APPLICATIONS OF COMPUTER SIMULATION IN HEALTH CARE

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ABSTRACT

Several hundred computer simulation models have been developed in the last 15 years to solve problems in the nation's health care delivery system. These models are categorized and reviewed according to 21 areas of application, along with discussion of general model characteristics. Charts showing trends in health care simulation modeling are given, followed by discussion of problems in model implementation and directions for future research.

INTRODUCTION

In the 25 years since the advent of digital computers, simulation has become an increasingly important aid to management decision making. Many of the simulation models and languages which have been developed have found application in one of the nation's largest and fastest growing industries, the health care industry (311). In an effort to learn just how pervasive simulation modeling was in health care, an extensive literature search and review of the health care journals was conducted. The 92 computer simulation models cited in the bibliography of this paper represent well over 1200 models of health care that were reviewed in this study, which includes essentially all published or generally available computer simulation models developed through May, 1978. To provide a framework for this review, these models were divided into 21 application categories as shown in Figure 1. Although many models are pertinent to several application categories, they usually are referenced in only one category. Also, due to length constraints of this paper, only representative examples of some modeling categories are discussed and the reader is referred to the bibliography and tabular list (see section on "Trends in Health Care Simulation") for information on simulation models not discussed in this paper.

Resources utilized in this literature search include the library of the Indiana University Medical School, the engineering and general libraries of Purdue University and the library of Regenstrief Institute for Health Care. Particularly useful sources of reference included the Abstracts of Hospital Management Studies (301), David Valinsky's chapter on simulation in Operations Research in Health Care (314), Brant Fries' "Bibliography Operations Research in Health-Care Systems" from the Operations Research journal,(304) and the cumulative and annual indices of many prominent health care periodicals.

COMPUTER SIMULATION

Many of the "computer simulation models" of health care systems reported in the literature are regression, econometric, or mathmatical models employing queuing theory, stochastic methods, or mathmatical programming for their solution In this study a more specific definition of computer simulation was employed to include only those simulation models or languages capable of having discrete events occur during the simulation, or models incorporating the methodology of "Systems Dynamics". In some instances it was not possible to discern from the published account of the model whether it was a discrete event simulation. This has no doubt led to several non-simulation models being unknowingly included in the review and several simulation models being inadvertently excluded.

FIGURE 1
AN OUTLINE OF COMPUTER SIMULATION IN HEALTH CARE

Hospitals - Systems Models
1. Admissions control
2. Beds
3. General and miscellaneous hospital systems

Hospitals - Departmental Models
4. Ambulance and Emergency Service
5. Laboratory
6. Radiology
7. Surgery and recovery room
8. Supply and support services

Ambulatory Care
9. Outpatient clinics
10. Dental practice
11. Pharmacy
12. Public health and disease control programs

Health Care Manpower
13. Manpower planning and forecasting
14. Manpower substitution and staffing

Health Care Systems Planning
15. Community and regional
16. National
17. Health maintenance organizations and prepayment plans

Other Health Care Models
18. Blood banks
19. Nursing homes
20. Education
21. Miscellaneous

HOSPITALS

Conceptually it is feasible (although insensitive) to think of a hospital as a large production facility where patients enter, queue in a ward to await service from various servers such as surgery or radiology, and eventually complete service at all of the stations required by their disease to be discharged or removed from the facility. Many simulation models have dealt with specific service units or departments as outlined in Figure 1, while some simulations have modeled an entire hospital system.

ADMISSION CONTROL SYSTEMS

Hospital admissions control was one of the earliest problems dealt with by computer simulation researchers. The problem has characteristics similar to a customer demand problem in any industry with the additional features that some of the demand is under direct control of the hospital admissions supervisor by virtue of scheduled or "call-in" admissions (patients are literally called in from a waiting list when the hospital drops below capacity). Furthermore, failure to meet emergency admission demands can have serious consequences.

One of the earliest admissions models was Bailey's Erlang telephone model of hospital admissions in 1954 (302). His queuing theory analysis assumed Poisson distributed patient arrivals and a negative exponentially distributed LOS. The appropriateness of these distributions has been substantiated by later studies and they form the basis of many patient generators and patient flow models used in health care simulations.

One of the earliest discrete simulation models, created in SIMSCRIPT by Fetter and Thompson in 1964 (45), evaluates admissions for a single unit, the maternity suite. Also in 1964, in England, Barr, et. al. at Oxford (7), simulated a maternity unit, including decision rules for patient admission and computing various measures of performance of the policies such as percent bed occupancy and number of turnaways. Rath, Wright, and Karp (171) simulated admission and discharge policies for a single unit, the Intensive Care Unit (ICU) with the decision policies being based largely on state of the patient's health. Robinson, Wing, and Davis (188) formulated a SIMSCRIPT model of an admissions system which was built in modular form. Rubenstein at the University of California (190) and Marsh at Ohio State (137) concentrated on developing computerized admissions scheduling algorithms to optimize hospital operation. These algorithms were tested in computer simulation models to determine how well they improved system performance, compared with the manual admissions scheduling systems currently in use. A simulation model was used to substantiate the results obtained from a semi-Markov decision process model of hospital admissions by Kao (110). Howland and Baldock (98) modeled the hospital patient flow block by a Markov transaction matrix using a multiple attribute Poisson patient generator to input patients to the Markov chain.

The admissions scheduling and control system (ASCS) developed by Hancock and his associates at the University of Michigan in 1975 has been part of several simulation models including an admissions simulation game used to teach admissions personnel to use the ASCS (16,72,74,84,106,107, 233,234). The FORTRAN models are well documented and come complete with questionaires used to obtain data for operation of the ASCS. Among other results, use of the model at hospitals near the University of Michigan has shown that the Hill-Burton and Poisson formulas for determining the optimum number of beds for a hospital tend to result in "overbedding" and that bed occupancy levels over 90% are not unreasonable to expect with a good admissions control system.

McClain (139) developed statistical analyses to compare average daily occupancy, admissions waiting line length, number of emergency patients turned away, and average length of stay for various simulated admissions policies. He concluded that autocorrelation in the simulated time series needs to be considered before comparing simulation output and that variance reduction techniques should be applied to obtain more meaningful comparisons. He also commented that queuing theory models of hospital admissions can be expected to give less realistic results than simulation models due to "bulk patient arrivals" which occur in the real world and in simulation but are input as mathmatical distributions in queuing theory models. Further reference is made to variance reduction by Schruben (195) who used antithetic random number streams in his simulation model of a hospital patient unit.

BEDS

When planning for the construction or enlargement of a hospital facility, a critical issue is how many beds to include. This may be dictated solely by economic considerations but often it is necessary to determine the marginal cost or benefit of the next patient bed. Simulation modeling of the proposed facility offers a simple method for this evaluation.

Much of the early research in bed modeling was directed toward determining obstetric bed and facility needs, based partly on the work of Thompson and Fetter in the mid 1960s (214). They concluded that Poisson models did not accurately predict maternity bed needs. They also demonstrated the increased cost effectiveness of larger maternity services, an idea pursued by Fischer (49) in his simulation of the potential savings two small hospitals could obtain by pooling their maternity services. Designing for the optimum number of Intensive Care Unit (ICU) and Coronary Care Unit (CCU) beds has been the subject of several models (110,171,202) including one which considered "ejecting" patients prematurely back to intermediate care facilities to alleviate a potential bed shortage (198).

The Emergency Medical Service (EMS) presents a difficult problem to the hospital bed planner since a certain number of beds must be reserved to accommodate emergency admissions. Handyside and Morris (75) simulated emergency admissions systems whereby emergencies are rotated to various hospitals by day of the week to improve EMS cost effectiveness by increasing bed utilization.

A problem similar to that of emergency bed allocation exists for general bed allocation where hospital wards are organized according to medical specialties (general medicine, surgery, orthopedic, pediatrics, etc.). Such organization can lead to short term overcrowding in one ward and empty beds in another. Rikkers (181) simulated the effect of maintaining flexible care unit boundaries for all hospital bed units, while Blewett (12) considered sharing beds between surgical specialties. The goal of these models was to cut down the waiting time for elective hospital admissions while increasing the average percent bed occupancy and reducing occupancy variance.

Another bed allocation policy issue is progressive patient care; assigning patients to wards ranging from intensive through intermediate to self care according to the severity of their illness. Fetter and Thompson (47) were also among the pioneers in this area in 1969. Their model was used by Hartman (83) a few years later to estimate the bed requirements for a 5 level progressive patient care hospital expansion program. Thompson and Fetter (215) also tested the theory that an all-single-room hospital has a higher occupancy level and resultant economic advantage due to the lack of patient bed moves which sex conflicts necessitate in multi-patient per room units. They concluded no economic advantage existed.

GENERAL

One of the early attempts at modeling the hospital as an entire system was made by Hindle (87) in 1967 who considered the hospital as a conglomeration of interacting queuing systems where patients and personnel queued to demand health facilities and other resources. The goal of his model was to discover the most efficient policy to manage distribution of the limited facilities and resources.

Hardison (79) simulated a hospital with variable departmental staffing and costs to determine how total hospital costs could be minimized by interaction among the departments to accomodate seasonal variations in patient care demand patterns. Systems Dynamics was used by Stearns, Bergan, Roberts, and Quigley (204) to help a hospital conceptualize and quantify the interrelationships of its various departments which led to development of a DYNAMO simulation model. This model helped improve patient care by allowing department chiefs to understand how their autonomous operations often had far-reaching consequences for other areas of the hospital.

In 1967 Mills and Fetter (144,145) developed CML (Conversational Modeling Language) which contains 175 assembly language blocks to be used to build simulation models. Using CML they built HOSPSIM (48) a simulation language created for planning and designing various hospital and health care systems.

AMBULANCE AND EMERGENCY SERVICE

Simulation models of ambulance service are fostered by the fact that the same modeling concepts apply to police, fire, and other emergency service systems. The three most often cited questions to be addressed by such a model are: 1) where should the ambulances be based (central hospital versus remote substations) to minimize delay in getting to the victims; 2) how many vehicles are needed; and 3) what is the maximum possible delay and is it acceptable? All of these issues are subject to cost constraints. A significant aspect of emergency transportation simulation is the development of a geographical mapping and routing algorithm to digitize the transportation minimization aspect of the problem. Often this takes the form of a grid superimposed on a map of the area.

Savas (191) addressed these problems with his cost-effectiveness analysis of alternate systems of ambulance service in New York City in 1969. A simulation of 175,000 emergencies showed a regionally dispersed system had definite cost and effectiveness advantages over a centrally located system. A GASP model developed by Messer (142) provided for interactive simulation where vehicle routing could be performed by a dispatcher at a computer terminal. A SIMSCRIPT model (51) for planning an EMS was validated by data from the Los Angeles area while Dekar (26) developed an EMS simulation model (EMSSIM) based on data from Detroit and Hamilton (73) developed a Monte Carlo emergency system simulation (ESSIM) in Philadelphia. Simulation was used to evaluate the final solutions of a branch and bound optimization model of ambulance service which eliminated many of the simulation alternatives and reduced the computer costs considerably in Swoveland, Uyeno, Vertinsky, and Vickson's model (211).

Finally, a very interesting study by Chaiken (19) monitored the dissemination of emergency service deployment models to operating agencies. Of the six models studied, only one, the Hypercube Queuing Model, was an ambulance deployment simulation, the rest being police or fire department models. Thirty-nine users requested the Hypercube Model, of which 29 actually used it. Seven users reported making changes to their system as a result of this SIMSCRIPT model, although some reported the data required for the simulation model was not easily attainable. Overall, the report is an excellent study of the dissemination, use, and implementation of simulation models.

A couple of simulation models have been developed to resolve the problem of the high cost of maintaining emergency room (ER) facilities versus the consequences of an inadequate EMS. Hannon's next event stochastic FORTRAN model (77) considered variable staffing and triage policies for the emergency room under sporadic patient arrival patterns to predict facilities utilization. Lodany and Turban (124) formulated a model with the goal of optimizing the cost of ER facilities versus the very high cost to patients of having to wait for ER service. Their GPSS model was based on Poisson distributed patient service times which they derived and justified.

LABORATORY

Relatively few simulation models of hospital laboratories have been developed. Some of the best research in this area has come from Finland where Vaananen, et. al. (222) have developed a GPSS simulation to model 21 lab technicians, 37 equipment types, and 64 of the test types performed in the lab. Conceptually the model is very similar to any production line queuing model and is generally applicable to any hospital lab for simulating the effect of personnel or equipment changes on the processing time for lab tests.

Dumas and Valinsky (34) considered level and policy decisions as two different simulation variations. Their policy decision model, of a microscopy laboratory, had a fixed level of demand for tests to be performed. The model was run to determine which scheduling and operating policies best met the fixed level of demand. In contrast to this, their blood bank model (223) placed emphasis on level decisions. In this model the operating policies for dispensing blood were considered fixed and various inventory levels were tried to find one that gave maximum blood availability with minimum blood outdating (see section on blood banks). In 1970, Rath and Balbas (172) designed a hematology lab simulation model, with the intent that the model be incorporated later into a general model of a complete hospital.

RADIOLOGY

The typical Radiology Department conceptually resembles a multichannel queuing model where patients arrive randomly to queue in a single line and await service by multiple servers. Different patients may require different services so the length of service time varies both randomly and by type of radiology procedure required by the patient. Output measures include queue length, patient waiting time, and facility utilization (133).

The pioneering work in radiology department simulation was done largely by Covert, et. al. at the University of Missouri (23). The generalized model developed there in 1966 allowed for 20 exam rooms, 20 x-ray technicians, 17 major exam types, and a variety of patient scheduling options. The GPSS model was written for use by non-computer-oriented radiology personnel. Validation of the model showed patient waiting times were simulated within 5% of actual data when the model was used to predict the effect that the required closing of an exam room for renovation would have on the department. This model was adapted and used at the University of Pittsburg by Kirsch (120) who concluded "that the model would be ideal for static closed systems which would not be subject to variance from outside the system." Lev, Caltagirone, and Shea (128) further built upon the model, creating a block structured patient flow model, written in GPSS with FORTRAN subroutines. Their patient flow data and diagrams are excellent representations of the radiology department from a simulator's perspective and would be useful for planning simulation models of any hospital radiology facility.

At the University of Georgia, Sullivan, Widegreen, and others (135,169,207,208,209,210, 229) pioneered in location analysis for hospital radiographic facilities. They published a seven part, 628 page summary of their work which included a GPSS simulation of patient flow in the radiology department. Other models have considered the effect of staffing level and scheduling on patient waiting time (180) and radiographic films storage and retrieval (41). Lim and Baum (133) in a paper written in 1974, summarized the four major radiology department simulation models developed to date (Covert, Widegren, Caltagirone (128), and Perry (164)) and offered some comments and a summary of radiographic department modeling.

SURGERY

Scheduling the use of surgical suites and recovery room facilities has received much attention from health care simulators due to the high cost of idleness for these facilities. Models have been coded in FORTRAN, GPSS, SIMSCRIPT, and other languages for this complex problem. In a classical simulation study, Kwak, Kuzdrall, and Schmitz (121,122) investigated the increased number of recovery room beds needed to handle the extra surgical patients resulting from an addition of 144 general patient beds to Deaconness Hospital in St. Louis. A complicating factor was that length of stay in Recovery Room (RR) beds was subject to random variation according to type of surgery, and efficient surgery suite scheduling depended on sufficient RR beds being available. The GPSS model they formulated determined the number of RR beds necessary to handle maximum surgical capacity. It was validated by data obtained from hospital operation after the 144 beds were actually added. The model is sufficiently general to be applicable to modeling an operating room-recovery room patient flow using data from any hospital.

Blewett and his associates (12) at Lancaster were concerned with modeling a speciality surgery, ophthamology, and wrote a program in FORTRAN to consider the effect of operating room schedule, increased surgical facilities and ward sharing. Their model was also validated by comparison with actual hospital data after a renovation took place. Other operating room models (6,39) have considered surgical scheduling priority rules; first come, first served, fixed case assignments to specific rooms and/or specific days, and other schemes. Avoiding surgery idle time due to patient cancellations and optimizing surgical staff assignment and responsibility delegation are other issues which have been simulated (159).

SUPPLY AND SUPPORT SERVICES

Only a few simulation models of hospital supply and support services were found in the literature the first one being Kilpatrick and Freund's oxygen tank inventory model in 1967 (118). This model simulated the availability of oxygen tanks when needed, as a function of variable patient demand, under various inventory policies and levels. The model was suggested to be applicable to other hospital inventory problems although other uses were not documented. Marsh and Swain (138) simulated a materials handling system (cart, elevator, conveyor) to determine how efficiently the proposed system met the needs of a large hospital being remodeled and expanded.

AMBULATORY CARE

OUTPATIENT CLINICS

Simulation of outpatient clinics has received a great deal of attention from health care modelers and literally dozens of excellent simulation models have been published in the literature. The general operation of an outpatient clinic lends itself easily to simulation modeling. Ambulatory patients may arrive either as scheduled visits or as walk-ins without an appointment. Upon arrival, patients queue to await medical services, often from several servers such as a receptionist, a physician or other health care provider, X-ray, pharmacy, patient billing, etc. Eventually patients complete all of the services required for their particular medical problems and depart from the system. The goal of simulation is to determine where the bottlenecks occur in the system, and to discern where additional servers or revised scheduling policies could improve or streamline system performance. Performance is usually measured in terms of patient waiting time versus physician idle time, cost per patient, or less quantifiable parameters such as improved community health. In the actual computer models, patients are generally created by a Monte Carlo or Poisson patient generator with statistically prevalenced medical needs. Service times may be Monte Carlo, negative exponential, or otherwise distributed according to the medical service being performed and subject to the statistical data available to the modeler. Patients are often modeled as entities "flowing" through the clinic, queuing, demanding service, and consuming resources.

Some of the earliest research in this area was again done by Fetter and Thompson (46). Their 1966 outpatient department simulator considered seven variables; appointment interval, service time, patient arrival pattern, no shows, walk-ins, physician arrival pattern, and interruptions, and the effect these seven variables had on the doctor idle versus patient waiting time relationship. In 1967, Williams, Covert, and Steele (230) investigated the improvement a staggered block scheduling system (8 patients are scheduled to report every half hour) could achieve over a single block (all patients are told to come at 8:00 a.m.) scheduling rule (see also 313,315). Obviously, the latter rule places total emphasis on doctor idle time while the former rule gives some importance to patient waiting time. Their research showed no idle time would accrue to the physicians under a block scheduling system and as a result, such a system was implemented at the outpatient clinic of the hospital where they gathered the patient flow data used in the model. Several other outpatient clinic models used to determine the most efficient scheduling policies for patients and/or physicians to report to the clinic include Miga (143), Katz (111), Berkowitz (11), Granot and Granot (67), Glenn and Roberts (64), and Steidley and Vanloh (205).

A university health service clinic was the subject of a simulation model by Baron and Rising (5,182). Their GASP model resulted in new scheduling policies being implemented that increased daily patient volume by 13% and decreased daily physician working time by 5% without changing patient waiting time in the clinic. Stuart (206) later used and recommended Baron and Rising's model for evaluating outpatient clinics of the U.S. Army. He based his comments on his sensitivity analysis and validation studies of the model which showed exactness of input data was not critical. Agarwal and Stafford (2) also simulated a university student health center, incorporating a 14 station transition matrix structure in their model to govern patient flow through the clinic. Their description and data derived from observation of the student clinic are excellent and show patient interarrival time to be cyclic exponentially distributed (negative exponential with the mean changing according to time of day) and patient service time to be Erlang-K distributed. Their model was used to simulate the need for an additional pharmacist in the university's outpatient pharmacy and data gathered after implementation of this suggestion by the hospital administration further validated the model (201). An unexplained disturbance in their model was the fact that random number seeds had a statistically significant effect on the simulation outcome.

An interesting study by Hirsch and Bergan (89) compared three types of ambulatory care systems; a prepaid group clinic, a fee for service group clinic, and solo practitioners. Output measures included cost, patient load per physician, physician time per patient visit, and waiting time for appointments. Extensive classification of patient medical needs, physician decision variables, visit outcomes, referrals, and other discrete characterizations of the health care system were tabularized and analyzed by the authors, making this model an excellent framework for evaluating ambulatory care systems. Internists, specialists, and general practitioners were included in the DYNAMO model. Data gathered from over 9,000 actual patients was used to implement and validate the model.

A prepaid group clinic was also modeled by Carlson, Hershey, and Kropp (17) who built a linear optimization-simulation model. The optimization routine determined staffing and facilities necessary to serve a given patient population at minimum cost, and the simulation program used this data to model clinic operation and determine patient waiting time. Regression was then used to relate waiting time to the staffing and facility parameters and thus form a new constraint for the optimization program. The whole process was repeated until convergence was achieved, usually requiring about five iterations.

Some other outpatient simulation models of interest include Warner and Freeman's (226) GPSS model of a multiphasic screening center in Gainsville, Florida and Dill, et. al's. (28) GPSS simulation of an outpatient endocrine metabolic clinic in South Carolina. Liebman, Reuter, and Reuter (132) used a FORTRAN next-event-chain simulation model to aid in the design of a prepaid group medical practice at a medical center, evaluating the optimum staff and room assignments for an innovatively designed clinic. Roberts, et al. (185) used the INS simulation language to model operational alternatives in outpatient clinics in their 6 volume study of the utility of models as an aid to health care decision makers. Yen (235), Lasdon (125), and Dilley and Larkins (29) simulated community health centers to determine optimum staffing and service patterns and health resource allocation.

Finally, in the area of statistical analysis, Eulenstein (40) applied control variate and antithetic random number variance reduction techniques to a simulation model of an outpatient clinic and compared the results to an ordinary Monte Carlo simulation to determine the variance reduction achieved.

DENTAL CARE

Several excellent computer simulations of dental practice have been developed, including an extensive project to evaluate the use of Extended Function Auxiliaries (EFAs) or "dental assistants" which was headed by Kilpatrick, Mackenzie, and Delaney at the University of Florida (119,134). Their simulation consisted of a patient generator, a treatment model, and a cost model. Extensive analysis of over 300,000 dental procedures recorded by time lapse photography indicated patient service times were gamma distributed of order one to four and yielded 67 distinct dental procedure categories. This data resulted in a model with over 300 dental practice parameters coded into a 720 block GPSS model. Validity testing was done at seven private practices for which baseline data had been recorded before introduction of EFAs into the practices. The study concludes by noting the great potential EFAs have for improving dental care delivery and the usefulness of the model for teaching dental students the principles of good practice management.

Systems Dynamics was used by Hirsch and Killingsworth (92) to simulate how dental practice would respond to dental manpower and dental insurance changes. Their results suggest a sudden increase of dental insurance benefits would worsen average dental health due to the large increased demand for major dental care which would partially inundate the system at the expense of routine preventative dental care. Further application of Systems Dynamics to dental health is given by Levin and Roberts' dental manpower model described in their book, The Dynamics of Human Service Delivery (130).

Dental practice management was the subject of a simulation model devised by Reisman, et. al. at Case Western Reserve (68,174,175,178,179). This simulation model was developed into an interactive dental practice management game for dental students to learn management techniques and for practicing dentists to evaluate the impact of auxiliary personnel or new policies and procedures on their practice. Extensive documentation developed for the practice management game includes a user's manual, an administrator's manual, and a computer programmer's documentation manual (176).

PHARMACY

The operation of a pharmacy can be conceptualized as a queuing model where patients queue to wait for their prescription and pharmacists act as servers to fill prescriptions, answer the phone, compound medications, do bookkeeping, and other tasks. The objective of pharmacy simulation is to find a balance between patient waiting time and pharmacist idle time. Variables include pharmacy manpower and the priority system by which the pharmacist chooses tasks. Myers, Johnson, and Egan (156) developed a FORTRAN model that yielded simulated results within 15% of actual observations and allowed simulation of the introduction of pharmacy assistant personnel to achieve further cost reduction (105). Harmon and Novotny (82) used GASP to develop a similar pharmacy model at a midwestern medical center.

PUBLIC HEALTH AND DISEASE CONTROL PROGRAMS

The topic of public health and disease control programs includes simulation models that analyze the cost effectiveness of medical care programs administered to groups of people with a specific, common medical need rather than groups of people with unique individual medical needs. An interesting variety of simulation models of this type have been developed. Two models, one by Pyecha, Voors and Poole (167), the other by Duce, et. al. (33) have dealt with disaster planning. The first model evaluates community medical resources and medical system effectiveness following a nuclear attack, for a time of up to one year. Duce's model predicts medical needs following any sort of natural or man-made disaster which produces mass casualties.

The benefit of early detection hypertension screening programs is also the subject of two simulation models. Both Feldman, et.al. (42) in 1970 and Hannan and Graham (78) in 1977 demonstrated by their models the economic and other benefits to society and employers of hypertension screening programs. Holder, et.al. (96) used a GPSS patient flow model called ALCOSIM to simulate the costs and effectiveness of various treatment strategies for public inebriates. Chorba and Sanders (20) created a discrete-time simulation model of tuberculosis prevalence which optimized the cost of prevention programs against medical and societal costs of unchecked spread of the disease.

Two DYNAMO models of community health problems are Kalgraf's Yellow Fever epidemic model (109) and Levin, Hirsch, and Roberts community narcotics control program simulation (129). The control of rabies in urban Columbia was the subject of a simulation model by Frerichs and Prawda (55). Roberts and Maxwell (186) simulated the cost-effectiveness of End Stage Renal Disease (ESRD) treatment. Their INS language model has a tree structure with probabilistic branching to activities. Application of the model to ESRD treatment programs indicated a potential quarter billion dollar savings in U.S. health care expenditures could be achieved by increased use of home dialysis in place of institutional dialysis.

HEALTH CARE MANPOWER

MANPOWER PLANNING AND FORECASTING

Although the average physician to population ratio in the U.S. has declined steadily since 1950 (311) and there actually is not a "doctor shortage", there is a maldistribution of physicians problem and especially a shortage of primary care physicians in many areas (312). This maldistribution results from a host of socio-economic and political factors that are complex to parameterize for a computer simulation model and possibly as a result of this, few simulation models have been reported. One GASP model recently developed by Standridge, et.al. (203) considered four elements; primary care physicians, the volume of services these physicians provide, the population, and the volume of services the population demands. These variables were projected forward in time using interrelationships developed from current statistical data from the State of Indiana. The model concluded that general and family physicians will decline in number and deliver less than half of the direct primary patient care supplied by the year 2000.

The supply, demand, and distribution of nurses was the subject of Bergan and Hirsch's DYNAMO model (10). Four sectors; education, employment, demand, and demography were modeled with 7 possible employment settings and 5 levels of educational preparation to estimate the impact of changes in programs and policies on nursing personnel. The model was initiated with 1972 data and used to predict nursing personnel behavior under various conditions for a four year time frame.

A publication of interest to health care manpower simulators is Vector Research's health manpower model summary reports (32) which reference 56 health manpower models of various types, developed in the period 1960 to 1973.

MANPOWER SUBSTITUTION AND STAFFING

Two ideas pertaining to medical personnel staffing have received attention in recent years, both of which lend themselves easily to simulation modeling. The first, variable staffing allocation, usually refers to transfering nursing personnel between units to meet changes in daily patient demand for care with the minimum total number of nurses. This is the principle of pooled resources which, of course, requires that nurses be cross-trained to perform a variety of nursing tasks. The second idea is manpower substitution; using a Physician Assistant (PA) or a Family Nurse Practitioner (FNP) to perform routine or non-critical tasks, such as giving physicals, that have traditionally been done by physicians. Both ideas have potential for reducing the cost of health care delivery.

While much of the variable nurse staffing research has led to development of mathmatical models, several good simulations have also been reported. Hershey (86) designed a Monte Carlo model which permitted fixed and variable staffing simulation to allow hospital decision makers to assess the sensitivity of savings to changes in staffing policy. Wandel (224) interfaced a Monte Carlo simulation model of daily staffing requirements with a dynamic linear program which optimized long term staffing policies such a hiring and firing, overtime, training, and transfer between fixed staff wards. His results indicated an 8% cost savings could be achieved with respect to currently used staffing policies. Raeside and Traub (170) designed a FORTRAN Monte Carlo model to create staff assignments for 26 medical residents to rotate between 14 training experiences in a given length training program in a teaching hospital.

Manpower substitution has become a common topic for health care planners. Questions to be answered by manpower substitution simulation models include deciding what tasks a physician should delegate to an assistant, how many assistants should a physician have, how much patient demand can be met by various medical manpower team combinations, and how is medical practice income related to the use of PAs or FNPs? Lazarus, et.al. (126) developed a BASIC model to answer these questions for rural physicians who input a description of their practice (personnel, patient type and load, office size, desired income and workload, tasks to be delegated to PAs, patient scheduling policies, etc.) to a computer via a portable, telephone-linked terminal to get an immediate analysis of how the use of PAs would affect their private office practice. Several practicing physicians are reported to have used the model which was also being demonstrated as a teaching tool for medical students. A similar model was developed by Mirable and Anderman (148) based on data from New York State's Appalachia region.

In 1973 Reid (173) simulated the ability of rural health care clinics staffed by an FNP to provide primary medical care to the local population while Dhillon (27) modeled the effect of increasing medical technology on the ability of PAs and FNPs to provide quality patient care in a rural setting. Unfortunately, little actual data was available with which to validate the model. Schneider and Harz (194) incorporated PAs into a GPSS model of a prepaid group practice. Patient service times were determined as a function of their symptoms and the size of the clinic was varied to determine how the PA-physician-exam room ratio should change for optimum use of the PAs. Uyeno (221) developed a "Task Capability Matrix" showing which members of a health care team (physicians, nurse practitioners and nurse assistants) were (functionally and legally (305)) capable of performing various medical tasks. Patients were modeled to flow through queues and engage members of the health care team as governed by the Task Capability Matrix. The SIMSCRIPT model was constructed to examine the effects of patient demand level, skill level of the medical personnel, and facilities on the optimum health care team composition. A similar model was written in FORTRAN by Reisman, et.al. (177) and a non-technical, user oriented simulation package, the MEDSIM model, developed at the University of California, was applied at St. Justine's Hospital in Canada to examine the effects of task assignment and patient care needs on six categories of medical personnel (123).

HEALTH CARE SYSTEMS PLANNING

COMMUNITY AND REGIONAL MODELS

Probably the greatest recent expenditure of money and effort for health care simulation has been in the area of comprehensive community and regional health care delivery system models. The issues to be considered are many and complex. However, the utility of a large scale, all inclusive health care model would readily be appreciated by the growing cadre of organizations and agencies undertaking responsibility for guiding and regulating the nation's health care system. Large research grants have been available for work in this area and several extensive projects with dozens of staff members have spent hundreds of man-months developing prodigious simulation models of community health care delivery systems.

One of the largest health care simulation projects undertaken to date is Geomet's Neighborhood Health Center (NHC) ambulatory care system model (146,165). Begun in 1969 and continuing through about 1974, this simulation model is built as three submodels, the population, the delivery system, and the cost submodels, each capable of independent or joint operation. An event calendar keeps track of every patient's moves through the clinic, allowing for 74 diagnostic categories, each of which requires a specific sequence of health care resource utilization for treatment. Actual health care delivery occurs at treatment stations where patients queue to await delivery of the care elements required by their diagnostic category. The program, written in PL-1, is overlaid in 500K bytes of core and takes 30 minutes of CPU time to execute a one day (250 patient) simulation of a large NHC. The model was constructed using data from the Mile Square NHC in Chicago and verified using data from NHCs in Salt Lake City, Utah, Norwich, New York, and Los Angeles, California.

A project directed by Sam Edwards for the Texas Hospital Association resulted in the development of the Health Services Simulation (37,99,149,150). Although this is a regression equation model rather than a simulation, its scope and uniqueness in the development of health care modeling warrents a comment. The model forecasts demand for medical care within a Standard Metropolitan Statistical Area (SMSA) for up to a 10 year future. Five separate validation studies and uses of the model indicate it is accurate to within 5% for a five year forecast of admissions and patient days in area short term hospitals.

A project at the Research Triangle Institute (RTI) of North Carolina resulted in a four volume report of a community health service simulation model in 1969 (63,112,113,162,227). The SIMSCRIPT model is based on data from a maternal and infant care project which provides comprehensive health care to expectant mothers and infants in three counties.

Other community health care planning models have dealt with planning and operating Family Planning Programs (FPPs), including models by Urban (220), Alessandra, et.al. (4), Colosi (22), and O'Connor (160). The latter two are interactive models designed for use by FPP directors to evaluate alternative strategies for allocation of program funds and resources, or for students to learn the concepts of FPP systems.

Other regional health care delivery system models include Fox, et.al's. FORTRAN model (53), Baum's model which emphasizes health care delivery to the poor (8), Moss' Health Services Node used as a building block in an Indian Health Service model (153), and Milsum's health submodel that interacts with population, pollution, transportation, and energy submodels to form a microcosmic model of the Greater Vancouver Region (147). Using the methodology of Systems Dynamics, Hirsch developed a DYNAMO model to be used for comprehensive health care systems planning (90). In 1976, Dei Rossi, et.al. (25) devised a Monte Carlo simulation model which calculates patient waiting time for hospital admission. This waiting time can be compared to acceptable standards to forecast areawide bed requirements in a manner superior to the Hill-Burton formula.

NATIONAL MODELS

As with community and regional health care delivery simulation models, the utility of a comprehensive national health care simulation model for future planning would be immense, and two groups in particular have undertaken to build such a model. In 1969, the Bureau of Health Manpower Education of DHEW contracted with a group at the University of Southern California (USC) to conceptualize a national health care manpower simulation model, while a group at RTI was to concern itself with actually building such a model. The result of these efforts was "A Conference on Health Manpower Modeling" on August 31 and September 1, 1970 (166). The USC model, Mark I, was conceived as three submodels including services, manpower, and medical education, which contained five separate populations interacting in three supply and demand markets via literally hundreds of relational equations and variables. Since the data required by these idealized equations was not available, a scaled down 30 equation version of the model, Mark II, was also formulated as a more practical if less accurate model. At the same time the RTI group developed an operational FORTRAN version of a health manpower simulation model. Their model had two submodels. The Monte Carlo patient generator, POPSIM, scheduled future medical needs for patients by an inverse geometric distribution while the hospital submodel, HOSPEP, used a log-normal length of stay distribution and a negative binomial number of hospital visits distribution. Discussion from the audience at the conference suggested both groups' models were too complex for hands on use by physicians or health care planners.

Continuing work on the USC model, Yett, et.al. (237) reported an operational, computer programmed version of the model in 1973. Further research fostered by the Bureau of Health Manpower resulted in a 1976 review study by Deane and Litkowski (24) of ten comprehensive models of the U.S. health care system. They evaluated the various modeling techniques used and concluded Systems Dynamics was the most feasible. They also developed a prototype model of the total U.S. health care system.

HEALTH MAINTENANCE ORGANIZATIONS AND PREPAYMENT PLANS

Health Maintenance Organizations (HMOs) are gaining acceptance and popularity in the American health care system at a rapid pace, following the enactment of P.L. 93-222, the HMO Act of 1973. Due at least partially to the complexity of the economic, social, and political issues to be considered in modeling the operation of an HMO, relatively few computer simulations have been formulated to date. Some of the issues which must be considered are: 1) ownership of hospital and other facilities versus contracting for hospital care; 2) the size and composition of the patient population necessary to break even on costs; 3) marketing strategies for patient recruitment; 4) services and benefits to include in the basic health care provision package; 5) enrollment fee; 6) method of physician remuneration and; 7) potential impact of changes in the U.S. health care system such as the enactment of a national health insurance program.

Moustafa and Sears (154) discussed these and other issues and outlined a basic HMO simulation model but did not build an actual computer simulation program from their conceptual framework. Hirsch and Miller (91) did build an HMO model, in DYNAMO, which has six population sectors; subscriber marketing, illness type, medical personnel and resources, inpatient facilities, preventative health care, and finance. The simulation was run using data from a study done to determine the feasibility of implementing an HMO at a major medical center. Based partly on an evaluation of the impact of different marketing strategies, benefit packages, and personal fitness programs as simulated by the model, a decision was made not to proceed with the proposed HMO. A FORTRAN model written by Morehart (151) was similarly used and in this case affirmed the financial feasibility of a statewide HMO system in Georgia.

OTHER HEALTH CARE MODELS

BLOOD BANKS

Hospital blood bank modeling is conceptually much like any inventory problem modeling with the added constraints that a stock-out should not be allowed to occur and that blood is a perishable commodity with a shelf life of 21 days. Other factors to be considered include the necessity of maintaining eight separate inventories, one for each of the major blood types and the allowance that blood received into inventory may be anywhere from one to 20 days old depending on how and from where it was received. "Reorder delay" is subject to variation and depends on donor availability, weather, season, bloodmobile collection schedules, and the proximity of other hospital blood banks or regional blood collection centers. Blood may be used in two ways; for immediate emergency requests, or it may be "cross-matched" to a particular patient and taken from inventory to be held in reserve for a given number of days for a patient whose physician anticipates a possible need.

Numerous mathmatical inventory models of blood banking have been developed, but due to the unique complicating factors of the blood banking inventory problem, computer simulation has also proven quite useful and several models have been created. Policy issues to be considered by a blood bank inventory simulation model include: 1) what inventory level to maintain; 2) the possibility of substituting Rh-negative blood for Rh-positive under limited conditions; 3) double cross-matching, a policy of pooling blood units that have been reserved for individual patients; 4) variation in the number of days a unit of blood is held in reserve if the patient does not use it after cross-matching; 5) alternative uses of the blood, such as plasma fractionation or freezer storage of red blood cells and; 6) selective cross-matching of older blood to patients deemed more likely to actually use it. The goal of blood bank simulation models is to minimize the amount of blood outdated because it was not used in 21 days, while keeping the inventory at safe levels.

Structurally, most blood bank simulation models appear to be similar, including those by Elston and Pickrel (38), Jennings (102), Nelson (157), and Rabinowitz (168). A Monte Carlo demand generator requests a certain number and type of blood units to be used or to be cross-matched each day. This demand is filled by depleting the inventory, replenishing the inventory by volunteer or call-in donors or from other blood banks, and removing outdated blood from the inventory. These models seem fairly general and appear to be applicable to a variety of blood banks, however, in the case of Nelson, it is pointed out that new Red Cross policies on returning unused blood and new blood storage technology would require "substantial modifications" to the model, suggesting a possible lack of model flexibility.

In related simulations, Yen and Pierskalla (236) simulated a centralized blood bank system which fed several smaller hospital blood banks, while Pegels, et.al. (163) simulated a blood collection system where the dates and locations of bloodmobile collections were variable and the object was to reduce seasonal imbalances between supply and demand for blood. The model is made available to community and regional blood collection agencies to optimize their particular schedule, for a cost of about $600, a cost deemed quickly recoverable from the benefits of more stable inventory levels.

NURSING HOMES

Staffing configurations, type of care, and cost are issues considered by a FORTRAN and a

SIMSCRIPT version of a nursing home simulation model (100,141). User's manuals for these models were written for non-computer-oriented health planners, administrators and regulatory agencies to use in simulating the efficiency and effectiveness of long term care facilities. An interesting example of the adaptability of health care patient flow modeling is the development of a pediatric hospital care unit simulation model and user's manual by Brayton (15), based on a modification of a nursing home simulation program.

EDUCATION

Most of the contribution of simulation to health care education has been in the area of interactive models to be used by health care students to gain simulated practical experience in a laboratory setting. In a sense, nearly all computer simulation models are suited to this purpose, however several models and languages have been developed specifically for educational purposes. Several of these models are not discrete time simulations, being optimization or mathmatical models coded in FORTRAN, BASIC, or other languages. However, due to the standard practice of calling interactive models of clinical experience "computer simulations," these models are included for completeness of this study.

Historically, one of the first developments in educational simulation was the Computer Aided Simulation of the Clinical Encounter (CASE) developed by Harless, et.al. (80,81). This model is used by medical students to learn diagnosis and management of diseases in clinical situations. Feedback from the computer after a simulated clinical encounter evaluates the student's performance based on accepted medical opinions of how the situation should have been handled. Johnson, Moller, and Bass (104) developed a similar simulation model for students to study management of congenital heart disease, while Braun (14) outlined some of the major applications of computer simulation in medical education and in clinical medicine and presented an example of the use of the Lister Hill abdominal-pain simulation. This is another medical student clinical encounter model, which was developed at the Massachusetts General Hospital.

Roberts, Kronman, and Fox (187) depart from clinical experience modeling in their development of a medical practice planning model useful for medical students to learn the rudiments of laying out their own private practice. The computer requests information such as desired income, working hours, task delegation to assistants, etc. from the students (similar to Lazarus' (126) or Mirable and Anderman's (148) manpower substitution models), then the model simulates how the students' ideas and values will interact to determine the characteristics of their practice.

In the area of health care delivery system planning, Baurn, Bergwall, and Reeves (9) created the SIMSCRIPT based Health Care Delivery Simulation for Urban Population (HEADSUP). Patients, staffing, utilization, facilities, location, and other system characteristics are interrelated by the model to allow health systems planning students to create HMOs, hospitals, or group practices and evaluate the effect of various policy decisions on patient waiting time, shortages of care, patient load served, and other performance measures. The Undergraduate Education Model, a FORTRAN model developed by Centner, et.al. (18) calculates staff, patient, space, and other resources required for medical student education. The model is to be used in health education facilities planning and budgeting. Finally, Warner and Griffith's recent workbook for hospital administration students (225) contains several exercises in computer simulation modeling.

MISCELLANEOUS

Several textbooks and articles on computer simulation in health care modeling do not fit into any of the previously defined categories. Included in this category would be Griffith, Hancock, and Munson's textbook for hospital administration students Cost Control in Hospitals which discusses several uses of computer simulation in the hospital environment (69). Levin, et.al.'s Dynamics of Human Service Delivery presents a mental patient "Treatment Drop-Out Model" written in DYNAMO (130), while "Strategic Modeling for Health Care Managers" also applies the Systems Dynamics methodology to several issues faced by health care planners and administrators (183).

A unique application of simulation is made by Garg (60) in his DYNAMO model of genetic defect incidence which simulates the long term effects of genetic counseling (selective abortion or selective mating) on the population. Donaghey (31) also developed an unusual use for simulation by modeling the growth and destruction of cell colonies using his FORTRAN based CELLSIM macro-simulation language.

IMPLEMENTATION OF HEALTH CARE SIMULATION MODELS

Relatively few of the published health care simulation models read in this study reported significant effects the simulation had had on the health care system being studied. From this it may be inferred that either the authors chose to use their limited journal space and conference presentations to document the model and the issues they modeled rather than the results of model implementation, or there were few extensive model implementation results to report. Discussion with hospital administrators, management engineers and simulation modelers suggests the latter to be true. Some reasons for the limited success in implementation that simulation modeling seems to have had in health care and suggestions for remedying the problem include:

1. Lack of Economic Incentive; The financial structure of the U.S. health care system does not require health care institutions to explicitly demonstrate cost effectiveness in their operation. Expensive tests are billed to third party payers and the public resultantly demands the best available care without regard to its cost. The solution to this

implementation problem lies outside the modelor's control. Health care institutions will not earnestly become concerned with using simulation modeling to lower the cost without decreasing the quality of their care unless they are economically or politically required or heavily rewarded for doing so. This contrasts sharply to the use of simulation in production industries where lowering cost and maintaining quality is a fundamental goal.

2. No Vested Authority; Health care administrators, physicians, elected public officials and patients all exercise control in various ways over the health care system. In production industries the management heirachy that exists insures implementation of simulation results that demonstrate potential for system improvements. The diversity of authority in health care facilities thwarts the simplicity of a single administrative decision to change the system. The solution to this implementation problem again lies mostly in the political sphere.

3. Non-Quantifiable Data and Inadequate Models; Human behavior systems are very difficult to quantify. Some health care simulation models just don't simulate actual system behavior accurately enough to warrent use of the simulation results. Evaluating the "success" of health care delivery systems is not simple to quantify either, so when a model is developed there is little agreement about whether the model really demonstrates a significant system improvement. Simulators are increasing their imagination and creativeness in quantifying health care systems and progress is being made in this area as models build upon each other's concepts and results. The computer languages, methodologies, and hardware systems available today for health care modeling have progressed a long way from the fledgling models of the early 60's, but there are still new ideas to be explored.

4. Dehumanizing Formulations: People understandably feel dehumanized by being measured and quantified as mere entities in a simulation model. Unlike industrial production lines, however, in health care the people who "produce" health care and the managers responsible for implementing a simulation's results are one in the same. Thus the credibility or likeability of a simulation modeler by his medical peers is a key factor in whether the model's results will have an influence on the system being modeled. Simulators and engineers must earn the respect and understanding of the nurses and medical staff they seek to model. Academic programs which place industrial engineers and prospective health care modelers in a medical "internship" so they learn the issues, professional environment, and vocabulary of their medical peers is an important step toward reducing the number of unimplemented simulation models.

5. No Committment to Followup: Freund (303) comments that publishable results can often be obtained after testing or implementing a model at a single site as opposed to demonstrating validity at a variety of locations. Simulation modelers must be committed to implementation and followup on their models, rather than just publishing, to insure effective use of the model's results.

TRENDS IN HEALTH CARE SIMULATION

The brief length of this paper does not permit inclusion of a bibliography of the health care simulation models reviewed for this research. For those interested, the 253 source bibliography, alphabetized by authors' last name, is available upon request from Regenstrief Institute for Health Care, 1001 West Tenth Street, Indianapolis, Indiana, 46202. Also available to supplement the bibliography is a table listing each model, indexed by subject, including such information (if available) as the computer language used, the computer system, source of project funding, location of development, source of publication, related publications, etc. Some of this information is summarized in Figures 2 through 6 which illustrate the historical trends of health care simulation modeling. The data for 1978 has been multiplied by a factor of 3 to account for the fact that only about the first 4 months of health care publications for 1978 were readily available in the literature search. The solid line in Figure 2 indicates, for each year, the number of models published for the first time. The dashed line accounts for multiple journal publications which document the same model. Thus the total number of publications is seen to be directly related to the number of models developed. Tables 1 to 6 summarize the form of publication, source of publication, computer language, and institutional affiliation of the principle author for the health care simulation models listed in the bibliography. All available journal articles on computer simulation models were included in the bibliography. However if a technical report documented the same model as a journal article, only the journal article was included, by virtue of its ease of availability. The 68 technical reports in Table 1 thus discuss models not directly presented as conference papers or journal articles.

THE FUTURE OF SIMULATION IN HEALTH CARE

If the amount of new model development and publishing taking place is an indication of the pulse of research being conducted in the health care simulation field, Figure 2 indicates research peaked in 1974 but is continuing at a moderate pace. Although the model groupings are somewhat arbitrary, Figures 3 through 6 show that the emphasis in simulation modeling may be shifting away from more "traditional" hospital and ambulatory care modeling toward Manpower, Systems Planning, and Other Health Care Modeling (see Figure 1). This anticipated trend will likely be hastened by increasing government involvement and regulation of health care. In January 1975 "The National Health Planning and Resource Development Act" (P.L. 93-641) created the Health Systems Agencies (HSAs) and the State Health Coordinating Councils (SHCCs) and gave them responsibility for approving the need for all new institutional health services and for reviewing the appropriateness of existing health services receiving government funds. These federal agencies are expressly mandated to contain the escalating cost of health care and have created a burgeoning market for health care simulation models. It appears the most promising area for health care simulation in the future will thus be manpower substitution, evaluation of costly laboratory tests and medical resource usage, National Health Insurance (NHI), and other cost containment strategies. The questions of how to locate, organize, and manage HMOs, how to predict the socio-economic impact of various NHI plans, and related problems will likely be quite difficult for queuing theory, econometric and regression researchers to model. However, the number of variables, interactions, objective functions, and length of the time frame for simulation models are limited only by the data availability, computer operating cost, and the imagination of the modelor. Health care simulation efforts may resultantly be expected to continue at least at the present levels or more likely to increase even beyond the 1974 high in the years ahead.

As has been true of previous simulation efforts, one of the more important results of computer simulation of health care cost containment programs will be the increased understanding of the systems being modeled which will result from constructing the models. In the future it will become even more imperative that health care modelers seek close ties and cooperation with physicians and health care administrators to insure utilization and implementation of the worthwhile models which are developed. This will also insure that the systems being modeled are the appropriate ones, the ones that have the greatest payoff potential.

CONCLUSION

This paper has described all of the currently published or generally available health care simulation models including hospitals, ambulatory care, manpower, health care systems and other health programs. The general and significant issues and characteristic examples of 21 areas of health care simulation were discussed. A list and bibliography of the models was referenced and trends in simulation model development were charted. Finally the problems and possible solutions for model implementation were outlined and suggestions were made for future research areas.

TABLE 1

FORM OF MODEL PUBLICATION OR DOCUMENTATION	NUMBER OF ARTICLES
Journal Articles	93
Technical Reports	68
Conference Papers	49
Theses	21
Books	6

TABLE 2

JOURNAL PUBLICATIONS	NUMBER OF ARTICLES
Health Svc. Research	13
Management Science	7
Inquiry	5
Simulation	5
Am. J. of Pub. Health	4
J. of Medical Ed.	4
Operations Research	4
Medical Care	3
O.R. Quarterly	3
Radiology	3
Transfusion	3
Hospitals	2
Socio-Econ. Plan. Sci.	2
Investigative Radiol.	2
Other	33

TABLE 3

CONFERENCE PRESENTATIONS	NUMBER OF ARTICLES
ORSA/TIMS Natl. Mtg.	18
Winter Sim. Conf.	12
Pittsburgh Sim. Conf.	7
Joint Sim. Conf.	4
Other Conferences	7

TABLE 4

THESES	NUMBER OF THESES
Ph.D.	10
Masters of Science	6
M. of Health Adm.	3
M. of Public Health	2

TABLE 5

COMPUTER LANGUAGE OF MODEL	NUMBER OF MODELS
GPSS	34
FORTRAN	28
SIMSCRIPT	17
DYNAMO	14
GASP	6
BASIC	3
INS	3
MAD	3
Other	6
Not Specified	80
Not Applicable	4

TABLE 6

INSTITUTIONAL AFFILIATION OF MODEL AUTHOR	NUMBER OF ARTICLES
Yale University	19
Univ. of Michigan	15
Res. Triangle Inst.	10
Geo. Inst. of Tech.	8
Pugh-Roberts, Inc.	8
Case-Western Reserve	8
Mass. Inst. of Tech.	6
Univ. of Florida	5
Univ. of Mass.	5
Texas Hospital Assoc.	5
Johns Hopkins Univ.	5
Univ. of Lancaster	4
Univ. of California	4
Northwestern Univ.	4
City Univ. of N.Y.	4
Regenstrief Inst.	4
Ohio State Univ.	3
Univ. of Pittsburgh	3
Univ. of Missouri	3
Univ. of Toronto	3
St. Louis Univ.	3
Other	90

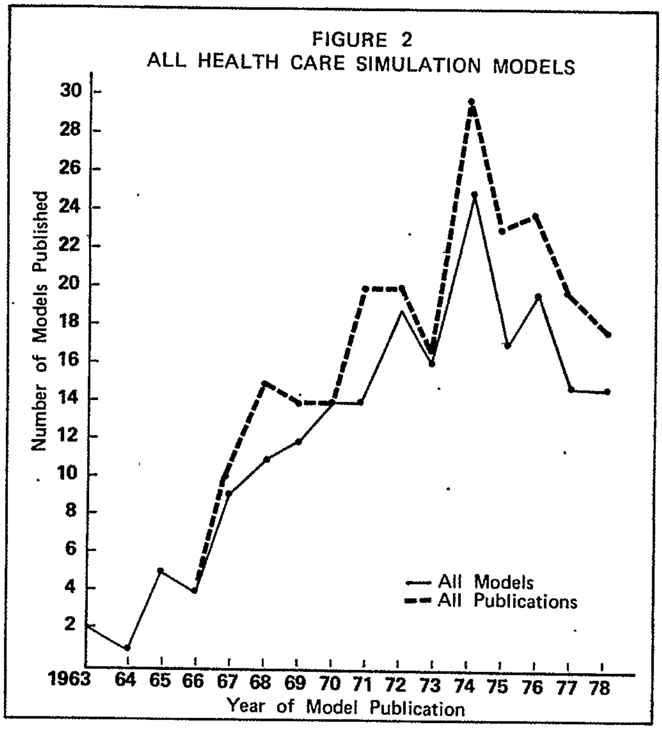
FIGURE 2
ALL HEALTH CARE SIMULATION MODELS
Number of Models Published
Year of Model Publication
All Models
All Publications

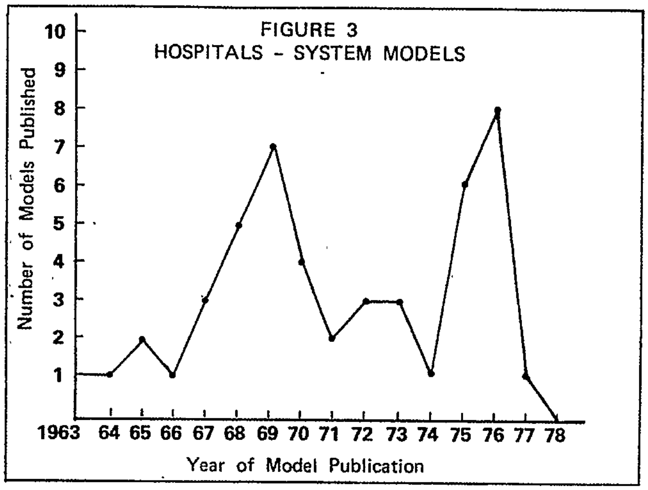
FIGURE 3
HOSPITALS - SYSTEM MODELS
Number of Models Published
Year of Model Publication

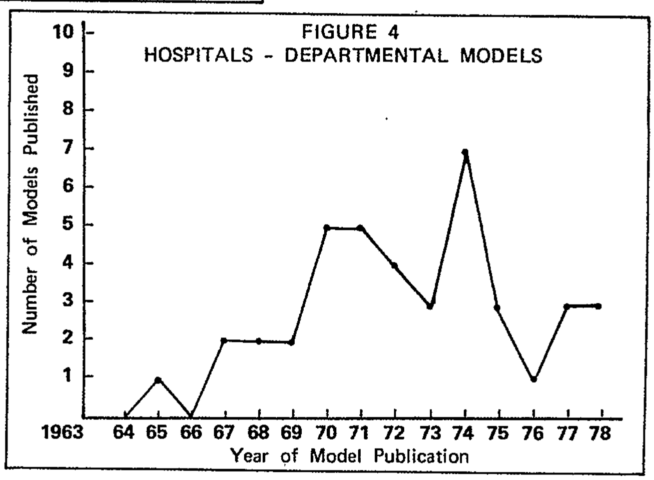
FIGURE 4
HOSPITALS - DEPARTMENTAL MODELS
Number of Models Published
Year of Model Publication

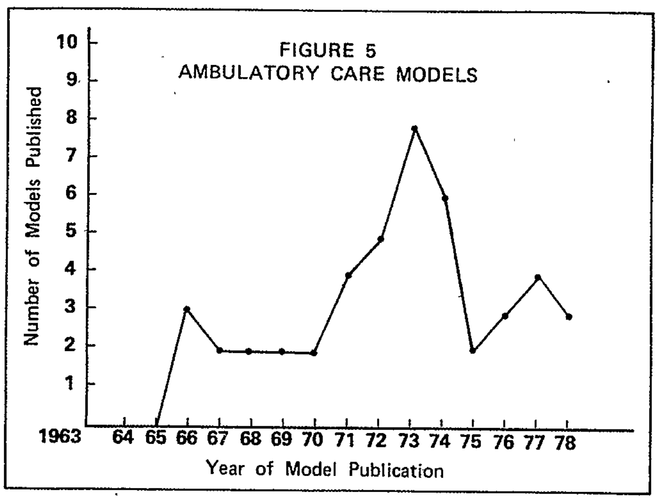
FIGURE 5
AMBULATORY CARE MODELS
Number of Models Published
Year of Model Publication

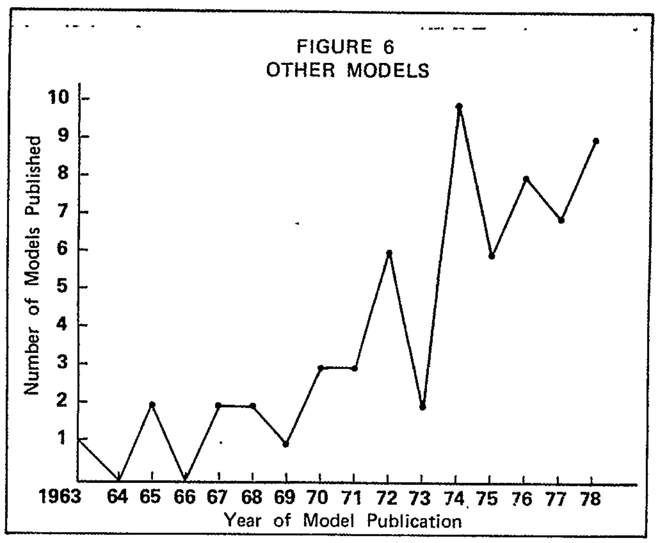
FIGURE 6
OTHER MODELS
Number of Models Published
Year of Model Publication