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Chapter 13

Applications of Operations Research in Health Care Delivery

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This chapter reviews the body of work in operations research in recent years which is devoted to health care delivery. Two important observations should be stated at the outset. First, although many problems faced by operations researchers in health care are not analytically different from problems in other industries, many others are quite unique due to certain characteristics of health care delivery systems. Some of these are the possibilities of death or low quality of remaining life, the difficulty in measuring quality and value of outcomes, the sharing of decisions among several decision makers (physicians, nurses and administrators), third party payment mechanisms for diagnoses and treatments, and the concept of health care access as a right of citizens in society. This chapter attempts to focus on areas involving these unique characteristics. Second, the breadth and richness of this field cannot be covered in the limited space here. Therefore problems, issues and principles are discussed with references provided for the inquisitive reader.

This chapter is separated into three major sections. First is system design and planning, which deals with large allocation decisions, both at the policy level and at the operational level. Second is management of operations, which examines monitoring and control methodologies at the operational and tactical levels. Third is medical management, which involves patient disease detection and treatment at the policy and at the patient levels.

1. System design and planning

1.1. Planning and strategy

In most industrially developed nations and in many developing nations, health care system design and planning occurs principally at the federal or regional level.

For the developed nations, with the exception of the United States, the interplay between history, culture, economics, politics, and other factors result in remarkably similar strategies for providing universal access and cost control, including some form of social insurance, common fee schedules for all payors, and formal or informal national budget caps. Because of these strategic choices, the federal and regional design and planning process largely determines the type and levels of facilities and technologies and frequently (perhaps implicitly) the levels of health care manpower and levels of services received by the population. This section covers the analytic tools developed in operations research to support these areas, such as regionalization, health districting and the expansion and contraction of services.

Regionalization of health care services is an important component of system planning and is common in countries such as the United Kingdom or Italy, but not in the United States due, in part, to the U.S. reliance on private markets for financing and delivery of health services. However, the operations research methodologies which underlie regionalization are robust and can be useful in the operation of multi-institutional systems, distribution of high technology equipment, and in other health care issues which could be useful in all health systems. Because regionalization is frequently sought to improve the cost or quality of a health care system through more effective distribution of services, regionalization questions are often optimal clustering problems (the decision maker attempts to partition the set services so that some objective is optimized) or resource allocation problems (the central authority must plan for and allocate scarce resources to regions or districts).

At the national planning level, Rizakow, Rosenhead & Reddington [1991] develop a decision support system, AIDSPLAN, which is a spreadsheet model to plan for the resources needed for HIV/AIDS related services in the United Kingdom. The model incorporates demand forecasting by patient categories, care protocols and resource and budget needs for central and local planners in the British National Health Service. It can also be used with the planning efforts of earlier math programming balance of care (BOC) models incorporated in micro-computer software to determine resource needs and allocations for entire health service regions and districts [Boldy, 1987; Bowen & Forte, 1987; Coverdale & Negrine, 1978].

Pezzella, Bonanno & Nicoletti [1981] provide an example of health service districting. In this paper, the authors develop a model by which local health departments in Italy are assigned into regional health structures. Dimensions of the analysis include an analysis of the demand for health services based on demographic, socio-economic, and geographical information, interviews with experts and surveys of special disease populations, and an analysis of available hospital services, which are considered in the proposed mathematical model for optimal districting. The authors note previous attempts to perform such regionalization by set partitioning, generalized assignment models, location and allocation models, and other linear programs. The authors use a linear program which has two objectives: to minimize the average distance of individuals from the nearest center, which improves access, and to minimize the deviation between proposed and existing districting which improves political acceptability. The model achieves the objectives by assigning hospitals to nuclei and then building reduced graphs in such a way that these distances are minimized. The authors apply the model to a case study of the Cosenza province in Italy and discuss two formulations of the optimal districting solution.

Another example of a regionalization question, the regionalization of CT scanners, is addressed by Bach & Hoberg [1985]. The authors consider total cost per year of a regional system of CT scanner operation, cost per scan, utilization levels, and average and maximum distance travelled by patients. They use a linear programming model which considers the total cost of operations for the CT scanner system as the sum of transportation costs (determined by patient travelling) and operational costs, such as staffing, supplies and facility support. The operational costs include fixed, threshold, and variable costs. The objective of the program is to minimize total cost. The authors apply the model to the Baden-Württemberg region in Germany. They consider a number of alternatives and rank-order them on the basis of total cost. They find that an increase in the number of CT scanners in a regional system does not necessarily increase the total cost of operation due to decreased travel costs.

Or & Pierskalla [1979] consider the problem of determining the optimal number and location of facilities in a region. Because the facilities involved are central blood banks, the researchers model the optimal allocation of specific hospital blood product needs to the central blood banks and the optimal number of routes of special delivery vehicles needed to make regular (routine) and emergency deliveries to hospitals. The unique characteristics of this problem involve the perishability of the various blood products. They present 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 system costs are minimized, and the hospital needs are met. With data from blood centers throughout the U.S., Cohen, Pierskalla & Sassetti [1987] demonstrate significant economies of scale within operating areas (such as laboratories, storage and administration) in central blood banks. Combining these results with actual transportation costs data, the authors evaluate site location and vehicle scheduling in the Chicago metropolitan area.

Many studies are conducted at the institutional level to plan the addition, expansion or contraction of services and facilities. In health care, this problem is complicated by the interdependence among services and among institutions created by crisscrossing physician privileges, patient comorbidities, unknown levels of latent demand, and potential creation of demand. To avoid these issues, most studies deal with self-contained services such as obstetrics, pediatrics, and psychiatry, or with broad-based workforce planning models. Schneider [1981] examines the question of how the closure of obstetric services might affect the case load and profitability of hospitals in three communities. He models three factors: comparability of services, patient load redistributions, and financial measures. Comparability of services determines if closures of services in some locations changes the overall regional level of service as measured by staffing, bed requirements, number of delivery rooms, and outcomes measures (including still births, neonatal mortality, percent primary Caesarian sections, and percent of breach deliveries). Patient load redistribution examines how the underlying patient volume is redistributed among remaining units after some units close and how this affects the service at related institutions. Financial analysis determines how direct, service-specific, and marginal costs are used to determine the net savings under closure conditions and the costs of increased services at remaining units that increase in volume. The author finds that most hospitals in the three communities would face significant losses on existing obstetric services, that five of seven hospitals would improve financial performance if their obstetric services closed, and that if one obstetric service were closed per community, overall costs would be reduced by 7–15% with comparable levels of service quality.

The opening of new services is also addressed. Romanin-Jacur & Facchin [1982] examine the effect of opening an independent pediatric semi-intensive care unit in a pediatric hospital. The unit would have its own rooms, staff, and instruments and be devoted to the care of severely ill patients. The question they raise is one of distribution of current capacity, in which the question is the reallocation of beds from the general ward to the new unit rather than addition to total capacity. The authors consider several classes of case arrival sources, including urgencies from the floors and the surgical ward, emergent admissions, and planned admissions. Each class is modeled with Poisson inter-arrival times for all services, except planned surgical operations, which are deterministic. Using length of stay from historical data, a simulation model is used to determine the optimal number of beds for the unit. The authors present a staffing schedule to optimize nurse distribution, based on optimal number of beds.

An important and frequently encountered question in service planning is whether a new service can improve productivity, quality, or cost performance in such a way that it is a desirable addition to other services offered by an institution or a health care system. In this setting, analysis with production functions can be of limited value and simulation models are frequently employed. For example, Hershey & Kropp [1979] analyze the productivity potential of physician's assistants. They observe that previous models predict that physician's assistants will expand service productivity. Although the authors acknowledge that there might be many non-economic arguments which explain this, their concern is that prior studies used production function analysis and perhaps, therefore, could have included systematic biases and flaws which overestimate the productivity potential of these professionals by underestimating costs such as congestion and supervision time of physicians. They develop a computer simulation model that incorporates more features and more complex details than had previous attempts. These include daily operating hours of the facilities, physical resources available, schedules of patients' appointments, patient arrival patterns, required services and service times, and sequencing of tasks to meet patient service requirements. The authors run the same information in a linear programming model and demonstrate that 393 patients can be seen per week in a practice with a physician's assistant, compared to 208 without one, and that net income and productivity will increase over time. However, because physician supervision time and congestion would increase during the initial periods of using a physician's assistant, there would be a significant short-term deterioration in patient waiting time without significant income increases. Thus, the authors conclude that although in the long term, full capacity utilization of physician assistants would increase productivity of physicians' practices, the short run costs may prohibit physicians from using them, probably because of initial losses in patient volume and the costs of supervisory time.

In a related application, Denton, Gafni, Spencer & Stoddart [1983] examine the savings from the adoption of nurse practitioners in Canada. The authors develop a cost model in order to estimate the costs of a parallel nurse practitioner–physician primary care model strategy, simulated over a 70 year period, 1980–2050, by using output of a demographic projection model. They find that nurse practitioners could reduce expenditures by 10–15% for all medical services and 16–24% for all ambulatory services in 1980, with increased savings over time. A sensitivity analysis demonstrates that these results were insensitive to age mix in the Canadian population.

1.2. Demand forecasting

Aggregate demand forecasting and daily census prediction is important in improving the efficiency of capital resource use in health care. Health services research tends to employ existing and well known operations research algorithms from other industries to perform forecasting rather than make new contributions to this literature. Because demand forecasting is a fundamental input to many other analyses in health care operations research, it is briefly included in this chapter. For example, demand forecasting is an important component of capacity utilization and service quality in hospitals, nursing homes, outpatient practices, and in nearly every other component of the health care system. Forecasting demand has two roles, the determination of aggregate need for services (the demand side), and census planning (the supply side). Analysis of demand on a daily basis drives hospital-wide decisions, including staffing, ancillary services, elective admission scheduling, and support services (including cleaning, food service, and linens), as well as decisions regarding new and contemplated services in the health care environment. Demand forecasting in health care resembles the structure of the aggregate planning problem in the manufacturing environment.

In excellent reviews of forecasting techniques, Harrington [1977] and Hogarth & Makridakis [1981] review the major techniques which are used in health care settings. First are qualitative approaches such as historical analysis, which employ analysis of similar settings or an organization's own institutional history to determine future demand. This technique, while inexpensive and easy to use, ignores environmental changes and does not support the analysis of new venture decisions. Another qualitative approach is the Delphi technique, in which future predictions are extracted from experts. The process is repeated until a consensus emerges. The Delphi technique is susceptible to ideological biases which make it difficult to use in settings where predictions may not conform to standard views of system operation. The other major areas of demand forecasting, which is the focus of this section, are techniques for demand forecasting which are analytically based. These techniques are illustrated by the following articles.

Kamentzky, Shuman & Wolfe [1982] use least squares regression analysis to determine the demand for pre-hospital care in order to make ambulance staffing decisions. The authors employ several independent variables, including area population, area employment, and indicators of socio-economic status, and control variables, including operational and clinical categories. The socio-economic variables include demographic variables such as persons per household, mean age, and ratio of blue collar to white collar workers, and indicators of social well-being such as median family income and percent of families with female heads. Operational classifications include emergent cases, transport to hospitals, inter-hospital transport, standby, and volume. Clinical characteristics include cardiac status, trauma, life threatening emergency, or minor care. Using data from Pennsylvania, the authors find that the socio-economic, operational, and clinical variables are all significant in predicting unmet need, and they validate the model so that the transport system could be improved.

Kao & Tung [1980] use demand forecasting for inpatient services in the British health service. They employ an auto-regressive, integrated moving average (ARIMA) time series model to forecast demand for inpatient services. The procedure for model development, parameter estimation, and diagnostic checking involves the use of deterministic trends with regular differencing between periods so that the basic trend is changed from period to period. This model is stratified by patient service and month of year, so that monthly admissions and patient days can be forecasted by service and length of stay estimates can be made. Compared to actual data, the model produces forecast errors ranging from 21.5% (deviation from the predicted) in newborn nursery to 3.3% in psychiatry. The authors suggest that the demand forecasting system can be used for bed allocation and aggregate nurse planning.

Johansen, Bowles & Haney [1988] demonstrate a model for forecasting intermediate skilled home nursing needs which combines elements of simple observational models and complex statistical approaches, and was utilization-based rather than population-based. The authors restrict their model to outpatient variables that were uniformly, clearly, and consistently collected and coded, including principal and secondary diagnoses, patient disposition, nature of admission, hospital size, metropolitan area, and marital status. Medical and demographic factors describe four risk categories into which patients could be assigned, indicating their overall risk for intermittent home care services. The authors first perform two-way tabulations on patients on the basis of these variables, then determine the predicted number of patients in each category using weighted averages. The expected cost per skilled nursing service is obtained by multiplying the expected number of patients in each category by the mean cost per patient. Sensitivity analyses determine the effects of changes in the health care system on these estimates. The authors determine the probability of need for service given the risk level of the patient, which ranges from a probability of 5% for a low risk patient to 80% for a very high risk patient. The authors note that this model incorporates easily observable characteristics, and provides good performance accuracy when compared with real data.

Kao & Pokladnik [1978] describe adaptive forecasting of hospital census, demonstrating how institutional and exogenous variables can be used in forecasting models to improve accuracy longitudinally. The authors argue that such models should be analytically credible, yet simple and easy to use. In their model, the census on any given day is a function of a constant component, a linear trend factor, and random disturbances, which are minimized by a discounted least squares analysis. The authors then observe that, in addition to the basic pattern of census at many institutions, there are internal and external factors which could explain additional census variations. For example, renovations, holidays, and administrative actions may close units from time to time; utilization review programs could change length of stay; natural disasters or epidemics could change demand for a short time. The authors use tracking signals, rather than smoothing, to improve hospital forecasting and trigger different rates of parameter updating. In a case study, these techniques are used to improve forecasting decisions by including adjustment factors for holidays, adding, opening and closing nursing units, and unexpected events.

Demand forecasting is important for many aspects of health care operations research and management. The chief difference between techniques is the degree to which subjective judgement influences the model. Some models, such as the Delphi technique, attempt to formalize explicit expert judgement. Others, such as econometric modelling, have implicit judgements (e.g., specification of the model). This impact of judgement, whether explicit or implicit, on the results of demand forecasting, can be strong, as Hogarth & Makridakis [1981] describe in their review of models. In choosing forecasting models, the degree of judgement should be considered, and various approaches to modelling and sensitivity analysis should be tried.

1.3. Location selection

Location of health care delivery facilities and services has much in common with the location aspects of many types of facilities or services which have a geographically dispersed customer base, and where there is a need to be close enough to customers for ease of access and/or speed of access, as well as a need for low cost of siting and operations. Health care facilities and services are different because they may be subject to public control laws and, in the case of emergency vehicle locations where there are maximum response time requirements, may need to balance closeness to customers and facilities.

Siting or location problems usually fall into one of five categories with somewhat distinctive characteristics.

The first category is the regionalization of health care facilities (see Section 1.1).

The second category is the siting or removal of a single facility, such as an acute care hospital or a central blood bank which needs to be geographically close to its customer bases (also see Section 1.1). Here the customers are the patients and their physicians, and (to a lesser extent) hospital employees. Generally, mathematical programming or heuristic approaches are used to determine optimal or near-optimal locations. Major consideration is given to the current location of similar institutions in the region.

The third category is the location of ambulatory neighborhood clinics, which are primarily used for routine outpatient medical and/or surgical care and for preventive care. Again, proximity to patients is an important criterion in the location decision, as are network linkages to the general and specialized hospitals in the region. The location of health maintenance organization facilities, surgi-centers, diagnostic centers such as CT-scanner centers and poly-clinics fall into this category (see Section 1.1). Sometimes network mathematical programming is used for this analysis. For example, in order to locate ambulatory medical service centers for the independently living elderly, a planning strategy advocated by Cromley & Shannon [1986] incorporates the concept of aggregate activity spaces used by the target population in the criteria for determining the facility location. This approach is particularly suited to services for the elderly, who tend to restrict activity to familiar areas of the community. A similar idea could be used for the location of pediatric health service centers near schools and/or recreation areas.

The fourth category comprises the location of specialized long-term care facilities. The primary criteria for these location decisions are not so much closeness to customer bases but costs of site acquisition and construction, cost of operation, and (to some extent) speed of access to acute care facilities. The types of facilities involved in this category are nursing homes, psychiatric hospitals, skilled nursing facilities, and rehabilitation centers.

The fifth category of health care location problems is the siting of emergency medical services (EMS). This problem involves determination of the number and placement of locations, number and types of emergency response vehicles and of personnel. This problem is similar to the location of fire stations, equipment and crews, in which speed of response is a primary criterion (see Chapter 5). Speed of response includes distance to the problem occurrence location, but also the distance from the occurrence location to the treatment facility. In this latter regard, the problem differs from fire stations, where the occurrence location and the treatment location coincide. For example, if the health care treatment location is near the edge of a populated region, it is probably not optimal to locate the EMS at the midpoint of the region or close to the treatment center, whereas it may be optimal to locate a firestation there. The EMS location problem receives the most attention from operations researchers. It is rich in problem structure, having sufficient technical complexity yet minimal political and sociological constraints. The primary methods used to solve this problem are mathematical programming, queueing analysis and simulation. The solutions may then be modified heuristically to satisfy non-quantitative constraints.

Fitzsimmons & Sullivan [1979] combine 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 queueing model. Fitzsimmons & Srikar [1982] enhance the CALL approach by adding a contiguous zone search routine that 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 include demand for 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 include service equity, fleet size, and workload equity.

Brandeau & Larson [1986] describe an enhancement of the hypercube queueing model for studying an emergency medical service system. The model does not select an optimal emergency service configuration, but instead provides 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 is used to configure the EMS system in Boston.

Daskin & Stern [1982] develop 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 [1981] describes a derivative of the maximum expected covering location model (MEXCLP) which accounts for vehicle busy periods. The model estimates the number of vehicles needed based on daily average calls. Eaton, Daskin, Simmons, Bulloch & Jansma [1985] describe the implementation of the maximum covering model in Austin, Texas. Eaton, Sanchez, Lantigua & Morgan [1986] incorporate weighted demand into the HOSC approach, and develop recommendations for ambulance deployment in Santo Domingo, Dominican Republic. Fujiwara, Makjamroen & Gupta [1987] use the maximum covering location model to identify 'good' solutions for ambulance deployment in Bangkok, Thailand. Each of these solutions is then analyzed by a Monte Carlo simulation. Model outputs include response time, service time, round trip time, and workload. Bianchi & Church [1988] combine the MEXCLP with another covering model, the Facility Location and Equipment Emplacement Technique, to develop an ambulance location pattern which places multiple homogeneous units at one location. Integer programming is 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. Some of the greatest application successes have been in the EMS category. Developments in this area are stimulated by the establishment of standards of performance by which public or contract services can be held accountable, improvements in information systems which support EMS operations management, and by special federal legislation in the U.S. which help pay for the establishment and operation of EMS systems.

1.4. Capacity planning

Capacity planning relates to those decisions regarding the appropriate levels of facilities, equipment and personnel for some demand. In health care, capacity planning usually focuses on decisions such as total bed capacity, surgical system capacity, bed capacity allocation to different services, capital equipment capacities, ancillary service capacity, and factors which affect capacity utilization such as patient flow, staffing levels and staff skill mix. In examining these factors, providers are seeking ways to increase the productivity of existing assets and improve service quality. Many of the studies drive the capacity planning process with an underlying queueing system and use simulation to obtain solutions.

The allocation of bed capacity within a hospital is a critical factor in operating efficiency. Dumas [1984, 1985] develops a simulation which incorporates diagnostic categories of patients based on sex, admission type, time of demand, four categories of beds, and physician type (attending or resident). Outcome measures include percent occupancy, average daily census, annual patient-days, and misplaced-patient days (when the patient was not on the intended unit). Secondary measures include 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 provides a method for evaluating a variety of patient placement rules. When applied to actual hospital data, the study results in a reallocation of beds, the creation of a new service, fewer misplacements, and reduced misplaced-patient days, but also resulted in increased transfers. The model does not incorporate costs for misplacement, transfers, and delayed admissions. The model can be used for the planned expansion, contraction or reallocation of beds as demand changes.

Similarly, Vassilacopoulos [1985] describes a general priority queueing simulation model that could be used to determine the number of hospital beds necessary to meet demand for inpatient services. The objectives of high occupancy, immediate admission of emergency patients, and a small waiting list for elective admissions were sought simultaneously.

Hospital waiting lists are investigated by Worthington [1987] to assess bed capacity and other characteristics of the British Health System. He uses a modified M/G/S queueing model which includes costs for patients who balk at long queues which, in turn, influence the length of the queue. The model tests the predicted responses to the long waiting list problem, such as increasing staffed beds, decreasing length of stay, combining waiting lists for different services, and introducing earlier feedback to general practitioners about the size of the queue.

Simulation models are widely used in capacity planning. Mahachek & Knabe [1984] simulate the flow of patients through two outpatient clinics, obstetrics and gynecology, which were to be combined. A simulation of surgical bed occupancy related to surgeon's schedule and category of the procedure (major, intermediate, or minor) is developed by Harris [1985]. A radiology service model developed by Sullivan & Blair [1979] predicts longitudinal workload requirements for radiology from medical services. The model is used to address the impact on capacity of centralization versus decentralization of radiology equipment and services. Ladany & Turban [1978] describe a simulation of an emergency room service. A simulation developed by Hancock & Walter [1984] evaluates the effects of inpatient admission policies and outpatient scheduling on the future workloads of ancillary services such as laboratory, physical therapy, and respiratory therapy.

Semi-Markov process models are also used to examine bed allocation and capacity questions, particularly in progressive patient care facilities. Hershey, Weiss & Cohen [1981] demonstrate, by using transitional probabilities for patient movements throughout the hospital, that the expected level of utilization can be modeled as a system with one unit with finite capacity. If the equilibrium rate of arrival at each unit, mean holding time at each unit, and the probability that the finite unit is at full capacity are known, then the utilization and service rate of the system can be determined. If multiple units are being considered for capacity changes, the authors recommend using simulation, with their model used for validating the simulation.

On a regional scale, Lambo [1983] uses optimization and simulation to improve efficiency and effectiveness in a network of rural Nigerian clinics. Optimization is used to establish an upper bound on the potential efficiency of a regional health center. Misallocation of personnel is the major constraint identified. Simulations at levels of both the center and individual clinics is used to evaluate operating policies and to determine the maximum capacity of the center.

Schmee, Hannan & Mirabile [1979] also address a broader regional capacity and services evaluation problem. They use 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 includes 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, non-dominated 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.

As shown in the preceding examples, capacity planning usually deals with 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 a fertile area for further work. In addition, in none of these studies are the capacity relationships studied with regard to economies of scale or scope and to quality levels of scale and congestion. Better models of patient flow and improved understanding of the delivery system for care hold promise as means to improve capacity planning.

2. Management of operations

2.1. Management information systems

Management information systems (MIS) are usually required to implement operations research models in health care management. There is a very large amount of literature on designing, planning, installing, and evaluating MIS systems. This literature will not be discussed here. Only a few brief comments will be made and some references given which can lead the interested reader into a range of writings on this topic. In combination with decision- and model-based support systems, MIS's have the potential to improve decision-making responsiveness, quality of patient care, and productivity. Quality of care improvements can result from reduced waiting time for physicians' orders to be carried out and results to become available, elimination of unnecessary services, reduction of errors, and increased provider and patient satisfaction. Productivity is improved by appropriate data availability for decisions about staffing patterns, scheduling, use of equipment and materials, and by elimination of redundant systems and actions. These benefits of MIS are succinctly summarized by Moidu & Wigertz [1989].

The elements of the hospital or office MIS for medical decision-making, billing, and planning as well as other activities are keyed to the patient identification number (PID) and the medical record (MR) [Pierskalla, Brailer & McVoy, 1990]. From the entire patient case mix, severity and resources consumed can be identified. Other MIS elements of importance are employee data, competitors' case mixes and resources, present and future regional demographics, income and resource cost patterns, market survey results of patient attitudes and preferences, private physician specialties, location and practice in the region, and competitors' known plans for the future. Using this information, different units at the management and care delivery levels construct models using statistics, operations research, management science and expert systems to make and support decisions. These decisions may involve expansion, contraction, new technology, mergers and acquisitions, and diversification. Operating decisions involve payroll and accounting systems, budget planning and analysis, admissions, discharge and transfer (ADT) systems, surgery and recovery room scheduling [Lowery & Martin, 1989], nurse staffing and scheduling, outpatient scheduling and appointment systems, purchasing, inventory control and maintenance, administrative personnel systems, and medical management of patients.

2.2. *Patient scheduling*

Controlling demand for services via scheduling can be very effective as a method of matching demand with the supply of services available. Outpatients frequently dislike waiting for service, and consequently balk or renege on appointments if waiting time is considered excessive. Inpatients, likewise, are dissatisfied with slow hospital service. Consequently, the problem of satisfying both patients and health care providers is a challenging one and most scheduling systems attempt to optimize the combined objectives of satisfaction of patients, satisfaction of physicians, and utilization of facilities.

Patient scheduling has many benefits which include reduced staffing costs and reduced congestion in the hospital and clinics. Appropriate supply of personnel, facilities, equipment and services can be more effectively provided to meet the smoothed flow of demand. An area of benefit that is just beginning to be addressed is the improvement in quality of care (in addition to patient satisfaction) that comes from reduction of congestion via effective demand and supply scheduling. Quality could be improved by providing the appropriate amounts and kinds of care at the appropriate times.

There are problems, however, in devising and implementing scheduling systems which meet the primary goals of minimizing staff and/or staff idle time (primarily physicians) and equipment idle time while maximizing or strongly satisfying patient needs. Some of these problems stem from inadequate information systems, others from resistance to change by staff or authorities who demand uniformity of approaches across institutions, and others from failing to capture key linkages and system interactions because of the complexity of the core delivery processes. This last set of problems occurs more frequently in hospital inpatient settings in situations where complex progressive patient care is needed rather than in outpatient settings.

2.2.1. Outpatient scheduling

Effective scheduling of patients in clinics for outpatient services is one of the earliest documented uses of operations research in improving health care delivery. Bailey [1975] applies queueing theory to equalize patients' waiting times in hospital outpatient departments. He observes that many outpatient clinics are essentially a single queue with single or multiple servers. The problem then becomes one of building an appointment system to minimize patient waiting time and keeping the servers busy. The appointment system must be designed to have the inter-arrival times of patients somewhat smaller than, or equal to, the service time. Unfortunately, outside the laboratory, the service system is more complicated. Some patients arrive late or not at all; some physicians arrive late; service times are not homogeneous but vary by the type and degree of illness; diagnostic equipment is not always available; there are unplanned arrivals of emergent patients and so forth. For these and other reasons many of the early outpatient scheduling models were not widely adopted.

However, more recent models and methodologies for effective outpatient scheduling show promise for successful implementation. The three most commonly used systems involve variations on block scheduling, modified block scheduling and individual scheduling. In block scheduling, all patients are scheduled for one appointment time, for instance 9:00 AM or 1:00 PM. They are then served on a first-come–first-service (FCFS) basis. Clearly, this approach has long patient waiting times, high clinic congestion and minimal staff idle time. Modified block scheduling breaks the day into smaller blocks (e.g. the beginning of each hour) and schedules smaller blocks of patients into those times. It has many of the characteristics of the block systems but patient waiting time is lowered. On the other hand, individual scheduling systems schedule patients for individual times throughout the day often in conjunction with staff availabilities. If scheduled inter-arrival times are not significantly shorter than service times, patient waiting time is reduced and staff idle time can be kept small. However, these systems require much more information on patients' illnesses and needs, triaging may be necessary by the appointment scheduler, and unforeseen events can cause severe scheduling problems. In spite of these potential drawbacks, individualized scheduling systems are most widely used in the United States.

The literature on outpatient scheduling is extensive, beginning in the 1950's and peaking in the 1960's and 1970's. Since much of it is based on queueing or simulation, studies were done to determine parametric distributions for patient service times. Scheduling schemes to reduce patient waiting time, while not increasing physician idle time, were analyzed using these distributions as inputs.

O'Keefe [1985] gives a very good description of the waiting times, congestion, and bureaucracy in consultative clinics in the British Health Service. A modified block system is used. Using heuristic methods he shows that some improvement can be made in spite of overwhelming resistance to change and extensive system constraints. Satisfying the scheduling system's non-patient stakeholders requires implementation of a policy that is clearly suboptimal for patients. The work is interesting in that it implicitly shows that, to effect change in a bureaucratic system, it is essential to address and/or change the incentives of the stakeholders running the system.

Fries & Marathe [1981] evaluate several approximate methods 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 optimal appointment system choice. Simulation is used by Vissers & Wijngaard [1979] to produce a general method for developing appointment systems for single server outpatient clinics at a hospital. They demonstrate that the key variables in the simulation of a single server system are: 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. Simulations using various values for the five variables allow design of an appointment method which meet predetermined standards for waiting time and idle time. Callahan & Redmon [1987] devise a combined time-based and problem-based scheduling system for a pediatric outpatient clinic. Two types of time slots are designed: short times for routine patient exams and long times for extensive exams. Time slots for different patient problems are allocated to specific presenting problems. The problem-based scheduling system improves staff utilization and patient satisfaction, suggesting that additional development of this triaging and time-slotting approach may be beneficial.

Outpatient scheduling will require further refinement in the future, as the emphasis on this mode of care delivery increases. Scheduling models need to include performance measures reflecting the costs and benefits for all participants. Segmentation of patients into categories with significantly different requirements for service can also enhance the performance characteristics of patient-scheduling systems. In clinics where emergent patients are reasonably frequent each day, the classification scheme must separate these patients from non-emergent other patients. Work by Shonick [1972] for emergent patients in acute care general hospitals, and by other authors in other settings, demonstrates that a truncated Poisson distribution provides a good fit for the arrival process of such patients.

An outpatient scheduling system which considers the stochastic variation of emergency patients separately from the stochastic variation of no shows and late arrivals of scheduled patients will better achieve minimal waiting time and minimal staff idle time.

2.2.2. *Inpatient scheduling*

There are three major dimensions of inpatient scheduling. First is the scheduling of elective admissions together with emergent admissions into appropriate units of the hospital each day (admissions, A). Second is the daily scheduling of inpatients to the appropriate care units within the hospital for treatment or diagnoses throughout their stay (transfers, T). Third is the scheduling of the discharges of patients to their homes or other care delivery institutions (discharges, D). Clearly, these scheduling activities (ATD) are linked and depend upon many characteristics of the patients and hospital.

The models used for inpatient scheduling are more complex, and require more data and better information systems than those for outpatients. Many different methodologies are proposed involving queueing models as represented by Markov and semi-Markov processes, mathematical programming, heuristic and expert systems, and simulation. There are also less formal modelling approaches more traditionally associated with rules-of-thumb and charting models. Because of the complexities of inpatient scheduling problems and because of relatively poor internal forecasting and information systems, most hospitals use informal or ad hoc methods. Consequently, neither the size of the facilities, staffing, nor facility utilization are well planned, resulting in inefficiencies caused by peaks and valleys of occupancy. The valleys create a situation of excess contracted labor. The peaks create congestion and, because of difficulties of finding appropriately trained personnel on short notice at typical wages, can lead to patient dissatisfaction, lower quality and higher operating costs. Those problems can occur throughout the institution, involving physicians, residents, nurses, aides, and ancillary, support and administrative services personnel. On the other hand, analytic inpatient scheduling can ameliorate many of these problems and improve effective and efficient (optimizing) use of hospital resources.

As with outpatient scheduling, the inpatient scheduling literature began to appear in the early 1950's and peaked in the 1960's and 1970's. Most of the studies on admission scheduling divide the patients into two categories: waiting list and emergency. Furthermore, most of these studies only cover admissions to a single service in the hospital (such as surgery, obstetrics, pediatrics or another single ward). The idea underlying these scheduling systems is to compute the expected number of available beds for the next day (or longer). The schedule system would then reserve a block of beds for the emergent patients randomly arriving in the next 24 hours and then fill the remaining beds from the waiting list of patients for elective admission. Typically, the amount of reserve beds for emergency will be based on the means and variances or probability distribution of their arrival patterns (usually a truncated or compound Poisson would be used) and on some measure of 'over-run of demand' such as 95% or 99% of the emergent demand would be satisfied daily or over some longer period. This variation on the classic inventory control problem is usually solved by simulation rather than analytic methods.

In computing the anticipated bed availability for the next day, many authors attempt to estimate the length of stay of current patients and then forecast expected discharges. Due to lack of severity of illness information and other factors and because there is no incentive to discharge patients on a systematic basis in pre-DRG days, these forecasts were not very accurate. Furthermore, none of the studies look at the hospital as a total system in that there may have been other bottlenecks in the institution such as radiology, laboratory, personnel staffing or transport which are adding unnecessary days to length of stay or causing other bed utilization effects.

For admissions scheduling, queueing and simulation models are most often used. This is true also for inpatient flows within the hospital. The most common scheduling rule is to compute the number of beds needed to accept a given portion of emergent patients and then to fill any remaining available beds with waiting list patients. Variations on this rule are used in most admissions scheduling systems today. Some studies try to optimize on the tradeoff between patients' satisfaction as to when they were scheduled for admission, treatment and discharge versus some measures of hospital efficiency such as minimization of deviation from some desired hospital census level.

Kuzdrall, Kwak & Schnitz [1981] model five operating rooms and a twelve-bed, post-anesthesia care unit. Each operating room and PACU bed are treated as a separate facility. Paralleling results found in job shop scheduling, the authors find 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.

Trivedi [1980] describes a stochastic model of patient discharges which could be used to help regulate elective admissions and achievement of occupancy goals. He also discusses the advantages of incorporating discharge forecasting, occupancy level management, and nurse staffing management.

Several authors construct patient flow models in hospitals as patients move progressively through different therapeutic or diagnostic units to obtain the appropriate treatment. The primary methodology used is to model the progressive care as a semi-Markov process where patients move randomly and progressively (depending on their conditions) from one unit to another and remain in each unit for a random period of time. Kao [1974] models the progression of coronary care patients, and Hershey, Weiss & Cohen [1981], Cohen, Hershey & Weiss [1980] and Weiss, Cohen & Hershey [1982] model the progressive care for obstetric patients. Kostner & Shachtman [1981] use a Markov chain analysis for patients with nosocomial infections. The primary purpose for modelling the progressive care in these studies are for bed planning (capacity) decisions, personnel scheduling decisions and care delivery decisions. However, it is also clear that these patient movements can be used for inpatient admission scheduling decisions and for other aspects of care evaluation, technology procurement and quality and cost control. Because of the lack of adequate data and information systems and complexity of these models, they have yet to be used in hospital settings. However, as cost pressures continue to grow, more effective patient scheduling methods will be needed to balance and plan staffing, facilities, equipment procurement and services. Much more research and applications need to be studied to link these systems for higher quality lower cost care.

2.3. Work force planning and scheduling

The management of human resources is a major activity in health care organizations. Because staffing costs usually represent the majority of the operating budget, this area will become even more important in the future as health costs are subject to increasingly tighter public scrutiny or regulation. Like many service organizations, the ability to match staffing resources to a fluctuating demand directly affects operating efficiency and the quality of service. The development of innovative approaches to the organization and management of nursing and other human resources holds great promise for further cost savings in the delivery of health services.

Although the planning and scheduling of health care personnel is not conceptually different than that of other personnel (one needs the right persons in the right places at the right times) there are several factors which make the problem in health care more complex. First, there is the interrelation among various highly trained and skilled personnel that must be available at the appropriate times for different patients. These personnel include different specialty categories of nurses, therapists, physicians, medical technicians and others. Staffing must be available 24 hours a day on all days, during which demand varies considerably. Personnel have preferences and requests for types of schedules and working conditions. Many function as relatively independent professionals with regard to the level and scope of tasks. Second, it is frequently difficult to measure quality of work, especially as it pertains to successful patient outcomes. This measurement difficulty presents problems in determining the mix of types and skill levels of personnel which are needed to obtain a given level of quality. Third, for most personnel categories there is a 'flat' organizational structure with few career paths available. As a consequence, human resource management must continually cope with ways to maintain personnel satisfaction and enjoyment for highly capable individuals over the period of many years, even decades, or face the high costs of absenteeism, turnover, and general dissatisfaction. Indeed, many debates about professional nursing activities are direct outgrowths of basic nurse staffing problems.

Most of the research in staffing and scheduling for health care organizations focuses on nursing. However, personnel availability and utilization in the laboratory, emergency department, respiratory therapy, HMO's, and other locations are also being examined.

Hershey, Pierskalla & Wandel [1981] conceptualize the nurse staffing process as a hierarchy of three decision levels which operate over different time horizons and with different precision. These three decision levels are called corrective allocations, shift scheduling, and workforce planning. Corrective allocations are done daily, shift schedules are the days on/days off work schedules for each nurse for four to eight weeks ahead, and workforce plans are quarterly, semiannual, or annual plans of nursing needs by skill level.

On any given day within a shift, the staff capacities among units may be adjusted to unpredicted demand fluctuations and absenteeism by using float, part-time, relief, overtime, and voluntary absenteeism. These 'corrective allocations' depend upon the individuals' preferences, their availabilities, and capabilities. Shift scheduling is the matching of nursing staff availabilities to expected workload among units on a daily basis for a four to eight week period in the future. For each employee days on and off, as well as shift rotation, are determined. The individual's needs and preferences must be considered to bring about high personnel satisfaction. The above two scheduling levels are tactical, in that they concern the utilization of personnel already employed within the organization with their known mix of specializations and experiences. Workforce planning is the long-term balance of numbers and capability of nursing personnel among units obtained by hiring, training, transferring between jobs, and discharging. Because of the time-lags involved, workforce-planning actions must be taken early to meet anticipated long-term fluctuations in demand and supply. Very few studies address this decision level.

The interdependence of the three levels must be recognized to bring about systematic nurse staffing improvements. Each level is constrained by available resources, by previous commitments made at higher levels, and by the degrees of flexibility for later correction at lower levels. Therefore, each decision level is strongly dependent on the other two. For best performance, one level cannot be considered in isolation.

The final component of the model is the coordination of staffing management activities with other departments. 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 & Haurie [1980] evaluate the relative efficiency of three controls applied to the supply and demand system of inpatient nursing care: regulating admission of elective patients, allocation of a floating pool of nursing personnel, and assignment of the unit's nursing personnel to various tasks. They conclude that the float pool is only slightly superior to admissions control for matching supply and demand for care, while task assignment is not an efficient means of controlling the adjustment of supply to meet demand. Shukla [1985] also examines admissions monitoring and scheduling to improve the flow of work in hospitals.

The earliest OR work on work force planning and scheduling in hospitals began with measuring the needs of patients for various types of care. Over time, such needs have come to include physical, hygienic, instructional, observational, emotional, and family counseling needs of patients. These types and amounts of care are quantified in patient classification systems and then related to the hours of different skilled personnel needed to meet them [CASH, 1967; Connor, 1961; Jelinek, 1964]. Models for corrective allocations are given by Warner & Prawda [1972], and Hershey, Abernathy & Baloff [1974].

Longer-term workload forecasting (one to two months) by skill level is needed for shift scheduling. Most forecasting in use merely extrapolates recent experience using adjustments for seasonal and weekend variations. Often the models used are simple moving averages, but occasionally regression and ARIMA time series models have been used. Helmer, Opperman & Suver [1980] use a multiple regression approach to predict nursing labor-hour requirements by ward, shift, day of the week, and month of the year. Pang & Swint [1985] also used multiple regression to predict daily and weekly laboratory workloads for scheduling purposes. Other forecasting models and applications are discussed in Section 1.2.

Shift scheduling which is effective (i.e., meets the health care needs of patients and the preferences of nurses at minimal cost) is a complex problem that attracts the interest of operations researchers. The earliest and simplest scheduling model is the cyclic schedule. This schedule repeats a fixed pattern of days on and off for each nurse indefinitely into the future. This type of schedule cannot adjust for forecasted workload changes, extended absences, or the scheduling preferences of individual nurses. Such rigid schedules place heavy demands on the corrective allocations and workforce planning levels. Hence, corrective allocation must be extremely flexible and workforce planning must more precisely forecast long-term workforce needs to avoid excessive staffing [Hershey, Pierskalla & Wandel, 1981].

The two most frequently cited and applied approaches to flexible scheduling [Miller, Pierskalla & Rath, 1976; Warner, 1976] include the preferences of staff in the scheduling decision. Miller, Pierskalla & Rath [1976] develop a mathematical programming system using a 'cyclical coordinate descent' algorithm. The model incorporates two types of constraints. The feasibility constraints consist of hospital policies that must be met (for example minimum and maximum length of a work shift ('stretch'). The second type comprises non-binding constraints that can be violated (for example, minimum staffing levels or undesirable schedule patterns determined by the staff nurses). When a non-binding constraint is violated, a penalty cost is assigned. Each staff nurse is allowed to assign relative weights to various violations of her/his non-binding constraints. The problem is formulated to minimize penalty costs of the scheduling patterns. Benefits of this approach include decreased difference between actual and desired staffing, higher average personnel satisfaction, and lower staffing costs than manual or semi-automated systems. In a commercial implementation, this model is modified to include variable length shifts and goal optimization to meet staffing needs and to satisfy nurse preferences.

For scheduling personnel other than nurses, Vassilacopoulos [1985] simulates as an $M/G/m(t)$ system the allocation of physicians to shifts in an emergency department. Tzukert & Cohen [1985] describe 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.

Workforce planning takes a longer time perspective and includes hiring, training, transferring between positions, and discharging employees. A variety of quantitative models of workforce planning appear in the literature. Worthington

& Guy [1988] describe a quarterly system of workforce allocations based on patient classification data for the previous three months. Baker & Fitzpatrick [1985] develop an integer programming model for the problem of reducing staff in a recreation therapy department with the objective of maximizing the effectiveness of staff retained. Multi-attribute utility theory is used to integrate performance and experience attributes, so as to obtain a utility surface for evaluating effectiveness. Shimshak, Damico & Burden [1981] use three queueing models to determine the effects of pharmacy staffing on prescription order delays.

Kao & Tung [1981] present a case study of long-range staffing planning. Their model is a combination of a linear program and an ARIMA forecasting system. The forecast is integrated with institutional constraints and patient care requirements in a linear program for assessing the need for permanent staff, overtime pay, and temporary help (differentiated by medical service, nursing skill level, and time period) and for evaluating the size of a float pool.

Cavaiola & Young [1980] develop an integrated system of patient classification, nurse staff planning, and staff budgeting for a long-term care facility. The basic staffing model uses mixed integer linear programming to solve the staffing allocation problem for the best assignment of nursing personnel based on a criterion called 'appropriateness' which served as a surrogate for quality of care.

Simulation is applied to a variety of workforce planning problems. Kutzler & Sevcovic [1980] develop a simulation model of a nurse-midwifery practice. Hashimoto, Bell & Marshment [1987] use a Monte Carlo simulation in an intensive care setting to evaluate cost, number of voluntary absences, staff call-ins, and total cost for a year at different staffing levels (FTEs per shift). Duraiswamy, Welton & Reisman [1981] develop 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. A simulation of obstetric anesthesia developed by Reisman, Cull, Emmons, Dean, Lin, Rasmussen, Darukhanavala & George [1977] enables them to determine the optimal configuration of the anesthesia team. Magazine [1977] describes a patient transportation service problem in a hospital. The solution involves queueing analysis and simulation to determine the number of transporters needed to ensure availability 95% of the time. A mixed-integer program determines the required number of shifts per week.

In addition to the three personnel decision levels, nursing management must also make policy and/or budgetary decisions which inevitably restrict alternative actions at the tactical levels. Trivedi [1981] develops a mixed-integer goal programming model based on financial data and staffing standards in the preparation of the nursing budget. The model allows examination of consequences of changes in understaffing, wage levels, 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. Looking at a similar problem, Hancock, Pollock & Kim [1987] develop a mathematical model to determine the cost effects of productivity standards and optimal staffing policies. One source of variation in productivity is the ability of the work force to absorb variations in workload. They recommend the establishment of optimal productivity levels and staffing, and determine the resulting budgets so that, if true potential productivity is known, the costs of productivity compromises needed to gain staff and management acceptance will also 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.

Leiken, Sexton & Silkman [1987] use a linear program to find the minimum cost staffing pattern of RNs, LPNs, and nurse aides that meets patient needs in a nursing home. The model's decision variables are the number of hours of each skill level to employ and number of hours each skill level should devote to each task.

In the three preceding examples the authors suggest policies to improve the overall long-term productivity of the nursing (and other) staff while reducing or minimizing costs. Implementation often encounters primary or secondary impacts caused by the suggested changes on organizational characteristics that are hard to observe objectively. One such attribute is changes (if any) in the quality of health outcomes, which may occur if skill levels are downgraded or time available to complete tasks is significantly reduced. Other such attributes include employee morale, turnover, absenteeism, training costs and other effects. In spite of these difficulties, long-term personnel policies must be examined along the lines suggested by these models in order to bring about improved productivity and reduced costs in health care delivery and future research should expand the breadth of existing models.

3. Medical management

3.1. Screening for disease

The introduction of, and improvements in, tests which detect diseases have resulted in advances in medical diagnosis and disease detection. These tests may be applied to an individual ('individual screening') or to large subsets of the population ('mass screening'). These cases are different modelling problems because the objectives of the decision makers frequently differ, and the constraints and parameters affecting the decisions may vary. For example, in mass screening the objective may be to minimize the prevalence of a contagious disease in the population subject to resource constraints and compliance levels, expressed as parameters for subpopulations. For an individual, the objective may be to prolong life (or the quality of life) and the constraints may be related to the individual's ability or willingness to pay and the parameters to the individual's characteristics. In each case the decision makers are also usually different persons, e.g., the public health official or HMO director for mass screening and the patient or patient's physician for individual screening.

Currently, mass screening programs are under discussion for the detection and control of HIV (Human Immuno-Deficiency Virus), the infectious virus which causes the Acquired Immuno-Deficiency Syndrome (AIDS). Mass screening programs are also used for hepatitis A, B, nonA-nonB, tuberculosis, syphilis, and other infectious diseases. In some countries, mass screening protocols for non-contagious as well as contagious diseases have been established for national health programs. In the U.K, for example, there is a mass screening protocol for the early detection of cervical cancer, intended to reduce the prevalence of the disease and save lives.

Mass screening programs, however, are expensive. Direct quantifiable costs of mass screening, such as those of the labor and materials needed to administer the testing are large, but indirect costs may be much greater. Indirect costs, for example, include the inconvenience and possible discomfort necessitated by the test, the cost of false positives which entails both emotional distress and the need to do unnecessary follow-up testing, and even the risk of physical harm to the testee (e.g., the cumulative effect of X-ray exposure or harm from unnecessary surgery).

The policy maker must consider several factors in choosing a mass screening protocol. First, mass screening programs have to be designed in light of the tradeoff between the testing cost, which increases both with the frequency of test applications and with the accuracy of the test used, and the testing benefits to be achieved from detecting the defect in an earlier stage of development. Second, such a design must determine which kind of testing technology should be used, as different technologies may have different reliability characteristics (false positive and false negative levels) and costs. Third, the frequency of testing must be decided. Fourth, because different subpopulations may have different susceptibility to the disease, the problem of optimal allocation of a fixed testing budget among subpopulations must be considered. Fifth, behavioral problems of attendance at the testing location and compliance with treatment after disease discovery must be included in the analysis. Many of these factors apply to models for individual screening as well.

The literature on screening models has a long history, but the last two decades have seen its greatest growth. Two major streams of knowledge contribute to this area. The first, and perhaps larger stream, is the work in epidemiology and biology. This work focuses primarily on descriptive modelling of disease processes, progression and causal factors. In the case of contagious diseases, very complex simultaneous differential equation and/or statistical models are frequently used to describe the growth, maturity and decline of various specific or general types of diseases. Interventions in the disease propagation are often modelled as changes in the progression parameters rather than as explicit decision variables. An early work, by ReVelle, Feldman & Lynn [1969], uses these approaches and models the epidemiology of tuberculosis under different scenarios and types of interventions. Under simplifying assumptions, the authors derive a linear program which can be optimized to determine the minimum cost solution for screening and treatments. An also excellent, but somewhat dated, book in this area is by Bailey [1975]. More recent work which gives a good flavor of this work in epidemiology and biology modelling literature includes the papers by Dietz [1988], Hethcote, Yorke & Nold [1982], Hyman & Stanley [1988] and May & Anderson [1987].

The second stream of research related to screening models is the work in maintainability (i.e., the modelling of decisions for inspection and maintenance of units or systems subject to deterioration or obsolescence). This literature contains the application of a large variety of decision models, including mathematical programming, Markov decision, and simulation. Simulation is frequently used in the epidemiological literature also. Two somewhat dated literature reviews in maintainability are contained in Pierskalla & Voelker [1976] and McCall [1965].

Much of the recent work on screening has been driven by the increased emphasis on major serious chronic diseases. In the case of non-contagious diseases, these have been cancer, heart disease and malaria. For contagious diseases, they are diseases that are largely sexually transmitted (STDs), most notably HIV and hepatitis B.

Models of screening programs for an individual frequently incorporate information on the disease's progression and then try to minimize the expected detection delay (the time from disease incidence until its detection) or maximize the lead time (the time from detection by screening until self-detection or until symptomatic). Characteristically, these models take a longitudinal time frame for the individual, because an individual, through his/her lifetime, is subject to different conditional probabilities of incurring the disease. Thus, screening schedules are determined sequentially by utilizing prior testing results, or simultaneously for an entire lifetime, such as every X years.

Using the etiology and progress of a disease and its relationship to screening effectiveness, the reliability of test and the lead time gained from detection can be modelled as a function of the state of the disease rather than the time since the defect's incidence, e.g., Prorok [1976a,b], Thompson & Doyle [1976], Schwartz & Galliher [1975], Thompson & Disney [1976] and Voelker & Pierskalla [1980]. Bross & Blumenson [1976] develop a mathematical model to evaluate a screening strategy, termed a 'compromise screening strategy', which consists of two stages of screening examinations with different harmful effects as well as reliabilities. The model is also applied to evaluate different screening intervals for breast cancer detection. Schwartz [1978b] develops a mathematical model of breast cancer, and then uses it later to evaluate the benefits of screening [Schwartz, 1978a]. Again the rate of disease progression was explicitly included as a factor affecting the probability of the disease detection.

Eddy [1980], well aware of the complexity of relationships among test reliabilities, disease development, and prognosis of breast cancer, develops the most comprehensive breast cancer screening model by focusing on two attributes that carry information about the effectiveness of the screening tests: the mammogram interval and the patient's age. By modelling these two factors as random variables, Eddy is able to derive analytical expressions for the sensitivity (true-positive rate) and specificity (true-negative rate) of test procedures, utilizing repeatedly the Bayesian statistical approach. The design of screening strategies to optimally allocate fixed resources, however, is only briefly discussed by Eddy. He uses the basic model to evaluate screening for other cancers, such as colorectal and cervical, as well as non-cancerous, non-contagious diseases. Eddy's work is very important, as it has been implemented by health agencies in national policy recommendations for screening intervals based on the individual's age, sex and prior histories. Eddy [1983] gives a good exposition on the importance of screening, the critical factors and parameters necessary for screening models, and a comprehensive sensitivity analysis of his model to various assumptions and parameters.

Kolesar [1980], using integer mathematical programming, constructs an optimal screening procedure to test for vision loss in suspected glaucoma patients. This model assumes perfect test reliabilities. The screening is done by choosing a subset of a grid of points covering the eye.

Less work has been done on mass screening models than on individual screening. Kirch & Klein [1974a] address a mass screening application that seeks an inspection schedule to minimize expected detection delay. The methodology is then applied to determining examination schedules for breast cancer detection [Kirch & Klein, 1974b]. Pierskalla & Voelker [1976] and Voelker & Pierskalla [1980] develop analytical models of a mass screening program and analyze them for both cases where the test procedures are perfect or imperfect. Optimal allocation of a fixed budget to different sub-populations is given in the perfect test case, whereas optimal decision rules concerning the best choice and frequency of testing are derived for the imperfect case.

Lee & Pierskalla [1988a] describe the stochastic processes underlying the progression of a disease in a population when mass screening programs and compliance regimens are instituted. The resulting models are useful for the analysis of the optimal design of mass screening programs for a country or agency which is attempting to control or eradicate a contagious or non-contagious disease. In the model, non-contagious diseases are shown to be special cases of contagious diseases when certain distribution parameters are held constant. In a later paper, Lee & Pierskalla [1988b] present a simplified model describing the stochastic process underlying the etiology of contagious and non-contagious diseases with mass screening. Typical examples might include screening of tuberculosis in urban ghetto areas, venereal diseases in the sexually active, or HIV in high-risk population groups. The model is applicable to diseases which have zero or negligible latent periods (the latent period is the time from disease incidence until it becomes infectious to others). In the model, it is assumed that the reliabilities of the screening tests are constant, and independent of how long the population unit has the disease. Both tests with perfect and imperfect reliabilities are considered. A mathematical program for computing the optimal test choice and screening periods is presented. It is shown that the optimal screening schedule is equally spaced for tests with perfect reliability. Other properties relating to the managerial problems of screening frequencies, test selection, and resource allocation are also presented.

In England and Wales, various health authorities and medical societies have proposed different national policies to screen for cervical cancer. Parkin & Moss

[1986] use a computer simulation to evaluate nine such policies and their cost-effectiveness. They conclude that the original mass screening policy based on five-yearly testing of women aged over 35 years appears to be the most cost-effective for the National Health Service.

Most recently, many operations researchers and others have been involved in research to reduce the prevalence via prevention or ameliorate the effects of HIV and AIDS in individuals and populations. Notably, the queueing and differential equation models by Kaplan [1989] and Caulkins & Kaplan [1991] have been instrumental in the implementation of needle distribution, cleansing and information programs for intravenous drug users (IVDU) in New Haven, CT and New York, NY. Homer & St. Clair [1991], with a differential equations model, also examine the policy implications of clean needle efforts to reduce the rate of incidence and prevalence of HIV in IVDU. The simulation modelling efforts of Brandeau, Lee, Owens, Sox & Wachter [1991] greatly clarify the policy discussions concerning legislation such as testing high-risk women to reduce the birthrate of HIV-infected infants, contact tracing of sexual partners of HIV infected persons and screening of applicants for marriage licenses. By and large, their work shows that these types of programs for most populations are not cost-effective and do not significantly affect the course of the HIV epidemic. In an excellent review paper, Brandeau, Lee, Owens, Sox & Wachter [1990] also discuss and evaluate the structure and other issues involved in models for policy analysis of HIV screening and intervention. They also highlight gaps in current research and important policy questions for further analysis.

In a variant and extension of the idea of screening individuals for HIV, Bosworth & Gustafson [1991] develop a microcomputer-based decision support system for persons with HIV or who are at some risk to contract HIV to obtain anonymous, current and nonjudgemental information on personal behavior, social support, referral services, and medical advances to treat HIV. The intent of the DSS is to help people cope with the very difficult situations they face if seropositive, or understand their risks if not. In addition, it is hoped that the information would lead to personal behavioral changes to reduce the future incidence of HIV.

Operations researchers have been attracted to the problem of screening for disease due to its importance, close ties to maintenance problems, and rich structure. More work is needed on the linkages to the epidemiology literature and to the construction and evaluation of models which can aid in decisions that are often based on sparse or incomplete data and incomplete knowledge of the disease etiology and propagation.

3.2. Clinical decision-making

The contributions of operations research methodologies to disease prevention and the management of ill persons constitute a large and growing area of both health services research and operations research. This area is a hybrid which draws upon the mathematics and structural analysis of operations research and solution approaches including optimization and simulation, as well as a deep knowledge of biological, economic, and sociological aspects of patient care. This section will review medical management in three areas. First is the use of *decision analysis* to aid in the structuring of medical decisions. Second is *performance improvement*. In this area, operations research methodologies which improve the accuracy of diagnoses, the ability to diagnose under uncertainty, and the performance of testing or treatment strategies are reviewed. This area is particularly relevant to current concerns about quality of care and practice efficiency. Third is the use of operations research techniques and *cost effectiveness* analysis (CEA) to analyze health care policies and those policies that affect large populations.

Decision analysis has become widespread in analyzing medical decisions, policies, and practice efficiency. One of the first principles of approaching a decision in which there is risk and uncertainty is to determine the attributes, structure, and outcomes of those decisions, along with their concomitant probabilities. Pauker & Kassirer [1987] provide an excellent review of decision analysis in health care and describe three important areas. First is the use of decision trees to show probabilities, outcomes, chance nodes, and decision nodes for complex problems, such as thyroid irradiation treatment during childhood or coronary artery disease treatment. These principles have been used in numerous health services research articles. The key part of this process of decision tree structuring is identification of critical nodes or those decision variables which are important to outcomes or which the decision-maker wants to modify. Second is sensitivity analysis, where the parameters, particularly *ex ante* probabilities of chance events, are manipulated to determine the effect on the resultant decision to either errors in data or uncertainty itself. Third is identification of unambiguous outcomes. This facet is a weakness of most medical decision analytic research, because outcomes, or end points of treatment, are sometimes difficult to determine. For example, although death itself is a clearly identified state, it is rarely clear that the decision in question can be implicated in a death which is proximal to the decision. This ambiguity is the basis for so-called severity correction or risk adjustment for mortality. Beyond mortality, however, other indicators, such as life expectancy, quality of life, satisfaction, morbidity, or complications, are more difficult to determine and more ambiguous to structure. The current state of the decision analysis literature regarding outcomes is encouraging however. Wasson, Sox, Neff & Goldman [1983] report that in a survey of published prediction rules for clinical decision-making, 85% of articles clearly identify and appropriately define outcomes.

Many decisions faced by the clinician or the health services researcher are either too complex or contain states which are highly interdependent. Traditional, normal-form decision trees or other closed-form approaches are not easily applied, which consequently leads to a situation where simulation models are useful. One such approach to this problem is simulation of logical networks (SLN). In a 1984 article, Roberts & Klein review the application of network modelling to endstage renal disease, chronic stable angina, renal artery stenosis, and hypercholesterolemia. They then describe a technique by which modelling for other areas can be done. These diseases tend to be chronic and involve multi-component analysis.

Medical decision *performance improvement* applications are seen in two areas. First is in improving diagnostic accuracy for chronic and acute conditions. Second is in improving performance of testing strategies. This latter area usually uses tree structuring and network modelling, but involves analysis aimed at optimization or efficiency improvement.

A good example of this work is by Fryback & Keeney [1983] in which a complex judgmental model predicting the level of severity of a trauma patient is reported. The assessment of a trauma patient is confounded by rapidly changing physiologic states, multiple conflicting indicators, frequent erroneous normal physical examinations, and a high incidence of fatalities. To develop the model, the authors first elicit trauma surgeon expert opinions to develop seven specific concerns about trauma, such as ventilation systems or circulation systems. The experts rank-order these concerns into a hierarchy of trauma severity. They then develop a function in which the severity of a patient was a function of age, co-morbidities, and the measures of the seven severity indicators. Because severity scores were not additive, and since any measure alone could result in death, the severity conditions are considered multiplicative. It is further determined that many of the attributes were non-monotonic, indicating that they each have optimal ranges, and that deviations on either side represented deteriorations. From this information a trauma score index is developed which predicts level of severity for all trauma patients. The authors then perform a validation of the index on patients retrospectively.

Demonstrating an application of operations research techniques to chronic disease decisions, Moye & Roberts [1982] model the pharmacologic treatment of hypertension. The authors develop a stochastic representation of hypertension treatment that predicts the outcome of hypertensive treatment regimens which were observed in clinical situations. The authors do this by using expert input to determine different treatment protocols and the outcomes which were associated with them. The authors include compliance, effectiveness of the treatment regimen, side effects, cost, and symptoms of hypertension, and used traditional cut-offs for normal blood pressure (140/90) as an outcome measure. From this, probabilistic statements about whether a patient had controlled blood pressure on a given visit are developed. The authors then use consensus input from experts about compliance, probabilities that patients do not return for visits when their blood pressure is not controlled, and probabilities that patients are lost to care. These parameters are then subjected to a 13-step algorithm which determines optimal treatment, given the outcomes and cost information. These results are validated by comparison to studies reported in the literature about treatment outcomes.

In another application regarding live organ transplantation, David & Yechiali [1985] use a time-dependent stopping process to match donor kidneys to recipients. The authors note that at any given time, donor kidneys become available but, on the basis of histo-compatibility, rarely match any recipient perfectly in a regional pool. Thus, the degree of match is frequently imperfect, which usually determines the survival of the graft over the post-transplant period. The problem here is to determine at any given time whether an organ should be accepted or passed over to allow for another potential donor in the future. The authors formulate a general setting for optimal stopping problems with a time-dependent failure rate and model the arrival of offers as a renewal process. They show that the lifetime distribution of the underlying process of mismatches has an increasing failure rate. The authors then examine heterogeneous Poisson arrivals and derive a differential equation for the optimal control function, which leads to a tractable equation particularly suited to this problem. The authors apply the solution to the problem using observed data from the clinical literature.

The third area where operations research has made substantial contributions to medical management is in *cost effectiveness analysis* (CEA), or *cost benefit analysis* (CBA). The general framework of the CEA, as reviewed by Weinstein & Stason [1977], includes the following elements. First is net health care cost. The net costs of health care include direct health care and medical costs for any given condition, to which are added the costs of adverse side effects of any treatment and from which is subtracted the cost of morbidity, since these are the savings which health care accrues from the prevention of disease. Second is the net health effectiveness, the increase in life years which result from the treatment, to which are added the increased number of years gained from the elimination of morbidity. The number of life years lost to side effects are then subtracted. These years are frequently adjusted for quality of life (quality-adjusted life years, or QALY). The ratio of net costs to net effects is the cost effectiveness ratio. CBA, on the other hand, sets a value on the net effects and then seeks to determine if the value of the benefits outweigh the net costs. However, this requires assignment of value to life, which is frequently a controversial topic. Despite this shortcoming, several methodologies of life valuation, including willingness to pay and human capital, consumption, and production valuation, have been developed. CEA expresses the relative efficiency of a given treatment, and by comparison of treatments for similar diseases or conditions, an efficiency frontier can be identified and an 'optimal' treatment selected. However, comparison of multiple treatments is frequently precluded because they have different structures of care or outcomes, and hence, are difficult to compare. Therefore, most decisions are aimed at efficiency improvement rather than optimality.

Beyond providing the decision analysis framework by which CEA decisions can be structured and analyzed, operations research contributes to CEA in other ways, particularly in the development of computer simulations which allow analysis of decisions where data are sparse, where waiting periods for outcomes are long, or where different treatments result in widely differing levels of effectiveness. Habbema, Lubbe, Van Ortmarssen & Van der Maas [1985] demonstrate this approach in making cost effective decisions for the screening of cervical carcinoma. The authors develop a program which uses a Monte Carlo simulation to determine the effects of various screening protocols on the morbidity and mortality of a typical population. Because of the long period over which cervical carcinoma develops (lag time) and over which it could recur if treated (recurrence lag), simulation modelling is well suited to this problem. The authors generate distributions of cancer rates under various screening strategies, and then, by using standard assumptions about costs and effectiveness, determine the cost effectiveness of these scenarios.

In a related application, Kotlyarov & Schniederjans [1983] simulate a stochastic equipment utilization function to assist in the cost benefit analysis of capital investment in nuclear cardiology instruments, including the nuclear stethoscope, mobile camera, and fixed cardiac computer. The authors again use a Monte Carlo simulation technique to generate the stochastic behavior of utilization of the equipment, and use standard economic information about reimbursement rates and acquisition costs to determine under what utilization patterns it is cost effective to invest in such technology.

The extensive work which is being performed in expert systems and artificial intelligence cannot be reviewed in this chapter. The reader should refer to the work of: Greenes & Shortliffe [1990]; Langlotz, Shortliffe & Fagan [1988]; Langlotz, Fagan, Tu, Sikic & Shortliffe [1987]; Rennels, Shortliffe & Miller [1987]; Shortliffe [1987]; Rennels, Shortliffe, Stockdale & Miller [1987]; Gabrieli [1988]; Perry [1990]; Miller & Giuse [1991]; Hasman [1987]; and Steinwachs [1985] for examples of important research about expert systems and artificial intelligence.

Finally, it should be mentioned that data technology is opening up many more modelling opportunities for operations researchers. Some hospitals are experimenting with the installation of bedside terminals. These terminals are used primarily for bed-side admitting, transferring and discharging, nurse and physician order entry, and chart documentation. Other clinical departments making significant use of new data technologies are the medical and radiation laboratories, pharmacy, infectious disease control, and respiratory and physical/occupational therapies. These departments use systems to automate scheduling, testing, reporting, and recording of sessions and/or results. The systems check for errors, test duplication, wrong test/treatment time, allergic reactions, and incompatible drug protocols, and often state the correct actions to be taken or procedures to be followed and may suggest alternatives. Modelling these systems can enable hospital personnel to reduce errors, increase timeliness, reduce costs, and make appropriate diagnostic and treatment decisions, thereby reducing risk and increasing satisfaction and successful outcomes.

The management of medical patients has been enhanced greatly by the application of operations research. Of all areas of operations research applications in health care delivery, this area is perhaps the fastest growing. These models form the basis of artificial intelligence, management information systems, and decision support systems applications. However, clinicians still hesitate to use expert systems or other DSS models for diagnosis or treatment. Of course, there are many possible reasons why some innovations are adopted while others may only stay in the research mode. It is a goal of present and future research to study this clinician-system process in order to understand the dynamics of adoption and diffusion. As this knowledge grows, operations research-based knowledge systems will become more useful to the practicing physician.

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