Review of Operations Research Improvements in Patient Care Delivery Systems

October 1, 1989

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This study was supported by grant #14200 from the
Robert Wood Johnson Foundation.

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ABSTRACT

A literature review of operations research in health care identified articles in the field since 1978. Despite major growth in OR in general, few major advances in OR applications in health care were identified. The search incorporated computer databases, ORSA Health Care section resources, and a manual review of key journals. Papers were included that used any of the core methods of operations research. The articles are categorized within a general service operations management framework, including patient scheduling, capacity planning, demand forecasting, system design, site/location selection, supplies/materials planning, vehicle scheduling, workforce staffing and scheduling, strategic planning, and direct patient services. Particular attention was given to workforce staffing and scheduling articles since this area comprises the largest segment of costs and care delivery in institutional settings.

INTRODUCTION

The field of Operations Research (OR) has experienced major growth in the past decade. Not only has the theory and methodology been expanded to allow us to cover more comprehensive and massively large operational problems facing industry, government and society but also models have been developed to handle decisions involving major strategic and policy choices. Examples of these operational and strategic decision problems range from integrated automobile design, supply, production and distribution to the design and structuring of stochastic telecommunications systems to national policies for screening for various diseases.

With few exceptions, this great progress in the past decade made in OR theory and methods and in the use of OR to solve major problems in industry, government and the military, has not carried over to significant new progress in the use of OR in health care delivery. The major uses and advances of OR in health care had their roots in the work of the 1960s and 1970s. By and large the 1980s saw refinements and/or reapplication of this earlier work. The major exception that has had significant new ideas and growth is the area of medical decision-making, particularly in screening and disease prevention and medical diagnostic decisions.

Unfortunately the uses of OR in improving access and delivery of care, increasing productivity, reducing costs and improving quality of delivery at the institutional level have seen but modest growth. There are perhaps many reasons for this reduced level of application and research. Some of the important reasons, however, must include the significantly reduced research funding for work on problems at the operational and strategic levels in local or regional institutional settings (hospitals, HMOs, long-term care, etc.) and the reallocation of the (substantially reduced) available research funds to broad national economic policy decisions on reimbursement at HCFA and to clinical decision studies at NCHSR and to experimental interventions elsewhere. The significance of this funding drop is that OR researchers turned their attention from health care delivery to industrial and other governmental problems, particularly in the Department of Defense. This also means that their masters' and Ph.D. students did not and do not work in health care delivery and indeed know nothing about the area. In the health care industry itself, another reason is the low level of salaries and positions available for OR trained employees relative to comparable positions in industry. Of course this comment applies to persons from many other fields who are relatively underpaid in the health care industry. It is somewhat ironic that an industry, which has captured more than 11.5% of U.S. GNP and attracted some of the nation's brightest and best young people to the medical profession with handsome financial and social rewards, has little or no interest in structuring the incentives to attract similarly bright and capable people to many of the other jobs in health care delivery.

Because there are so few OR trained employees in health care delivery institutions at any level, and in particular at managerial levels, there is no infrastructure to seriously examine issues of productivity, access, cost and quality as is done in medium-sized to large-sized companies. Furthermore, the nature of the health care cost reduction efforts essentially only relates to reduction in lengths of stay, work force, programs or treatment protocols. Few, if any, cost/productivity/quality improvements have been made as the result of a systematic study of a situation, its modelling and evaluation of alternatives and its studied implementation and evaluation.

In reviewing the OR literature in health care delivery we have located many good studies that continued this exciting work of the 1960s and 1970s. We would like to have found more and, in particular, more in the U.S. health care system.

This review of the literature on operations research in health care attempts to bridge a segment of the gap between the comprehensive reviews by Fries (1979 and 1981) and the present time. The works cited below were identified by computer searches of the MEDLINE, BRS Colleague Health Planning and Administration databases. The search strategy involved a wide variety of health care topics linked with operations research. The initial structure of the search was based on the taxonomy used by Fries. Unfortunately, many OR-related works are categorized by the National Library of Medicine in ways that do not identify their relevance to operations research. For example, many probabilistic OR applications are categorized as mathematics instead of OR-related, others are listed in various areas of information systems or under medical headings. Journals that publish a substantial number of works about operations research in health care were also manually searched to identify additional articles for review. In addition, the ORSA Health Care Section's nascent collection of member's Curriculum Vitae was searched for publications not previously identified. Eventually, over 400 articles were identified and evaluated for inclusion in the review.

The primary criteria for inclusion was the presentation of solutions to health care delivery problems in institutional settings such as hospitals, long-term care and/or ambulatory facilities and that differed in or extended the type, detail, and quality of works addressing similar problems in the reviews by Fries. Papers were included that used any of the methods that form the core of operations research. Papers were not included that only discussed medical or management information systems or did not use systematic modelling of a decision problem.

The articles included in the review are categorized within a general service management framework (Mabert, 1982), with some modifications to adapt the framework to the health care delivery system. This categorization was chosen to give a management decision focus rather than some other focus such as technique, methodology or physical locations or entities. The articles reviewed were placed in the following categories:

1. **Outpatient/Inpatient Scheduling.** These articles explore problems related to the scheduling of patients to receive services. Since only two articles that focused primarily on inpatient scheduling were identified, this section primarily includes articles on outpatient scheduling. If one is interested in more work on inpatient scheduling, see the articles previously reviewed by Fries.

2. **Service Capacity Planning.** A number of articles were identified that address the allocation of limited resources across services or satisfy performance objectives for a service unit.

3. **Service Demand Forecasting.** Articles primarily concerned with predicting demand for service(s) in the future are included here.

4. **Service System Design.** These articles usually are concerned with service delivery design, especially staff skill mix and technology related decisions.

5. **Site/Location Selection.** A substantial amount of work has been done concerning facility or service location, especially regarding ambulance location. Some articles on facilities' location can also be found in category 9 "Strategic Planning."

6. **Supplies/Materials Planning.** Articles that focus on inventory controls, materials requirement planning, and related problems are discussed in this section.

7. **Vehicle Scheduling.** A few articles were identified, mostly related to ambulance dispatch, which concern vehicle scheduling or analogous problems, in health care. Articles about the scheduling of bloodmobiles and blood delivery are included in the excellent review by Prastacos (1984).

8. **Staffing and Scheduling.** Appropriately matching service personnel with the demand for service has been a

fertile area of OR work. Articles included here encompass scheduling, manpower planning and other human resource management problems. Many articles in this section cover nurse staffing, scheduling and allocation in various services in the hospital.

9. **Strategic Planning.** Articles in this section involve strategic planning studies ranging from comprehensive health care delivery models to facilities sizing to specialized functions such as kidney transplant needs.

10. **Service Delivery.** Articles included here discuss direct patient care problems, especially those concerning medical management. The very large medical decision-making literature is not included in this review because of the review's focus on management rather than medical decision-making. However, some articles using OR techniques relating to management issues are reviewed.

In addition to the written review, tables designed to indicate key information about each article are included in that section. The major components of each study are recorded in the tables, including the target service involved, performance measures included in the decision, intervention variables, and operation research methodology. This arrangement should allow readers to quickly identify published works related to their area of interest.

Only articles published in the English language were reviewed. This is not to say that very good articles in other languages do not exist, but rather that our limited time and our limited capabilities would not permit their review.

We also apologize to any authors whose papers have inadvertently been excluded in this review. It has been our intent to conduct as thorough a review as possible in a rather short time period. We would appreciate hearing from any authors of works published after 1978 which have not been included so that they may be included in a future revision of this review.

Finally, it should be mentioned that there is a major need for more high quality OR studies and research in health care delivery. There are many forces shaping health care delivery today - aging, demographic shifts, explosions of technologies and therapies, manpower shortages, falling disposable incomes, physician surpluses, etc. OR has the tools and methodologies to structure the decision processes involving these forces relative to health care delivery so that cost effective, quality effective, access effective decisions can be made. In the concluding section of this review, we point out a few of the many areas which could benefit from more OR studies and research.

References (Introduction)

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1. Outpatient/Inpatient Scheduling

Effective scheduling of patients for outpatient services has become very important to health care providers. Controlling demand flows for services via scheduling can be very effective as a method of matching demand with the supply of service available. The high cost of medical personnel in non-productive activities can be reduced by appropriate patient scheduling which minimizes staff idle time. Patients, however, dislike waiting for service, and consequently balk or renege on appointments if waiting time is considered excessive. Consequently, the problem of satisfying both patients and health care providers is a challenging one. In the past, the problem of staff idle time was addressed by increasing patient waiting time in order to obtain the most productivity from physicians. Increased competition for patients has led to a more balanced, better coordinated approach to outpatient scheduling which attempts to maximize the satisfaction and utilization of both patients and physicians.

Hodgson et al. (1977) used integer quadratic programming to schedule thirty clinics for five-day cycles. They sought to maximize cross-consultation among related clinics; available space, personnel, ancillary service, and physician commitments were included as constraints. O'Keefe (1985) described a typical outpatient operation problem, which he viewed as primarily a political problem. Satisfying the scheduling system stakeholders requires implementation of a policy that is often suboptimal. Although operations research tools are readily applicable to this type of problem, the solution must also include a plan for implementation, educating system stakeholders and monitoring system performance.

Fries and Marathe (1981) evaluated several approximate models to determine the optimal variable-size multiple block (VSMB) appointment system. Patient waiting time, physician idle time, and physician overtime are the criteria used to compare various methods. The weights assigned these three criteria greatly affect the appointment system choice. For a three-period problem with twenty-four total patients, various appointment systems are compared. The VSMB system is more flexible and produces better results if the cost of patient waiting has been reasonably estimated.

Simulation was used by Vissers and Wijngaard (1979) to produce a general method for developing appointment systems for outpatient clinics at a hospital. The appointment system is treated as a block appointment system with one to all patients scheduled in any block (appointment time). They demonstrated that the variables included in the simulation of a single server system could be reduced to five: the mean consultation time, the coefficient of variation of the consultation time, the mean system earliness, the standard deviation of patients' punctuality, and the total number of appointments. Simulation runs of various values for the five variables mentioned will allow design of an appointment method which meets predetermined standards for waiting time and idle time.

Rather than use mean service times across all patients for a clinic, Callahan and Redmon (1987) devised a problem-based scheduling system for a pediatric outpatient clinic. This system was compared with an existing, modified block scheduling system. Time slots for different patient problems were allocated to specific presenting problems. Data were collected on the amount of time the patient spent from check-in to exit, with additional data points at weighing and entry into the examination room. Staff time use and patient satisfaction were also measured. The method by which allocation of time to the problem mix was not described. The problem-based scheduling system improved staff utilization and patient satisfaction, suggesting that additional development of this approach may be merited.

Kuzdrall et al. (1981) modelled five operating rooms and a twelve-bed post-anesthesia care unit. Each operating room and PACU bed were treated as a separate facility in GPSS V. The main purpose of the study was to evaluate two scheduling policy alternatives. The authors found that a policy which schedules the longest surgeries first resulted in a 25% savings in operating room time compared with a policy of random scheduling.

A different approach to managing elective admissions is taken by Trivedi (1980). He described a stochastic model of patient discharges which could be used to help regulate elective admissions and achievement of occupancy goals. He noted that larger units should be run at a higher occupancy level than small units, if demand and overflow risks are similar. He also discussed the advantages of incorporating discharge forecasting, occupancy level management, and nurse staffing management. More work needs to be done to combine these variables into a coherent elective admission control system.

Outpatient scheduling will require further refinement as patient expectations rise. Models need to include performance measures reflecting the costs and benefits for all participants. Classification or segmentation of patients into categories with significantly different requirements for service will also enhance the performance characteristics of patient-scheduling systems.

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Outpatient/Inpatient Scheduling

Reference	1	2	3	4	5	6	7
TARGET SERVICE							
Outpatient	*	*	*		*		*
Surgery/PACU				*			
Inpatient						*	
INTERVENTION VARIABLES							
Mean Consultation Time			*	*			*
Consultation Time Variation							*
Mean System Earliness							*
S.D. of Patient Punctuality							*
Number of Appointments		*	*			*	*
Patient Problem	*		*	*			
Organizational Politics					*		
Appointment Intervals		*					
Education of Stakeholders					*		
Monitoring System Performance					*		
Discharge Forecasting						*	
Nurse Staffing Management						*	
PERFORMANCE MEASURES							
Total Time in System	*			*			
Staff Idle Time	*	*					*
Patient Satisfaction	*						
Patient Waiting Time		*					*
Staff Overtime		*		*			
Cross-Consultation			*				
Percent Occupancy						*	
METHODOLOGY							
Simulation				*			*
Nonlinear Programming			*				
Modified Block Scheduling	*						
Variable Size Multiple Block		*					
Other						*	

2. Service Capacity Planning

Service capacity planning examines variables affecting the capacity of a service provider. In health care, capacity planning usually focuses on variables such as bed capacity, surgical capacity, bed allocation to different services, capital equipment alternatives, patient flow, ancillary service capacity, and, to a limited extent, staff skill mix. A substantial amount of research has been directed at service capacity planning. Since health care resources are increasingly limited, providers are seeking ways to increase the productivity of existing assets, as well as improvements in service quality.

The allocation of bed capacity within a hospital is a complex yet critical factor in operating efficiency. Dumas (1984, 1985) developed a simulation which incorporated diagnosis categories of patients based on sex, admission type, time of demand, four categories of beds, and physician type (attending or resident.) Outcome measures included percent occupancy, average daily census, annual patient-days, and misplaced patient-days. Secondary measures included requests for admission, reservations, refusals due to inability to schedule a satisfactory admission date, wait list reneging, transfers and proxy measures for opportunity costs of these events. The simulator provided a method for evaluating a variety of patient placement rules. The study resulted in a reallocation of beds, the creation of a new service, fewer misplacements, and reduced misplaced patient-days, but increased transfers. The model did not incorporate costs for misplacement, transfers, and delayed admissions.

Vassilacopoulos (1985) described a general priority queueing simulation model that determined the number of hospital beds necessary to meet demand. The objectives of high occupancy, immediate admission of emergency patients, and a small waiting list for elective admissions were sought simultaneously. The simulation was designed to create or eliminate beds as needed to maintain predetermined levels of occupancy and waiting list length, and permit all emergency admissions to occur without delay. Statistics were then tabulated concerning the frequency distribution of beds, time between bed complement change, and the probability of a change when the bed complement is at a certain level. The model results were used to reallocate the bed complement for three services in a hospital.

Kao and Tung (1981) used an $M/G/\infty$ queue to approximate the patient population processes in each medical service of a hospital. Month-to-month demand fluctuations were incorporated in the model, but day-of-week and hour-of-day fluctuations were ignored. A Poisson admitting process was assumed. Two units were simulated to determine if the forecasted occupancy and overflow rates could be duplicated. The two methods were in agreement if adequate beds were allocated to the two units. As fewer beds were allocated, the analytic model increasingly overestimated the overflows.

Kapadia et al. (1985) reported two queueing models which incorporate multiple service channels and high and low priority units. Blocking and displacement of low priority units (elective surgeries) by high priority units (emergency surgeries) is examined. Application of the models to surgical beds (waiting spaces) and surgical teams (servers) is discussed. The average waiting time overall and by priority class, average queue length, and the average number of high and low priority units in the queue are analyzed. The models have not been applied to an actual problem.

A simulation of surgical bed occupancy related to surgeon's schedule and category of the procedure (major, intermediate, or minor) has been developed by Harris (1985) in BASIC. The model simulates the system for up to fifteen months and provides data on daily bed usage, bed occupancy rate, maximum and minimum bed requirements for each day of the surgical schedule (up to twenty-eight days), and the percentage of procedures cancelled. The simulation demonstrated economies gained by rearranging the surgical schedule and pooling beds assigned to surgeons with similar specialties.

Semi-Markov process models have also been used to examine bed allocation questions, particularly in progressive patient care facilities. Hershey et al. (1981) demonstrated that the expected level of utilization can be described in a linear relationship including some basic patient flow data for a system with one unit with finite capacity (such as a CCU). If the equilibrium rate of arrival at each unit, mean holding time on each unit, and the probability that the finite unit is at full capacity are known, the utilization and service rate of the system can be determined. If multiple units are being considered for capacity changes, they recommend using simulation, with their model used for validating the simulation. Schmee et al. (1979) used a discrete-time semi-Markov process to describe the movement of a patient from one care level to another within a progressive patient care system. The system included four levels of hospital care, extended care in a nursing home, and home care. Well-being and death are considered absorbing or terminal states. The optimum, nondominated solution(s) are then found using linear programming, seeking the patient movement in the system which achieves a high probability of patient recovery, while minimizing cost. A theoretical application is discussed.

When waiting time does influence demand and customers are external, as in outpatient services, simulation has been the method of choice for most researchers. Ittig (1985) describes an analytical approach to this problem. He incorporates the negative effect of waiting time on demand by obtaining an estimate from a manager of the effect on demand of reduced waiting time. Both a linear and exponential model (more reliable over a broad range) are analyzed and solved for a typical clinic.

Capital investment decisions in health care are often difficult because of the need to include both monetary and other benefits. Kotlyarov and Schniederjans (1983) evaluated three nuclear cardiology diagnostic instruments by using a Monte Carlo simulation to determine economic costs and benefits, such as labor, supplies, amortization, maintenance and reimbursement combined with a subjective ranking of instrument benefits by medical experts. Finally, the benefits were combined into a net benefit score. The benefits considered were benefits for the nuclear cardiology staff and management, and did not include relative improvement in patient outcome as a result of access to the equipment.

Several studies have used simulation to study the flow of patients through a health care service. Mahachek and Knabe (1984) examined staff size, staff mix, facility size and composition, patient scheduling, waiting time, and direct labor costs for two outpatient clinics, obstetrics and gynecology, which were to be combined. GPSS was used for the simulation. Results of the simulation were crucial in discovering several unanticipated problems in the plan to combine the clinics, such as the formation of a queue larger than waiting room capacity. Jones and Hirst (1986) presented a study of the simulation of a surgical unit, and its use in bidding for resources in a political environment. They discuss the simulation in detail, as well as the process by which management used the study to seek funding for increased capacity. The authors found visual simulation persuasive in obtaining consensus among internal stakeholders, and potentially useful in influencing external decision makers.

Ladany and Turban (1978) described a simulation of an emergency room service. They examined the question of how many beds to provide in the unit, and how many beds should be staffed during an average period. A queueing model was used to analyze the problem, and a Monte Carlo simulation used for the solution. The effectiveness of the unit was measured by total cost, including the cost of service and a subjectively determined cost of waiting. When they attempted to validate the model by applying it to an existing emergency room, more than the existing number of beds and staff were recommended. The authors concluded that the cost of waiting was underestimated by hospital administration as compared with the cost estimated by physicians.

A simulation developed by Hancock and Walter (1984) evaluated the effects of inpatient admission policies and outpatient scheduling on the future workloads of ancillary services such as laboratory, physical therapy, and respiratory therapy. An existing Admission Scheduling and Control System Simulation was extended to model patient flow and track the day of stay. Ancillary load was determined based on clinical service, type of admission, day of stay, and ancillary department. Inpatient admission and outpatient scheduling tactics were evaluated for their effects on work load by the day of the week. They concluded that outpatient clinic scheduling had a crucial impact on ancillary department workload. MOVE

Lambo (1983) used optimization and simulation to improve efficiency and effectiveness at rural Nigerian clinics. Optimization was used to establish an upper bound on the potential efficiency of a health center. Misallocation of personnel was the major constraint identified. Simulations at the center and individual clinic levels were used to evaluate operating policies and to determine the maximum capacity of the center.

O'Kane (1981) described a simulation model of a radiology department. The simulation, SIMRAD, written in FORTRAN IV, is described in some detail, but no specific application is included. Although results were not included, the model is reported to have been used to examine the effects on patient waiting time of changing the number of radiographers available, determining the effects of decentralizing radiology equipment and services, appointment methods, and other patient flow related questions. Another radiology model developed by Sullivan and Blair (1979) predicted workload requirements for radiology from medical services over time. The workload requirements result from two random variables: (1) the number of procedures per unit time, and (2) the time required to complete each procedure. The model is used to address a capacity planning problem that evaluates centralization versus decentralization of radiology equipment and services.

Waiting lists for health care have been a problem in Great Britain for many years. George et al. (1983) briefly described an LP formulation that sought the optimal throughput of general surgical patients in a local British hospital, giving priority to cases of higher urgency. Constraints included admissions by diagnostic and urgency category, available bed-days, available surgeon time, available operating theatre space, and surgery types. The objective of the study was to increase understanding about the problem of reducing surgical waiting lists. The model provides predictions of the effects of changes in the constraints. Hospital waiting lists were also investigated by Worthington (1987). He used a $M(\lambda_q)/G/S$ queueing model which included patients not treated because of discouragement concerning the length of the waiting list, thus incorporating feedback in the system, which influences the length of the queue. He used the model to test the theoretical effects of typical responses to the long waiting list problem such as increasing beds in service, decreasing service time (length of stay), combining two waiting lists, and introducing earlier feedback to general practitioners about the size of the queue.

Service capacity planning is interdependent with patient scheduling, forecasting, service system design, and other elements of the service delivery system. Inpatient capacity planning centers in general on bed or procedure capacity. The objective is usually to maximize the use of finite capital equipment resources or to minimize inefficiencies and delays in delivering health care service. While substantial work has been done on capacity planning in health care, the relative cost and effectiveness of altering key variables affecting capacity and the system interactions among the many aspects of care delivery remain fertile area for further work. Better models of patient flow and improved understanding of the delivery system for care hold promise as means to improve capacity planning.

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Service Capacity Planning

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
TARGET SERVICE																			
Inpatient	*	*				*			*	*						*		*	*
Surgery			*		*			*		*									
Outpatient							*						*						
Emergency Room												*							
Obstetrics/Gynecology														*					
Ancillary				*							*								
Radiology															*		*		
Physician Office																			
INTERVENTION VARIABLES																			
Bed Allocation	*	*			*	*		*	*	*		*							*
Schedule Rules				*										*	*				*
Admit/Placement Rules	*	*		*					*	*									
Operating Policies													*				*		
Procedure Time (Length)																	*		*
Procedures/Unit Time																	*		
Diagnosis/Urgency			*		*			*		*									
Surgeon Time			*		*														
Facility Size/Capacity			*		*	*		*		*				*	*			*	*
Waiting Time							*			*				*					
Staffing Levels												*	*	*	*				
Staff Mix														*					
Discharge Forecasting																			
Queue Size Feedback																			*
PERFORMANCE MEASURES																			
Percent Occupancy	*	*			*	*		*										*	
Average Daily Census	*	*			*			*					*						
Annual Patient Days	*	*						*											
Patient Placement	*	*																	
Admission requests	*	*																*	*
Reservations	*	*						*											*
Refusals	*	*																*	*
Reneging	*	*			*														*
Patient Transfers	*	*														*			
Opportunity Costs	*	*																	
Patient Throughput			*			*		*								*			
Workload				*													*		
Day of Week				*				*											
Patient Waiting Time										*		*		*	*				

Service Capacity Planning

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Queue Length										*				*				*	*
Hours of Operation																			
Supervisory Time																			
Demand for Service							*		*										
Costs											*	*		*		*			
Benefits for Staff											*								
Patient Outcome																*			
Length of Stay																			
METHODOLOGY																			
Simulation	*	*		*	*			*	*	*	*	*	*	*	*		*	*	*
Semi-Markov						*										*			
Linear Programming			*				*						*						
Queue									*	*		*		*	*			*	*
Exponential Programming							*												
Other																			

3. Service Demand Forecasting

The role of forecasting is critical in making decisions to achieve some future benefits with regard to established goals. In making these decisions, it is often necessary to forecast those factors which provide inputs to or affect outputs of the system once the decisions are implemented. In the health care delivery system, forecasts are required to estimate future <u>need</u>, <u>demand</u>, or <u>utilization</u> of specific services. <u>Need</u> generally refers to the underlying epidemiologic occurrence of disease in the population. <u>Demand</u> refers to that part of need which presents itself for service or treatment and <u>utilization</u> is that part of demand which is actually served or treated.

Forecasts of need, demand, and/or utilization provide the basis for making appropriate resource allocations within the service delivery setting. These allocations involve planning for the appropriate amounts of resources, their control, their consumption and their evaluation as to effectiveness. These resource allocation decisions can frequently be classified into short range decisions (frequently day-to-day), intermediate range decisions (monthly, quarterly or occasionally yearly), and long range decisions (three, five and ten years). Short range decisions often involve fixing work load and manpower staffing levels, inventory control, scheduling of operating rooms, laboratories and radiology, and preparing meals. Some examples of intermediate decisions are nurse schedules, seasonal staffing levels, assignment of different skill levels to different tasks and temporary bed reallocation for different services. Long range decisions involve such items as the types and amounts of services offered, the overall manpower staffing required to meet those levels, renovation and construction of new facilities, capital and budgeting needs and the design of the organizational structure. Most decisions involve minimizing costs and meeting certain effectiveness, quality, and/or accessibility criteria.

In addition to resource allocation, forecasting is used to study the etiology and progression of diseases through various stages and types of treatment. Such study often later leads to resource allocation decisions, and, in its own right, is useful for the planning of disease diagnosis and therapies.

The types of forecasting models primarily used in health care delivery modelling are;

1. Multiple linear regression, often with non-linear variables or linearizing transformations.
2. Exponential and/or adaptive smoothing.
3. Auto regressive integrated moving average, ARIMA, (Box Jenkins) models.
4. Markov processes and in particular, Markov chain models.
5. Delphi techniques and other group process techniques such as nominal group or analytical hierarchies.

Each of these modelling techniques has strengths and weaknesses depending on the particular application and involving such factors as the length of the planning horizon (short, intermediate or long range), data availability, seasonality, trends, ability to incorporate random or known phenomena, costs of implementing the model, and assumptions of the model.

A forecasting model for a particular application should meet certain criteria for the user. In the first place the model should be credible. The forecasts should be believable and make sense to the user. Second, the model should be as simple as possible. Unnecessary complexity should not be introduced. Third, the model should be flexible and able to handle changing phenomena over time. The model should be statistically accurate. That is, the predictions should be within the range of statistical confidence. And, finally, the model or forecast should be unbiased in the sense that it does not consistently over-estimate or under-estimate the phenomena being forecasted. In many of the papers reviewed below, the authors experiment with several different forecasting models to find the one which is most appropriate for the application they are considering. In some cases a regression model is the most appropriate; in others, it is exponential smoothing, or ARIMA, or Markov chains. In one case, a Delphi model appeared to give good results. There is not one type of model which is good for all applications.

The applications to which forecasting models have been applied are considerably varied. The feature they have in common is that they wish to predict the need, demand, utilization or preference choices for certain services in the health care delivery setting. Kamentzky, et. al, (1982) forecast the demand and the need for emergency transportation services by clinical categories of services. They use a linearized non-linear multiple regression model. The best model was obtained after testing many variables and finding that four census variables were able to forecast emergency transportation demand and need very effectively. These four independent variables were: population in the area, employment in the area and two indicators of socioeconomic status. In later work they used these forecasts to determine optimal emergency vehicle location and placement strategies for short to intermediate time periods and the capacity of the entire emergency transportation system under maximum usage conditions for longer time horizons. In this way they were able to forecast the pre-hospital care needs in the region. Also, looking at emergency transportation services, Aker and Fitzpatrick (1986) forecast the short run emergency and routine ambulatory demands for a region using Winter's exponential smoothing model. In order to obtain the best fit and best estimates, they used goal programming to establish criteria for the forecast quality and quadratic programming to optimize the estimates for the objective functions in the goal program. This model was an improvement over their multiple regression models and simple exponential smoothing. It is, however, a very complicated model and would need to be implemented by persons with backgrounds in mathematical programming. Again, the forecasts were used to determine the appropriate numbers of vehicles in appropriate locations to meet the demand for emergency help.

Several authors have provided models to forecast admissions, census and discharges from hospitals. Day-to-day admissions forecasting is done to determine the best utilization of hospital beds, and for appropriate allocation of personnel by services, meal planning, laboratory loading and staffing, and inventory supplies. Census and discharge forecasting were also used for evaluating the appropriate utilization of services, bed availability for new admissions and resource allocation decisions. Kao and Pokladnik (1978) used a non-linear regression model to capture the daily variation for each day of the week to forecast hospital census. In the model they also used an adaptive smoothing criteria to handle exogenous inputs as they occurred randomly throughout the year. For example, the person doing the forecast would modify the model's parameters in the case of major changes in the institution which would affect the census such as opening or closing a particular wing or ward of the hospital or adding new capacity in some other area such as the operating theater. In other cases where changes were occurring so rapidly that the forecasting model could not take them into account quickly, the user would modify the model to speed its adaptation to new data by giving more weight to the newer data and less to the old. In a third case, with short term changes that would affect the forecast, then disappear and be irrelevant in the future, the user would instruct the model to ignore the short term change. This interactive approach to forecasting between the forecast user and the model requires that the forecast user be quite knowledgeable about the model and its capabilities and limitations. Using this adaptive approach, however, the authors were able to forecast hospital census quite effectively. The results were then used for planning and resource allocation purposes. In another paper, Kao and Tung (1980) used an auto regressive integrated moving average model (ARIMA) to forecast monthly and yearly patient days and admissions in a hospital by type of service. In one case, they forecasted patient days and admissions separately using the ARIMA models. In a second case, they forecasted only admissions using the ARIMA model and estimated the length of stay by services by using past averages. Then they calculated the patient days using the fact that patient days equals admissions times length of stay in each service. These models worked effectively in the large public general service hospital and were used for planning and resource allocation decisions.

Kao and Tung (1980b) also developed a forecasting system for projecting nursing hour requirements. Monthly statistics of admissions by service for the previous five years were used in an ARIMA model. The forecasts were combined with the estimated length of stay to generate patient days by service. These forecasts were later used for resource allocation and staffing decisions (see Section 8).

In another paper Webb et al. (1977) tried to use simulation to forecast emergency admissions and discharges but the model did not forecast sufficiently well for decision making. Finally, Wood and Steece (1978) used an ARIMA model to forecast dietary classes of meals by first forecasting the patient census; then forecasting the fraction of census for the specific dietary meal categories. They used these forecasts to minimize the expected weighted costs of the dietary program where the cost of under-forecasting the demand for dietary meals was somewhat higher than over-forecasting. These meal forecasts were then used in menu, staff, and inventory planning and control.

For health care settings outside of the general acute care hospital, several authors looked at predicting the need and demand for services in nursing home and long-term care facilities, psychiatric services, alcohol and substance abuse facilities and dialysis treatment clinics. Regardless of the setting, forecasting is needed to anticipate resource allocation decisions, strategic decisions of facility location and sizing and in several instances, appropriate therapies and disease progressions. Johansen et al. (1988) constructed a simple probability model which forecasts the expected total hospital post-discharge patient needs for skilled home nursing services. The model has minimal data needs since it only uses four categories of patients. An estimate is made for the probability that a patient in each category needs home care services. Then the expected total number of patients to be discharged is estimated for each category. Finally, the expected total home care needs are computed weighting the discharges by the appropriate probabilities and summing over the four categories. This model was not tested in an actual setting so the authors did not determine the effectiveness or statistical validity of the model. However, they did use oncological and myocardial infarction data to predict the number of patients with these diseases who need home nursing services. In addition, they computed the expected costs for these services based on the expected total number of patients needs.

In a very extensive study undertaken in British Columbia by Lane et al. (1985) the authors evaluated three alternative forecasting models to forecast the demand for various types of interdependent long-term care services in the home, at nursing facilities and at extended-care facilities for patients who transition among different states of health and different care facilities. The three types of models were: a two-year moving average model that is a form of exponential smoothing; a linear multiple regression model; and a first order Markov chain model. The persons needing long-term care were classified into nine different states: two involved home living supplemented by self-care or some professional help; four addressed nursing care facilities at various levels of personal capabilities and professional care needs; one state was an extended care facility; another state was for patients discharged from the program alive; yet another was for patients who died. Persons would progress from one state to another as they became older and less able to take care of themselves until they died or left the program for other reasons. If they left they had the possibility of returning to the program in one of the first seven states, that is, at home or one of the nursing or extended care facilities. In applying the two-year moving average and regression models, each of the states was treated independently and annual forecasts were made of the number of people who would be in that state based on the number of people in that state in past years. In the Markov chain model, the states were dependent.

Persons made transitions from one state to another with certain probabilities. These probabilities were computed based on available data. To forecast the number of people in any state in the coming year involved multiplying the transition probabilities from each of the other states to that state by the number of people who were in each of those states in the current year. Not unexpectedly, it was found that the Markov chain model was a significantly better model for forecasting future numbers of people in each of the various states of the system. This model was superior because it was able to handle the dependencies and movements between and among the states, whereas neither the moving average nor the linear regression model has that capability. Given that statistically valid forecasts could be made using the Markov chain model, the authors then suggested its use as a tool for resource allocation in long term care settings for both intermediate and long-term decision-making.

Fisher and Knesper (1983) also used a first order Markov chain to forecast the utilization of endogenous depression psychiatric services. In order to forecast these utilization levels, the authors first constructed a Markov chain model of endogenous depression as a disease. In this model the authors defined four states of depression from very low endogenous depression to very high depression. They defined three additional states based on whether the patients became hospitalized, and were depressed or not depressed when they made their last visit to the psychiatrist. Using this Markov model the authors could then forecast the number of people in each state. In addition they could forecast such factors as incidence, prevalence, recovery rates for different treatment regimens, and severity in disease at different points of time.

Based on the Markov endogenous depression disease model, they then constructed a second Markov chain model to forecast the utilization of psychiatric services by persons in different states of the disease. This second model had many more states, because the researchers handled not only the severity of the patients depression but also the timing of visits to the psychiatrist. The model included states for whether the patient made a visit exactly K weeks previously, K weeks and one day previously, K weeks and two days previously, etc. This time factor was included because for low or moderately depressed patients, the psychiatrist would see them weeks apart. Whereas for highly depressed patients, the psychiatrist visits might be only days apart. The authors applied this model to data from clinical visits to psychiatrists' offices and found that the model had a statistically good fit and could forecast levels and utilization of psychiatric services.

Trivedi et al. (1987) described a semi-Markov model for forecasting the supply of physicians, nurse practitioners, and physician assistants in the state of Washington. The model incorporates the stochastic nature of the education and distribution process. Monte Carlo simulation was used to determine the relative size of errors from the model. When compared with actual data, the model indicated less than 1% error. Despite the fact that physicians change their practice site infrequently, the inclusion of transition states between primary care delivery sites had a significant effect on the total manpower estimate.

Ford (1985) evaluated three simple linear and piecewise linear forecasting models and one multiple linear regression model used to forecast alcohol and drug abuse needs and demands. Three of the models were used to forecast alcoholism bed needs and one to forecast drug abuse beds needs. Since none of the models yield the same forecasts and in some cases differ quite substantially, it is important to understand their strengths and weaknesses and how these affect the actual forecasts. The author provides a table listing the input needs, the types and units of analysis, the assumptions underlying each model, and their strengths and weaknesses for forecasting purposes. The author does not, however, provide a detailed statistical analysis of the goodness of fit of the forecasts with the actual data which would be helpful in making a choice among the models.

In a different setting, Gardner (1979) tested twenty-five Box and Jenkins ARIMA models versus a multiple regression model to forecast the demand for blood tests in a hospital laboratory. He first forecasted the aggregate number of lab tests per month, then used simple exponential smoothing to breakdown this aggregate into individual types of tests. Given the individual types of tests he then forecasted the inventory materials needed to conduct the tests as well as personnel needs and facility availability. In comparing the simple exponential smoothing to 25 different Box and Jenkins ARIMA models, Gardner found that the simple exponential smoothing was as good or better than any of the Box and Jenkins models. Consequently, he recommended use of the multiple regression followed by the exponential smoothing to decompose the aggregate into specific individual test types.

Finally, a paper by Oliver and Berger (1979) tried to predict actual consumer choices in seeking flu inoculation. The behavior of consumers is modeled by two different models; the Behavioral Intention Model (BIM) and the Health Belief Model (HBM). The two models are extensively compared in their conceptual strengths and weaknesses and in their ability to forecast flu inoculation behavior. The results obtained by the authors suggest that a combination of the two models would be more effective in predicting this consumer behavior than either model separately. This paper represents an interesting application of consumer behavior theory used in business marketing to the decision processes made by persons seeking or not seeking health services. Few of these consumer choice models in the marketing literature have found their way into the health literature. With hospitals and other health care institutions doing more and more explicit marketing of their services it is even more important that they understand how all of their customers, including patients and clinicians, make decisions about the choice and mode of health care delivery.

In summary, forecasting the need, demand and/or utilization of services or of progression of diseases is essential for most decisions made for the allocation of resources and for tactical and strategic planning in the health care settings. While there are many possible models that can be used, some are better for certain types of forecasting than others. For example, when there are many dependencies between states of the system and those dependencies can be modelled by a Markov process, these Markovian models tend to be superior to those that assume independence between these states and ignore the dependencies. When one does not understand the causal relationships among the variables which need to be forecast, then ARIMA or exponential smoothing models may be better employed since they depend only on past data for the variables and not any causal relationships. When there is independence and an understanding of causal relationships, multiple linear or non-linear regression may be more appropriate. Each of these models has strengths, weaknesses and limitations. The forecaster should be well aware of them and ascertain that appropriate models are used in appropriate ways. The models should be tested for their statistical validity employing such measures as goodness of fit, T-tests, R^2, Chi-square, and other statistical techniques. Finally, the model to be used should be credible, as simple as possible, flexible, statistically accurate and unbiased.

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Service Demand Forecasting

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13	14
TARGET SERVICE														
Outpatient		*		*										
Inpatient				*			*	*	*				*	*
Emergency Medical Services	*					*								
Dietary														*
Home Health Care					*					*				
Skilled Nursing Home										*				
Extended Care Facility										*				
Regional Health Care												*		
Substance Abuse			*											
Laboratory Tests				*										
Preventive Medicine											*			
INTERVENTION VARIABLES														
Area Population			*			*								
Area Employment						*								
Socioeconomic Indicator(s)			*			*								
Daily Census							*	*	*					*
Patient Care Categories					*					*				
Disease State		*												
Service Visit Interval		*												
Provider Education												*		
Provider Distribution												*		
Behavioral Intention Model											*			
Health Belief Model											*			
FORECASTED MEASURES														
Need			*			*								
Demand	*		*	*		*				*				
Utilization		*			*		*	*	*		*			*
Admissions							*	*					*	
Discharges													*	
Supply												*		
METHODOLOGY														
Multiple linear Regression				*			*			*	*			
Exponential/Adaptive Smoothin	*						*			*				
ARIMA				*				*	*					*
Markov		*								*		*		
Delphi, Nominal Group, Etc.														
Goal Programming	*													
Non-Linear Programming	*													
Simulation												*	*	
Probablity					*									

4. Service System Design

A wide variety of research has been conducted in recent years concerning the design of patient care systems. Empirical research on alternative patient care systems has increased, but has had a limited impact due to methodological flaws. Operations researchers have examined some specific system design problems, but the works discussed here do not address, in most cases, large system problems. Questions addressed here focus on the appropriate mix of staff and technology for some specific aspects of the patient care system.

A recurring question in health care systems design is the relative value of physician extenders, such as nurse practitioners and physician assistants. Denton et al. (1983) developed a cost model for the Canadian health care system which allowed them to examine the potential savings from increasing the use of nurse practitioners. The study reported conservative estimates of savings of 10% of system health care costs. Reducing the physician supply concommitant with the projected increase in NPs is assumed. The consequences of adding physician assistants to a one-physician office practice was examined by Hershey and Kropp (1979). The effects on patient waiting time, waiting room congestion, practice hours, and supervisory requirements were found to offset productivity gains from using physician assistants. They used a combination of linear programming and simulation to estimate the benefits of using physician's assistants. They identified several factors of typical service design that are significantly affected by the addition of one physician assistant. However, PAs who can function with little or no supervision added significantly to the productivity of the service. Carlson et al. (1979) used a recursive optimization and simulation method to address a hypothetical problem concerning physician assistants, based on actual data. They sought to minimize total annual cost subject to the constraint of an average patient waiting time of thirty-five minutes or less. The intent was to choose the best among four different skill level alternatives for the use of physician assistants. The optimization model was solved, then the results incorporated in the simulation model. A linear regression of the simulation results for the variable of interest was then determined and incorporated in the optimization model as a constraint. The process was repeated until the waiting time was less than thirty-five minutes. This recursive method is not an optimal algorithm, but a heuristic which provides a solution that satisfies the constraint.

A generalized model for the design of outpatient clinics simulated by Stafford and Aggarwal (1979) led them to several conclusions about such systems. Different sizes of calling population significantly affect performance measures such as patient waiting time, size of queues, and medical staff idle time. Different levels of staffing have a significant effect in areas with a high patient load, but not otherwise. Increased levels of staffing decrease waiting time, queue size, and increase medical staff idle time. Most importantly, the authors concluded that a hypothetically typical clinic exhibits economies of scale as the calling population increases.

Romanin-Jacur and Facchin (1987) used a G.P.S.S.-F. simulation of a pediatric semi-intensive care unit in order to determine the bed complement and nursing staff number and organization. The unit was partially designated as an SICU, with the remaining beds designated for routine pediatric care. Overflow admissions could be held in a short stay unit. The objectives of the study were to minimize the number of urgent patients admitted to the short stay pediatric service and to minimize the number of non-urgent patients not admitted at all with the constraint that no urgent patients be rejected. They also sought to minimize the size of the nursing team due to cost.

While many materials handling systems in health care are highly labor intensive, Swain and Marsh (1978) described the design of an automated hospital materials handling system involving the flow of supply carts through a cart washer/dryer. Five solution alternatives were proposed and simulated to determine the average utilization of the system and the length of the queue at the end of the day. Service time in the cleaning system had to be decreased, and the cart style changed to avoid a lengthy queue of soiled carts.

Appropriate supervision of health care workers has seldom been examined by operations researchers. Parker et al. (1986) developed a linear goal programming model which attempted to identify the best form of supervision for Village Health Workers (VHW). The nominal group technique was used to identify system objectives, performance measures, and resource constraints. Decision tree diagramming was used to organize the information in a hierarchy. Next, relevant decision variables were generated and scaled for importance and current performance. A procedure similar to conjoint analysis was then applied to determine the relationships of decision variables with performance measures and resource constraints. Both rigid goal constraints and allowable deviations are included in the model. The objective was to minimize goal deviations, with multiple goals weighted by importance. Decision variables are identified which most efficiently utilize scarce resources to increase system performance, based on previously identified priorities. Parker et al. (1988) used a very similar method to identify optimal community health worker task allocation in Haiti.

Nursing care structures were empirically studied by Shukla (1982) to determine the relative productivity of team, modular, and primary nursing. Modular nursing was slightly more productive than the other two structures, but the marginal differences were not large. Surprisingly, primary care nursing provided the least amount of direct care to patients. Shukla suggests that other variables such as the structure of support services may have a greater impact on nursing productivity than the nursing care delivery structure itself.

Little work has been published which models the full system of inpatient care. In such a setting the examination of alternative systems of nursing care would be particularly suited to simulation. The interdependencies of nursing with a variety of ancillary and support services could be much better understood if an adequate system model were developed. Experimentation within real systems is difficult at best, and more OR efforts in this area could have disproportionately large benefits.

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Service System Design

Reference	1	2	3	4	5	6	7	8	9
TARGET SERVICE									
Outpatient		*						*	
Inpatient						*	*		
Physician's Office	*		*						
Community Health				*	*				
Radiology									
Hospital Materials Management									*
INTERVENTION VARIABLES									
Staff Skill Mix	*	*	*						
Calling Population Size								*	
Number of Staff							*	*	
Unit Bed Allocation						*			
Total Service Time							*		*
Staff Assignments				*	*		*		
Supervision Requirements				*					
Equipment Requirements									*
PERFORMANCE MEASURES									
Total Annual Cost	*	*		*	*	*	*		
Staff Idle Time								*	
Queue Size			*					*	*
Patient Waiting Time	*		*					*	
Health Outcome		*		*	*				
Patient Placement						*			
Appointment Refusals						*			
Staff Size						*			
Average Utilization									*
Employee Turnover				*					
Supervisory Time			*						
Hours of Operation			*						
Workload			*						
METHODOLOGY									

Service System Design

Reference	1	2	3	4	5	6	7	8	9
TARGET SERVICE									
Outpatient		*						*	
Inpatient						*	*		
Physician's Office	*		*						
Community Health				*	*				
Radiology									
Hospital Materials Management									*
INTERVENTION VARIABLES									
Staff Skill Mix	*	*	*						
Calling Population Size								*	
Number of Staff							*	*	
Unit Bed Allocation						*			
Total Service Time							*		*
Staff Assignments				*	*		*		
Supervision Requirements				*					
Equipment Requirements									*
PERFORMANCE MEASURES									
Total Annual Cost	*	*		*	*	*	*		
Staff Idle Time								*	
Queue Size			*					*	*
Patient Waiting Time	*		*					*	
Health Outcome		*		*	*				
Patient Placement						*			
Appointment Refusals						*			
Staff Size						*			
Average Utilization									*
Employee Turnover				*					
Supervisory Time			*						
Hours of Operation			*						
Workload			*						

Service System Design

Reference	1	2	3	4	5	6	7	8	9
METHODOLOGY									
Simulation	*		*			*		*	*
Queueing Theory	*					*		*	*
Linear/Integer Programming	*		*	*	*				
Other		*		*	*		*		

5. Site/Location Selection

Most of the OR applications discussed in this section address Emergency Medical Service (EMS) vehicle and/or station location. Regional planning of facility location is discussed with other planning issues. The lack of recent work related to hospital location reflects the decrease in construction of major new facilities at new locations in the last decade. One of the major components of health care cost control has been financial and regulatory disincentives for new facilities. On the other hand, sophistication of EMS location management systems has increased significantly in the last decade, and the works discussed below show substantial growth in this area.

Hodgson (1986, 1988) described an hierarchical location-allocation model which incorporates the tendency of greater facility size and scope of services to attract more patients. He argues that his model is more realistic than the P-median model, which ignores advantages of higher service facilities, and is driven by the least distance factor. An application in India is discussed.

Frequently, the number of facilities and the location of facilities are related decisions. Bach and Hoberg (1985) developed a planning model which helps plan the number and optimal location of CT scanners in a region. The model seeks to minimize total costs, including operational, capital, and transportation costs. The model was applied to a problem in a region of the Federal Republic of Germany, with the surprising result that an increase in CT scanners from the existing level could reduce total costs, due largely to the reduction of travel costs.

Or and Pierskalla (1979) also considered the problem of determining the optimal number and location of facilities in a region. But because the facilities involved are central blood banks in a region, the researchers also modeled the optimal allocation of specific hospital blood product needs to those central blood banks and the optimal number of routes of special delivery vehicles needed to make regular (routine) and emergency deliveries to the hospitals. They presented algorithms and models to decide how many blood banks to set up, where to locate them, how to allocate hospitals to the banks, and how to route the supply operation of vehicles so that the total transportation costs (regular and emergency) and the total system operating costs are minimal, and the hospital needs are met. The algorithms were tested on data from the Chicago metropolitan area.

Regional planning of health care services often presents a problem of optimal allocation of health services in an equitable manner. One of the facets of this problem is the partition of the region into health districts that provide an integrated, uniform set of health services, yet maximize scale economies. Pezzella et al. (1981) examined a health districting problem in an Italian province. Mathematical programming was used to find optimal districting, incorporating demand for service, hospital service capacity, and political structuring of the region (counties). A heuristic method is then used to identify politically reasonable solutions.

The problem of site selection for a regional blood bank, like many health care facility location problems, must consider internal and external space requirements as well as numerous transportation requirements. Price and Turcotte (1986) described a quick and relatively simple solution which depended only on transportation criteria: ease of product delivery, easy access for donors, and convenience to both public and road transportation. Data to support more elaborate techniques was lacking, so a series of gravity models was used to determine potential sites. A supplemental strategy advocated by Cromley and Shannon (1986) included aggregate activity spaces of the target population in the criteria used in the facility location process. This approach is particularly suited to services for the elderly, who tend to restrict activity to familiar areas of the community.

Uyeno and Seeberg (1984) described an application of a heuristic algorithm which approximates the P-median model for ambulance location. The solution was then further refined by simulating dispatch, response, and interaction of a two-level ambulance system, using GPSS V. The simulation was used to verify the optimality of the P-median solution, skill mix and other policy evaluations, effects of population changes, and identification of system problems and possible solutions.

Groom (1977) developed an EMS model which combines the range and availability of vehicles in an attempt to satisfy standards of performance. They conceptualized the covered area as a set of nodes. A matrix of travel times between all possible pairs of nodes was estimated, using a shortest path algorithm. The geographical distribution and frequency of incidents was determined from historical data. The procedures defining the operating system include operating a single- or double-tier service, and the length of time required for EMS activation. Vehicle availability was calculated using standard queueing theory.

Benveniste (1985) proposed a model using non-linear programming that simultaneously determined ambulance locations and their service zones. The location of demand and servers was represented by a grid of cells. The objective was to minimize the total expected travel distance.

Fitzsimmons and Sullivan (1979) combined a deployment model with varying fleet sizes to determine the appropriate level of ambulance service. The computerized ambulance location logic (CALL) simulation program combines the Hooke-Jeeves optimum seeking search routine with an EMS queuing model. Results were evaluated by comparison with the existing system and two cost-effectiveness measures. Fitzsimmons and Srikar (1982) enhanced the CALL approach by adding a contiguous zone search routine (CZSR), which was developed from a database of interzone travel times. Development of the CZSR enabled the authors to discard the Hooke-Jeeves heuristic. The CZSR relocates all deployed vehicles sequentially to zones contiguous to each vehicle's starting location. Individual and cumulative vehicle response times are then determined, until a cumulative minimum value is identified. Model outputs included demand on hospital emergency services, ambulance utilization and workload, mean response time, probability of all vehicles being idle, distribution of response time, mean response time by zone and dispatch guidelines. Objective criteria used to evaluate siting alternatives included service equity, fleet size, and workload equity.

Brandeau and Larson (1986) described an enhancement of the hypercube queueing model for studying an emergency medical services system. It does not select an optimal emergency service configuration, but does provide a variety of performance measures for any given configuration. The user must decide which configuration represents the best trade-off of the performance parameters. The model was used to configure the EMS system in Boston, with estimated annual savings of $150,000 compared to previous performance.

Charnes and Storbeck (1980) used goal programming for siting a two-tiered EMS system, so that a maximum number of emergency calls are served within a given response time. The model is innovative in solving for two types of coverage which provide mutual back-up services. Storbeck (1982) extended the goal programming approach to include slack and natural slack in the coverage model. Over- and under-attainment of demand coverage in a given coverage solution is considered natural slack. Manipulation of this natural slack can be accomplished by altering coverage relationships within the goal programming framework. The model unites maximal and multiple coverage objectives, thereby increasing policy options and planning scenarios.

Daskin and Stern (1981) developed a hierarchical objective set covering (HOSC) model to find the minimum number of vehicles required to cover all zones while maximizing multiple coverage of zones within performance standards. Daskin (1982) described a derivative of the maximum covering location model (MEXCLP) which accounted for vehicle busy periods. The model estimates the number of vehicles needed based on daily average calls. Eaton et al. (1985) described the implementation of the maximum covering model in Austin, Texas. Eaton et al. (1986) incorporated weighted demand into the HOSC approach, and developed recommendations for ambulance deployment in Santo Domingo, Dominican Republic. Fujiwara et al. (1987) used the maximum covering location model to identify "good" solutions for ambulance deployment in Bangkok, Thailand. Each of these solutions was then analyzed by a Monte Carlo simulation. Model outputs included response time, service time, round trip time, and workload. Bianchi and Church (1988) combined the MEXCLP with another covering model, the Facility Location and Equipment Emplacement Technique (FLEET) to develop an ambulance location pattern which places multiple homogenous units at one location

(MOFLEET). Integer programming was used to determine the optimal solution. The benefits of this approach include easier dispatching, reduced facility costs, and better crew balancing, without altering the service level.

Facility location is a complex and data hungry problem. Other than the EMS location problem, little work was discovered in this area of OR applications in health care. Several approaches to the EMS location problem have been developed which have had success in actual use. Developments in this area have been stimulated by the establishment of standards of performance by which public or contract services can be held accountable, as well as improvements in information systems which support EMS operations management.

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Site/Location Selection

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
TARGET SERVICE																					
EMS		*	*	*	*		*	*	*	*	*	*	*	*						*	*
Hospital															*	*		*			
Clinic						*									*	*					
Radiology	*																				
Blood Bank																	*		*		
INTERVENTION VARIABLES																					
Facility Locations	*	*	*	*	*	*					*	*			*	*					*
Travel Time/Distance		*				*					*			*	*	*	*		*	*	
Level of Service					*					*				*	*	*					
Number of Facilities	*			*											*	*	*				
Service Demand		*		*	*					*				*			*	*		*	
Service Capacity				*	*												*	*	*	*	
Number of Vehicles							*	*	*	*	*	*					*				
Political Factors									*	*								*			
Public Transportation						*													*		
PERFORMANCE MEASURES																					
Cost	*		*	*					*			*					*	*			
Response Time				*	*		*	*	*	*			*	*						*	
Response by Time Limit				*	*		*	*	*	*										*	
Demand							*								*	*					*
Service Equity										*	*							*			
Physical Access						*															
Total Trip Time													*								
Workload											*		*								
Staff Skill Mix			*																		*
Level of Service												*									
Other		*		*							*										
METHODOLOGY																					
HOSC/MEXCLP			*				*	*	*	*			*								
Simulation												*									*
Queueing Theory				*								*									
Linear/Integer Program			*																		
Nonlinear Programming		*			*													*		*	
P-Median																					*
Other	*		*	*		*					*			*	*	*	*		*		

6. Supplies/Materials Planning

Hospital Inventories

The analysis, control and cost reduction techniques for handling non-perishable inventories and supplies in hospitals and other health care delivery institutions have not received much attention in the recent literature or in practice. Indeed, most inventory control is generally done in an ad hoc manner by clerks and administrators. In those cases where operations research techniques have been applied to inventory control it has been primarily through the use of standard inventory models which were developed decades earlier in industrial and military settings. A good reference for these latter models and their applications is Silver and Peterson (1985).

In the published literature concerning applications of inventory models in health care settings there is little emphasis on models that minimize the costs of inventories. Some use costs as a budget constraint in computing the inventory stock levels. Most applications ignore costs and concentrate only on the amounts of inventory needed to provide a desired level of service, namely, to minimize the probability of shortages occurring. Under this criterion the inventory stock levels in health care institutions will tend to be very high, since it is well known in inventory theory that the amount of inventory needed to go from a 5% risk of shortage to a 2% risk of shortage increases exponentially. So, to reduce risk to smaller and smaller levels requires an ever increasing stock of inventory on hand.

In industrial settings, it is often found that the costs of carrying inventory ranges between 20% and 35% of the value of the inventory carried. This carrying cost includes such items as the interest cost of capital invested in the inventories, breakage, spoilage, theft, insurance, heat, light and space utilized. Consequently, having very high levels of inventory can result in significant additions to the costs of the firm or institution. In health care institutions, inventory costs are undoubtedly high, especially for those inventory items that require significant lead time to replenish. Under retrospective reimbursement these costs were easily passed on to the payers; now with prospective reimbursement it is far more difficult to do so. Hence, it is important to trade-off the benefit of reduced shortages with the cost of carrying inventory or look to other methods of inventory control such as just-in-time (JIT) shipments.

One of the exceptions to looking only at the risks of shortage is the paper by Ebrahimzadeh et al. (1985). The authors developed a simulation model to compute the optimal inventory levels for a multi-item pharmacy warehouse in Israel which minimize total costs and decrease the probabilities of shortage. They compared two models. The first is an Economic Order Quantity, EOQ, model, which follows the policy (Q, T) where at the end of each time period T an order is placed for a constant amount Q_i for each drug i. The amounts (Q, T) are computed optimally for each drug by simulating various levels for Q and time periods for T. The second model is more complex and follows a policy denoted by (r, R, T). In this model at the end of each time period T the inventory level for drug i is examined and if it is below a level r_i then an order is placed bringing the amount of the drug inventory level up to the level R_i. Again, using a simulation they optimally compute the numbers r_i, R_i and T which minimize the total costs of the system. In their analysis, each of the models performed much better than the system currently in use; and the second more complex model (r, R, T) was the better of the two. Not only were costs lowered significantly but also shortages were reduced.

A second paper which considers cost minimization is an application of EOQ analysis for the supply and processing of sterilized items in hospitals done by Fineman and Kapadia (1987). In this analysis the authors determined the amount of inventory needed to maintain sufficient sterile supplies for items which had multiple reuse after sterilization and for items which have only a single use and then were discarded. Examples of multi-use sterile items are surgical clamps, scalpels, linen, bed pans, etc. and single use items would be such items as bandages, disposable thermometers, syringes, etc. In this model the authors compute the economic order quantity levels to minimize the total replacement, processing and stocking costs of the inventory items concerned.

Another paper which looked at the scheduling and processing of sterile supplies and other surgical supplies in the surgical suite was done by Steinberg et al. (1982). In this paper the authors apply the concepts of materials requirements planning (MRP) to plan the availability of surgical suite supplies. The model does not compute optimally the amount of inventories needed based on costs or other criteria, but rather computes the amount of inventory needed in advance to meet the known demand for surgical items used by each physician for each type of surgery, etc. Essentially the authors compute a bill of surgical materials needed for physician 1 for a particular type of surgery, for physician 2 for another type of surgery, for physician 3 for a third type of surgery. They take these surgical bills of materials and decompose them into their component inventory parts. Each inventory part is then stocked in sufficient supply to meet the scheduled surgical needs for the next few days or week. They do not take into consideration random unexpected emergency surgery or the costs of stocking the inventory items. The assumption is made that for seven days into the future all surgery is known in advance and that it is a simple task to obtain the items which would be in short supply in sufficient time to meet the seven-day planning horizon. The application is a direct extension of industrial production techniques to a health care environment. MRP is a useful analysis for considering stock availability in many settings and the reader is referred to the text by Nahmias (1989) for a full discussion of MRP strengths and weaknesses as a planning and inventory tool.

Several other papers apply inventory models for non-perishable items in health care delivery settings: i.e., Nagaty (1988), Satir and Cengiz (1987), Worrall (1981) and Quick (1982). Nagaty and Quick each applied inventory analysis for items in public pharmacies in developing countries. For such large multi-item inventories Quick pointed out the need to categorize the inventories into groupings that make the analysis easier. Quick used the "ABC" stratification that classifies inventories into three categories based on their procurement costs:

A -- Those inventories which comprise about 10%-20% of the products but have about 70%-80% of the costs

C -- Those inventories which have 10%-20% of the costs and comprise 70%-80% of all the products

B -- Those in between which would have somewhere between 15%-30% of the costs and 15%-30% of the products

Clearly the category A items are by far the most costly and need significantly more control than the very large number of products which have much lower costs. It should be mentioned that the Ebrahimzadeh et al. study mentioned earlier also emphasized those items in category A of the ABC analysis. In other industrial studies inventories are often grouped according to other criteria as well as costs, such as, breakability, size, sensitivity to environmental conditions, or risks of shortage.

In summary, for nonperishable inventories, hospitals and other health care institutions have made little use of optimal inventory control and analysis as reported in the literature. This could be an important area to examine further to obtain significant cost reduction for certain items in certain health care settings.

Blood Bank Inventories

Most of the published literature on inventory control done in the health care setting has concerned the management of blood bank inventories at the regional and local levels. Blood bank inventory management presents a great challenge because of the perishability of blood and blood products and the fact that presently the only source of supply is human donors. Coordinating the supply, processing and storing of these perishable items with the transfusion needs of patients requires the analysis of the entire blood inventory system.

An excellent survey of the literature on blood inventory management was done by Prastacos (1984). In his review Prastacos described the blood banking system and decisions involved within the different system hierarchies: at hospital blood banks, regional blood centers and inter-regional blood programs. Decisions among the hierarchies of institutions are classified by whether they are operational, tactical or strategic. An example of a hospital blood bank operational decision would be scheduling the orders for blood products; a tactical decision would be determining inventory levels; and a strategic decision would be determining policies for sources of blood supply. An example of regional blood center operational decision would be when to schedule collections; a tactical decision would be to determine the optimal inventory allocation to hospitals; and a strategic decision would be to design the network configuration of supply, processing, storage and distribution within the region.

The blood banking literature is rich in models and analysis for aiding decision-making at each hierarchical level for each type of decision. The Prastacos review summarizes this literature up to 1984. In some more recent work Sapountzis (1984, 1985) developed inventory shipment levels for blood from a central blood center to hospitals based upon the age of the blood and the probabilities of not being used in time before the expiration date.

In another paper Schwartz et al. (1989) analyzed which blood screening tests should be used by blood centers in order to reduce to an acceptable level the probability of HIV infected blood being transfused. The model was used at a national consensus conference at the NIH in Bethesda to determine the national policy for blood screening for HIV. The model allowed for multiple sources of populations with difference risks and characteristics in the donor pool, for different sequences of tests with different specificities and sensitivities, for different states of the progress of HIV within the donor, and for donor registration and notification programs in the event of HIV positive donations.

Much work has been done in the optimal siting of facilities for the collection, processing, and inventory storage of blood products for regional blood centers and in the routing of collection vehicles and inventory distribution vehicles from these facilities. This work is described in other parts of this review paper. In section 5, Site Location and Selection, the siting of such centers is considered.

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Supplies/Materials Planning

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13
TARGET SERVICE				Review	Review						Review		
Non-Perishable Medical Supplies	*	*	*	*		*			*		*	*	*
Blood Bank					*		*	*		*			
INTERVENTION VARIABLES													
Pharmacy Inventory	*		*			*							
Reusable Sterile Supplies		*										*	
Disposable Sterile Supplies		*										*	
Age of Blood							*	*					
Probability of Expiration							*	*					
HIV Screening Tests										*			
PERFORMANCE MEASURES													
Total Cost	*		*			*			*				*
Replacement Costs		*											
Processing Costs		*											
Stocking Costs		*											
Probability of Shortage	*												
Deterministic Demand												*	
Total Utilization							*	*					
HIV Infected Blood Transfusion										*			
METHODOLOGY													
Simulation	*												
EOQ	*	*											
Materials Requirements Planning				*								*	
ABC Analysis	*					*							
Other							*	*		*			

7. **Vehicle Scheduling**

Little work has been done recently on vehicle scheduling as it relates to health care. Tactical policies for dispatch of EMS vehicles have been examined by a few researchers. Simulation appears to be the technique of choice in examining alternative dispatching policies. Many researchers have approached this problem by assigning the closest vehicle, and adjusting vehicle locations to best satisfy demand. (See the Site Location section.) Other than emergency and non-emergency patient transfers, the scheduling of blood donor mobiles and blood delivery vehicles, and mobile CAT scanners, few opportunities concerning vehicle scheduling occur in health care.

Baker et al. (1984) tackled the problem of incorporating measures other than response time in planning Emergency Medical Services by using multi-attribute utility analysis. The purpose of the study was to model the evaluation of the trade-offs between response time and personnel such that the quality of care is optimized. The two types of personnel included were Emergency Medical Technicians and paramedics. Once a utility function was developed, a simple nonlinear program could be formulated to maximize the utility function subject to specified constraints, such as budget.

Davis (1981) simulated ambulance deployment by using separate time distributions for travel to the scene, time spent at the scene, travel time to the hospital, time spent at the hospital, and time to return to base. Further refinements included multiple casualty calls, variations in time at the scene by type of incident, variations in EMS call rates by day of week and time of day, and variations in travel time based on time and day variables. The model was developed in GPSS. Results were compared based on the frequency of responses exceeding six minutes. Liu and Jui-Lee (1988) used a different language (SLAMII) to simulate an EMS. The purpose of the model was to assist in developing an ambulance dispatching policy. Requests for service and ambulances available are treated as queues.

Taylor and Templeton (1980) described an application of a multi-server queue model to an ambulance service that provides emergency and non-emergency transport. The model uses a cutoff priority rule to maintain adequate response times for high and low priority calls. The results were applied to determine the number of ambulances required for an urban EMS that also provides non-emergency patient transfers.

OR applications concerning vehicle scheduling problems in health care are rare outside of the EMS and blood banking environment. Other problems that could be conceptualized in this framework usually involve the scheduling of skilled services, such as home nursing care. Scheduling the nurse's workload and incorporating travel time may merit further research. In the hospital setting, patient transport services seldom operate on a scheduled basis, since the benefits of controlling the workload of ancillary departments, such as radiology, supersedes benefits from scheduling the workload in the transporter department.

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Vehicle Scheduling

Reference	1	2	3	4
TARGET SERVICE				
Emergency Medical System	*	*	*	*
INTERVENTION VARIABLES				
Response Time	*			*
Staff Skill Mix	*			
Budget	*			
Time to Scene		*		
Time at Scene		*		
Time to Hospital		*		
Time to Return to Base		*		
Number of Casualties		*		
Patient Classification		*		
Time of Day		*		
Day of Week		*		
Requests for Service			*	
Number of Vehicles Available			*	*
PERFORMANCE MEASURES				
Total Cost	*			
Utility	*			
Comparison to Standard		*	*	*
METHODOLOGY				
Simulation		*	*	*
Queueing Theory		*	*	*
Nonlinear Programming	*			
Multiple Criteria Utility Theory	*			

8. Work Force Scheduling

The management of human resources is a major concern in health care organizations. Staffing costs usually represent the majority of the operating budget. Like many service organizations, the ability to match staffing resources to a fluctuating demand directly affects operating efficiency and the quality of service. Although most of the research in staffing and scheduling for health care organizations has focused on nursing, similar problems in the laboratory, emergency department, and respiratory therapy have also been examined.

Hershey et al. (1981) conceptualized the nurse staffing process as a hierarchy of three tactical levels, differentiated by time horizon and precision. Their conceptual model is also applicable to other services. Corrective allocation adjusts the staff distribution across nursing units within a shift. Shift scheduling matches staff capacity with forecasted workload over a two- to eight-week period. Effective manpower planning balances the number and capabilities of nursing personnel over the long term. Researchers emphasized the interdependence of all three levels. Each level is constrained by available resources, by previous commitments made at higher levels, and by the amount of flexibility preserved at lower levels. Strategic planning, performance monitoring and coordination of efforts with other departments are included in the model. The model has not been empirically verified although it is logically consistent and represents a structured way of viewing interactive planning and operating decisions.

Forecasting Workload

Helmer et al. (1980) used a multiple regression approach which predicted nursing man-hour requirements by ward, shift, day of the week, and month of the year. At the hospital for which the methodology was developed, almost 50% of the nursing hours could be varied with the workload, making accurate forecasts very beneficial. The model was much better at forecasting monthly census for a particular ward (R^2 = .96) than for forecasting the number of patients in a specific patient classification on a given shift on a given day (R^2 = .61). Forecasting shift work load more than one day ahead continues to present a difficult problem. Pang and Swint (1985) also used multiple regression to predict daily and weekly laboratory workload for scheduling purposes. Of ten predictor variables studied, they found variables with significant influence varied according to the lab section involved. The number of daily admissions was the single most influential predictor of daily work load. Patient census (plus nursery) was the most influential variable for predicting weekly work load.

A very different approach was taken by Nutt (1984) who used the decision models of experienced staff nurses as a decision support tool for staffing decisions. Two methods were developed and tested at two clinical sites. One method used hypothetical cases with staffing values correlated with severity of illness indicators relevant to neonatology. The criteria scaling method decomposes the decision to determine the relative weight assigned to severity indicators over a range of values, such as days since birth. Then a curve of required nursing hours is plotted for each indicator. Both methods worked well at the site where they were developed. The authors concluded that their methods were easy to develop and apply to staffing decisions. No time horizon for the validity of either method was identified.

Corrective Allocation

Corrective allocation of nursing staff tries to balance workload and staff across nursing units. Floating, per diem pools, part-time staff, overtime, voluntary time off, and the reallocation of patients have been used to address the problem. No new research was identified in this area. The development of patient classification systems has increased the objectivity involved in corrective allocation decisions. The systems allow determination of the demand/supply mismatch on each nursing unit, and can facilitate decision-making about distributing the supply of nursing resources across units. The determination of what skill level of personnel to assign to which unit remains a matter of judgement for the shift supervisor in most institutions.

Scheduling

Operations researchers have made significant contributions to the shift scheduling problem. Scheduling has traditionally been devised to repeat a cyclical pattern on a regular basis. This type of schedule cannot adjust for forecasted workload changes, extended absences, or the scheduling preferences of individual nurses. Rigid scheduling places demands on the corrective allocation and manpower planning levels. Corrective allocation must be more flexible; manpower planning must more precisely forecast long-term manpower needs to avoid excessive staffing (Hershey, Pierskalla, and Wandel, 1981).

The two most frequently cited approaches to scheduling (Warner, 1976; Miller et al. 1976) attempt to include the preferences of staff in the scheduling decision. Miller et al. (1976) have implemented quantitative nurse scheduling based on mathematical programming, using the cyclic coordinate descent algorithm on a computer. The model incorporates many constraints, divided into two types. The feasibility set binding constraints consist of hospital policies that must be met (for example minimum and maximum length of work stretch.) The second type contains non-binding constraints (for example, minimum staffing level rules and undesirable schedule patterns determined by the staff nurses) that can be violated. When such a non-binding constraint is violated, a penalty cost is assigned. Each staff nurse is allowed to assign relative weights to various violations of non-binding constraints. The problem is formulated to minimize penalty costs of the scheduling pattern. Benefits of this approach include decreased variation between actual and desired staffing, higher personnel satisfaction, and lower costs than manual or semi-automated systems.

Arthur and Ravindran (1981) took exception to the previous model's priority structure of objectives. They describe a model capable of seeking four objectives: (1) minimum staffing requirements (2) desired staffing requirements (3) nurses' preferences and (4) nurses' special requests. The model uses goal programming followed by a heuristic procedure to determine a two week schedule. Although the model is simplistic in many respects (for example, all full time personnel, no scheduled overtime, every other weekend off), it does offer flexibility in prioritizing the four objectives. This permits the decision maker to weight the four objectives according to subjective preferences.

Few operations research models have included shifts of varying length. Cooper (1981) applied a linear programming model to a scheduling problem that involved eight, ten, and twelve hour shifts in a respiratory therapy department. He used a network model to provide an integer solution. The objective was to minimize the number of staff hours worked each day, subject to meeting patient care requirements. The new solution saved six staff hours per day, resulting in an 8.1% increase in productivity, and a 7.5% decrease in salary expense, assuming the extended hours were not paid at overtime rates.

Vassilacopoulos (1985) has proposed a method for allocating physicians to shifts in an emergency department. The objective was to minimize the overall patient waiting time and the queue size at any particular time, within the constraints of always staffing at least one doctor, with a predetermined number of total doctor hours to distribute. The patient arrival rate was evaluated and found to approximated by a Fourier series of three harmonics, with periods of 24, 12, and 8 hours, corrected by a day-of-week trend. The department was simulated as a M/G/m(t) queueing system. Actual service times were not determined, but simulated on a probability distribution. The model does not schedule specific physicians, but does suggest the number to have on duty during any four-hour period during the week.

The assignment of health care personnel to specific clients has been examined rarely. Tzukert and Cohen (1985) described a mixed-integer program that assigns patients to dental students in a clinic. Issues of efficiency, varied educational experiences, facility and faculty constraints, and continuity of care are incorporated in the model.

Manpower Planning

Manpower planning includes hiring, training, transferring between positions, and discharging employees (Hershey et al. 1981). Quantitative models of manpower planning are appearing more frequently in the literature. Khan and Lewis (1987) introduce a network flow approach to perform basic allocation tasks. Minimum and maximum staffing levels must be predetermined to optimize unit staffing allocations at minimal cost while meeting average estimated demand. The objective is to determine the minimal number of employees to staff three nursing units. They conceptualize the problem as a minimal flow problem through a capacitated network. The algorithm proceeds iteratively by gradually increasing the flow along the arcs so minimum staffing requirements are met. It terminates when an optimal scheduling scheme is identified, provided one exists. One limitation is the assumption that no allowance is made for staff preferences or shift rotation. Although titled a scheduling system, it actually allocates minimal staffing on each shift to determine total staff required for a typical day. The model is better suited to manpower allocation issues.

Worthington and Guy (1988) describe a system of manpower allocation based on patient classification data for the previous three months. They used a patient classification system to reallocate staff according to workload, primarily for annual budgeting. One of the fundamental assumptions was that heavy overwork occurred when demand exceeded staff hours available by 40%. Patient classification data was combined with staff allocation based on equalizing the probability of reaching this level once every forty days. This method allocates more staff to units with highly variable workloads. They then proposed that small groups of similar units pool their staff resources because of the balancing effect of floating staff across units. The solution could allow a 13% saving in staff expenses if each employee is still expected to achieve one in forty days of heavy overwork. The allocation procedure used is straightforward, but the authors used a subjective approach in developing the heavy overwork standards. These standards would have to be tested under actual work conditions.

Baker and Fitzpatrick (1985) developed an integer programming model for the problem of reducing staff in a recreation therapy department. The study concerns determining who to terminate in a hospital recreational therapy department when a one position reduction is required and no seniority rule is in effect. The objective function maximizes the effectiveness of staff retained, under budget and Equal Employment Opportunity Commission (EEOC) constraints. Multi-attribute utility theory (MAUT) is used to integrate objective and subjective criteria of effectiveness into a preference structure. The utility value developed is used as a proxy for employee effectiveness (utility of a staff member) rather than the utility of the criterion used to rate that staff member. Performance and experience were the two attributes selected for use in obtaining a utility surface for evaluating effectiveness. Once the utility values were determined, integer programming was used to optimize department effectiveness under several staff skill mix strategies. The budget constraint had little effect because the salary differential among the employees was small. The EEOC constraint (10% minority staff) did affect the solution because one position had to be reserved for compliance with the constraint. Shimshak et al. (1981) used three queueing models to determine the effects of pharmacy staffing on prescription order delays. A priority discipline model with preemptive service and multiple servers best suited the system being modelled. The model results led to a decision to preserve the existing staffing level.

Connell et al. (1984) compared the cost reduction effectiveness of two heuristic planning models that determined staffing levels and food production rates in a hospital setting. The Search Decision Rule (SDR) performed better than the Management Coefficients Model and the existing master labor schedule. Sites with different production technologies were included to determine any relationship between planning production systems. The alternatives were compared by means of simulation. The authors concluded that aggregate planning systems known to perform well in manufacturing also performed well in a service setting.

Goyal and Yadav (1979) developed a simple heuristic for allocating doctors to health centers in a state in India. The model is designed to increase the total number of patients seen per day by better allocation of doctors, and to incorporate doctor absenteeism and patient population differences into the decision.

Kao and Tung (1981) present a case study of long range staffing planning. Their model is a combination of a linear program and a statistically-based forecasting system. They note that the methodology is dependent on the organizational structure and the type of data base available to them for generating input parameters. They first developed a forecasting system for projecting nursing hour requirements. Monthly statistics of admissions by service for the previous five years were used in an autoregressive integrated moving average time series model (ARIMA). Then the forecasts were combined with an estimated length of stay to generate forecasts of patient days by service. The forecast was integrated with institutional constraints and patient care requirements in a linear program for assessing the need for permanent staff, overtime pay, and contracting temporary help, differentiated by medical service, nursing skill level, and time period. Next the model was expanded to evaluate the size of a float pool. To do this, researchers set the level of aggregation of nursing hour requirements by skill type at the medical service level, due to limited historical data below that level. Once aggregate requirements are determined, individual unit requirements could be determined by using the bed complement on each unit as a proxy measure of the proportion of medical service staff on each unit. The model includes numerous policy assumptions unique to the institution, resulting in a linear program with 1326 variables and 1011 constraints. Forecasted fluctuations and day-to-day fluctuations greatly affect agency personnel use. Since the forecasts were monthly, daily fluctuations were not included. As a result, actual fluctuations in census were much wider than those forecasted, and the benefits of the float pool were underestimated. Another problem contributing to the errors was the need to use Texas Hospital Association recommendations for nursing hours per patient day due to the absence of actual patient classification data.

Cavaiola and Young (1980) developed an integrated system of patient classification, nurse staff planning, and staff budgeting for a long term care facility. The patient classification system reduced indicators of patient demand to twenty-five categories by using nonlinear multiple regression. Psychosocial criteria were not included. The basic staffing model used mixed integer linear programming to solve the staffing allocation problem for the best assignment of nursing personnel based on a criterion called appropriateness. Appropriateness serves as a surrogate for quality of care. Costs, regulatory requirements, and other constraints were included. Staff resources were allocated for a twenty-four hour period, by skill level, but <u>not</u> by shift. The manager performed shift scheduling. The model can show the effects of altering the total number of hours of patient care provided, regulatory changes, and alteration in demand estimates on staff mix, appropriateness of assignment, and budget. In addition, budget changes can be evaluated for effects on staffing mix, appropriateness, and service level. The model requires data on staff mix boundaries, salary costs, personnel budget, subjective appropriateness measures for every combination of skill level, task, and patient classification category. The model assumes a twenty-four hour time span for each allocation of staff, no part time employees, and only eight-hour shifts. The portion of each worked shift available for patient care must be determined. Boundaries on the time allocated to various tasks, and the priority structure of the tasks were derived from published research and expert judgement.

Cleland (1982a;1982b) proposed and refined a group of indices that provide a theoretical approach linking manpower planning with the quality of care. One measure is the nursing classification census score (NCCS) which combines census and patient classification data. This is a measure of average patient classification, or work load. She then proposes another index that combines staff hours worked and level of competency (determined by job classification.) The points awarded to different job classifications are arbitrary in the proposed model and would need to be empirically determined. This competency full time equivalency score (COFTES) is then divided by the NCCS to determine the tetradic score (TS) which is an adequacy ratio that measures the appropriateness of staffing for a specific patient mix.

Simulation has been applied to a variety of manpower planning problems. Kutzler and Sevcovic (1980) developed a simulation model of a nurse-midwifery practice. The model can simulate the consequences of admitting new prenatal patients to the practice each week. Varying the caseload additions produces forecasts of workload and discharges, based on probability. The simulation will assist a nurse-midwife in determining a cost-effective caseload. Hashimoto et al. (1987) used a Monte Carlo simulation to evaluate cost, number of voluntary absences, staff called in, and total cost for a year at different staffing levels (FTEs per shift) for an ICU. The model was validated with historical data, and the results were presented to the staff nurses, who participated in the selection of the level of staffing for the next year. Different staffing levels were preferable based on cost, quality of care, and staff preference. Quality of care was assumed to be higher if fewer agency staff were required. The staff's preference was selected as the optimal solution, as it fell between the extreme values of least expensive and highest assumed quality. Duraiswamy et al. (1981) developed a simulation for a similar problem, including seasonal variations in patient demand and staffing supply. They simulated a twenty-bed Medical Intensive Care Unit, including patient census, patient acuity, and required staffing on a daily basis, for one year. Recommended staffing levels did not include non-productive time. The model determined the number of calendar days of overstaffing, understaffing, and optimal staffing for a range of staffing levels.

A simulation of obstetric anesthesia developed by Reisman et. al (1977) enabled them to determine the optimal configuration of the anesthesia team. The model identified the number of emergency, urgent, and routine overloads experienced per day for any given staffing configuration of anesthesiologists and assistants. Manpower planning decisions were based on administrative weights assigned to risk aversion for each type of overload.

Smith (1982) studied a problem in an anesthesia department that was unable to staff adequately. Unpredictable and uncontrollable absences, variation in the size of the staff, and seasonal fluctuations of staff availability were incorporated into a dynamic programming model with the objective of minimizing the number of cancelled procedures. The outcome of applying the model led to a long-term decision to increase the anesthesia staff, and a short-term decision to reduce their commitments to reduce the frequency of cancellations.

Zachariah et al. (1987) evaluated productivity of health care facilities in Jamaica, and developed recommendations to improve staff productivity. Maximization of personnel productivity was the objective of the project, based on policy maker judgments about the cost effectiveness of various services. No details of the model are included, but it reportedly was designed to compute demand for services, convert demand to service units, compute time required to meet the demand based on critical work station times, select the appropriate clinic structure, calculate clinic hours, clinic schedule, staff requirements, compare staff requirements with staff available to provide information on training, recruitment, and redundancy strategies, compare regional differences in critical personnel needs, compute the expected cost-effectiveness index for a region, and provide sensitivity analysis concerning certain policy variables.

Another manpower planning application has been described by Todd and Coyne (1985). They constructed a computer model that permits planning of different grades of medical staff. They assumed 100% of all new outpatients could be seen by consultant or senior registrar physicians. All inpatients were assumed seen within 48 hours of admission. This enabled a calculation of existing workloads per doctor and of future workload given adjustment of grades to bring specialties into balance, based on clinicians' estimates of average workload by specialty. The model consists of a series of "what if" projections to determine the effect on different grades of staff of correcting career imbalances within specialties; what consultant expansion is possible within financial constraints following such a staff adjustment; the consequences on workload of both the above changes; junior staff requirements to meet current needs; and how this relates to a balanced career structure within a specialty.

Magazine (1977) described a patient transportation service problem in a hospital. The solution involved queueing analysis and simulation to determine the number of transporters needed to ensure availability 95% of the time. A mixed-integer program determined the required number of shifts per week. Although the study led to several recommendations for reducing department costs, only the scheduling pattern solution was implemented.

Strategic Planning and Policy

In addition to the three tactical levels and performance monitoring, nursing management must also make strategic decisions which inevitably restrict alternative actions at the tactical levels. Trivedi (1981) developed a mixed-integer goal programming model based on financial data and staffing standards, but also incorporated users' judgement and institutional norms in the preparation of the nursing budget. The model allowed examination of consequences of changes in understaffing, the wage scale, impact of changing skill substitution rules, personnel policies, and forecasted patient volume and mix. Model objectives include minimization of expenditures, of understaffing, and of the number of part-time employees. Each objective can be weighted. All are converted into dollar amounts. Trivedi made several assumptions in modelling the problem. He assumed the availability of an estimated total dollar amount for salary expenditure in each cost center. This budget can be exceeded or underspent. Part-time employees work a set number of hours per week. A limited amount of substitution takes place among personnel of different skill levels, determined by legal constraints and hospital policy. This is given an explicit value for each personnel category with respect to each of the other categories. Understaffing is valued in wages saved, which may not reflect the actual costs and benefits of understaffing. The model did not incorporate costs for recruiting extra staff, costs in turnover resulting from understaffing, or costs associated with changing substitution rules. Another potential problem is that skill class substitution was determined by supervisor judgement. In the model, demand was differentiated according to forecasted patient mix and by weekday or weekend. He also assumed that full time staff provide better quality of care. The problem is also formulated to assume no overstaffing. With this design, deviations between goals and achievable outcomes are minimized. The degree of multiple goal satisfaction is more important than the actual value of the objective function.

Brandeau et al. (1987) have developed a budget model that forecasts revenue and expenses for any given change in medical school faculty effort (teaching, research, and patient care.) The model provides a five-year forecast for financial planning purposes based on a particular configuration of faculty effort, including differences based on sizing various departments to examine the financial consequences of alternative strategies of specialty and effort mix. The model has been implemented at several medical schools.

Leiken et al. (1987) modelled the effects of price competition on the use of RNs, LPNs, and nurse aides in a nursing home. They tried to find the minimum cost staffing pattern that meets patient needs and incorporates all relevant task times. The model's decision variables are: how many hours of each skill level to employ, and how many hours each skill level should devote to each task. The model imposes constraints such that all patient needs are met; any minimum staffing requirements in effect are satisfied; the solution does not exceed labor availability; the definitions of the variables are satisfied; and no negative numbers are allowed for the decision variables. The objective was to minimize total personnel cost per day. The linear program ignores variability in the normal amount of time to perform a task, so staff requirements are rounded up if fractions of FTEs occur. A potential flaw in the methodology concerns identifying the tasks each skill level could perform. They asked all RNs, LPNs, and Aides to identify tasks they felt they were capable of performing, regardless of current guidelines or regulations. Of forty identified tasks, some were restricted to RN only activity after the initial solution, which then increased the staff requirements. They concluded from the model results that the cost/quality battle will be reflected in nursing home staff mix. Another potential flaw in the model is the failure to include any costs or measures of quality.

Policies about skill mix, control of admissions, benefits, and the use of float pool, overtime, or on-call staff all may affect the cost and quality of care. Hancock et al. (1987) developed a mathematical model to determine the cost effects of productivity standards and staffing policies. One source of variation in productivity is in the capabilities of the members of the work force to absorb variations in the work load. They recommend establishing a technical basis for what productivity levels can be achieved, how one should staff, and the resulting budget. If true potential productivity is known, the costs of compromises to the productivity standard to gain acceptance by staff and management will be known. The model also provides information for determining the costs of management policies about overtime, full and part time staff, the quality of worker selection, and other related decisions. The average capability of the work force is usually equal to a work force utilization of 120% to 135%. The standard is usually set so 95% of individuals in good health between 18 and 65 are capable of performing at or above 100% with an average value 120%, where no allowances have been added for fatigue or personal time. The researchers described how to include such standards into a model for planning staffing allocation and overtime policies. The model requires estimates of demand, regular and overtime wages, and the average productive capability of the staff. By assuming that overtime is worked at the same productivity level as average regular hours and ignoring the effects of overtime on staff satisfaction, they determined that a policy of allowing a maximum of two hours overtime reduces wage costs and increases productivity. The model also leads to the conclusion that the smaller the unit, the more crucial is worker selection and varying staff with demand to maximize productivity and decrease costs.

Feldman and Hundert (1977) used the Nursing Home Simulation Model to examine the financial and quality impact of alternative staff mixes, total number of staff, and fixed or flexible scheduling of patient care services. The model has two modules, a nursing care simulation module and a cost module. The nursing care module produces effectiveness and efficiency measures. The integrated cost and nursing modules generate cost predictions. Application of the simulation to a new facility resulted in upwardly revised staff allocations and adoption of a flexible schedule of patient care activities.

Organizational strategy on pricing and quality of service constrain staffing decisions at the tactical levels. Goldstone and Collier (1982) describe a methodology used in Great Britain which links quality of care to staffing allocations. They assume that staffing and quality measures are strongly correlated, and that the staffing decision is derived from an established quality objective. The derived staffing allocation is then monitored for performance in terms of quality objectives.

Strategic decisions can conflict in their effect on tactical staffing decisions. For example, setting a very high productivity standard as well as high quality standards may lead to uncertainty at the tactical levels about which strategic objective has priority. On the other hand, many industrial organizations have demonstrated that with appropriate incentives, organization and employee-management relationships high productivity and high quality are complementary. No research on such decisions in health care at the institutional level were found.

Links with Other Organizational Activities

The final component of the Hershey, Pierskalla, and Wandel, (1981) model is the coordination of staffing management activities with other departments. Corrective allocation could be coordinated with task assignment. For example, if a nursing unit is short staffed, ancillary departments could transport patients. Shift scheduling should be coordinated with scheduled admissions and surgeries. Collart and Haurie (1980) evaluated a tactical level of coordination. They assessed the relative efficiency of three controls applied to the supply and demand system of inpatient nursing care. The controls were: regulating admission of elective patients, allocation of a floating pool of nursing personnel, and assignment of the unit's nursing personnel to various tasks. Admission control affects the demand for care. Float pool and personnel task assignments affect the supply of care. The formulation of the model led to a complex stochastic control problem which could not be solved in a closed form. A sub-optimal open-loop feedback technique was substituted and the relative efficiency of the three controls assessed by simulation. The design incorporates a model of the disease state process and a staff utilization coefficient allowing for different skills, with efficiencies for various tasks. The model assumes that the supply of staffing is less than or equal to the total demand for care. Demand for care was estimated by two head nurses, as was the distribution of work among three classes of personnel.

Collart and Haurie concluded that the float pool was only slightly superior to admissions control for matching supply and demand for care, while task assignment was not an efficient means of controlling the adjustment of supply to meet demand.

Vries (1987) studied control of supply and demand for care, and found that the effects of admission scheduling could be predicted in the utilization measure he called work pressure. The goal of his study was to match activities and costs. He identified a rather broad range of acceptable work pressure: 85-125%, which is not validated. Consequences of proposed surgical admissions for workload were predicted rather well. The goal variable was to meet standards of capacity utilization. This was complicated by the lack of established work load and staffing requirements standards. He advocated use of trial and error to develop a model that would provide the proper decision support. Vries used the variation coefficient of the work pressure as an indicator for the stability of the balance of supply and demand. The coefficient was defined as the standard deviation divided by mean. Lower values indicated stability of work pressure. He found that variations in utilization must be smoothed by corrective allocations of staff, with shift scheduling established at a level that meets the average demand.

Three methods of admission monitoring were compared by Shukla (1985): flexible staffing systems with admissions monitoring based on hospital census, nursing unit census, and nursing unit patient classification (work load index). Such admissions control systems have relied heavily on physician cooperation in the past, and have not been popular because of their impact on medical practice. Variation in workload index was smallest for the system based on patient classification. As a result of admissions monitoring, this system required staffing adjustments only 12% of the time, compared with 27% with a census monitoring system, and 46% without a monitoring system.

Manpower planning could be coordinated with facility planning, marketing, and budgeting (among others). The model of staff allocation in a long-term care facility (Cavaiola and Young, 1980), discussed previously, did incorporate budgeting with manpower planning. No other descriptions were found of organizational efforts coordinated at this level.

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Work Force Scheduling

REFERENCE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	2
TARGET SERVICE																						
Nursing	*			*	*	*	*			*	*	*		*	*	*	*	*	*		*	
Laboratory																						
Respiratory Therapy									*													
Emergency Department																						
Obstetrics/Gynecology																				*		
Pharmacy																						
Outpatient																						
Ancillary		*					*	*														*
Physicians			*										*									
Anesthesia																						
Long Term Care											*										*	
SYSTEM LEVEL																						
Forecast Workload																	*	*		*		
Scheduling	*								*								*					
Manpower Planning		*		*	*	*		*		*		*	*		*		*	*	*	*		*
Policy			*								*			*			*				*	
Service Coordination							*										*					
INTERVENTION VARIABLES																						
Workload			*	*	*	*							*	*		*		*				
Nursing Unit																*		*				
Shift																*			*			
Varying Shift Length									*													
Day of Week				*												*		*				
Month										*						*		*				
Admissions							*			*										*		
Patient Census								*		*								*			*	
Employee Preferences	*														*							
Personnel Policies	*	*		*			*				*			*				*	*		*	
Desired Staffing	*	*																	*			*
Minimum Staff Requirements	*			*														*	*		*	
Patient Classification				*					*	*			*								*	
Full Time & Part Time Staff							*				*			*	*			*				
Facility Size/Capacity																						
Waiting Time																						
Diagnosis																						
Absenteeism													*		*							
Staff Mix		*	*	*	*	*	*				*			*							*	
[illegible]												*										

Work Force Scheduling

REFERENCE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
PERFORMANCE MEASURES																						
Actual Census																*						
Penalty Costs																						
Employee Satisfaction										*												
Variance																		*				
Total Hours Worked									*						*							
Number of Employees															*				*			
Staff Effectiveness		*									*											
Staff Mix				*																		
Patient Throughput													*									
Workload								*				*								*		
Waiting Time																						*
Queue Length																						*
Demand for Service							*															*
Costs		*	*	*				*		*	*			*	*				*		*	
Revenue			*																			
Benefits for Staff																						
Patient Outcome										*		*			*							
Appropriate Assignment				*																	*	
Appropriate Staffing					*	*	*															
Staff Efficiency											*											
METHODOLOGY																						
Queue											*											*
Network									*										*			
Utility		*																				
Budget			*								*											
Statistical				*	*	*	*					*		*		*		*				
Linear/Integer Programming		*		*					*									*			*	*
Nonlinear Programming	*						*															
Simulation							*	*		*	*				*					*		*
C/B or C/E																						
Other			*	*	*	*		*					*	*					*			

Work Force Scheduling

REFERENCE	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
TARGET SERVICE															
Nursing	*	*				*			*			*	*	*	
Laboratory			*												
Respiratory Therapy															
Emergency Department											*				
Obstetrics/Gynecology				*											
Pharmacy					*										
Outpatient										*					*
Ancillary												*			
Physicians								*			*				
Anesthesia				*			*								
Long Term Care															
SYSTEM LEVEL															
Forecast Workload		*													
Scheduling	*									*	*		*		
Manpower Planning				*	*		*	*						*	*
Policy									*						
Service Coordination						*						*			
INTERVENTION VARIABLES															
Workload				*	*			*	*			*	*	*	*
Nursing Unit	*					*							*		
Shift	*											*	*		
Varying Shift Length															
Day of Week	*										*		*		
Month															
Admissions			*									*			
Patient Census			*			*			*						*
Employee Preferences	*												*		
Personnel Policies	*								*				*		*
Desired Staffing															*
Minimum Staff Requirements							*		*		*	*			*
Patient Classification		*		*		*			*					*	
Full Time & Part Time Staff	*				*										*
Facility Size/Capacity										*					*
Waiting Time											*				
Diagnosis										*					
Absenteeism							*								
Staff Mix				*				*	*						*
[illegible]															

Work Force Scheduling

REFERENCE	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
PERFORMANCE MEASURES															
Actual Census															
Penalty Costs	*														
Employee Satisfaction	*														
Variance	*											*		*	
Total Hours Worked															
Number of Employees															*
Staff Effectiveness															*
Staff Mix									*						
Patient Throughput															*
Workload		*	*				*	*	*			*			*
Waiting Time					*						*				
Queue Length											*				
Demand for Service				*			*								*
Costs	*							*	*	*				*	*
Revenue															
Benefits for Staff						*			*						
Patient Outcome															*
Appropriate Assignment															
Appropriate Staffing						*	*								
Staff Efficiency															
METHODOLOGY															
Queue					*						*				
Network															
Utility															
Budget									*					*	
Statistical		*	*			*						*		*	
Linear/Integer Programming										*			*		
Nonlinear Programming	*								*						
Simulation				*	*		*				*				
C/B or C/E															*
Other		*				*		*	*			*			*

9. Strategic Planning

In order to prepare for a future conducive to the achievement of its goals an organization must plan. It is not a question of why to plan or of when to plan. Strategic planning must go on continuously to give direction to the organization and to provide criteria on which to measure achievements. The only questions of interest to organizations which do strategic planning is how to plan, what to plan and when and what to implement from the plan.

OR's contribution to strategic planning is a newer phenomena than the idea of strategic planning itself which finds its origins in the earliest recorded histories of Babylonia and the Bible. For centuries, strategic planning was done by individuals and/or small groups of leaders. They would determine the mission, objectives and courses of action for their organization or state. But times have changed and the level of complexity introduced in strategic planning frequently requires systematic and analytical approaches to planning. Most health care delivery organizations now have complex structures, highly developed and rapidly growing technologies, a wide range of skilled and talented personnel, major interactions with many other social, political and economic structures and coordination and competition with many other health care delivery institutions.

Although the earliest work in OR for the war effort before and during World War II had major strategic implications, the early OR work in health care delivery has been characterized primarily by tactical operational studies, a few of which had strategic components. Recognition of the many successes of operations research in tactics and operations raised the question about using it further for strategic planning purposes. In some cases it is an excellent tool and in others it has not been as useful.

OR's contribution to the strategic planning effort hinges on several aspects innate to the model building effort underlying OR analyses. Because the nature of an operations research activity involves some type of model this means it is essential to understand clearly the goals and objectives of the organization and to understand the systematic workings and functions of the organization. OR models this structure, its system flows and cause-effect relationships in order to formulate alternative courses of action. OR then provides mechanisms to evaluate these alternatives based on the system's objectives subject to those factors which constrain the system's productivity or effectiveness. OR then asks "what if" questions about different future scenarios and after an alternative is chosen, OR aids in the process of implementation and evaluations. Finally, since the strategic planning of complex situations should be done as an interactive group process, the OR person as a member of a team of people from the medical, legal, technical, social, political and/or financial areas provides the modelling framework to build a clear and common view of the problem.

The OR studies in the section on strategic planning are organized in three groups. The first are those studies which provide comprehensive health care delivery models for defined populations. These models not only analyze the optimal allocation and utilization of resources, but also the movement of patients through the care delivery process. The second set of review articles are those which look only at the allocation and utilization of a few specific resources such as the number of beds, number of physicians, number of health visitors, etc. The third set of studies handles planning for specialized health care delivery functions such as the creation of health promotion centers, kidney transplantation needs, the number and size of burn care centers, etc.

Comprehensive Health Care Delivery for Defined Populations

Possibly the most extensive strategic planning OR effort in the health care setting has been undertaken by the Operational Research Services Group of the Department of Health and Social Security in the United Kingdom. Strategic planning for Health and Personal Social Services (HPSS) by the ORS began in the early 1970s. The issue was that there is a large number of health and of personal social services which are often independently given to many sub-groups within the population such as the elderly, the mentally ill or handicapped, the physically handicapped and others which have certain characteristics in common. For example, there is often a wide range of alternatives in coordinating and delivering care to these persons at widely different costs. Overlapping and often competing services were being provided by several different organizations each facing difficult financial constraints. Furthermore each organization had a range of professional opinions about the desirability of alternative patterns of care and resource uses. Coupling this lack of coordination with the lack of data on how care was currently being given, lack of a structure or model for organizing the data and for evaluating alternative plans for the future contributed to the need for a comprehensive analysis of this very complex system of care delivery to these populations. The result was the "Balance of Care" project (BOC). Other reviews have documented some of the earlier work on this project. The BOC model was originally formulated as a linear program with the objective of minimizing the total cost of the system subject to constraints that all persons received an "ideal level" of care and that the resource availabilities were not exceeded. The idea was to find the most cost-effective resource allocation for the defined populations. Ideal levels of care had been prescribed by the field workers-physicians, nurses, social workers and others. It was soon realized that there were no feasible solutions to the problem. The budget of the Department of Health and Social Security could not deliver the ideal levels of care to these persons. Consequently it was decided to try goal programming and multi-objective programming approaches to find the best possible care delivery within available resources. This approach subsequently evolved into constructing an "inferred worth" mixed integer mathematical programming model which determined the acceptable levels of care within budgetary and other resource constraints. These acceptable levels of care were also defined by the workers in the field. Indeed, the inferred worth objective function is essentially the utility function of these field workers for care for their clients. This model was quite complex involving relationships among various types of services using resources such as nursing home beds, acute beds, geriatric and/or medical beds, hostel beds, psychiatric community nurses, domiciliary physiotherapists, home nurses, health visitors, etc. The model had 31 services with differing resources utilization. There were six client groups involving the elderly, the mentally ill, the physically handicapped, etc. who could be classified into 145 categories of health care and/or social needs such as appendicitis, hernia, varicose veins, depression, nutrition, family relationships, community interaction, etc. Finally, there were up to 13 modes of care delivery such as normal hospital stays, day surgery, adult training center days, home help, meals on wheels, etc. Since conceptually every client could participate in every service from every category of health care delivery in every mode of treatment, there were 31x6x145x13=350,610 different cells in this classification scheme. Not all of the cells were permitted however. Only those cells defined by field workers as most important were analyzed in the model. The model then tried to provide the types of care that delivered the best acceptable levels of care to all persons in the service population subject to the budget and resource constraints of the Department of Health and Social Services. It should be noted that the health aspects of care were centrally planned through the National Health Service system and the personal social services aspects were decentrally planned through the local social service authorities in the districts. There was a great need for coordination and cooperation between these groups in implementing the results of the study. The model was first applied at the national level to determine overall resource needs from the governmental authorities. Later, it was applied at the local level by the area and the district health and social services authorities. These authorities determined the specific tactical and operational programs for the clients within their district or area.

Because the BOC model was a very complex system and needed a large computer and much data, it was difficult to operate at the local level. To make it more broadly useful, it has recently been divided into subsystems involving particular client groupings. Assumptions are made about resource consumption between a particular client grouping and other client groupings that simplify the math programming model such that heuristic rules can be used. Some submodels of the BOC model are available on a microcomputer that utilizes data base management and spread sheet systems for the analysis.

The Balance of Care model is described in the papers by Coverdale and Negrine (1978) and Gibbs (1978). Good discussions of the application of using the Balance of Care model in various districts within England are given by Borley, et. al, (1981) and Nicholls (1981). Finally, the paper by Boldy (1987) gives a brief update of the history and current status of the model.

In an interesting study done in the United States by Burton et al. (1978) the problem was posed to devise a method for evaluating alternatives to institutionalization for the elderly. It quickly became apparent to the OR group that the problem should be broadened to include institutionalization as one component along with other innovative proposals and existing programs such as nutrition, meals on wheels, mental health, homemaker services, medicare/medicaid, welfare, legal aid, clinics, counseling, housing and a variety of volunteer programs as well as other standard institutional programs dealing with acute and long-term care. What was needed was a cost effective solution selecting among these alternatives. This is a large complex problem requiring the technical knowledge of a large number of professionals and health services delivery personnel. A multidisciplinary team of OR experts, general practitioners, nurses, community physicians, administrators, social workers, community representatives and elderly clients was assembled to analyze the problem and alternatives. The OR members of the team structured the model working closely with all of the other members to form an integrated plan. The OR team constructed a linear programming model using a first order Markov chain for evaluating the various care delivery packages for the elderly. The work involved 20 to 30 team members and took more than four years to complete. In similarity with the Balance of Care model, packages of care were defined depending on the services needed by the elderly at different stages of their health and physical and mental well-being. These service packages linked the types of services to the particular types of facilities depending on the health and social status (state) of the patient and the available resources. The model was used to analyze and improve the status quo, by asking "what if" questions about needs and future resource availabilities. The Markov model handled changes in patients' health and social stati (states) resulting from the various interventions and analyzed patient movements over time from one set of states and service packages to another.

Besides the model building and structuring, the OR members facilitated team effectiveness and interactions by helping the team develop a common set of definitions for patients, services and service packages, procedures for estimating the cost of providing service packages under alternative delivery systems, and a system for determining the status (state) of individual elderly persons and procedures for obtaining the transition probabilities in the Markov chain. The model was applied to study the delivery of services in Durham, North Carolina and in Cleveland, Ohio.

Just as Burton et al. (1978) considered regional strategic and operational planning for only a single large population subgroup (the elderly), Leff et al. (1986) considered a single population subgroup the mentally ill. Working with persons from the mental health care delivery system, these authors constructed an OR model that chooses among various program packages and allocates resources among alternative therapies available for treatment of the mentally ill. The model is a large linear program incorporating a Markov chain which handles the transitions among different functioning levels (states) of patients depending upon the specific therapies used for treatment and the different outcomes they might produce. The patients could move forward or retrogress in their treatment. The model was used to analyze the status quo and to do sensitivity analysis on different objectives and goals under changing resource constraints on the system.

The model is dynamic so that over time progressions through various treatment modalities and resource availabilities can be evaluated. New patients enter the system annually and patients leave cured or for other reasons. The types of service packages available involve custodial, adaptive and promotive service options. The overall goal of the model is to provide those service packages that increase clients function levels in a cost effective manner. Increase in function level can be viewed in various ways. The authors specifically locate those service packages that (1) maximize the net overall function level, (2) maximize the total forward improvement function level, (3) minimize the number of clients at the lowest end of the function level range, and (4) minimize the overall total census in all function levels by the end of the strategic planning period. These different objectives result in slightly different resource usages and different service packages. Decisions then must be made appropriately by the community for those clients in the region.

In another paper dealing with mental health services provisions, Franz et al. (1984) suggest a chance constrained multi-objective mathematical programming model using sequential solutions of linear programs to minimize a weighted multi-objective function. The function includes such goals as remaining within budget, reducing regional center patient loads, meeting a projected increase in demand, maintaining psychiatric hours within the range available, providing mental health education for the patient, providing in-school education programs and keeping total staff hours within the range available. These goals are to be achieved in a probabilistic sense in that the treatment plans should be chosen so that the stated goal would be achieved within a given preassigned probability. The priorities and the probabilities for the different goals would be set by the providers and managers of mental health care delivery within a region. The model is quite complex and would be difficult to explain to providers and managers in the system.

Finally, it should be mentioned in this section that the paper by Lane et al. (1985) discussed in the Service Demand Forecasting section of this review may also be used for strategic planning and resource allocation for the elderly needing different care packages depending on their different function levels at the time. As the researchers note, the Markov chain model did the best job of forecasting the transitions of people over time among different service packages involving nursing homes, home health and extended care facilities. The same Markov chain model could also be used to plan for the appropriate resources in these different transition stages.

Strategic Planning for Specific Resource Availability and Utilization

The models in this section deal with strategic questions such as what should be the number of beds and number of physicians or other personnel by services to meet the needs of a region, a hospital or other institutions. Indeed most of the papers are concerned with the planning for optimal number of beds or physicians by service to meet regional or hospital needs.

In a strategic planning model for a regional planning agency, Ruth (1981) constructed a mixed integer mathematical programming model to plan the medical and surgical bed needs for the region for a given time period. It is a large comprehensive model that takes into consideration characteristics of the population in the region, the levels of care needed regarding the number of primary, secondary or tertiary beds, the locations of the hospitals and a quality measure concerning the conformance of beds to predetermined standards. The objective of the regional planner in this case is to determine the most cost effective allocation of beds to hospitals by levels of care and locations that meets the needs for accessibility of patients to services at appropriate quality levels. Ruth then applied the model to data from the state of Rhode Island hospital system as an illustration of its planning capabilities.

In another paper in the same topic area, Duncan and Nobel (1979) constructed a linear programming network flow model for planning the availability as well as the allocation of hospital beds by specialty within each hospital within a health district. The total number of beds in each specialty at each hospital are constrained by upper and lower bounds. These bounds are set by the planning agency or by the physical constraints of the hospitals in the network. The objective of the network flow model is to maximize the total number of beds in the system subject to budgetary and other resource constraints and the upper and lower bounds. This objective was chosen as a proxy for providing the maximum amount of care for a given cost. Taket and Mayhew (1981) used a simple gravity model and a population morbidity model to forecast the needs and uses of a health facility in a region. This model is intended to be used for strategic planning for the number of beds and distribution of inpatient facilities in different localities. Building a more complex model, Aspden et al. (1981) constructed a model for health care resource allocation in Czechoslovakia. Their model is a non-linear mathematical program that plans for the consequences of changes in resource levels, the number of patients in various clinical categories and the quality and amount of care received. The outputs are the number of beds and physicians by specialties for the entire country. They illustrate the model by examining data involving seven specialty categories--general surgery, general medicine, obstetrics and gynecology, traumatic and orthopedic surgery, otorhinolaryngology, pediatrics and opthamology. Finally, in a paper that also deals with determining the appropriate number of physicians and short-term general hospital beds in a region, Anderson and Bartkus (1984) constructed an econometric simultaneous equation model to forecast the needs for these resources for the state of Indiana. This paper is more of a forecasting model than a strategic planning and allocation model because it does not consider other resources, costs or the locations of the beds and physicians in the state.

None of the above models for planning the number of beds and/or physicians consider the use of other resources or other types of health care facilities or changing technologies. Consequently, these models do not handle the impact on resource needs and availabilities caused by such factors as ambulatory surgery, earlier discharges to other facilities and the home, increase in psychiatric beds, and changing nursing patterns. The models are more useful for shorter planning horizons because they make implicit assumptions that the exogenous factors affecting bed and physician utilization are changing very little over the planning horizon except perhaps for demographic and morbidity level changes by specialty. In recent years many other factors are causing significant changes in bed utilization. So for longer horizons these and other factors would need to be included in these models.

Using a stochastic model for strategic planning at a single institution, Graves et al. (1983) modelled the competitive impact on a public hospital of an increase of the number of mental health psychiatric beds at a nearby general hospital. They use two queueing models, one for the public hospital and one for the general hospital to measure the impact of this change on the occupancy and treatment plans at the hospitals. The model does not directly account for multi-year long-term chronic patients at the public hospital and consequently underestimated bed needs. These patients could have been considered by a modification of the model or by separately analyzing their needs and incorporating the results later. For example, in the Markov model, transitions could be allowed to a state where patients became long-term (hence almost permanent) chronic bed-users. These patients would then slowly transition out of the state to death or other states. The model showed that the public hospital faced strong competitive losses of insurance paying shorter term patients from the beds' increase at the private hospital.

For many years operations researchers have considered the problem of strategic planning for adequate numbers of health care professionals in various institutions, regions, states and the nation. Much work was done in the 1970s under the various manpower planning acts and recently some work has been going on in nursing, but little is being done in other health personnel areas. (The nursing area is covered elsewhere in this review.) There are only four papers to mention on the recent literature on resource planning for health care personnel. In their paper, Edwards et al. (1983) present a deterministic input-output linear flow model to forecast and assess the need for care given by health visitors (nurses, social workers, etc.) in an NHS District in England. Exogenous factors in the model were the geography and demography of the district, the clients' expectations for care delivery and other characteristics of the National Health Service Delivery System itself. The independent variables under the control of the district were the budgets for health visitors within certain ranges, work levels and service relationships with the general practitioners, and clerical and physical office support. The purpose of the model was to plan the health visitor workload, the types and needs of clients covered by the visits and the costs of the visits. Variations in the exogenous factors as well as other parameters were analyzed by using sensitivity analysis for different scenarios via an interactive computer program. From the final outputs of the model, recommendations were made at the district and area levels for providing health visitor services.

Berghmans et al. (1984) were concerned with determining the number, common size and location of health centers for a new city being built in Saudi Arabia. Since the city was being created de novo, the authors had the ability to plan the structure for the entire health facilities system. The number and types of medical and health care delivery personnel needed to staff these sites were given by the size of the facilities. The authors model this location problem as a version of the classical p-centers problem in operations research that is to find the location of the facilities in a region to minimize some function of costs or travel distance so that all of the customers in the region were no further than a given distance from a location where they could receive service. The algorithm for the p-centers problem gives a minimal cost or minimal distance solution for the location of the facilities. Because the facilities were structured to be identical in size and composition, this solution also provided planning for all of the personnel needed at each site.

In two papers, Ittig (1978a and 1978b) represents a linear programming model for planning the levels of physicians by specialty and service for an HMO in a region. The model determines the minimum cost solution for the number of primary and secondary services physicians for an HMO based on population demographics, support service needs and inpatient referral needs. The model is based on the flow of patients internally through the

HMO and externally through the hospital and emergency rooms. Because the model is a linear program, it does not capture the nonlinear relationships that trade off the amounts of ambulatory services and levels of hospitalization and the amounts of primary care given by secondary services physicians and vice versa. The form of these nonlinearities are generally difficult to determine and frequently data is not available for their measurement. The model was applied to data from the Buffalo, New York region.

Taking a different perspective on planning, Morey and Dittman (1984) presented a nonlinear programming model to plan for price and/or cost changes on the profit/surplus funds available to a hospital for future uses. The approach of the model is to establish prices and allocate costs appropriately among the services in the hospital to maximize the profit or net surplus to the hospital. This planning model is useful to a hospital facing continually changing reimbursement schemes. It perhaps had more applicability in the days of retrospective reimbursement; however, the appropriate allocation of overhead and other costs still applies to profit maximization today.

A linear programming model of a diagnostic radiology department is presented by Hosios et al. (1978) to optimally allocate radiographic equipment dollars to the hospitals in a region in Canada. Because input/output models are currently in use in the area, the extension of I/O models to a linear program was an obvious next step for the planners in the region. The model tradesoff several objectives involving efficiency and costs. However, it does not include objectives or constraints involving quality of radiographs or different equipment-technician configurations. Modifications of the model along these lines could be made but were not presented in this paper.

In a totally different area of strategy and planning, Lee et al. (1987) built a series of connected models to model the costs and outputs of education in medical schools in a state. The particular state was concerned that medical education costs were growing at a rate that the state could not fund. Researchers were also concerned with over and under supplies of physicians in different regions within the state. The overall model consisted of a linear Markov flow model of the medical school education process combined with nonlinear financial flow and policy evaluating submodels. The outputs for the model were the number of medical schools and the levels of faculty, facilities and financial resources needed to educate various numbers and specialty types of medical students in the state under different policy scenarios. The model was used by the Board of Regents in the state to present proposals to the state legislature for future funding. Long-term outputs of the model were the number of physicians by various specialty categories practicing in different parts of the state to meet the changing needs of the population.

<u>Strategic Planning for Specialized Health Care Delivery Functions</u>

By changing their organizational structures and by introducing new medical care technologies, hospitals have increasingly done strategic and tactical planning for the introduction of new programs. At the regional level, public health authorities have also developed plans for the introduction and control of new technologies, programs and organizational structures to prevent disease and reduce morbidity and mortality in their regions.

Hatcher and Rao (1984, 1985) used a simulation model to measure the impact on a hospital's revenues from opening a health promotion center affiliated with the hospital. The health promotion center could include such components as a wellness center, a cafe, a minimarket, cardiac rehabilitation, patient counseling, child care and adult care. The model uses as inputs, various demographics of the potential user populations, resources and growth rates in the area, and fixed and variable costs of providing the various components of the center. Outputs of the model are the total profits and losses to the hospital, levels and types of services provided, resources consumed in the services, and value to the community in terms of morbidity and mortality. The decisions to be made were whether to add or delete a component, introduce new technologies, market to different populations in the area and determine the amount of staff and other resources needed.

In a series of studies over several years, Davies (1979, 1985a, 1985b) and Davies and Davies (1986, 1987) present a complex simulation model to plan renal dialysis and kidney transplantation services in a region, a country or groups of countries. The model forecasts dialysis machine and kidney transplant needs and the effects on waiting lists as well as costs of different availabilities of these resources. In the earliest paper, the model had been developed to plan resource needs for a single renal unit. Later, sophisticated matching and other medical technology capabilities were added to the model and the geographic scope of the model was broadened to include much larger regions. The model now incorporates the progression of patients through various treatment regimens and incorporates patient and donor organ characteristics, treatment history and treatment availability. It still evaluates the effects on waiting lists and costs so that planners can make decisions on how to structure regional or national organ donor pools and technology availabilities. The model is available to British health officials and has recently been made available to other members of the European Economic Community.

Using a queueing network model, Blair and Lawrence (1981) built a hierarchical network for planning the availability of burn care units and the number of burn care beds in each HSA region in New York. The model combined a Markov process with a heuristic optimization technique. The idea of the network hierarchy was that burn patients were to be treated in their own HSA area until all of the beds were full. The overflow patients would then be sent to empty beds at other HSAs according to certain protocols. Because it was an interacting network of burn units rather than individual noninteracting units, researchers were able to show that the number of beds could be significantly reduced by the sharing excess demand. It was quite unlikely that all beds in all regions would be full at the same time so that overall less beds were needed and significant cost reductions could be realized.

There was a time in the late 1970s and early 1980s when the federal government was experimenting with large community intervention programs to control hypertension. Much of the expenditures of these programs were aimed at encouraging people to seek blood pressure testing at a facility in their region. Nichols and Weinstein (1978) set up a sequential flow model to determine the optimal allocation of resources for hypertension control programs. A key and important finding of their model was that expenditures at later stages of the decision process yield greater results in hypertension control than expenditures at the early stages. Essentially they found that it was much more cost effective to direct programmatic resources to encourage those patients who began treatment to continue their treatment (and thereby control their hypertension) than to target public relations and advertising at the general population to seek testing. The reason for the cost effectiveness at the treatment rather than the screening stage is that most persons with hypertension do not seek treatment or do not seek secondary screening and confirmation even though their first screen is positive. Hence, the dollars directed toward initial screening are largely wasted. This is an important finding if society wishes to reduce the total amount of hypertension in the population in a low cost manner. In a follow-on note, Ahmed (1978) generalizes the Nichols and Weinstein model, improves the algorithm and tests the sensitivity of the finding when other forms of cost functions are utilized. He shows that the Nichols and Weinstein results still hold under these different cost functions.

Tingley and Liebman (1984) constructed a linear integer goal program to allocate funds to state agencies for nutritional food programs for Women, Infants and Children in a state. The model is based on a priority system that categorizes the participants by their conditions and needs and allows a weighting of the priorities to achieve competing goals. The outputs of the model are the resource allocations for delivering certain levels of services to the different categories of participants. Data from Indiana were used to analyze the sensitivity of the model to different priority weights and goals.

An issue that frequently arises in nursing homes is whether (i) the home should utilize beds that become empty when residents go to an acute care hospital for treatment and then place them on a priority list for the first open beds on their return or (ii) hold the original beds open until their return. Hannan and Gimbrone (1987) analyzed the issue using a queueing simulation model to test these two readmission strategies for the nursing home. They showed that holding the original beds open was less expensive than the priority readmission strategy because the latter strategy frequently resulted in significantly longer stays at the acute care hospital because return beds were not available at the nursing home. This result held under varying sizes of nursing homes (beds), types (skilled or other), number of days held in reserve for the patient (30 to 210 days) and sex of patient/patient bed ward.

In summary OR strategic planning has been undertaken in health care delivery at national, regional, local and institutional levels to provide lower cost, better access, higher quality or wider ranges of services to groups within the population. More can be done in this regard as we face changing technologies, demographics, and political, economic and social structures in health care delivery.

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TARGET SERVICE																				
Balance of Care						*	*		*									*		
Care for the Aged								*												*
Mental Health																	*		*	
Hospital(s)		*		*						*					*				*	
Health Maintenance Organization																				
Regional/National Health Care			*	*	*						*	*	*	*						*
Physicians		*		*																
Home Care																				
Nursing Home/Long Term Care																				*
Health Care Personnel				*																
Radiology Services																				
Kidney Transplant/Dialysis										*	*	*	*	*						
Burn Care					*															
Hypertension Control	*																			
INTERVENTION VARIABLES																				
Institutional Care					*			*												*
Custodial Care																				*
Adaptive Care	*				*					*	*	*	*	*						
Health Promotion	*																			
Nutrition Program								*												
Meals on Wheels								*												
Mental Health Services								*												
Homemaker Services								*												
Medicare/Medicaid								*												*
Welfare								*												
Legal Aid								*												
Gerontology Clinics								*												
Social Services Counseling								*												
Housing								*												
Volunteer Programs								*												
Social Status of Clients								*												
Health Status of Clients	*		*					*		*	*	*	*	*						*
Functional Level																				*
Alternative Therapies										*	*	*	*	*						
Resources Available			*		*					*	*	*	*	*	*	*				
Population Demographics		*																		
Hospital Locations																				
Quality of Care			*																	
Beds Available				*	*										*				*	*
Amount of Care Recieved			*	*	*					*	*	*	*	*		*				
Econometric Factors		*																		
Competitor Activity																			*	
[illegible]										*	*	*	*	*						*

Strategic Planning

REFERENCE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PERFORMANCE MEASURES																				
Health Status								*		*	*	*	*	*		*				
Social Status								*												
Cost	*			*	*			*		*	*	*	*	*	*	*	*		*	*
Functional Level										*	*	*	*	*		*				
Regional Patient Load					*					*	*	*	*	*		*	*			*
Percent of Demand Satisfied					*												*			
Service Utilization					*					*	*	*	*	*						*
Patient Education																	*			
Staff Utilization				*												*	*			
Patient Outcomes	*									*	*	*	*	*						
Location of Services				*																
Number of Beds Available		*	*		*										*					*
Number of Physicians Required		*	*	*																
Treatment Plan																			*	
Bed Utilization																			*	*
Surplus Funds/Profits																				
Medical Education																				
METHODOLOGY																				
Linear/Integer Programming								*							*	*	*			
Nonlinear Programming			*														*			
Simulation										*	*	*	*	*						*
Markov					*			*												
Queueing					*														*	*
C/B or C/E																				
Network					*										*					
Utility																				
Statistical																				
Other	*	*		*																

REFERENCE	21	22	23	24	25	26	27	28	29	30	31	32	33	34
TARGET SERVICE														
Balance of Care										*				
Care for the Aged						*								
Mental Health								*						
Hospital(s)	*	*							*			*	*	
Health Maintenance Organization				*	*									
Regional/National Health Care			*	*	*		*							*
Physicians				*	*		*							
Home Care														
Nursing Home/Long Term Care														
Health Care Personnel														
Radiology Services			*											
Kidney Transplant/Dialysis														
Burn Care														
Hypertension Control											*			
INTERVENTION VARIABLES														
Institutional Care				*	*									
Custodial Care								*						
Adaptive Care								*			*			
Health Promotion	*	*						*			*			
Nutrition Program														*
Meals on Wheels														
Mental Health Services														
Homemaker Services														
Medicare/Medicaid														
Welfare														
Legal Aid														
Gerontology Clinics														
Social Services Counseling														
Housing														
Volunteer Programs														
Social Status of Clients				*	*									*
Health Status of Clients				*	*						*	*		*
Functional Level						*		*						
Alternative Therapies								*						
Resources Available	*	*					*	*						
Population Demographics	*	*		*	*		*					*	*	
Hospital Locations												*		
Quality of Care												*		
Beds Available														
Amount of Care Recieved			*											
Econometric Factors														
Competitor Activity														
Price and/or Cost Allocation	*	*	*						*					

Strategic Planning

REFERENCE	21	22	23	24	25	26	27	28	29	30	31	32	33	34
PERFORMANCE MEASURES														
Health Status	*	*						*						*
Social Status														
Cost	*	*	*	*	*		*	*			*	*		*
Functional Level						*		*						
Regional Patient Load														*
Percent of Demand Satisfied														
Service Utilization	*	*	*											
Patient Education														
Staff Utilization														
Patient Outcomes											*	*		
Location of Services												*	*	
Number of Beds Available													*	
Number of Physicians Required				*	*		*							
Treatment Plan														
Bed Utilization														
Surplus Funds/Profits	*	*												
Medical Education							*							
METHODOLOGY														
Linear/Integer Programming				*	*			*				*		*
Nonlinear Programming							*		*					
Simulation	*	*												
Markov						*	*	*						
Queueing														
C/B or C/E														
Network														
Utility														
Statistical														
Other											*			

10. Service Delivery

Operations research has significantly influenced the development of medical decision-making techniques. Medical decision-making is a field of study in its own right, and only a few studies representative of more elaborate OR applications in medical decision-making are included here. The development of artificial intelligence-based expert systems will continue to stimulate growth in this area. While some of these applications are concerned with specific treatment decisions, several address policy recommendations for dealing with major health problems, such as cervical cancer. Perhaps as notable as the many developments in the field of medical decision-making is the lack of OR approaches to similar problems for clinical decision makers in nursing, physical therapy, respiratory therapy, and other health care specialties.

Several researchers have addressed the problem of determining an optimal policy for screening for cervical cancer. Parkin and Moss (1986) evaluated nine screening policies for cervical cancer by simulating the policies over a thirty-year period. Screening results were calculated as reduction in mortality, reduction in person-years of life lost, and reduction in discounted life-years lost (discount rate 5%). Testing women over thirty-five at five-year intervals proved most cost-effective. The results were sensitive to the rate of compliance with the policy. Simulation was also used by Habbema et al. (1987) and Habbema et al. (1985), using the MISCAN software.

Their simulation also included quality of life-years as an outcome measure. Eddy (1983, 1987) developed and validated a Markovian model that predicted the effects of alternative cervical cancer screening strategies. The results were expressed in woman-years saved plotted against total cost, for each alternative frequency of screening, for women over twenty years of age. A revision of the model including more recent empirical data is presented in the later article. Eddy and many others have looked at optimal screening decisions for breast, colon-rectal and other forms of cancer.

In recent years much work has gone on for optimal screening and intervention for contagious diseases and, in particular, for HIV-AIDS. This literature has expanded enormously and as most of it does not include institutional decision-making, it is not reviewed here. The reader is referred to the policy review paper on OR policy models by Lee et al. (1989) for a description and taxonomy of papers in that area.

Kolesar (1980) developed an integer programming methodology for determining the best search of the visual field in glaucoma patients to detect vision loss. The model appears to provide a much more efficient search than current clinical methods. Sonderman and Abrahamson (1985) used linear and mixed-integer programming to design treatment regimens for radiation therapy of malignant tumors. The model identifies the optimal direction and intensity of the beams for treatment. Application to a specific case is included.

The appropriate medical decision regarding accepting or declining a transplant opportunity is becoming routine. David and Yechiali (1985) developed a mathematical model of this situation as a time-dependent stopping problem that has a time-dependent failure rate, and a nonhomogeneous Poisson arrival rate. Application of the model to actual kidney transplant data enabled the researchers to determine the optimal transplant policy.

McCann-Rugg et al. (1983) described a goal-programming application that calculated appropriate diets for diabetic patients. The program allowed the operator to customize the diet to suit individual food preferences, while adhering to recommended nutritional standards for fat, protein, vitamins, and minerals. The program output was compared to manual calculation of such diets. The computer model was significantly faster, was equal to manual calculation in meeting most nutritional requirements, and came much closer to satisfying goals for total calories and fat content.

Computer-based treatment planning has been described by several investigators. A Markovian model was described by Leonard and Kilpatrick (1978) with a specific application to the treatment of a dental disorder. The model produced optimal treatment selection that achieved 93% agreement with two clinical experts. The duration of discomfort following treatment, treatment and care system costs, and referral costs are included in the model's selection of optimal treatment. Patient opportunity costs (such as lost wages) were also included.

Roberts and Klein (1984a, 1984b) presented a detailed description and several applications of a new simulation language, SLN, designed to model and simulate logical networks. They used the technique to simulate a variety of medical decision processes, including end-stage renal disease, chronic stable angina, renal artery stenosis, hypertension, and hypercholesterolemia. England (1988) used the SLN language to evaluate an exponential receiver operating characteristics (EROC) model. He evaluated the performance of the EROC model against the maximum-likelihood estimate method, and found the EROC model equally effective for curve fitting, but especially helpful in selection of an operating point for multiple sequential tests. Moye and Roberts (1982) developed a stochastic model for pharmacologic treatment of hypertension including five patient outcomes and two cost outcomes. Drug potency, side effect occurrence, patient compliance, and cost are combined to represent both physician and patient perspectives on the therapy. Assumptions were made about medical, economic, and psychological factors that affect the effectiveness of treatment. The model, compared with empirical data, accurately predicted the distribution of patients among treatments, and yielded valuable information about the efficacy of various therapeutic combinations.

Medical decision-making relies to some extent on subjective judgement. Fryback and Keeney (1983) constructed a trauma severity index based on one physician's professional judgement. Multi-attribute utility theory was used to develop the index in a two-stage process. First, a trauma severity index was determined for the optimal patient (a disease-free twenty-five year old.) Then an adjustment was made for other ages and health states. The model includes nonmonotonic utility functions for various physiological functions, as well as interdependent functions. The model appears to have strong face and construct validity.

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Service Delivery

REFERENCE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
TARGET SERVICE															
Women		*	*			*	*					*			
Kidney Transplant	*														
Respiratory Therapy															
Diabetics										*					
Dental Disorder									*						
Radiology/Radiation Treatment				*											*
Trauma Patients					*										
Other											*		*	*	
INTERVENTION VARIABLES															
Screening Interval		*	*			*	*					*			
Rate of Compliance											*	*			
Radiation Treatment															*
Organ Arrival Rate	*														
Organ Failure Rate	*														
Food Preferences										*					
Nutritional Standards										*					
Discomfort									*						
Treatment Cost									*		*				
Referral Cost									*						
Patient Opportunity Cost									*						
Drug Potency											*				
Side Effect Occurrence											*				
Age					*										
Health Status					*										
PERFORMANCE MEASURES															
Mortality Reduction						*	*					*			
Person-Years Lost		*	*			*	*					*			
Discounted Life Years						*	*					*			
Quality of Life Years						*	*								
Calcualtion Speed										*					
Nutritional Value										*					
Total Calories										*					
Agreement with Experts									*						
Patient Outcomes											*				
Cost											*				
Validity					*										

Service Delivery

REFERENCE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
METHODOLOGY															
Linear/Integer Programming								*							*
Nonlinear Programming										*					
Simulation				*		*	*					*	*	*	
Markov		*	*						*						
C/B or C/E		*	*			*	*					*			
Network				*										*	
Utility					*										
Statistical											*				
Other	*	*	*		*						*				

Further Research

Operations research applications in health care are becoming more sophisticated. Many of the developments of the past decade demonstrate that health care decisions rarely consist of achieving one objective. Techniques allowing pursuit of multiple objectives involving the cost, availability and quality of care can contribute much to making explicit the interactions of these objectives as decisions are made to deliver low-cost, high-quality health care under the many constraints of the present health care environment. Other developments, particularly in models of "packages of care" to manage the appropriate care in the appropriate setting for large numbers of patients, have considered the integration of health and social work programs in large, complex care delivery settings.

Unfortunately these developments, although sophisticated and comprehensive, have only been applied in a few places in Europe and the United States. Much more can and should be done to use OR ideas, techniques, modeling approaches, and implementation and evaluation methods to improve health care delivery. We will now suggest some of these possibilities for further research and application.

Presently in the United States, large computer information systems and data bases are being constructed, not only on patient records and charges in hospitals, HMOs, etc., but also on outcome measures of morbidity, severity, treatment effects and mortality.

Accounting systems are being installed that collect and allocate costs and resources used, rather than just charges applied to DRGs and other aspects of care delivery in and outside the hospital or HMO. Combining these databases with the available databases on personnel (skills, tasks, salaries, etc.), patient workloads, resource needs by DRG and severity, enrollee needs, utilization of resources in ambulatory settings, patient demographics, and data on institutions (e.g. their locations, capacities, structures, etc.), we are poised to do the types of analyses that can model treatment decisions involving efficacy and efficiency in managed-care programs broadly and in particular between and inside institutions.

Just as industry is realizing a great need for research inside and between divisions of companies on how to combine R & D, supplies, manufacturing, distribution, sales, financing and marketing to deliver low-cost, high-quality products and services to meet consumer desires, health care delivery is also recognizing the necessity for research to integrate appropriate care at the appropriate time in the appropriate place to deliver low-cost, high-quality, available care to meet patient needs. Much of the industry-based OR research can be modified, adapted and applied to research and applications in the health care system. However, some new approaches, unique to health care issues, will need to be developed.

In the next decade, one of the highest payoff research and application areas in the sense of reducing costs and improving quality of care delivery using OR modeling and analysis techniques is the linking of strategic planning decisions to decision-making at the tactical and operational levels of an organization. In doing optimal patient care scheduling, personnel scheduling (particularly nursing), ancillary services scheduling, inventory and process control modelling, etc. and linking these tactical and operational activities, it is essential to integrate these decisions with longer term models of nurse staffing task assignment structure, physician staffing availability, service changes, technological additions and improvements, new facility openings, facility closings, vertical care delivery additions, and other strategic changes.

In this way, smooth transitions and optimal solutions can be found that more globally achieve the various organizational objectives. More particularly, research needs to be done to study where and how cost economies of scale or scope can be achieved; and how quality improves or deteriorates with scale, scope, skill mix, organizational structures and performance. More work needs to be done on optimal selection of "packages of care" by different provider types and treatment effects on populations.

A recent study of primary care nursing in a large teaching hospital found that two-thirds of an RN's time was spent on non-nursing activities in which the RN qualification was neither needed nor used. That raises questions about whether this organizational mode is a good use of a scarce and costly resource. In another institution beleaguered by a nursing shortage, RNs are allowed (within wide ranges) to choose their hours, days and number of days they wish to work, thus putting a heavy burden on the use of outside registry nurses to fill the gaps in service. Clearly these are not efficient or effective approaches to quality and cost-effective patient care. They are at best stop-gap solutions to a difficult problem that can be more effectively solved.

Contrary to popular belief, higher quality care is possible at lower cost. Operations research has shown this to be true in manufacturing and in many service industries. It is also possible in health care delivery. However, there are many forces working against change and for the maintenance of the status quo. It will take the determined effort of teams of multi-discipline-based providers, administrators, OR analysts and, in some cases, governmental bureaucrats to provide higher quality, lower cost patient care.

As noted in the papers reviewed in this manuscript, there have been many successes in the past decade. However, with the constant changes in all aspects of society _ including the nature of medical care delivery _ there is continual need for new OR-based analyses to improve care delivery.