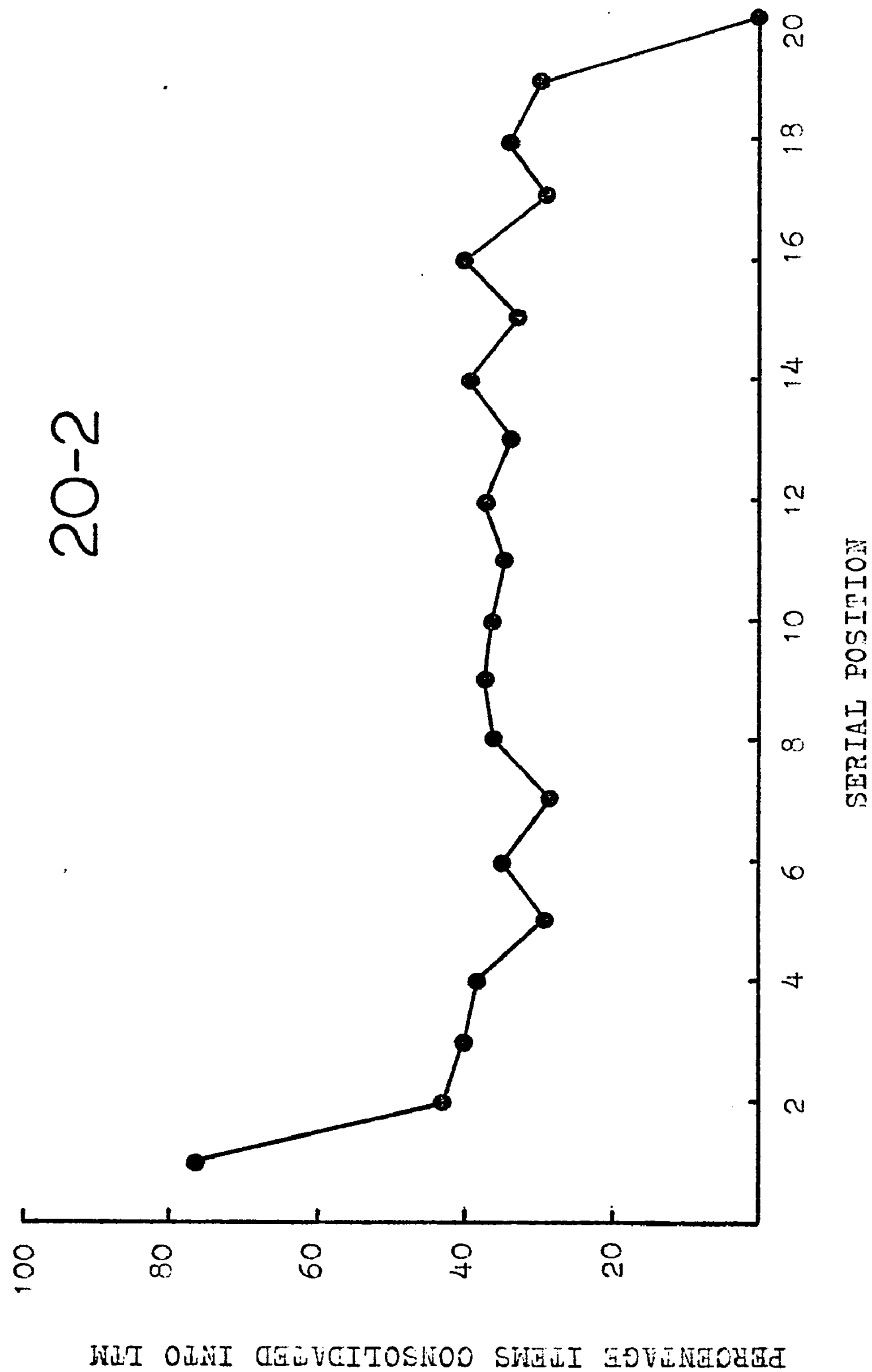

20-1
PERCENTAGE ITEMS CONSOLID. INTO LTM
100
80
60
40
20
2
4
6
8
10
12
14
16
18
20
SERIAL POSITION

Figure 28. The simulated probability of an item being consolidated into LTM as a function of its serial position in a list 20 items long. Items presented one every two seconds. The consolidation time was normally distributed with a mean of six sec. and a standard deviation of 3.75 sec.


20-2
PERCENTAGE ITEMS CONSOLIDATED INTO LTM
100
80
60
40
20
SERIAL POSITION
2
4
6
8
10
12
14
16
18
20

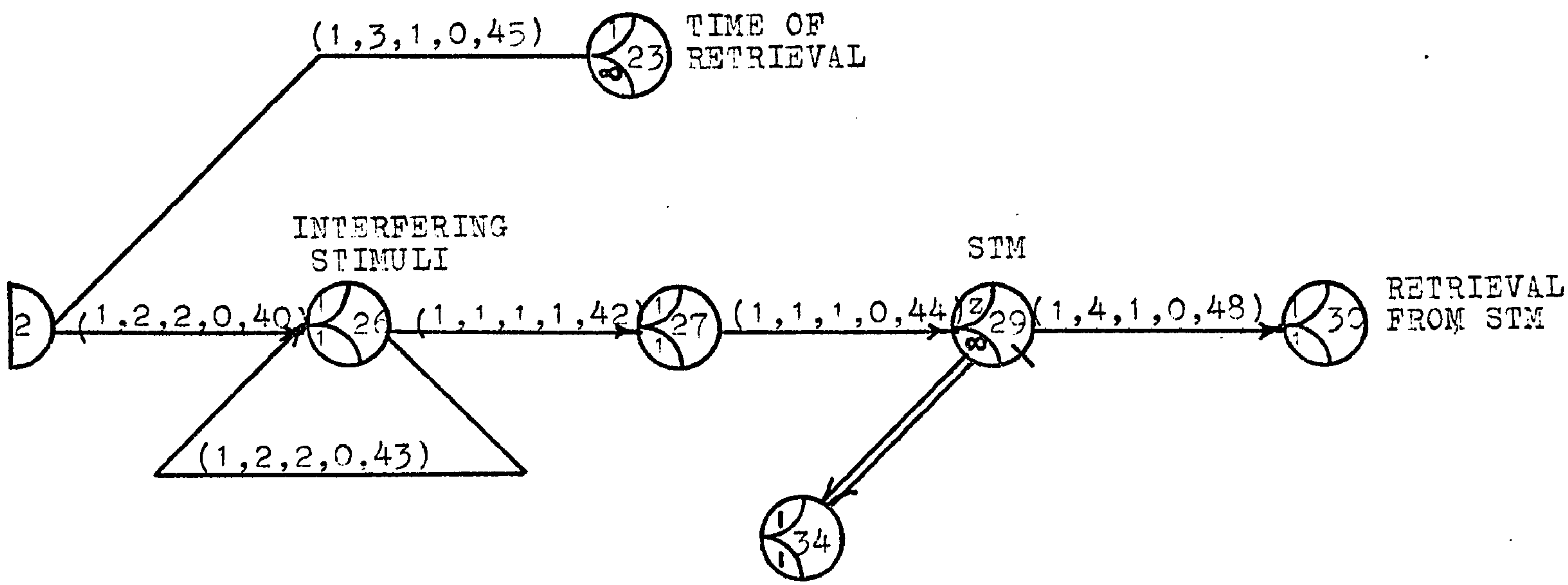
effect the ease with which items are initially recalled.

Assume that initially a subject decides to recall as many items as possible from STM. Assume also that even under optimal conditions there is some interference from the environment which will hinder this retrieval process. Figure 29 represents a possible network description of the process of retrieval from STM.

A previous analysis of the simulated mean number of items entering LTM demonstrated that approximately 7.5 items were consolidated (for a 20-2 item presentation). This suggests that the remaining 12.5 items are still filed in STM. Therefore, the initial number of items in Q node number 29 prior to retrieval was set at 12 (it will become apparent later that this parameter can take on any value greater then 6). The maximum number of items permitted in N29 is infinite.

Subjects begin recall by attempting to retrieve the last item stored in STM. Thus retrieval also follows a LIFO convention. Items are retrieved every 2 seconds. This retrieval time is simulated on the service activity emanating from N29. The value of 2 sec. per item is only an estimate and students might wish to generate an empirical distribution of item recall times following an actual free recall experiment. Ekstrand and Underwood (1962) have provided some data concerning response times when they compared paced responding with unpaced respond-

Figure 29. The GERTS network description of retrieval from STM for unit IV: free recall and the serial position effect.



PARAMETER SETS (SEC.)

1) 0.0
2) 3.0, 0.0, 8.0, 3.0
3) 14.0
4) 2.0

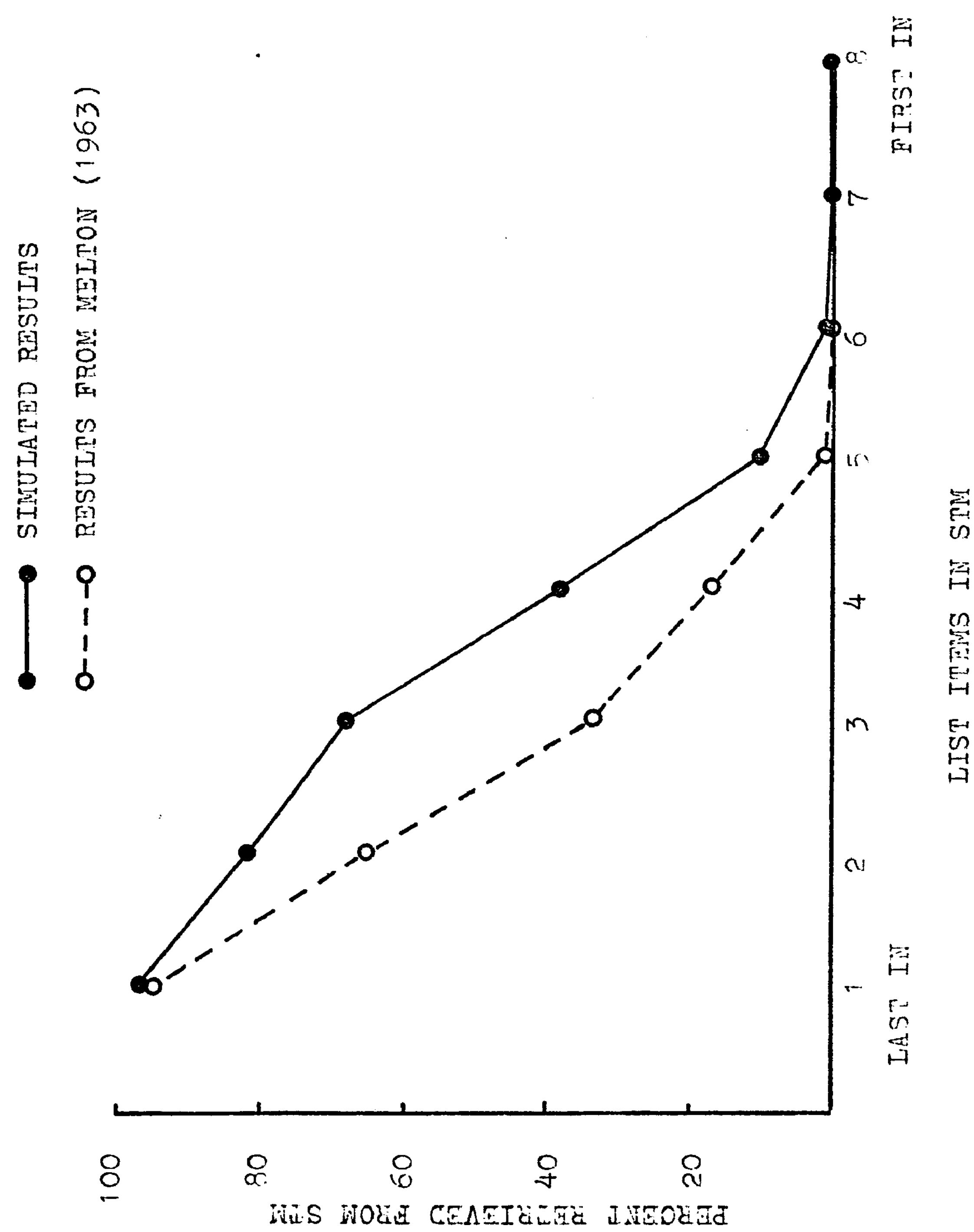
ing in a free recall situation.

Returning to figure 29, it can be seen that N2 initiates the simulation of this network. The arrival of the first interfering stimulus requires a time interval represented by the parameter set on P(2,26). Arrival times for interfering stimuli are assumed to be normally distributed with a mean of 3.0 sec. and a standard deviation of 3.0 sec. These values were estimated by trial and error and resulted in the best fit to empirical data offered by Murdock (1962). It is suggested that the time parameters associated with the interfering stimuli are related to the subjects attention during the free recall task. At some time, students might wish to test this notion by performing a free recall study whereby the extent of external stimulation would be varied (i.e. visual and auditory distractions presented). An extreme example of interference occurs when additional items are presented immediately following the presentation of the first list. Wickelgren (1973) points out that although the last list items have an advantage, this advantage can be overcome with extra interpolated activity. The number of interfering stimuli is tallied with counter #1 on P(26,27).

Recall that for a 20 item list, item #20 is in STM when the interference begins. This item will be retrieved unless an interfering stimulus arrives at N29 first. In this case the interfering stimulus will be retrieved [P(29,30)] and the subject will either report an incorrect item, or realize that he has retrieved an incorrect item, report nothing, and continue his search of STM. The simulation of the network in figure 29 will continue for 14 sec. At this time sink node, N23, will be realized.

One hundred simulations of retrieval from STM were performed. Fifty computer traces were analyzed in order to determine the probability that a given item in STM would be retrieved. The results of this analysis are graphed in figure 30 along with empirical data collected by Melton (1963). Since Melton used the distractor technique to prevent rehersal, the experimental situations are not completely analogous. If one assumed some rehearsal takes place in the free recall paradigm during the recall interval, then the percent retrieved from STM should be greater for the data generated by the simulation model- as is the case. It is important to realize that although the last item to enter STM (position 1 on the abscissa) corresponds to list item #20, the remaining items in STM do not necessarily correspond to preceding list items (e.g. 19, 18, 17,...); some of the preceding items may have been consolidated and await retrieval from LTM. This has interesting implications for predicting variability in the order that the first few items will be recalled by a subject. For example, referring to figure

Figure 30. A comparison of the simulated percentage of items retrieved from STM with empirical results from Melton (1963). Simulated data is based on the analysis of 50 computer traces.

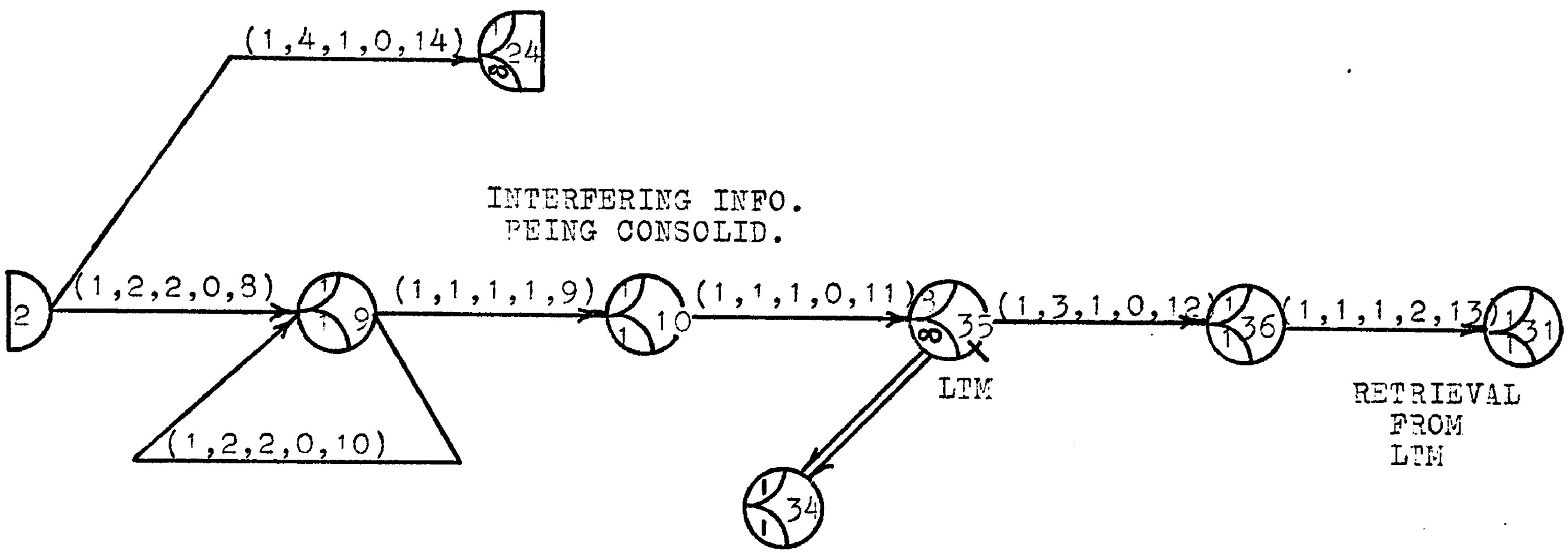

SIMULATED RESULTS
RESULTS FROM MELTON (1963)
PERCENT RETRIEVED FROM STM
100
80
60
40
20
LIST ITEMS IN STM
LAST IN
FIRST IN
1
2
3
4
5
6
7
8

30, 50% of the time approximately 3.6 items are retrieved from STM. Since roughly 67% of the last 17 or so items reside in STM (see figure 28) and items are retrieved on a LIFO basis, then subjects should retain the correct order (items would be recalled in order of descending list position) for all but 33% of the first 3.6 items recalled. This assumes that the last list items to enter LTM will be retrieved.

The network representing the final aspect of the free recall simulation, retrieval from LTM, is shown in figure 31. The simulation of this network begins immediately following the cessation of the second module. That is, a subject is assumed to initiate a search of LTM subsequent to his search of STM. The only new parameter introduced in this network is the retrieval time of items from LTM time parameters associated with P(35,36) . Retrieval from LTM is assumed to take a constant time of 3.85 seconds. This value gave the best fit to Murdock's (1962) empirical data for a 20-2 presentation and should be verified in some future test of the model. It should be related to the subjects inter-response time following 14 seconds of responding. A more extended discussion of the number of free parameters associated with each of the teaching units will take place in chapter 7.

It is also assumed that interference effects the retrieval of items from LTM. This is because some

Figure 31. The GERTS network description of retrieval from LTM for unit IV: free recall and the serial position effect.



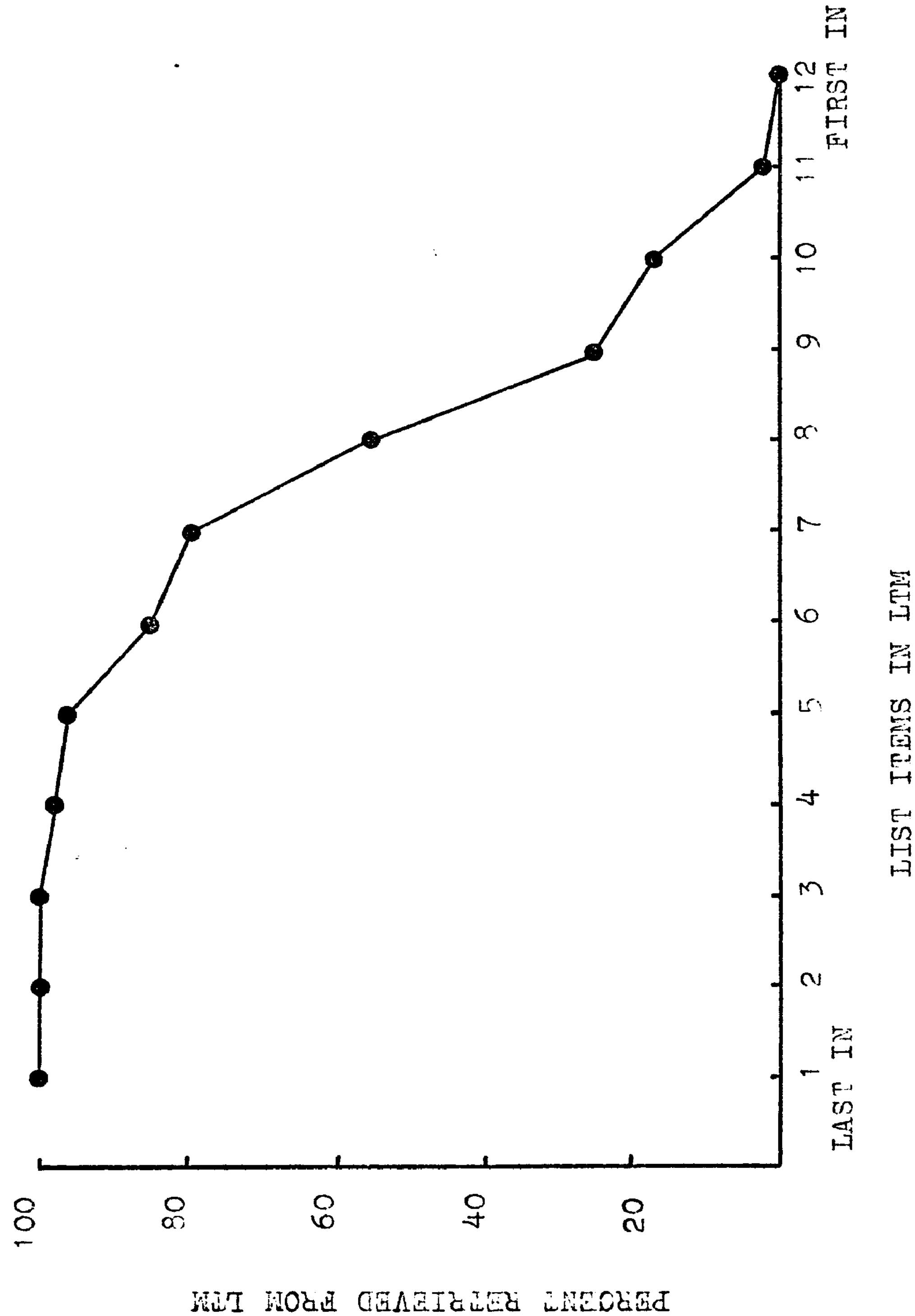
PARAMETER SETS (SEC.)

1) 0.0
2) 6.0, 0.0, 12.0, 3.75
3) 3.85
4) 76.0

interfering stimuli which had effected the retrieval of STM are now being consolidated. These interfering stimuli "push down" list items already in the LTM queue, and since service is on a LIFO basis, make it more difficult for them to be retrieved. The activity associated with P(2,9) represents the consolidation time. It is normally distributed with a mean of 6 sec. and a standard deviation of 3.75 sec.- made identical to the first module. Counters associated with P(9,10) and P(36,31) determine the mean number of interfering stimuli and the number of items retrieved respectively. N24 is tne sink node and terminates the simulation of this particular module after 76 seconds. Hypothetical subjects have a total of 90 sec. in which to recall as many items as possible (Module 2 + Module 3).

Fifty traces were again analyzed following the simulation of the network in figure 31. Figure 32 presents the relationship between the list items position in LTM and the simulated probability that the item will be retrieved from LTM. Just as with STM retrieval, it is apparent that items last to enter LTM have the greatest probability of being retrieved. Although longer lists have more items entering LTM (holding presentation times constant), fewer of the initial items on the longer list will be retrieved from LTM. For example, simulations of the consolidation process for 20-1 items resulted in a

Figure 32. The simulated probability of an item being retrieved from LTM as a function of its position in LTM.


PERCENT RETRIEVED FROM LTM
100
80
60
40
20
LAST IN
1
2
3
4
5
6
7
8
9
10
11
12
FIRST IN
LIST ITEMS IN LTM

mean of 3.99 items entering LTM. This means that the first list item into LTM corresponds to 3.99 on the abyscissa of figure 35. Such an item has almost a 100% chance of being retrieved. On the other hand, a simulation of the consolidation of lists 40-1 in length resulted in a mean of 7.69 items entering LTM. From figure 35 we know that approximately 63% of the time the first item entering LTM will be retrieved for this experiment. By the same reasoning, lists presented at a slower rate have resulted in more items being consolidated into LTM. For instance, the first module predicts that on the average 7.44 items will be consolidated into LTM for lists presented at 20-2, while an average of 3.99 items will be consolidated for lists presented at 20-1. From an inspection of figure 32 it is apparent that a greater percentage of the time the first item presented will be retrieved when 3.99 items have been stored (20-1 presentation).

The student can now combine the results of the three networks to generate a family of serial position curves. A list item is recalled by either retrieving the item from STM or retrieving the item from LTM. The probability of recalling an item in a given serial position is therefore:

$$\begin{aligned}\Pr(\text{Recall}) = {} & \Pr(\text{item in STM}) \times \Pr(\text{retrieval from STM}) + \\ & \Pr(\text{item in LTM}) \times \Pr(\text{retrieval from LTM})\end{aligned}$$

The first module provides information concerning the probability that a given item is consolidated into LTM or remains in STM. The next two modules simulate the probability of retrieval from STM and LTM respectively. Figures 33, 34, 35, and 36 present the resulting simulated serial position curves for various list lengths and presentation rates. Data from actual free recall studies (Murdock, 1962) is also shown in the aforementioned figures for comparison purposes. The simulated results are quite consistent with the empirical data in terms of predicting the primacy effect, the recency effect, and the asymptote for each serial position curve. Murdock also has demonstrated the serial position effect for 15-2 and 30-1 list presentation conditions. These situations could certainly be simulated by students using unit IV.

The present model offers several additional predictions which might be empirically tested. First, it was assumed that retrieval of items from STM proceeds at a more rapid rate than retrieval from LTM. This assumption should be reflected in the inter-response times generated by subjects in an actual free recall study- e.g. there should be two relatively separate distributions of inter-response times.

With some variablity, the model also predicts that items will be recalled in an order which is the reverse

Figure 33. A comparison of the simulated serial position curve for a 10-2 presentation rate with empirical data by Murdock (1962).

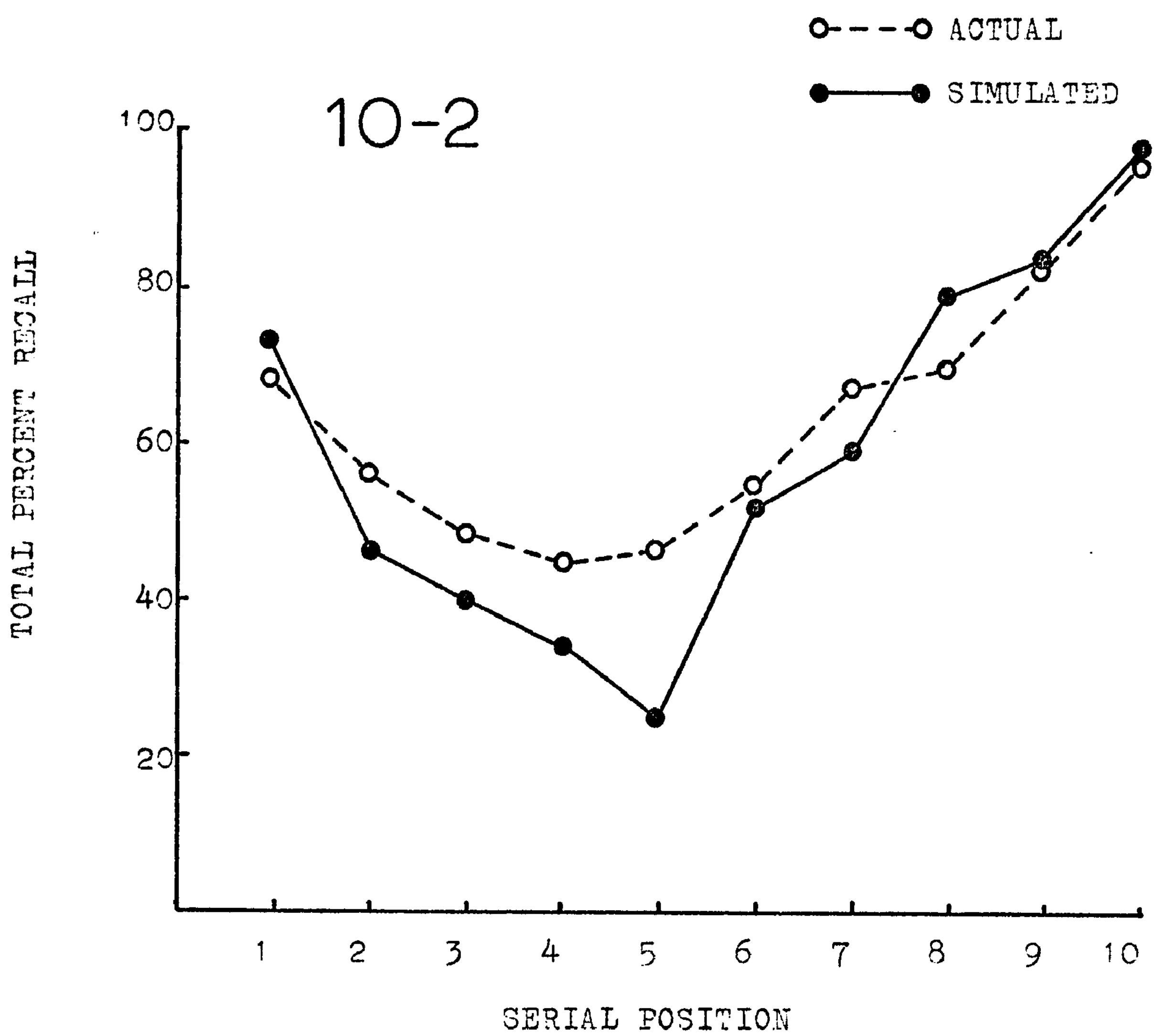

10-2
ACTUAL
SIMULATED
TOTAL PERCENT RECALL
100
80
60
40
20
1
2
3
4
5
6
7
8
9
10
SERIAL POSITION

Figure 34. A comparison of the simulated serial position curve for a 20-1 presentation rate with empirical data obtained by Murdock (1962).

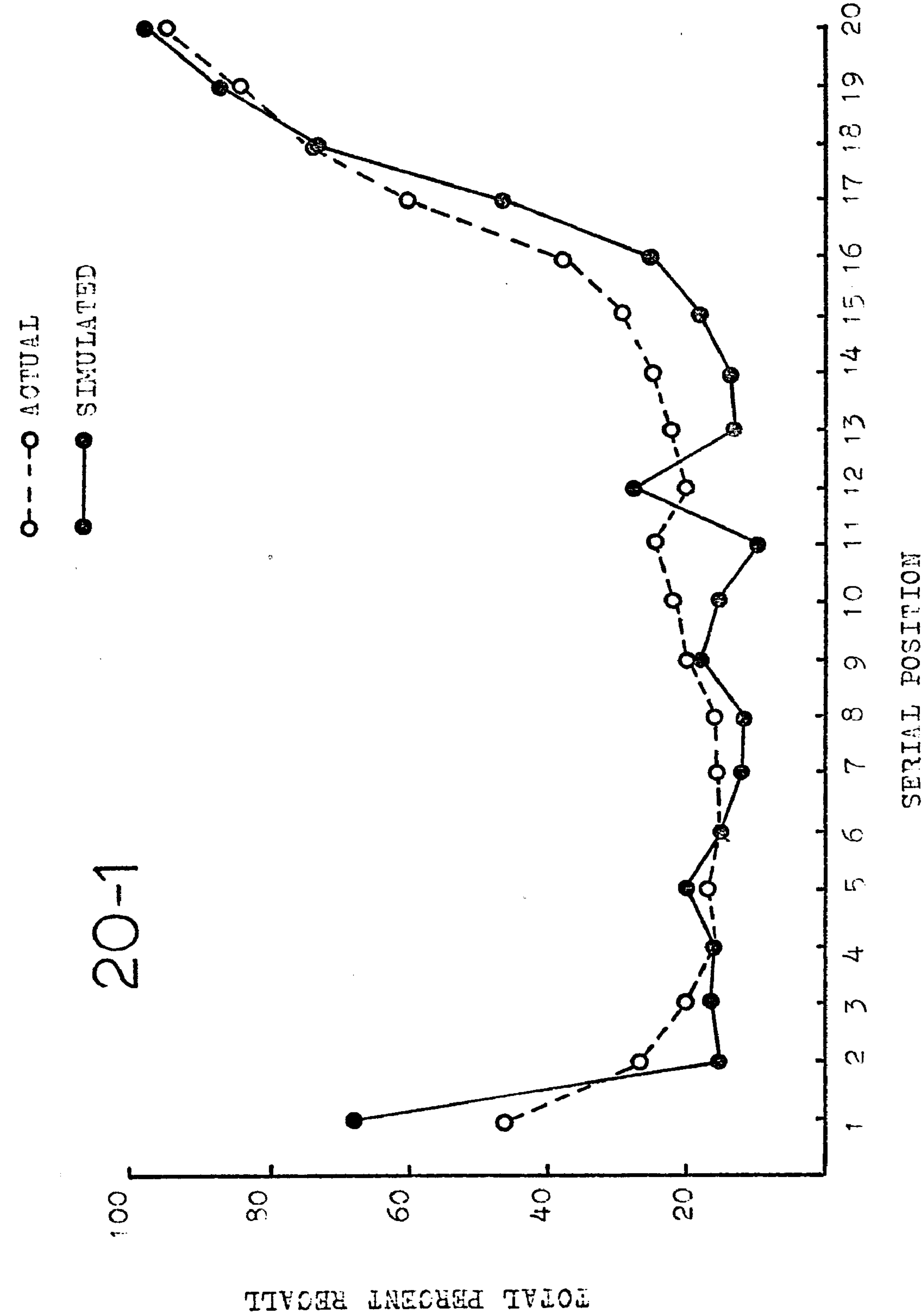

20-1
ACTUAL
SIMULATED
SERIAL POSITION
TOTAL PERCENT RECALL
100
80
60
40
20
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20

Figure 35. A comparison of the simulated serial position curve for a 20-2 presentation rate with empirical data obtained by Murdock (1962).

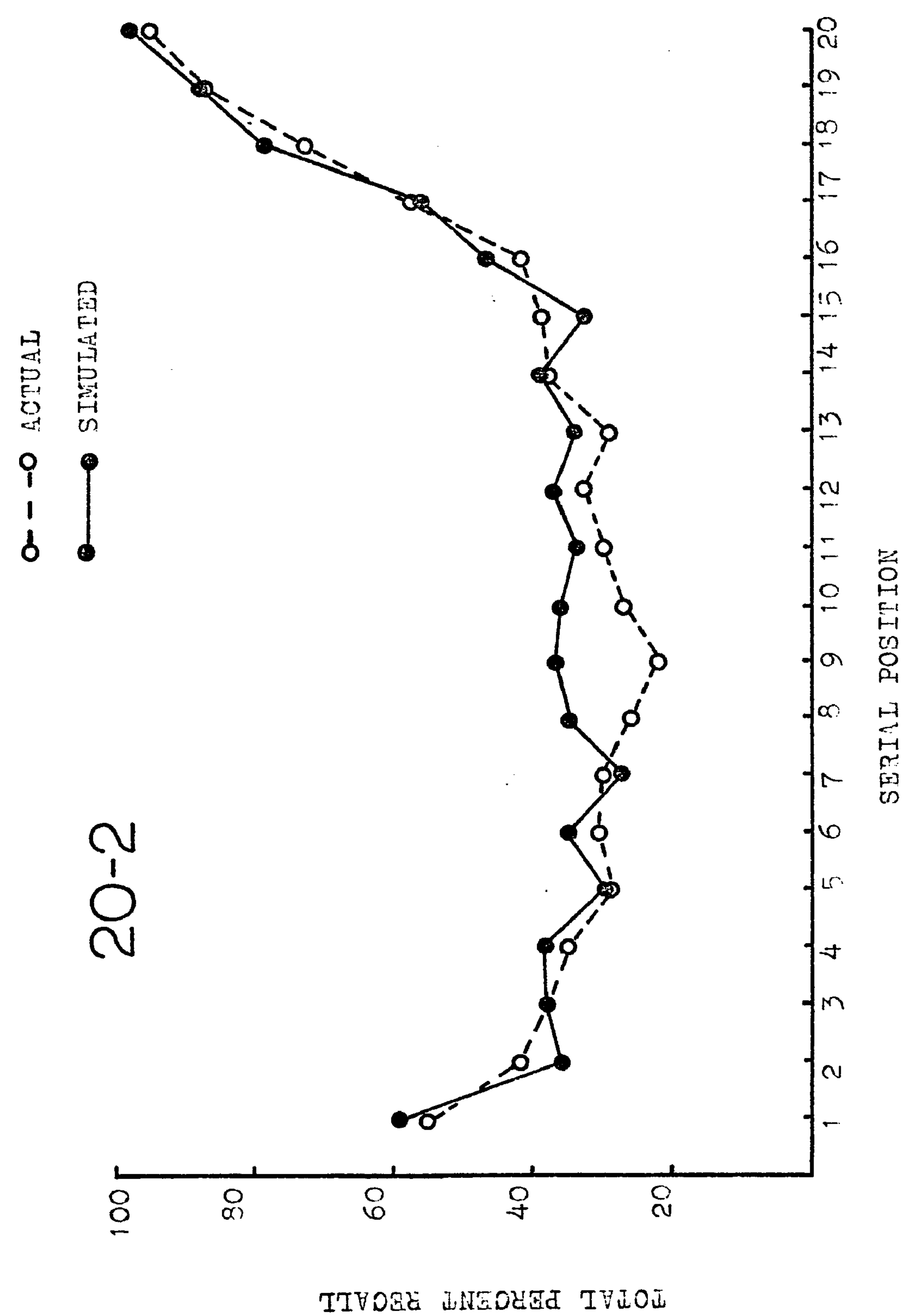
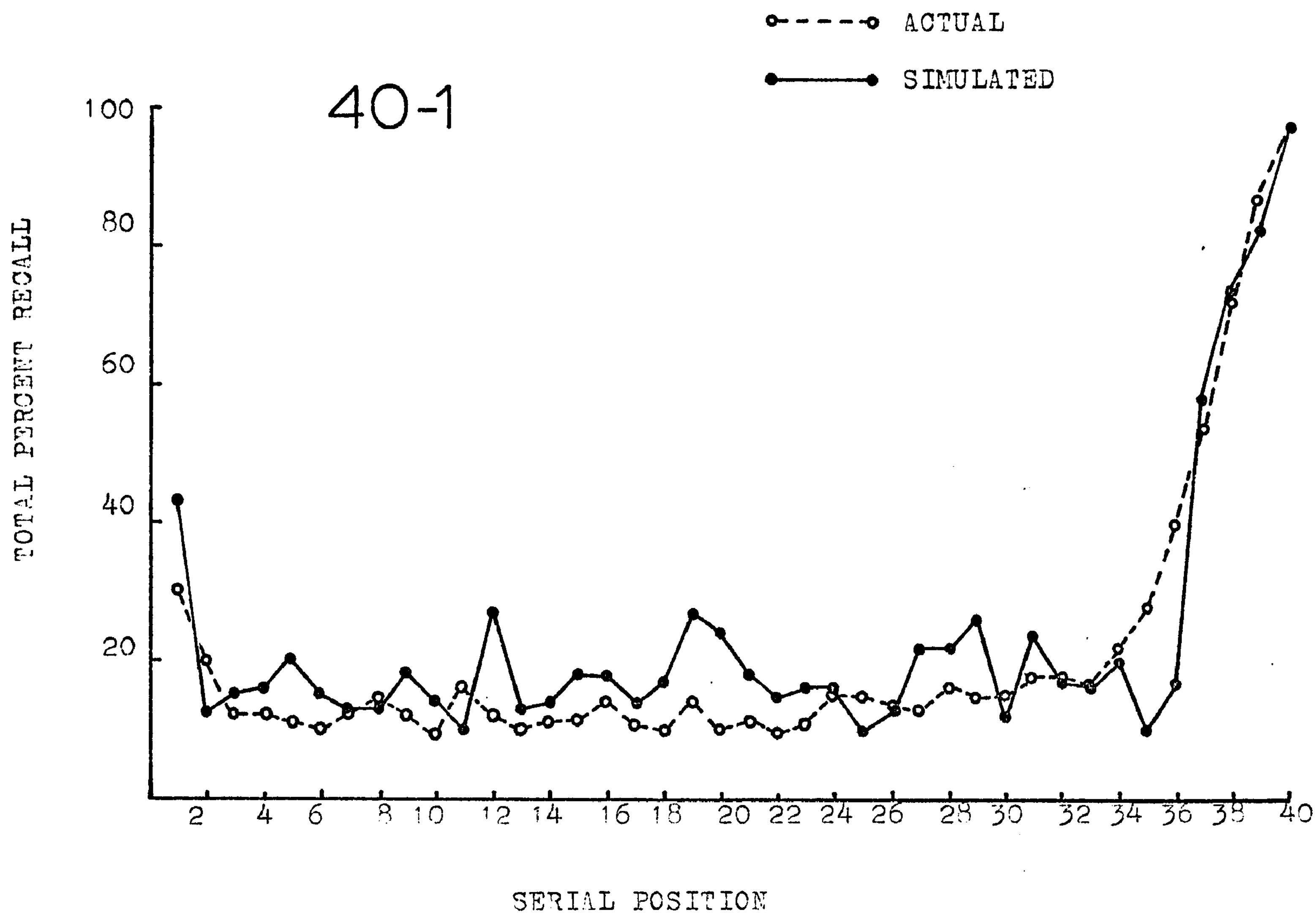

20-2
ACTUAL
SIMULATED
TOTAL PERCENT RECALL
100
80
60
40
20
SERIAL POSITION
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

Figure 36. A comparison of the simulated serial position curve for a 40-1 presentation rate with empirical data obtained by Murdock (1962).


40-1
ACTUAL
SIMULATED
TOTAL PERCENT RECALL
100
80
60
40
20
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40
SERIAL POSITION

of the presentation order. This is because retrieval from STM and LTM is on a LIFO basis. There is some evidence (Hulse, Deese, & Egeth, 1975) that this may only be partially correct since subjects tend to report the last positions first, the first items next, and then the items in the middle. The present model could account for this finding if retrieval from LTM was based on FIFO; however, the primacy effect would then no longer be a funcion of list length. A comment has already been made concerning the predicted variability in the order of recall of the first 3 or 4 correct items. The model predicts no variability in recall order once a subject begins his search of LTM.

The present model assumes that the average consolidation time for each item is related to the amount of time an item was rehearsed. Rundus and Atkinson (1970) provide some evidence for a test of this notion. In their study subjects were instructed to rehearse out loud, and this rehearsal was recorded and later analyzed. They found that, for the first portion of the list, subjects were rehearsing items in direct relation to their proximity to the beginning of the list; whereas a relatively constant amount of rehearsal occurred for items in the middle and at the end of the list. Therefore, the assumption of a constant consolidation time per item is only partially supported.

A further interesting prediction concerns the effects of simulating a delay between the presentation of the list and the start of the recall interval. The model assumes that interference begins as soon as the final list item has been presented. The question then becomes how long must the delay interval be before list items in STM will be "pushed down" to such an extent that they will not be retrieved during the subsequent search of STM? This, in turn, would eliminate the recency effect in the serial position curve. Since it is assumed that items are retrieved from STM every 2 seconds, a total of 7.5 items will be retrieved from STM. Interference enters the system on the average every 3 sec. A simple calculation indicates that an average delay interval of 22.5 sec. will be required before the recency effect will be negated. Glanzer and Cunitz (1966) provide support for this prediction. They varied the length of time between the presentation of the last item of a 15 word list and the recall test, and found that the recency effect was partially eliminated when a 10 sec. interval was used and completely eliminated when a 30 sec. delay was used.

Under certain conditions the model also predicts the disappearance of the primacy effect- in fact sub-asymptotic performance should eventually result. For instance, there should be a certain critical list length

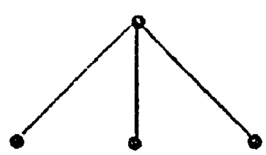
(>50 items) where this occurs. Interestinly, extremely long presentation rates should result in virtually all items being consolidated, yet the initial items on the list should not be recalled since retrieval from LTM is modeled as LIFO. Both predictions are subject to experimental verification.

In addition to generating and testing specific predictions, it is anticipated that students using unit IV will receive an appreciation and understanding of the free recall paradigm and the serial position effect. More specifically, they should become quite familiar with: various explanations for primacy, recency and the asymptate of the serial position curve; the importance of the consolidation process and the retrieval process; some suggested effects of proactive and retroactive interference on free recall; and the effects of manipulating list length and presentation rate.

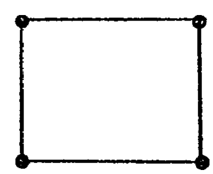
Unit V
Communication Patterns in Groups

It is well-known that the ability of members of a group to communicate with each other to a large extent determines the efficiency of the group and the satisfaction of its members. When opportunities for communication are restricted, there is a definite impact on group performance. The communication network refers to the pattern of communication opportunities in a group.

A diagram may be drawn to represent a particular communication network. Two of the more popular configurations are shown below for 4-person networks:



WHEEL



CIRCLE

The dots represent persons or positions in the network, and the lines signify communication channels between positions. Most channels provide two-way communication between persons. The important characteristic of a wheel network is that one person communicates with all others, while the other members can only communicate with this central person. In the circle, all members are equal in the sense that each of them can communicate with his two neighbors and no one else. The wheel is typical of a centralized network since all communications are forced through a central position. The circle, and other similar configurations, are decentralized. Bavelas (1950) has proposed an index of centrality for various communication networks.

The usual laboratory study of communications in small groups consists of forming a group to resolve some problem and imposing limits on the communication permitted among the members. Members can communicate by passing messages back and forth through the channels that are available to the individual. For instance with certain simple problems each member of a group is given a card with a geometric symbol written on it and the group's task is to discover which symbol is on all cards. The optimal solution requires members to get all the information to one position as quickly as possible. This type of problem is ideal for the wheel. The various groups are usually compared in terms of how efficient they are in solving the problem (number of messages required, time to solution, etc.) and in terms of the subjective reactions of the participants (satisfaction).

The evidence concerning how the different kinds of networks affect group performance is not entirely consistent. Shaw (1964), after a review of countless communication network experiments, draws two general conclusions: a)the major differences in group performance and satisfaction are between the centralized and the decentralized networks; b)the direction of the differences depends upon the task. When the task is simple, the speed and coordination offered by centralized networks may make them more effective. In fairly complicated problems the most efficient solution requires each member to work on part of the problem by himself. Decentralized networks, such as the circle, appear to facilitate the handling of these problems. It has also been found (Glanzer & Glaser, 1961) that individuals in decentralized networks send more messages than persons in centralized networks, regardless of the type of task. This may be because centralized networks have fewer channels.

Shaw (1964) has also suggested that the various effects of communication networks upon group performance can be attributed to two general processes- independence and saturation. Independence refers to the answer-getting potential for a given position in the network. For instance, persons in peripheral positions in centralized networks have low independence because of their limited freedom of action. In general, independence varies as a function of the configuration of the network and is greater in decentralized than centralized networks. The saturation experienced by a position is the sum of all the input and output requirements placed upon that position- the number of channels which a position must deal with, the number of messages that the position must handle, and the requirements of the task. When the required number of messages passes a certain optimal output level, effects are produced which run counter to the effects of a favorable position in the network. This may be the case when the central person in a wheel network is attempting to solve a complex problem. Here saturation is increased because communication demands are increased and because data manipulation procedures are more demanding.

The basic premise of unit V is that both the structural and the functional characteristics of communication networks can be readily incorporated into a GERTS framework. For example, the saturation process, which lies at the heart of group communication theory, can be described with parameters associated with the Q node.

The present unit simulates the behavior of a 4-person centralized network (wheel) and a 4-person decentralized network (circle). It will become apparent that students can also simulate various degrees of task difficulty and information distribution using the configurations presented in unit V.

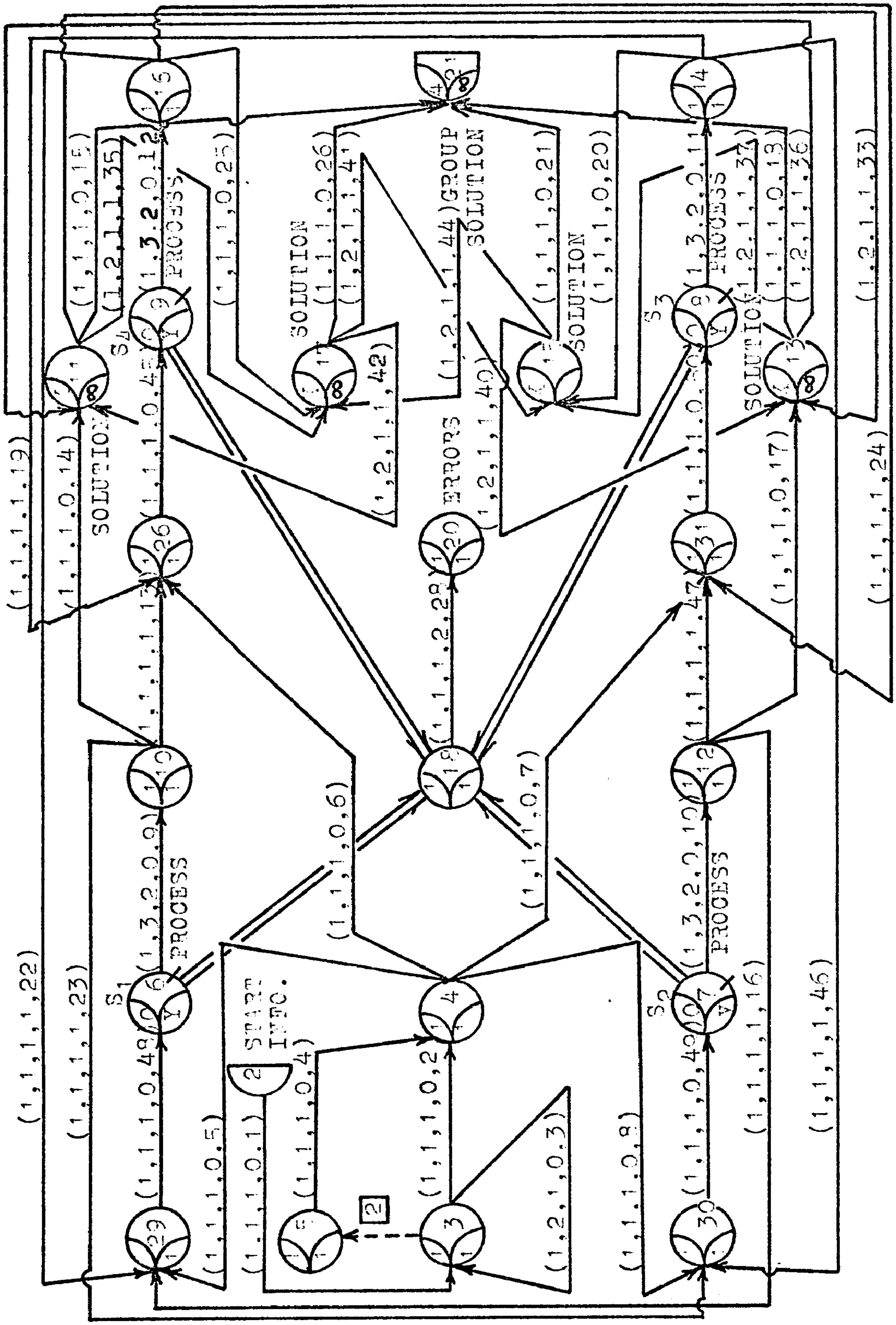
The group communication problem to be simulated is taken from Mulder (1960). The problem is considered complex since it requires participants to perform artithmetical computions as opposed to simple identification tasks. An example of a complex problem follows:

> "A small company is moving from one office-building to another. It must move four kinds of equipment: a) chairs, b) desks, c) filing-cabinets and d) typewriters. How many trucks are needed to make the move in one trip?"

There are eight items of information required to solve the problem: the company owns a total of 12 desks, 48 chairs, 12 typewriters, 15 filing-cabinets, and that one truckload can move 3 desks, or 24 chairs, or 12 typewriters or 5 filing-cabinets. In Mulder's (1960) study the information was typed on separate cards and each individual in the 4-person network received 2 cards. The participants were seated around a circular table with each subject separated by a partition. The partitions had slots to enable subjects to pass written message cards to individuals with whom they were allowed to communicate. For completion of the group task each participant must know the problem solution. The most important data collected were time scores, number of communications, and total number of errors committed.

The GERTS network in figure 37 is designed to simulate the behavior of a 4-person circular communication structure solving a complex problem. The simulation is initiated when source node, N2, schedules P(2,3) to be completed. N3 simulates the generation of information cards at the start of the experiment. The feedback loop P(3,3) insures that more than one piece of information

Figure 37. A GERTS network representation of the 4-person circle communication network for unit V: communication patterns in groups.


START INFO.
PROCESS
PROCESS
PROCESS
PROCESS
SOLUTION
SOLUTION
SOLUTION
SOLUTION
GROUP SOLUTION
ERRORS

is distributed to each participant. Only two cards are presented to each subject in the complex problem suggested by Mulder; this is accomplished in figure 40 when N3 is replaced by N5 and only one additional input will enter N4.

N4 is realized each time the activity associated with P(3,4) is completed. Each of the 4 activities scheduled by N4 represents the presentation of a separate information car to a subject: N4 schedules activities which terminate at N29, N30, N31, and N26. These nodes in turn, input into one of the four queue nodes- N6, N7, N8, and N9 respectively. The queue nodes represent the four participants. Virtually no time has elapsed in the simulation [P(3,3) has a brief time associated with it so that P(3,4) will be completed prior to P(3,3)] at the point when all eight pieces of information have been distributed to the four subjects.

No items are stored in any of the queues at the start of the simulation; therefore, any information will be immediately processed by the queue upon its arrival. The processing time is analogous to the time required to perform arithmetic calculations on some information. Process time is directly related to problem difficulty. Each of the service times associated with P(6,10), P(7,12), P(8,14) and P(9,16) simulate process times and are normally distributed (assuming each new piece of information requires a different amount of time to analyze). Varying the process time will alter the total solution time and is independent of the number of messages and errors.

The parameter, Y, in each of the queue nodes signifies the maximum amount of information which can be stored before an item balks. The balking process simulates the generation of errors by each of the subjects. All items of information which balk from the four queue nodes pass to N18. P(19,20), which emanates from N18, has a counter associated with it enabling the programmer to tally errors. It is assumed that if a problem is too difficult (the process time is long or there are too many items to process) then a subject will begin to generate errors. It is also assumed that Y is equal for all participants. Varying Y will alter the mean number of errors produced by the network but will not change the solution time or the number of messages generated.

Information which has been analyzed by a subject is then communicated to neighboring subjects. In the circle network each subject sends two messages. For example, subject #1 is represented by N6 in figure 40. He is only permitted to communicate with subject #2 (N7) and subject #4 (N9). After an item of information is processed, N10 will become realized. N10 schedules inputs into N30 and N26 which eventually serve as new items to be analyzed by subject #2 and subject #4 respectively. Counters are associated with these branches and all others which simulate the transfer of messages. There is also a branch leading from N10 to N11. The realization of N11 represents the solution of the problem for subject #1. Each subject has a solution node. The parameter, X, on the solution node signifies how many items of information and communications are required before a given participant solves the problem. X is also related to the difficulty of the problem. Varying this parameter effects the total number of messages sent, the total time to solution and the total numbers of errors made by the group.

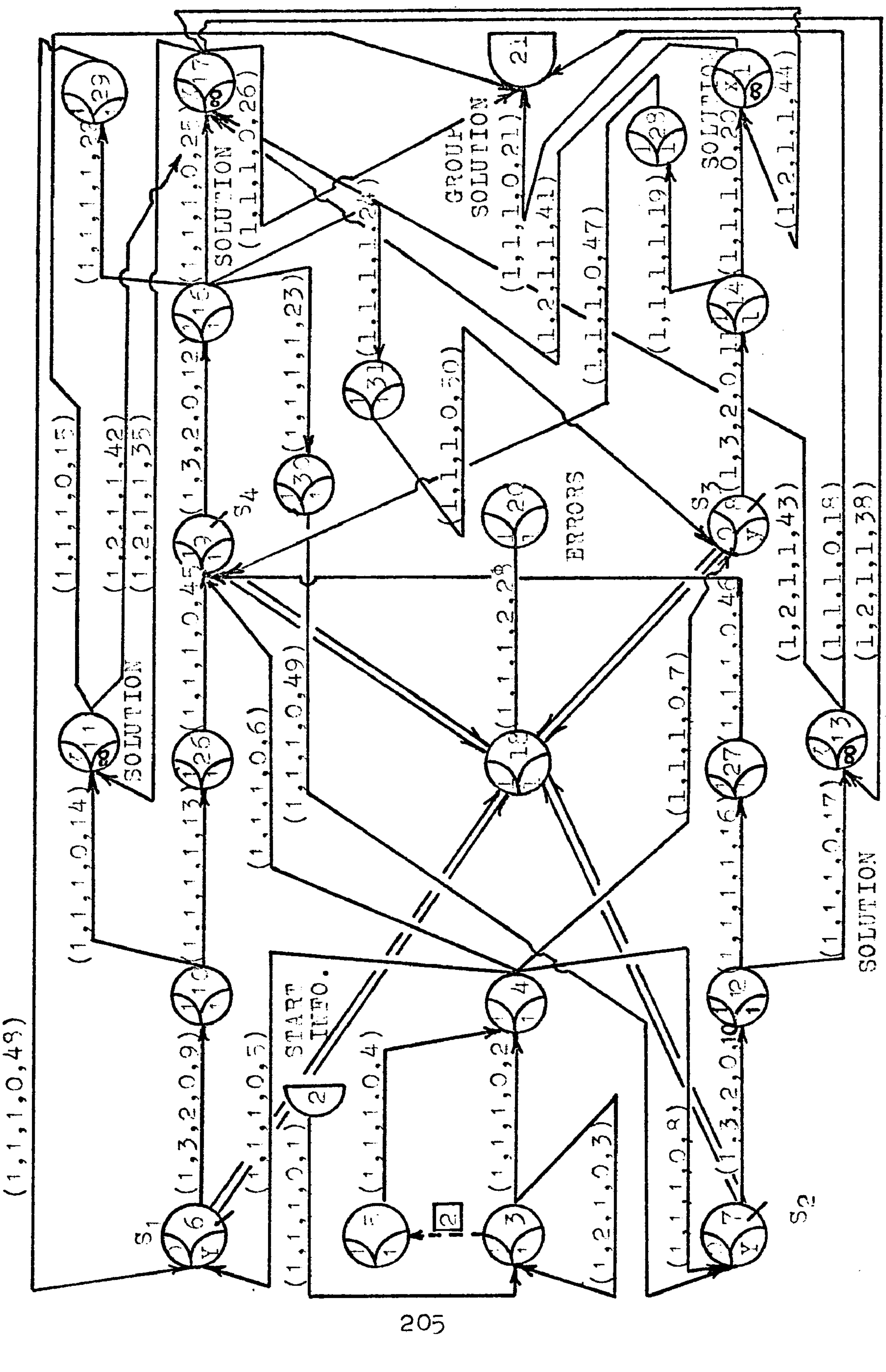
For the circle communication network, the parameter X was estimated first; it was varied until an accurate prediction was derived of the mean number of messages sent. The value for X was then held constant and Y was varied until an accurate estimate was made of the mean number of errors committed. Finally, both X and Y were held constant and the mean time to solution was estimated by varying the process time.

Each of the four individual solution nodes (N11, N13, N15, and N17) have branches leading to the group solution node, N21. This is the network sink node. In addition, subjects who have reached a solution are assumed to immediately communicate their solution to neighboring subjects. Messages containing the correct solution are not analyzed arithmetically but are assumed to serve as direct inputs into individual solution nodes. For instance, the realization of N11 simulates the solution of the problem by subject #1. He immediately announces his solution to the experimenter [P(11,21) is completed] and also communicates it to subject #2 and subject #4 via P(11, 13) and P(11, 17). A given simulation run terminates when all participants have reached a solution.

The simulation of the wheel communication network functions in a similar manner. Figure 38 shows the GERTS representation of this configuration. If the same problem is to beconsidered, eight items of information are again distributed equally among the group members. The principle difference in this network is that each subject can communicate only with subject #4. He, in turn, can communicate with each of the others. Will this limitation result in the predicted decrement in group performance for the wheel network as opposed to the circle network for this problem?

One hundred simulations were performed on the circle network and the wheel network. For all simulations, X was set equal to 5, Y was set equal to 6 and the process time had a mean of 210 sec. and a standard deviation of

Figure 38. A GERTS network representation of the 4-person wheel communication network for unit V: communication patterns in groups.


START INFO.
SOLUTION
ERRORS
GROUP SOLUTION
SOLUTION
SOLUTION
SOLUTION

60 sec. Six predictions resulted. They are shown in table 11 along with the empirical findings of Mulder (1960).

In all cases, the simulated data is in the same direction as the actual experimental results. That is, the group communicating in the circle pattern on the average took less time to solve the problem, made fewer errors, and sent more messages than those communicating in the wheel network. The agreement between empirical and simulated data would be even closer if the parameters, X and Y, took on different values for each individual in the network.

Several investigators have suggested that the manner in which the problem information is distributed among the positions will influence the performance of the group and that the distributional effects will be different for different network configurations. Increasing the information input from external sources should have the same effect upon a position as increasing the centrality of that position (Shaw, 1964). Students might test this notion for the complex problem by initially sending five items of information to one position and one item of information to each of the three remaining positions.

There has been no empirical data collected on a 4-person communication network solving a simple problem. Students might try lowering the value of the X parameter

Table 11

A Comparison of Simulated and Empirical Group Performance in Two Communication Networks

	Mean Time (sec.)		Mean Errors		Mean Messages	
	Wheel	Circle	Wheel	Circle	Wheel	Circle
*Empirical	976	847	1.54	.69	28.6	32.8
Simulated	930	917	2.95	.58	27.9	35.6

*From Mulder (1960)

and reducing the processing time in each of the networks in unit V to predict the solution of such a problem for each network configuration. One could assume that Y is a function of the intellectual capacity of an individual subject and would remain a constant (Y = 6). Students could then perform an actual 4-person group communication experiment to verify their predictions. Results from studies of larger and smaller networks suggest that the wheel is slightly superior under these conditions.

Teaching Units in Retrospect

The intent of this chapter was to use the GERTS language to model behaviors which are representative of five areas in psychology, and to suggest possible benefits which might be derived from the use of these models in the classroom setting. The five teaching units in no way exhaust the possibilities for using GERTS to simulate behavior. Some of the principle advantages of this approach are reviewed below.

First it is hypothesized that the graphical nature of each unit will result in students acquiring a better understanding of the relationships among the elements of a system. This is particularly true when components of the GERTS network have physical analogs such as specific neurons in the spinal reflex unit and the participants in the group communication unit. The distincion between independent variable and dependant variable should become clear and the student should also develop a concern for considering the effects of several independent variables. Since all aspects of the program must be quantified, students also become aware of the importance of certain initial assumptions.

Many of the units are modular in nature. This has the advantage of permitting students to isolate segments of the model and to test these components independently. It also means that an instructor can simplify or expand a unit to meet his needs. Certainly students who contribute to these units or who develop there own models, should, out of necessity, become completely familar with the literature in the area they are working.

The GERTS network is stochastic. This results in a greater flexibility to simulate different behavioral measures. Feedback also plays a major role in many of the models. The GERTS analysis should provide a more complete understanding of the effects of homestatic mechanisms than would a verbal description alone.

It may be a disadvantage that students are not required to perform actual experiments, although certain predictions may suggest laboratory experimentation and could lead to actual data collection. Finally, and perhaps most important, students will be introduced to mathematical modeling and to the simulation approach as a tool for generating data and testing theories.

The success or failure of these units partially depends upon the instructors and the students ability to learn the GERTS format. The learning process may not be too involved since only two components are necessary to describe a network-nodes and branches. I have on several occassions, presented an overview of the GERTS technique to undergradute students in a 50-minute class period, and several students have successfully developed GERTS models as independent projects.

Unit II, spinal reflex mechanisms, was introduced to an undergraduate class in physiological psychology at Moravian College. After studying the model, students were requested to suggest possible extensions or manipulations of the model. They could either vary the parameters related to stimulus inout, modify the structure of the network (e.g. remove or add neural components), or alter the functioning of a simulated physiological element (e.g. raise threshold). They were then asked to predict the behavior of the model under the altered set of conditions. Three of their suggestions were analyzed with GERTS and served as the basis for classroom discussion. They were:

> 1. Remove the primary spindle afferent from the extensor muscle and test the resulting knee jerk reflex.
> 2. Sever the dorsal root ganglion providing afferent activity from flexor muscles.
> 3. Determine the threshold for the knee jerk, and consider the rate at which the magnitude of the stretch reflex approaches an asymptote.

For comparative purposes, the last analysis was also performed as an actual laboratory exercise using a knee jerk apparatus designed by Lafayette Instruments. Although initial student reaction has been favorable, a comprehensive analysis of the effectiveness of unit II and the other four units remains to be made (see chapter 7).

V

A Simulation Model of the Vertebrate Retina

A teaching unit was described in the previous chapter which simulated the activity of skeletal muscles and their innervation by spinal neurons. In the present chapter, a model of the vertebrate retina will be presented to further emphasize the utility of using GERTS to analyze physiological systems. Much of the material in this section is based upon an unpublished study by Schroeder, Shortess, Theisen and Whitehouse (1971). Suggestions are made for expanding the model to include more recent experimental findings.

Numerous investigators (Hartline, 1938; Maturana, et. al., 1960) have provided data concerning the electrical activity of the frog retina in response to simple and complex visual stimuli. More recently, a number of physical as well as mathematical models have been developed to account for this data (Sutro, 1968; Moreno-Diaz, 1968). None of these experimenters have attempted a computer simulation of the underlying neural processes. An exception is the work of Didday (1970); however, his simulation model used a strict information processing approach (did not consider events occurring at the neural level) and was principally concerned with the functioning of the entire visual system.

A major advantage of the network approach to neural modeling is that the physiological integrity of the system is retained since each neural element is completely defined. This permits a direct comparison between the properties of neural and simulated elements.

Overview of the Vertebrate Retina

In the retina there is a basic repetitive structural organization which is modified somewhat as one moves from the center of the retina to the periphery. Although ten retinal layers have been identified (Polyak, 1941; Polyak, 1957), the vertebrate retina is primarily comprised of three cell body groupings: photoreceptor neurons, intervening bipolar and amacrine cells, and ganglion cells, with the latter transmitting information directly to the brain by means of temporal patterns of impulses. These components formed the nucleus for the simulation model. For simplicity, horizontal cells, located between receptors and bipolars, were not included. Horizontal cells are believed to have inhibitory effects and function in the coding of complex stimuli (Nake & Nye, 1970). They should probability be included in some future extension of the model, which would simulate the reception of more complex stimuli such as moving edges.

The photoreceptor cells, the rods and cones, absorb light energy. Rods have low thresholds and function optimally under conditions of dim illumination. Cones, on the other hand, have higher thresholds and are believed to dominate in providing for acuity and color vision. Both types of receptors have higher thresholds under conditions of continuous light stimulation (light adaptation) and become more sensitive with time in the dark (dark adaptation).

A certain number of bipolors receive inputs only from cones, whereas the remainder of the bipolars receive inputs from both rods and cones. Whether or not bipolors generate spikes of their own remains controversial; however, localized graded potentials, representing excitation from rods and cones, do exist in this region (Werblin & Dowling, 1970). Amacrine cells have also been identified in this area. These neurons may have several functions: to spread effects aroused by bipolar cells to several ganglion cells or possibly back to receptors, and to inhibit ganglion responses (Malmfors, 1963; Dowling, 1968).

The final integrative structure at the retinal level is the ganglion cell. The present model will attempt to predict the probability that a typical ganglion cell will fire and the latency of the response under several stimulus conditions.

Simulation Model

The actual number of retinal neurons modeled and their interconnections was derived from a sketch of a cross-section of the retina provided by Polyak (1941). Figure 39 shows typical retinal components converging on one representative ganglion cell. The model contains 12 rods and 8 cones, a ratio representative of a region approximately 3 to 4 degrees from the fovea (Osterberg, 1935). Rod convergence or summation at the bipolar level is apparent since 12 rods excite five bipolar cells, while eight cones provide primary excitation to six bipolar cells and secondary excitation to the other five bipolar cells.

Several assumptions were required before the retinal components could be described in network form. Table 12 lists these assumptions, and whenever possible, offers a rationale for each in terms of available data. The integration time for bipolars, the amacrime, and the ganglion cell was estimated as 50 msec. Although there is no direct evidence concerning this estimate, post-synaptic potentials develop in motorneurons and last for about 15 msec. (Sherington, 1941), and several authors (Guyton, 1972; Deutsch & Deutsch, 1973) have suggested that the integration time is much longer in sensory neurons. Absolute thresholds for bipolars, the amacrine cell, and the ganglion cell, were arbitrarily assigned

Figure 39. A detail of the retinal components converging on one representative ganglion cell.

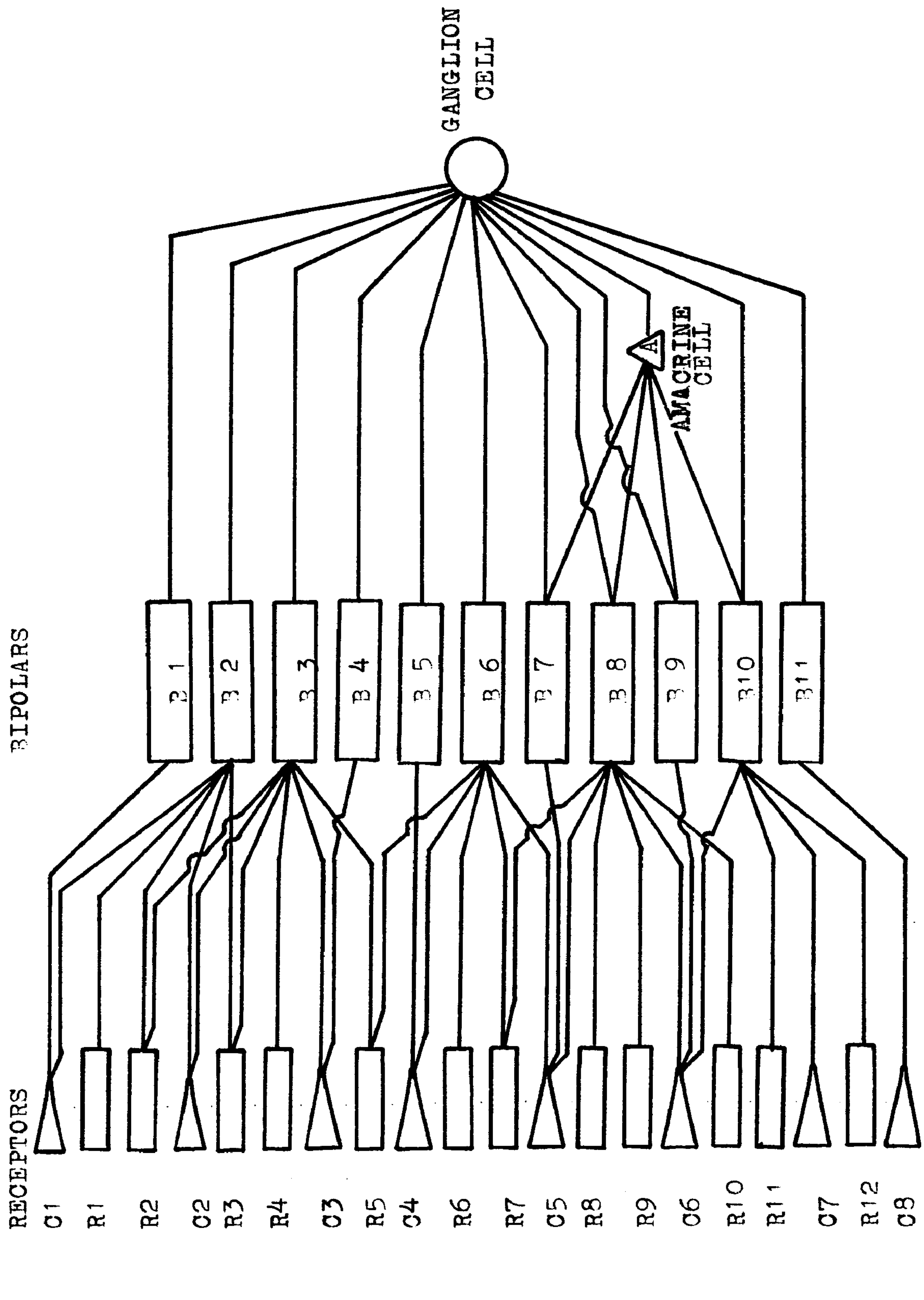

GANGLION CELL
AMACRINE CELL
A
BIPOLARS
B 1
B 2
B 3
B 4
B 5
B 6
B 7
B 8
B 9
B10
B11
RECEPTORS
C1
R1
R2
C2
R3
R4
C3
R5
C4
R6
R7
C5
R8
R9
C6
R10
R11
C7
R12
C8

Table 12

Model Components and Their Functional Characteristics

Component	Characteristic	Functional Description	Source
Rod:	Absolute Threshold.............	1 or 2 quanta	Hecht, Schlaer & Pirenne (1942)
	Latency to develop generator potential at threshold.........	80 msec.	Gouras & Link (1966)
Cone:	Absolute Threshold.............	3 or 5 quanta	Gouras & Link (1966)
	Latency to develop generator potential at threshold.........	30 msec.	Gouras & Link (1966)
Bipolar:	Absolute Threshold.............	1 to 6 inputs	Estimate
	Integration time...............	50 msec.	Estimate
Amacrine:	Absolute Threshold.............	2 inputs	Estimate
	Integration time...............	50 msec.	Estimate
Ganglion:	Absolute Threshold.............	6 inputs	Estimate
	Integration time...............	50 msec.	Estimate

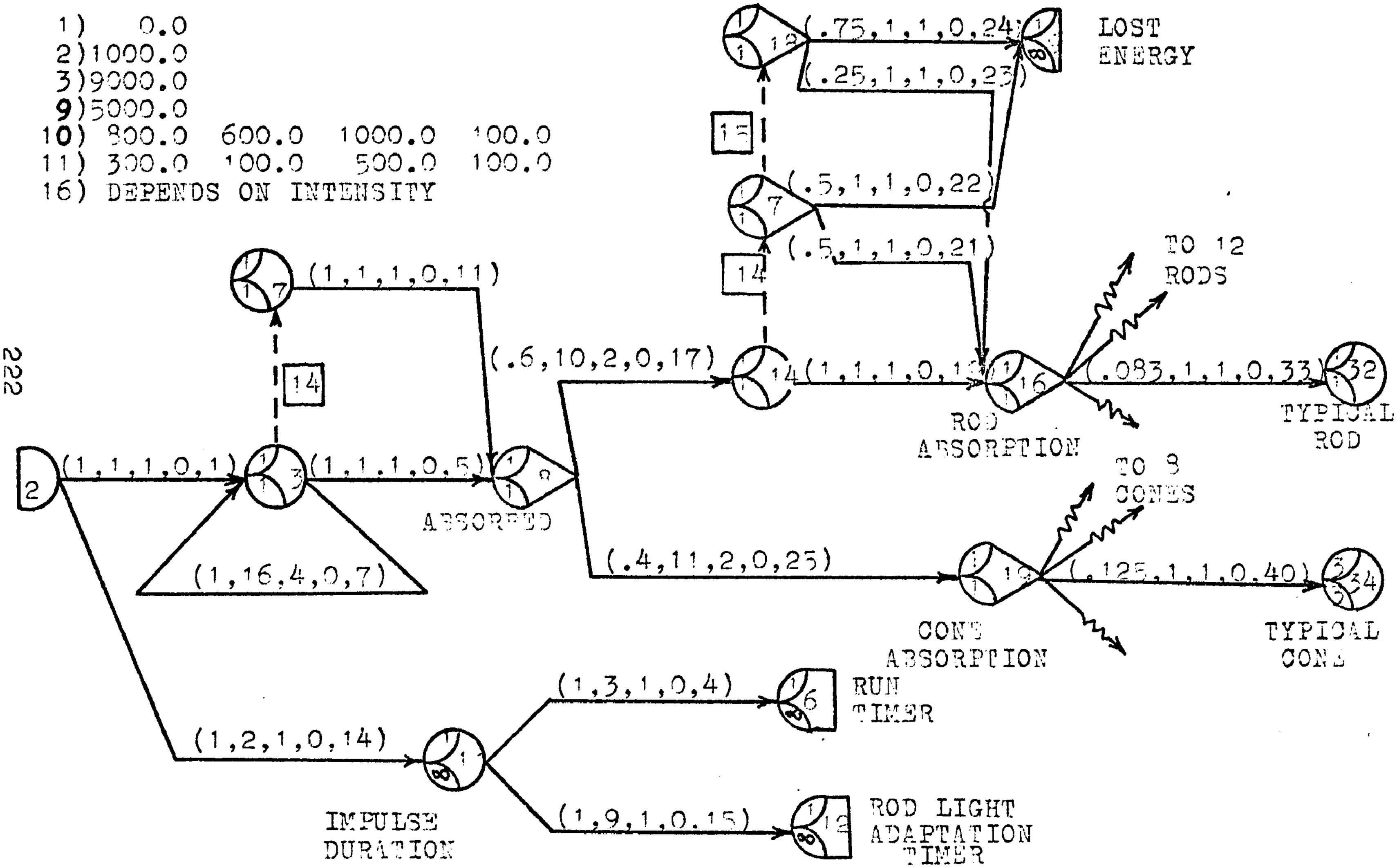
the values listed in table 12. A sensitivity analysis determining which model parameters are the most significant determinants of overall performance, has yet to be made.

Figure 40 illustrates a GERTS network which simulates light energy being absorbed by two receptors. The complete model developed by Schroeder et. al. (1970) is not shown here because of space limitations and has a total of 20 receptors. Source node, N2 initiates a simulation run by scheduling two activities: P(2,3) generates the first hypothetical photon being absorbed by the retina; P(2,11) is associated with the duration of the stimulus. Each time an activity incident to N3 is completed N3 will be realized and will output still another photon P(3,8) will be activated . The last hypothetical photon will fall on the retina when P(2,11) has been completed and N3 is replaced by N7. Since the hypothetical light energy schedules a given number of branches during a designated time interval, both intensity and duration can be manipulated. For example, energy absorbed at the rate of 50 photons per 100 msec. could be simulated by placing a time parameter of 2 msec. on P(3,3) and a parameter of 100 msec. on P(2,11). After the simulated stimulus terminates, the program continues processing these inputs until the run timer, N6, is realized- usually for one sec.

Figure 40. A GERTS network description illustrating stimulus input control, light adaptation, and energy absorption in the retinal simulation model.

PARAMETER SETS (.1 MSEC.)

1)	0.0			
2)	1000.0			
3)	9000.0			
9)	5000.0			
10)	800.0	600.0	1000.0	100.0
11)	300.0	100.0	500.0	100.0
16)	DEPENDS ON INTENSITY			

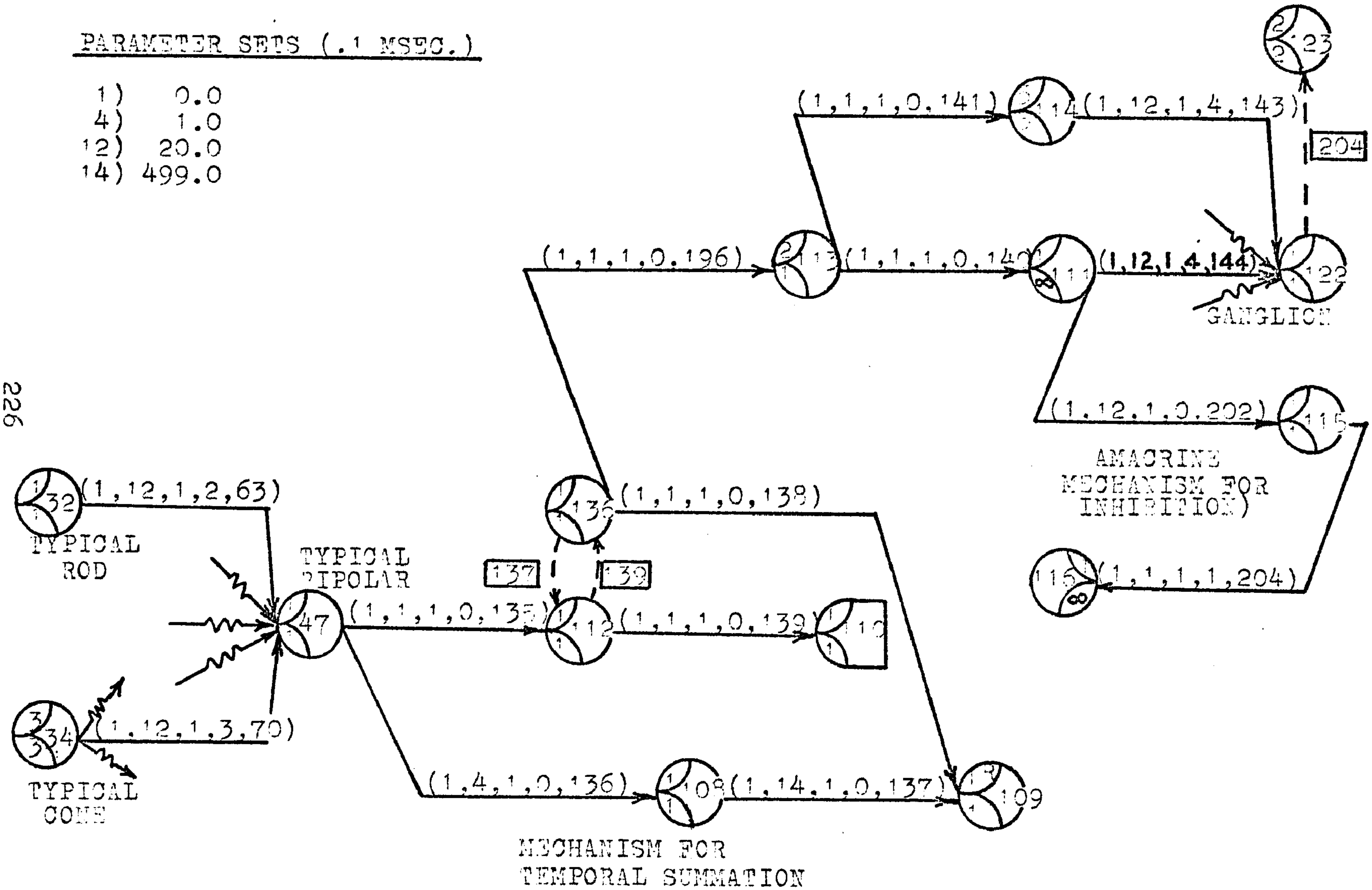


Since there were 12 rods and eight cones modeled, it was assumed that 60% of the photons would be absorbed by rods, whereas 40% would be absorbed by cones. Therefore, N8 schedules P(8,14) to rods with a probability, p = .6, and P(8,19) to cones with a probability, p = .4. The absorption time (within a receptor) was simulated with the time parameters associated with branches leading to receptor nodes. These times were assumed normally distributed with means of 80 msec. and 30 msec. for rods and cones respectively (see table 12). At the start of a simulation it was also assumed that both rods and cones were fully dark adapted. The mechanism of light adaptation in the rods was accomplished with the adaptation timer noted in figure 40. It operates in the following manner: P(2,11) intiates adaptation. Following this brief interval (100 msec.) a network modification occurs which alters the proportion of energy being absorbed by the rods; i.e. instead of 100% of the energy being effective only 50% is actually absorbed. This same process is repeated again after 500 msec., lowering the rod absorption probability to .25. In this manner, rods which have received long exposure to light simulate little absorption. Light energy scheduled for absorption by rods causes N16 to be realized. Activities amanating from N16 terminate in one of 12 nodes, each associated with one of the rods modeled. N32 represents a typical rod. P(16,32) will be scheduled with a probability equal to .083. In a like manner, branches emanating from N19 have associated with them the probability that a photon will be absorbed by one of eight cones. Receptor thresholds were specified as they were in unit II of the previous chapter; that is, by the number of branch realizations required for receptor node activation (see table 12). It should be noted that the typical cone (N34) has a higher threshold value than the typical rod (N32).

After a given receptor node was realized it would activate all branches emanating from it. The complex pattern of branches from receptors to bipolar cells followed the synaptic connections outlined in figure 39. Figure 41 shows representative inputs from a typical rod and cone to a bipolar cell, N47. The complete model contains 11 bipolar cells. The conduction time from a receptor to a bipolar cell was assumed to be 2 msec. for each branch. This same conduction parameter was used throughout the model.

The state of a particular bipolar node depends on the number on inputs arriving from either rod or cone nodes (spatial summation), and the time that had elapsed since the arrival of the last input (temporal summation). Figure 41 illustrates how spatial and temporal summation is simulated for N47. Spatial summation can occur

Figure 41. A GERTS network description illustrating spatial and temporal summation, and inhibition in the retinal simulation model.


PARAMETER SETS (.1 MSEC.)
1) 0.0
4) 1.0
12) 20.0
14) 499.0
(1,12,1,2,63)
TYPICAL ROD
(1,12,1,3,70)
TYPICAL CONE
TYPICAL BIPOLAR
(1,1,1,0,135)
(1,1,1,0,139)
(1,1,1,0,138)
137
139
(1,4,1,0,136)
(1,14,1,0,137)
MECHANISM FOR TEMPORAL SUMMATION
(1,1,1,0,196)
(1,1,1,0,140)
(1,1,1,0,141)
(1,12,1,4,143)
(1,12,1,4,144)
204
GANGLION
(1,12,1,0,202)
(1,1,1,1,204)
AMACRINE MECHANISM FOR INHIBITION)

because six receptors, each having a potential excitatory influence, have processes which converge on N47. The simulated bipolar cell summates these inputs until its threshold is surpassed. The mechanism for temporal summation operates in the following manner: suppose an input from a receptor arrives at this node. The activity associated with P(47, 112) will immediately be completed. P(112, 139) will then be scheduled and will also be immediately completed causing N112 to be replaced by N136. It 50 msec. passes without a second input to the bipolar cell, then the activity associated with P(108, 109) will be completed and N112 will replace N136 once again. If on the other hand a second input arrives before 50 msec., then P(113, 114) will be scheduled. N136 will be realized and at the same time N136 will schedule P(136, 109). This branch results in the realization of N109. It should be noted that N109 has a "R" associated with the number of releases required for its realization. The R signifies that events that have been scheduled to end on this node are to be removed (cancelled) when this node is realized. In effect, the first input which has not as yet resulted in the completion of P(108, 109) will be removed and consequently N136 will not be replaced by N112. Spatial and temporal summation was also modeled at the amacrine and ganglion cell levels.

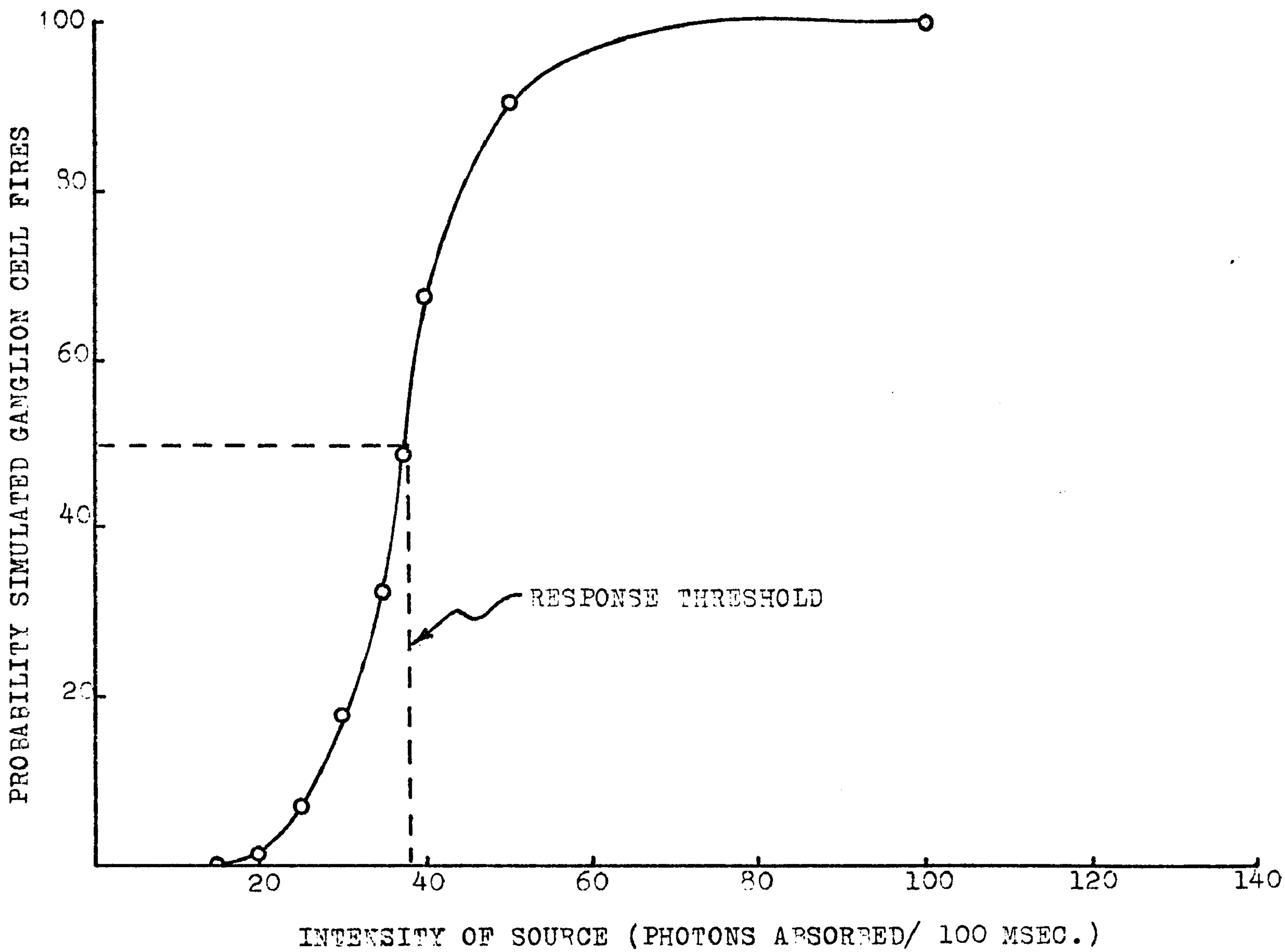
The two releases required on N113 represents the threshold for the bipolar cell. Stimulus information is transmitted to the ganglion cell (N122) and to a hypothetical amacrine cell (N115) following the realization of N113. Three other simulated bipolars also influence N115, but these cells are not shown on figure 44. N111 can only be realized once. Additional outputs to the ganglion cell from N113 must travel via N114 which has a higher threshold (5 releases are required for each realization of N114). In this manner habituation is simulated in the bipolar cell.

The amacrine cell is modeled to inhibit ganglion cell firing. It does so by directly raising the threshold of N122. That is, when P(115, 116) has been complete, N122 will be replaced by N123.

The response of the vertebrate retina to light was simulated using 11 different intensity levels ranging from 15 to 500 photons absorbed per 100 msec. (Schroeder, et.al., 1970). Data predicting the probability of realization was collected on nodes which simulated ganglion cell firing. Median latencies were estimated from the computer generated histograms.

Figure 42 indicates the percentage of computer runs in which a simulated ganglion cell fired at least once for various values of intensity. The response curve appears sigmoidal in shape- a common characteristic of many psychophysical threshold functions. Points at

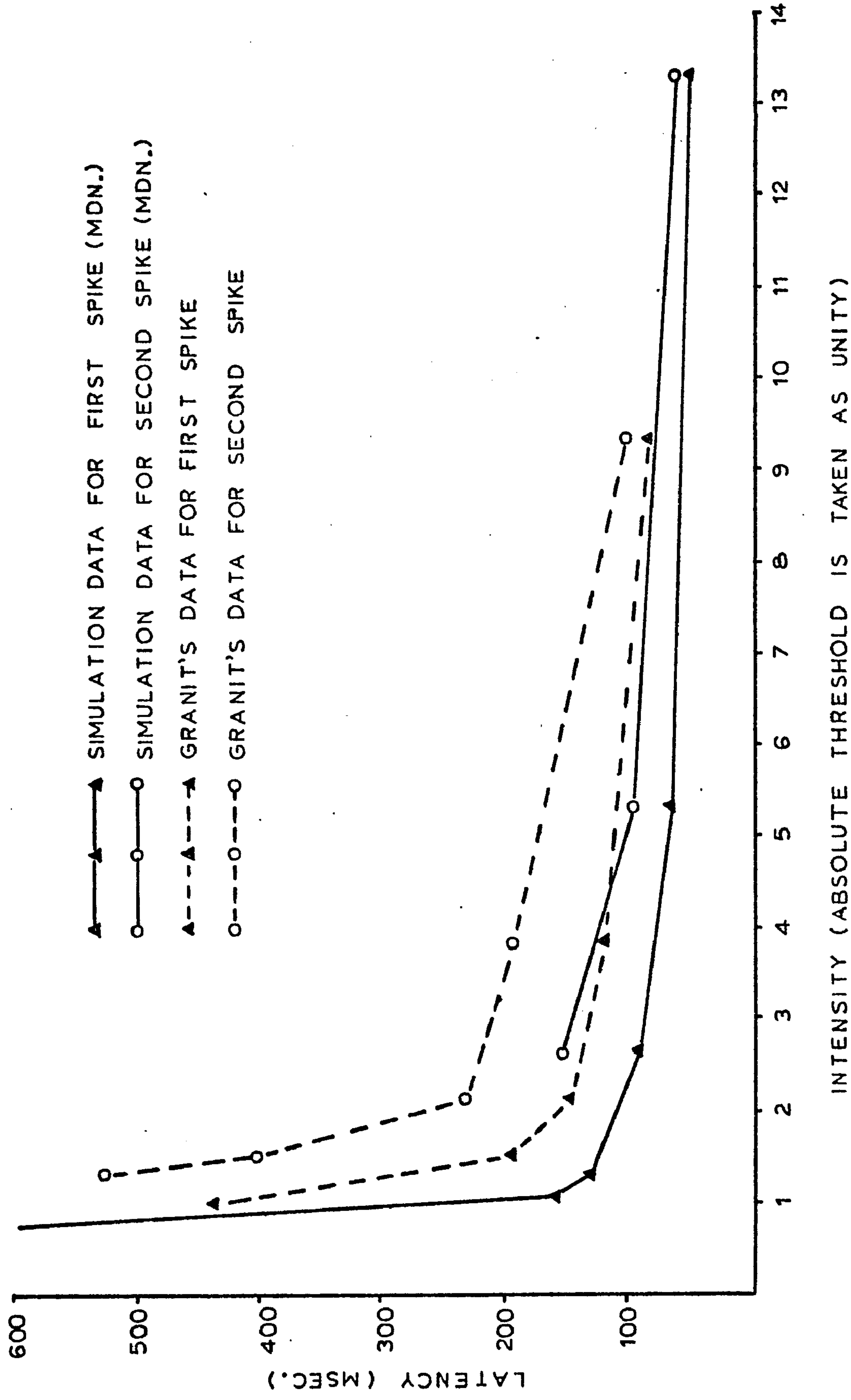
Figure 42. The probability that the simulated ganglion cell will fire as a function of the intensity of the stimulus. The threshold for this neuron, 38 photons, can be read directly from the graph.


PROBABILITY SIMULATED GANGLION CELL FIRES
100
80
60
40
20
RESPONSE THRESHOLD
20
40
60
80
100
120
140
INTENSITY OF SOURCE (PHOTONS ABSORBED/ 100 MSEC.)

lower intensity levels are more reliable than those at higher levels since they are based on a larger number of runs. The ganglion cell will respond 50% of the time when 38 photons per 100 msec. are absorbed. This result compares favorably with empirical data from the cat retinal ganglion cells (Barlow, Fitzhugh, & Kuffler, 1957). It seems to be higher than human psycholphysical functions (Denton & Pirenee, 1954); however as Barlow, et.al. pointed out, their cat ganglion cell thresholds were higher than corresponding cat behvioral thresholds.

Granit (1955) recorded the spike activity of an optic nerve fiber in the guinea pig at different values luminance. The dashed lines figure 43 present the time elspsing from the onset of the stimulus to the first spike, and from the onset of the stimulus to the second spkie for his data. The comparative median latency data for the simulation model is shown by the solid curves on the same figure. In both instances the latency decreases rapidly to some asymptotic value as the intensity increases. It is also apparent that the latencies for simulated responses are shorter by some constant value. This is probably because Granit's data were taken at the optic nerve level rather than the ganglion cell level.

Figure 43. A comparison of simulated ganglion cell latencies with latencies to the first two spikes recorded from the optic nerve of the guinea pig (Granit, 1955).


SIMULATION DATA FOR FIRST SPIKE (MDN.)
SIMULATION DATA FOR SECOND SPIKE (MDN.)
GRANIT'S DATA FOR FIRST SPIKE
GRANIT'S DATA FOR SECOND SPIKE
LATENCY (MSEC.)
600
500
400
300
200
100
1
2
3
4
5
6
7
8
9
10
11
12
13
14
INTENSITY (ABSOLUTE THRESHOLD IS TAKEN AS UNITY)

Proposed Revisions of Retinal Model

The model presented in this chapter could be modified in numerous ways. Since there is available a fair amount of both anatomical and physiological data concerning the frog retina, perhaps model predictions should emphasize frog retinal responses.

It is expected that the number of receptors and bipolars could be substantially reduced without a loss in the validity of the model. At the same time, initial revisions of the model should serve to build up the inner plexiform layer as detailed by Dowling (1968). For instance one could:

1) increase the number of amacrine nodes
2) create a number of interactions among amacrine nodes
3) have ganglion nodes primarily influenced by amacrine rather than bipolar nodes.

An additional degree of flexibility could be achieved by extending the outer plexiform layer. Horizontal cells with appropriate connections might be introduced to supplement some of the existing receptor-bipolar connections. Other revisions would include altering the GERTS format (introducing new subroutines) as to achieve a more economical system and to improve on the physiological integrity of the components.

It is possible to simulate receptive fields for frog ganglion cells by organizing rod and cone nodes in a two dimensional matrix. Simulated visual stimuli could then be selectively introduced into the center or periphery of this field, and the results compared with empirical findings. Increasingly more complex stimuli could be simulated (i.e. moving edges, etc.) but this would certainly necessitate alternations in the existing input control. Hopefully, the final result of these efforts would be a model which could generate appropriate response patterns for specific cell types, and could suggest the relative roles of such mechanisms as lateral inhibition in determining the neural code of the ganglion cell response.

VI

Considerations for Applied Psychology

The applications considered in this chapter are of primary interest to the industrial and organizational psychologist. Two problems will serve as examples. The first concerns using GERTS to aid in the planning of manpower requirements. The second application, in the field of human factors engineering, involves simulating the inflight refueling operation of a jet aircraft. Other organizational problems problems which might be analyzed by means of GERTS will also be mentioned.

A Manpower Planning Analysis

At the management level, there is considerable interest in the topics of personnel selection, labor turnover, recruitment, and promotion. Personnel managers naturally focus on careers and are concerned about length of service and about departure rates. Although numerous mathematical models have been developed to aid in predicting the movement of men within an organization, it is doubtful that most managers possess the mathematical sophistication to utilize them. Bryant (1965) addresses the situation in the following passage:

> "Two major criticisms have been made by experienced personnel managers and line managers of the work hitherto published: one is that while, for the most part, the mathematical content of papers such as those discussed in this survey tends to be beyond the comprehension of those responsible for the implementation of manpower policies, the conclusions derived from the analyses merely confirm what had been know (or intuitively suspected) for years... The other criticism is that existing models are well in advance of experience of implementation, and that further research is needed, not so much on the development of new and perhaps more complex models as on the simplification of existing models so that they may be used by managers in practical situations."

In the present section, it is suggested that GERTS may serve as a vehicle for communicating and analyzing manpower planning models.

The number of men who will move from a given level in an organizational hierarchy to another level over a year is of major interest to organizational planners. The assumption used most frequently in prediction is that these proportions remain fixed over a long period (Markovian assumption). Bartholomew (1967) developed a Markov chain model of an organization that is hierarchical in form. His model focuses particular attention on promotion and termination in an open system. He assumes there are k grades arranged in increasing order of seniority. New entrants are recruited into the lowest grades and all vacancies occurring higher up are filled from the next lower grade. Different wastage rates (the probability of an employee leaving a level after an interval) can be considered for each grade. Also different promotion rates can be considered for each grade. These probabilities, along with the probability of remaining at a level, comprise the transition matrix of the model. As an example, Bartholomew (1967) offers transition probabilities which reflect the kind of conditions one might find in a typical management hierarchy. These values are presented below in matrix form for $k = 5$:

Year (N + 1)

		I	II	III	IV	V	LEAVES
	I	.65	.20	.00	.00	.00	.15
Year	II	.00	.70	.15	.00	.00	.15
	III	.00	.00	.75	.15	.00	.10
(N)	IV	.00	.00	.00	.85	.10	.05
	V	.00	.00	.00	.00	.95	.05
	LEAVES	.00	.00	.00	.00	.00	1.00

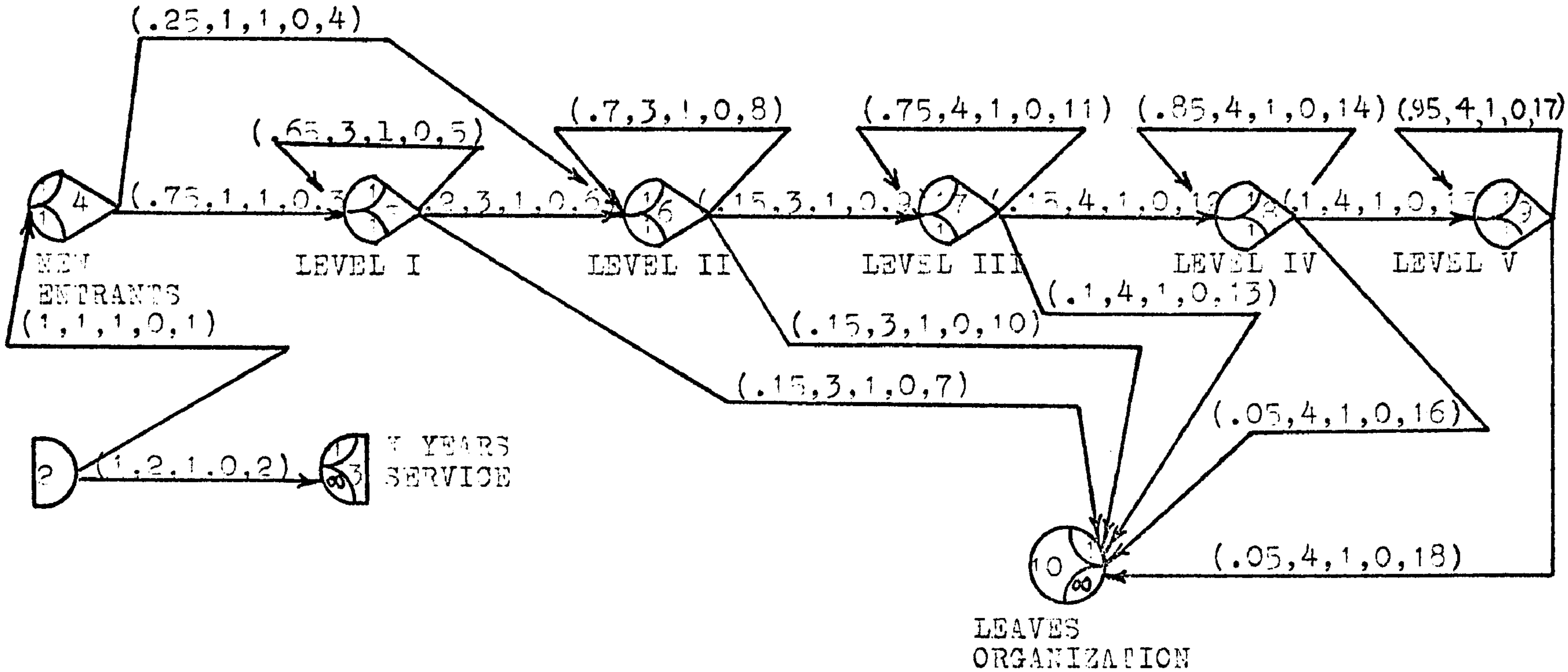
It should be noted that the wastage rates decrease as one moves up the hieraracy. This reflects the finding that mobility to other firms is usually more common for young employees at the lower levels. Also the promotion rates decrease as one moves up in the organization. Finally, individuals who leave the organization do not return.

The GERTS network corresponding to the transition matrix shown above is presented in figure 44. Each organizational level is represented by a node and transition probabilities are represented by branches connecting nodes. N2 initiates the simulation. The time parameters associated with P(2,3) can be varied, and relate to the simulated length of service in the organization. Therefore, the realization of N3 terminates the simulation. N4 is a probabilistic node and serves to distribute the new entrants to each of the levels as specified by the programmer. In figure 44 it is assumed that 75% of the new employees enter the organization at level I and 25% enter the organization at level II. Therefore, the initial probability vector, π, equals (.75, .25, .00,.00,

Figure 44. A GERTS representation of the movement of labor within a hierarchical organizational structure.

PARAMETER SETS (YEARS)

1) 0.0
2) X
3) 1.0
4) 2.0



.00). The wastage rate for each grade is represented by a branch leading to N10. Feedback loops around each of the levels correspond to the probabilities of remaining in each position. The probability of promotion is represented by a branch leading from a lower level to the next higher level.

Bartholomew's (1967) model assumed that promotions and terminations occurred at equal intervals (one year) for each grade. This assumption may not be realistic for all firms. Since the GERTS system can be used to analyze semi-Markov processes, it is possible for personnel managers to consider the effects of having different evaluation periods at each level. For instance, in figure 47 it is assumed that a decision is made concerning each employee at level I and level II every year (time parameter set #3). On the other hand, individuals at higher managerial levels (III, IV, and V) are evaluated every second year (time parameter set #4).

Four hundred simulation runs were performed with x representing 40 years service and four hundred runs were performed with x simulating 20 years service. Nodes 6, 7, 8, 9, and 10 were designed as statistics nodes and information was collected concerning the average time that transpired prior to the first realization of each node and the probability of its realization prior to network realization. Several interesting questions can now be considered. For instance, the probability that an individual will remain associated with an organization after x years can be determined by subtracting the probability that N10 was realized from 1.0. For the simulations performed, an employee has a 17% chance of remaining in the organization after 20 years service, and an 8% chance of being in the organization after 40 years service. An individual also has approximately a 10% chance of becoming a top manager (reaching level V) under the promotion policy modeled. Finally, it takes employees, on the average, 1.75 years, 5.22 years, 12.79 years, and 20.31 years to reach levels II, III, IV, and V respectively.

The effects of alterations in termination or promotion policies can be readily ascertained using GERTS analysis. The practical value of predictions such as these is considerable in providing management with necessary inputs for long term ecomonic planning. In addition to the primary advantage of a graphical description of the system, the GERTS analysis of manpower requirements should be especially efficient when alalytical procedures become cumbersome- when many organizational levels are considered or when different evaluation periods apply at each level. Chapter 3 provides a more detailed analysis of the advantages of simulating Markov processes via GERTS.

A GERTS Simulation of an Inflight Refueling Operation

A human factors engineer often relies on simulation by digital computers to analyze the performance of a man-machine system when the system becomes extremely expensive and complex. The purpose of this technique is to allow prediction of system effectiveness early in the development stage and to enable the comparative evaluation of alternative system designs. Usually the designer first performs an analysis of the man-machine system and the tasks under consideration. The behavior of each operator is arranged into ordered, discrete actions known as subtasks and empirical data is collected concerning these activities. The data is introduced into a digital computer which then sequentially simulates the performance of each subtask by each operator.

The purpose of the present section will be to demonstrate, by example, how data from a task analysis can be efficiently formulated in GERTS terminology and analyzed by this technique. The task to be considered is the inflight refueling of a receiver aircraft by a tanker aircraft taken from Siegel and Wolf (1969).

The mission goal of the inflight refueling task is for the pilot of the aircraft to be refuelled to insert, in mid-air, a probe into a drogue extended by the pilot of the tanker aircraft. The speed and relative degree of success of the operation is critical for this task.

A basic task analysis was performed (pilots were interviewed) and the sequence of subtasks was listed. Performance times for each sub-task were determined on the basis of estimated proficiency for the "average" pilot (Siegel & Wolf, 1969).

Figure 45 demonstrates how the inflight refueling operation can be graphically represented using GERTS. Each subtask can be represented by a branch in the network. Nodes signify the start or completion of a subtask.

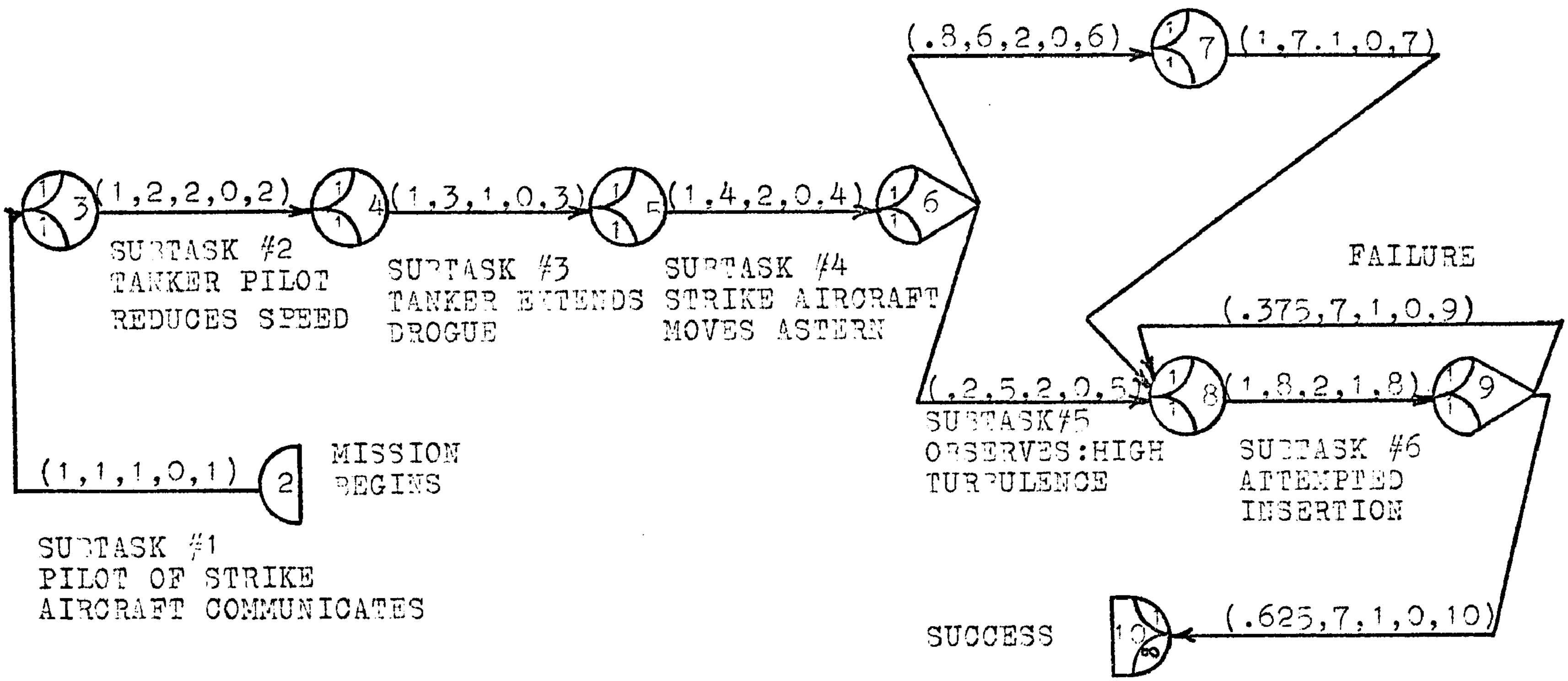
The operation begins with the tanker and the strike aircraft flying abreast of each other at the speed greater than optimal for inflight refueling. Initiation of the simulation occurs when the pilot of the strike aircraft (the plane refueling) communicates to the tanker pilot that he is "ready to refuel". This message requires only 4 sec. and is represented by the activity parameters associated with P(2,3). Subtask #2 involves the tanker reducing its speed while the strike pilot waits. P(3,4) simulates subtask #2 with the following time parameters: $t_p = 2$ and $t_D = 2$. At this point the tanker extends its drogue subtask #3 on P(4,5). The strike pilot then moves his aircraft astern of the tanker requiring a mean time of 14 sec. P(5,6) .

Records indicate that 80% of the time the aircrafts encounter low turbulence, whereas 20% of the time they

Figure 45. A GERTS network diagram of the inflight refueling operation analyzed by Siegel and Wolf (1969).

PARAMETER SETS (SEC.)

1)	4.0			
2)	12.0	0.0	30.0	4.0
3)	11.0			
4)	14.0	0.0	30.0	4.0
5)	10.0	0.0	20.0	2.0
6)	4.0	0.0	8.0	1.0
7)	0.0			
8)	10.0	5.0	15.0	1.0



meet high turbulence. Air turbulence critically effects the amount of time which is required to observe the steadiness of the drogue prior to attempted hookup. In figure 48, if P(6,7) is scheduled (low turbulence condition), then an average time of 4 sec. is required for this subtask. An average of 10 sec. is required if P(6,8) is taken (high turbulence condition). At this point in the operation, an attempt is made to insert the probe into the tanker. The activities associated with P(8,9) represent this subtask. A counter (c = 1) has been placed on P(8,9) to tally the mean number of attempted hookups simulated. Of 16 actual test flight, 10 resulted in successful engagement of the probe on the first attempt (Siegel & Wolf, 1969); therefore, P(9,10) is scheduled 62% of the time. N10 is the sink node and signifies that the mission is completed. On failure to excute the last subtask, it is assumed that previous observations of drogue motion will be recalled and applied to each subsequent attempt. P(9,8) simulates failure to perform the mid-air insertion.

Five hundred simulations were performed on the network just described. The results indicate that the total refueling operation requires an average of 60.7 sec. with a minimum time of 39.7 sec. and a maximum time of 101.8 sec. The mean number of attempted insertions was 1.45.

A human factors engineer might suggest how, with appropriate system alterations, various subtasks could be made more efficient. The predicted effect on the total system could be determined with the simulation model just described and the benefits of design changes could then be weighed against the costs which would incur.

An obvious modification would involve a hypothetical reduction in air turbulence. Interestingly, reducing the probability of high turbulence to 1% has almost no effect on the simulated system's performance: the mean time to mission success only decreases to 59.4 sec., while the minimum and maximum times remain approximately the same. On the other hand, increasing the probability of successful insertion to 99% would reduce the total task time to an average of 6.1 sec. and also change the minimum time to 40.0 sec. and the maximum time to 74.5 sec. Although, the latter modification would certainly reduce some of the longer missions, it is not clear how easily such a reliable performance could be achieved.

Additional Applications

Historically, industrial engineering and industrial psychology have shared many interests. A common denominator probably developed out of the scientific management movement which had its origins early in this century. For example, Taylors (1911) classic studies at the Bethlehem Steel yards have been of interest to both disciplines. Taylor spent several decades attempting to improve the work environment so as to optimize productivity. It is unfortunate that today industrial and organizational psychologists have been slow to accept some of the more recent innovative techniques of operations research.

Whitehouse (1966) has demonstrated how G.E.R.T. might aid management. In a more recent publication, Whitehouse (1973) has applied GERTS network analysis to additional problems which might be of interest to the applied psychologist (particularly the human factors engineer). Several of these problems are listed below:

1. The analysis and sequencing of space experiments (p. 326)
2. The analysis of reliability problems (p. 386)
3. The analysis of traffic flow at a highway intersection (p. 467)
4. A GERTS model of student mobility in a university (p.469; taken from Burgess, 1970).

This list should become more extensive in the near future because of the inherent flexibility of the GERTS system.

VII
Conclusions

Two somewhat related problems remain to be considered: a)What is the validity of the models proposed in the present paper? b) How might the adequacy of GERTS as a methodological tool for psychologists be evaluated? These issues will be discussed in the present chapter.

Model Validation Considerations

From a survey of the applications considered in this paper, it is apparent that the flexibility and power of the GERTS network approach is great. With this system, the researcher is tempted to construct large and complex models that presumably offer greater realism than is usually feasible with models subject to more through mathematical analysis. This added complexity is not necessarily bad- the computer simulation models might be more accurate or predict to a very large class of data. However, questions of validity do seem to take on added significance for computer simulation models.

Despite its importance, the problem of testing computer models remains perhaps the most elusive of all the unresolved issues associated with computer simulation techniques (Naylor & Finger, 1967). Horn (1969), who recognizes that there is no single appropriate validation procedure, suggests the following definition: validation is the process of building an acceptable level of confidence that an inference about a simulated process is a correct or valid inference for the actual process.

Validation is certainly problem dependent. When the models are used for descriptive analyses, as was proposed in chapter 4, then the actual historical record produced by the system being simulated can be used to verify the accuracy of predictions. If modles are to be used for prescriptive purposes, as exemplified in the applied problems of chapter 6, then a researcher is probably interested in examining the behavior of a system under different combinations of policy conditions. In this case the actual outcome of the policy chosen can eventually be compared with the output predicted by the simulation model.

Atkinson, Bower, and Crothers (1965) have suggested a more elaborate scheme for evaluating mathematical models which also seems appropriate for validating computer simulation models. Typically a model developer uses a portion of his data to estimate parameters, and then uses the model to predict the remainder of his data. Atkinson, et.al. suggest that everal levels of validity can be distinguished according to the extent the model predicts beyond the data used for estimation: the most modest type of prediction is curve fitting. This level is reached when the parameters are estimated from the very data that is being predicted. The next higher level of prediction involves using parameters estimated from part of the data to predict some other aspect of the data. Finally, the most satisfactory situation arises when the estimated parameters are used to generate completely a priori predictions of behavior in a new situation.

Most models formulated as teaching units fall somewhere between the middle and highest level in this hierarchy, depending upon one's definition of new experimental situations. For instance in unit I, the same parameters which were estimated from sensory activation data and data concerning the development of fear were subsequently used to generate data simulating the critical period. In unit II, spinal neurons, whose parameters were developed to simulate stretch reflex behavior, appear to adequately simulate the flexion reflex. In addition, a limited sensitivity analysis was performed on unit II to determine which of many model components are most significant in the overall performance of the system (e.g. removal of the Golgi tendon organs and the spindle organs). The model developed for unit III is the only one whose adequacy has not been shown superior to level I (curve-fitting). This does not imply that it would be just as profitable for students to study a mathematical equation offering the best fit to the data. Hopefully the structure of the network itself will lead to an understanding of the classical conditioning paradigm independent of the predictions generated by the model. The parameters in unit IV were estimated to simulate Melton's (1963) findings concerning short term memory and Murdock's (1962) empirical data for items presented at a 20-2 rate. These same parameters effectively simulated a whole family of serial position curves. Finally, parameters for unit V were estimated on the basis of experimental evidence collected with a circular group communication structure. A rèlatively high level of validity was achieved for this simulation model when it was also shown capable of predicting performance data for a group communicating in a wheel configuration.

Although there are statistical tests available for comparing simulation output with actual human performance, several authors (Frijda, 1967; Horn, 1969) have questioned their appropriateness. They argue that the degrees of freedom of a computer program are extremely large, and the tests themselves are subject to questions of validity. Simple comparisons of means, ranges, and variances, or graphical comparisons of data distributions will usually capture most of the available information. In this context, it has been suggested (Horn, 1969) that perhaps an adequate test of "goodness of fit" might be a Turing test of the simulation data by experts who are directly involved with the actual system. If the simulated data is presented to the experts and they are unable to distinguish this data from empirical data, then the model has passed the Turing test and is adequate. Even if the simulation model is contradicted by empirical data, additional modifications could be made. Certainly a simulation should not be discarded unless a better model is available.

The Adequacy of GERTS As a Tool for Psychologists

This study has attempted to demonstrate the possible applicability of GERTS network analysis for problem areas in psychology. The flexibility of this technique has been stressed throughout. Other possible criteria for evaluating the utility of GERTS might include accuracy of solutions generated, the potential cost involved, and the ease of learning the language.

In chapter 3 it was demonstrated that, where analytical procedures exist for solving Markov chain models, the GERTS approach can provide solutions within specified error tolerances. Other investigators (Bazley & Davis, 1960) have also found that Monte Carlo calculations are in agreement with theoretical results from matrix calculations. Solutions derived from many of the models in chapters 4, 5, and 6 would be extremely difficult to obtain by any procedures other then GERTS network analysis.

The cost of applying GERTS depends primarily upon the complexity of the system modeled and the number of runs required. For example, average execution cost on the CDC 6400 system for simulating a network associated with the teaching units in chapter 4 was $3.12; whereas the mean execution cost for analyzing a Markov chain in chapter 3 was $1.56. If the expense of having individual students execute several jobs is too high, instructors have several options. They may have all students study the appropriate units but only select representative parameters for actual simulation, or they may have students work in small groups. The latter approach, of course, has the disadvantage of not enabling instructors to tailor the units to meet individual student needs.

A final consideration in evaluating the utility of GERTS for psychologists is the ease with which the language can be mastered. This is especially important for students who operate in short time frames. This issue was discussed briefly in chapter 4. The next step in evaluating the effectiveness of the five teaching units should involve an adequately controlled study which compares the academic performance of the students who acquire GERTS modeling experience and who generate simulated data with those receiving only traditional classroom experience.

Future modeling work in psychology might also utilize a recent extension of the GERTS III Q language- the Q-GERTS network language (Pritsker, 1975). The Q-GERTS language is designed to provide the user with a more extensive set of node types. Among the more important innovations is the development of the S-node (selector node). The S-node enables the network analyst to designate more than one service activity emanating from a Q node or arriving at a Q node. It provides the choice mechanism for selecting which service activity should be performed or selecting from a set of parallel queues inputing into an S-node. As an example, the S-node might be introduced into teaching unit V. Here it would represent one aspect of the behavior of a problem solver, in the central position of a wheel communication network, who must receive and send numerous messages. Such an individual might adapt a particular decision strategy associated with the S-node (e.g. pass problem information to the Q-node, individual occupying a peripheral position, which has the largest remaining unused capacity). Another valuable capability of Q-GERTS is the opportunity for modification of Q-nodes or S-nodes.

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Vita

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He went through the Chicago public school system and graduated from Lane Technical High School in 1962. The same year he entered the Chicago branch of the University of Illinois. In 1965 he transferred to the Urbana campus of the University of Illinois where he received his B.S. degree in general engineering and his B.A. degree in psychology.

While in graduate training in the Psychology Department at Lehigh University, he held a teaching assistantship and a N.S.F. traineeship. He received his M.S. in Psychology from Lehigh University in June, 1970.

He has had four semesters part-time teaching experience with the Allentown extension of the Pennsylvania State University. He has also had one-half year experience as an industrial psychologist working on test development. Since the fall of 1974, he has held the position of Instructor in the Department of Psychology at Moravian College.

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