Modelling resource availability in general hospitals: design and implementation of a decision support model

Citation for published version (APA):

Kusters, R. J., & Groot, P. M. A. (1996). Modelling resource availability in general hospitals: design and implementation of a decision support model. *European Journal of Operational Research*, 88(3), 428-445. <https://doi.org/10.1016/0377-2217%2895%2900201-4>, [https://doi.org/10.1016/0377-2217\(95\)00201-4](https://doi.org/10.1016/0377-2217(95)00201-4)

DOI:

[10.1016/0377-2217%2895%2900201-4](https://doi.org/10.1016/0377-2217%2895%2900201-4)
[10.1016/0377-2217\(95\)00201-4](https://doi.org/10.1016/0377-2217(95)00201-4)

Document status and date:

Published: 01/01/1996

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
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- The final published version features the final layout of the paper including the volume, issue and page numbers.

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Case Study

Modelling resource availability in general hospitals Design and implementation of a decision support model

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Received 1 October 1994; revised 1 July 1995

Abstract

Admission planning in general hospitals means selecting elective patients from a waiting list in order to obtain optimal utilisation of the available beds, nursing staff and operating theatre facilities while taking into account emergency admissions. Also, a wide variety of other factors, often situational and not explicitly stated, play a part in this decision process. As such, it is a complex problem which is difficult to handle for any decision maker. In this paper a statistical model for the prediction of resource availability is presented. The model is first tested on empirical data. On the basis of the model a DSS was designed which is now in daily use in several hospitals. Problems encountered in that implementation process will be stated. The results obtained with the model show that such an approach based on statistical data provides sufficiently accurate results to be useful.

Keywords: Decision support system; Forecasting; Health services; Modelling

1. Introduction

Admission planning is the key activity which allows a hospital to balance the daily demand for hospital facilities against the availability of these resources. Choosing the ‘right’ patients from the waiting list to balance the needs of the patients themselves, hospital management, nursing staff and medical staff is not a simple task. The many factors involved in controlling a speedy throughput of patients on the one hand and the optimal use of scarce resources on the other make this a ‘wicked’ problem. As such it is unlikely that models exist which are capable of generating an optimal solution. The final decision will have to take

into account such a variety of factors that it can only be taken by a human decision maker. However, it is possible to supply support to this decision maker. In this paper a description and a test of such a support system will be presented. The main support provided by the computer model is in the area of predicting the resource effects of decisions. A series of resource availability models will be presented. On basis of these models a decision support system has been developed and tested in practice. The paper concludes with some of the results obtained.

2. The admission planning system

Admission planning can be defined as (de Haas, 1984): “The selection of patients to be

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admitted from a waiting list, and the provision for emergency admissions, taking into account the available resources of staff, space and means and the medical, social and functional urgency of the admission per patient.”

From this definition it may be concluded that an admission planning system consists of four elements:

- set of goals,
- waiting list registration system,
- admission planner,
- prediction system.

2.1. Goals

The first element is a set of goals, for “selection” is a goal oriented activity. The main hospital goals in this area can be stated as:

- Optimizing patient throughput. This means minimizing the time spent on the waiting list, allowing for a reasonable time span between the call for admission and the actual admission. It also means accepting no unnecessary delays during the stay in hospital.
- Maximizing hospital resource utilization. The main resources which play a part in admission planning are beds, operating theatre facilities and nursing staff.
- Optimizing availability of emergency services.

Apart from these rather obvious goals a lot of other goals can be distinguished. These may be subjective and are often not explicitly stated. Also goals may change over time again without this change necessarily being recorded. However, any admission policy will have to take these into account if it is to be acceptable to all parties involved.

2.2. Waiting list

The definition of admission planning mentions “selection from a waiting list taking into account the available capacities”. Admission planning tries to balance the demand for and supply of hospital facilities. When achieving this balance, only the demand side of the equation is available for manipulation. The supply of resources can in the short run be considered as fixed. Demands are

managed or manipulated by the waiting list, which represents the decision space of the admission planner. This requires a waiting list registration system from which information regarding the demand for care may be taken.

2.3. Admission planner

Given the proliferation of subjective and often conflicting goals it is not likely that an admission plan made by a computer programme will ever be accepted in hospitals. A hospital may be characterized as a professional bureaucracy (Mintzberg, 1983). In such an organization decisions are accepted only if they are backed up by professional expertise. A piece of software cannot provide this expertise. It is possible to formulate a set of explicit quantitative goals which can be used as constraints for any proposed solution. However this will not be sufficient to base a decision on. In essence any admission planning system is a man-machine system.

2.4. Prediction system

A final element is a prediction system which can predict the effects of an admission decision. As was stated before it is not feasible to try to take into account all relevant goals explicitly. Part of this prediction system will be incorporated in the admission planner who will try to take as many goals as possible into account. It is however possible to distinguish a number of goals that can be stated explicitly and described objectively. An automated prediction system focused at these goals can be envisaged. Such a system would lighten the burden of the admission planner. Also, it would provide better quality planning since the prediction system would be aimed at statistical data handling, an activity in which humans are notoriously poor. The evaluation of qualitative data, an activity not very well suited for computers, is carried out by the human planner. In this paper such a prediction system will be described. It will be aimed at the prediction of resource availability. The resources included are those which most affect patient throughput, namely beds, operating theatre facilities and nursing staff.

3. Methods used

The models will predict resource utilization and emergency admissions. In principle this problem can be approached in two ways. Firstly one may use subjective estimates as supplied by medical or nursing staff. Secondly, it is possible to use statistical data. Studies (Briggs, 1971; Gustavson, 1968; Warner, 1976) show that both methods on average perform equally well. However it appears that over time more and more problems are encountered in enlisting the cooperation necessary for the subjective method. Also, it appears (Kahneman et al., 1982) that in supplying these subjective data, people tend to put a disproportionate stress on recent occurrences. This so-called “recency-effect” will not influence the average of the estimation, but will increase its variance strongly. Taking into account these reasons, and considering that statistical data are often easy to collect, it was decided to use statistical data and methods for developing this model.

The models that will be presented all operate on the principle of extrapolation. Based on the situation at the moment of the admission planning decision a prediction of the situation during the next few days is made. The approach is an expanded and revised version of a model that was earlier introduced by Rubinstein (1977). Predictions are based upon the assumption that types of patient may be distinguished each characterized by a certain resource consumption. Assuming that such a classification of patients is available the model development is straightforward.

The next question is: is it possible to design a patient classification system in such a way that the resource consumption within a class is sufficiently similar to be used as the basis of prediction. An additional problem is that only information which is available at the moment of planning may be used in this classification. Patients will be divided into groups on the basis of information that is in principle available at the time of admission. For patients on the waiting list personal data (age, gender, type of insurance) are known. Also the admitting specialist is known, a preliminary diagnosis and, if appropriate, an indication of the surgical procedure. For emergency admis-

sions none of these data is available. For this group we were obliged to work with rough averages.

Design of the classification and testing of the models was based on the data of 19417 patients that were obtained from two large Dutch hospitals. Available data included final diagnosis and type of surgical procedure. The first three digits of the code of the final diagnosis (based on the international classification of diseases) and the first two digits of the procedure code (based on the international classification of surgical procedures) were used as proxies for preliminary diagnosis and surgical procedure. The error introduced in this way is acceptable since Leske et al. (1978) showed that differences between preliminary and final diagnosis are mainly found in the last two digits of these codes and exactly those two digits were excluded from the classification.

A classification was designed relative to each resource included in the study:

- beds,
- operating theatre facilities,
- nursing staff.

3.1. Beds

The goal of the classification is the division of the patient population into a number of groups with a more or less similar length of stay. Both from literature and from the available data the conclusion may be drawn that the major point on which a classification split should take place is the diagnosis. Considerable effort was spent on finding meaningful clusters of diagnosis, but without success. Therefore the diagnosis itself was taken as a basis for classification. It can be noted that diagnostic related groups (DRGs) (Nedertigt, 1985) explicitly base classification on information that is available only after admission. This means that DRGs cannot be used for our purpose. Further classification on the basis of gender and admitting specialism resulted in an improvement of the results (i.e. correlation with length of stay). The data showed little correlation between length of stay and age or means of insurance, factors that are sometimes found in literature.

These factors were therefore not included in the classification.

3.2. Operating theatre facilities

The most obvious basis for classification aimed at obtaining groups with homogeneous consumption of operating theatre facilities is the surgical procedure used. The first two digits of the surgical procedure indeed provided a suitable classification. Other variables mentioned in literature (age, specialist, gender and operating physician) did not result in significantly better results. Therefore these variables were not included in the classification.

3.3. Nursing staff

With respect to workload patients were first classified into those that undergo surgery and those that do not undergo surgery. A further classification was then carried out according to surgical procedure if appropriate or diagnosis otherwise. Several other factors were looked at. It was found that further classification both on age and gender increased the quality of the results. With respect to age a choice was made for a simple division into two groups (< 80 and ≥ 80). Another possible variable is the amount of time already spent in hospital. It is possible to envisage a workload curve as presented in Fig. 1(a),

indicating that the workload demanded by the patient depends on the time spent in hospital. It was found that a very simple care profile as represented in Fig. 1(b) provides sufficient information for surgical patients. In this profile a distinction is made between the day of surgery plus the following day on the one hand and the other days on the other hand. For non-surgical patients a profile presented in Fig. 1(c) was found to be sufficient.

A remaining question concerns the type of distribution function that will be used in the models that will be presented next. Having tried several theoretical distributions it was concluded that the log-normal distribution would be the best (or least bad) choice. However, in many cases the quality of the fit ranges from poor to non-existing. In this study we therefore opted for empirical distributions.

4. Bed availability

4.1. Introduction

In this section first some definitions will be presented. Next the model will be defined. Finally some results obtained using this model will be presented.

For a consistent use of language the status of the system at the moment of decision and the

Fig. 1. Patient workload.

status at the moment of admission will be defined as follows:

- The status at the moment of decision (day t) is:
 - all admissions on this day have already taken place (including emergency admissions),
 - all discharges on this day have already taken place.
- The status at the moment of admission (day $t + y$) is:
 - all emergency admissions have taken place (note that this in essence means that beds have been set aside for them),
 - all discharges have taken place,
 - no elective admissions have taken place.

These assumptions concerning the status are not essential to the model, but in order to achieve a consistent use of language, it is necessary to make these or similar assumptions.

4.2. The bed availability model

The model predicts the number of beds available at some time in the future. Starting with the number of available beds on day t one can, by predicting the changes, find the expected number of available beds on day $t + y$. These changes are:

1. the number of elective admissions on the days $t + 1, \dots, t + y - 1$,
2. the number of emergency admissions on the days $t + 1, \dots, t + y$,
3. the number of discharges on the days $t + 1, \dots, t + y$. This last element consists of three parts:
 - 3.1. the number of discharges from the patients, present on day t ,
 - 3.2. the number of discharges from the emergency admissions on the days $t + 1, \dots, t + y$,
 - 3.3. the number of discharges from the waiting list admissions on the days $t + 1, \dots, t + y - 1$.

Each of these changes will now be looked at separately.

4.2.1. Waiting list admissions

First we will look at the number of waiting-list admissions during the following days. Since we

are planning at a fixed time horizon of y days, the admissions that are planned in the intermediate period are known. These patients have already been notified.

4.2.2. Emergency admissions

The number of emergency admissions are of course not known. However, according to literature (Newell, 1954; Handyside and Morris, 1967) it can be assumed that the number of emergency admissions per day is Poisson distributed. This was confirmed using the available data. The parameter of this distribution may differ per day of the week. Let $NEA(t)$ be the number of emergency admissions on day t . These follow a Poisson distribution with parameter $\lambda_{NEA}(t)$. Assuming that $NEA(t_1)$ is independent of $NEA(t_2)$, $t_1 \neq t_2$, we now have for the total number of emergency admissions on the days $t + 1, \dots, t + y$:

$$E\left\{\sum_{i=1}^y NEA(t+i)\right\} = \sum_{i=1}^y \lambda_{NEA}(t+i)$$

and

$$V\left\{\sum_{i=1}^y NEA(t+i)\right\} = \sum_{i=1}^y \lambda_{NEA}(t+i).$$

4.2.3. Discharges

4.2.3.1. Discharges among already hospitalized patients. The patients in hospital at day t are split into G groups with similar length of stay per group. Let $F_g(y)$ be the cumulative distribution function (c.d.f.) of the length of stay for patients from group g , $g = 1, \dots, G$, $F_g(y|a)$ the c.d.f. of length of stay, given that the patient has already spent a days in hospital, and $NP_g(t, a)$ the number of patients from group g , present at day t , that have already spent a days in hospital.

It follows that:

$$F_g(y|a) = \frac{F_g(a+y) - F_g(a)}{1 - F_g(a)}.$$

Let $ND_g(t, a, y)$ be the number of discharges within y days from patients from group g , present at day t , that have already spent a days in

hospital, and let $ND_g(t, y)$ be the number of discharges within y days from patients, present at day t . $ND_g(t, a, y)$ may be seen as the result of a sampling from a binomial distribution with parameters $NP_g(t, a)$ and $F_g(y|a)$, so that:

$$E\{ND_g(t, a, y)\} = NP_g \frac{F_g(a+y) - F_g(a)}{1 - F_g(a)}$$

and

$$V\{ND_g(t, a, y)\} = NP_g \frac{(F_g(a+y) - F_g(a))(1 - F_g(a+y))}{(1 - F_g(a))^2}.$$

Assuming that separate discharge decisions are independent we get:

$$E\{ND(t, y)\} = \sum_{g=1}^G \sum_{a=1}^{\infty} E\{ND_g(t, a, y)\}$$

and

$$V\{ND(t, y)\} = \sum_{g=1}^G \sum_{a=1}^{\infty} V\{ND_g(t, a, y)\}.$$

Often additional information is available. It is possible that discharges on day $t+1$ are known on day t . This can be incorporated into the model.

Let $NP_g^*(t, a)$ be the number of patients from group g on day t that have spent a days in hospital and will not be discharged on day $t+1$. We now get:

$$E\{ND(t, y)\} = \sum_{g=1}^G \sum_{a=1}^{\infty} \left(NP_g^*(t, a) - NP_g(t, a) + NP_g^* \times \frac{F_g(a+y) - F_g(1+a)}{1 - F_g(1+a)} \right)$$

and

$$V\{ND(t, y)\} = \sum_{g=1}^G \sum_{a=1}^{\infty} \left(NP_g^*(t, a) \times \frac{(F_g(a+y) - F_g(1+a))(1 - F_g(a+y))}{(1 - F_g(1+a))^2} \right).$$

4.2.3.2. Discharges among emergency admissions. We will now have a look at the number of patients to be discharged from the emergency admissions during the next few days.

Let $NED(t+i, y)$ be the number of emergency patients, admitted on day $t+i$ and discharged at the latest at day $t+y$, and $F_s(t)$ the c.d.f. of the length of stay of emergency patients.

The number of discharges may be considered as the result of a sampling from a binomial distribution with parameters $NEA(t+i)$ and $F_s(y-i)$. This means, since $NEA(t+i)$ follows a Poisson distribution, that we are dealing with a binomial distribution “mixed” with Poisson weights. The result (Feller, 1968) can be shown to be a Poisson distribution with parameter $\lambda_{NEA}(t+i) \cdot F_s(y-i)$. This gives for the total number of discharges:

$$E\left\{ \sum_{i=1}^y NED(t+i, y) \right\} = \sum_{i=1}^y \lambda_{SI}(t+i) \cdot F_s(y-i)$$

and

$$V\left\{ \sum_{i=1}^y NED(t+i, y) \right\} = \sum_{i=1}^y \lambda_{SI}(t+i) \cdot F_s(y-i).$$

4.2.3.3. Discharges among planned admissions. Lastly we will look at the number of discharges from the waiting list admissions during the next few days. This may again be considered as the result of a sampling from a binomial distribution.

Let $NWA_g(t+i)$ be the number of waiting-list admissions on day $t+i$ from group g and $NWD_g(t+i, y)$ the number of waiting-list admissions on day $t+i$ from group g that are discharged at day $t+y$ at the latest.

The number of discharges may again be seen as being binomial distributed with parameters $NWA_g(t+i)$ and $F_g(y-i)$. This gives:

$$E\left\{ \sum_{i=1}^{y-1} \sum_{g=1}^G NWD_g(t+i, y) \right\} = \sum_{i=1}^{y-1} \sum_{g=1}^G NWA_g(t+i) \cdot F_g(y-i)$$

and

$$\begin{aligned}
 V \left(\sum_{i=1}^{y-1} \sum_{g=1}^G \text{NWD}_g(t+i, y) \right) \\
 = \sum_{i=1}^{y-1} \sum_{g=1}^G \text{NWA}_g(t+i) \cdot F_g(y-i) \\
 \times (1 - F_g(y-i)).
 \end{aligned}$$

Now we have discussed the different factors influencing bed availability, it is possible to join them together in order to achieve a prediction of bed availability on day $t+y$. Since all the changes are caused by separate decisions made for different patients, it is not unrealistic to suppose that they are statistically independent. Thus it is allowed to calculate the expectations and the variance of bed availability as the sum of the expectations and variances of the different components. We have shown that the bed availability is determined by a number of independent stochastic variables. It is now possible, quoting the Lindeberg–Feller version of the central limit theorem (Feller, 1968), (every uniformly bounded sequence of mutually independent random variables obeys the central limit theorem), to state

that bed availability follows a normal distribution. Since we have determined how to calculate the parameters of this distribution it is now possible to provide confidence intervals for bed availability. Used in this way, this model provides a planner with an estimation of the number of beds that will be available at day $t+y$ with a certain probability.

4.3. Assessing the model

For each prediction obtained by using the model, the expected volume and the variance of the bed availability may be calculated. This makes it possible to calculate:

- the prediction error,
- the number of beds that will with a certain probability be available,
- the realized prediction efficiency that accompanies this probability.

The notion efficiency is here defined as the fraction of the expected bed availability that was in reality available. For instance, if with a certain probability 10 available beds were expected and 9 beds was the realization, then the prediction efficiency is 0.90. In order to assess the reliability of

Table 1
Results of prediction of bed occupancy three days ahead, using a theoretical overflow of 5%

Specialist	Men				Women			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
General surgery	56.7	0.7	4.7	1.00	51.7	0.4	4.1	1.00
Plastic surgery	1.3	0.1	1.4	0.99	3.0	0.0	1.1	0.99
Gynaecology	0.0	0.0	0.0	0.00	50.0	1.4	1.1	1.00
E.N.T. surgery	4.6	0.1	2.7	0.99	3.9	0.1	1.9	0.99
Neuro surgery	22.4	0.4	1.4	1.00	18.1	0.3	2.5	0.99
Eye-surgery	2.9	0.0	1.1	1.00	3.6	0.0	2.7	0.99
Orthopaedics	1.5	0.0	0.6	0.99	2.6	0.1	0.3	1.00
Jaw	17.5	0.3	3.0	0.98	24.8	0.2	2.7	1.00
Urology	2.2	0.0	2.2	0.98	2.6	0.0	1.4	0.99
Paediatrics	19.9	0.4	3.0	0.99	5.8	0.1	1.6	0.97
Other	14.4	0.0	4.7	0.98	7.8	0.2	2.5	0.99
Total	143.0	2.1	3.0	1.00	173.9	2.8	3.3	1.00

(1) Mean of realized bed occupancy.

(2) Prediction error.

(3) Realized overflow percentage with a theoretical overflow value of 5%.

(4) Realized efficiency with a theoretical overflow value of 5%.

the model we now have to take a look at the prediction error and the realized overflow that goes with a certain theoretical overflow probability.

The effect of using the model may best be seen from the realized efficiency, while realizing of course that this realized efficiency depends on the chosen theoretical overflow probability. We have to keep in mind that efficiency is not overflow probability. For instance, if in a certain period expected bed availability is 20 and the realization is 19, then the overflow probability is 1 which is at first glance a bad result. However, 19 out of 20 patients may be accommodated, giving an efficiency of 0.95. Not so bad a result after all.

4.4. Results

Some results are presented here, obtained by applying the model to the data for two large Dutch hospitals referred to in Section 3. To this end, for each day for which data were available, a prediction was generated for the bed availability on each of the following seven days. These predictions were generated for each specialism, and within each specialism for each gender. Since data were available for ten specialities and a children department on each day for $(11 \times 2) - 1 = 21$ groups, predictions were made from 1 to 7 days ahead, giving a total of $21 \times 7 \times 365 = 53\,655$ predictions. Results of predictions three days ahead using a theoretical overflow possibility of 5% are presented in Table 1.

It can be seen that the prediction errors are quite small. Furthermore, the realized overflow, which should be around 5% is in fact slightly smaller. From this, it would seem that the model fits quite well on the data. If we now look at the realized efficiency, it may be seen that it is extremely high, indicating quite satisfactory performance of the model. Similar results are obtained for all specialists, indicating a general usefulness of the model. Also if we look at the realized efficiency of all specialities together we see that it is 1.00. This means that when using this model, while some patients may not be placed at their proper wards, their admission will not be endan-

gered, because some other wards will almost certainly have spare beds.

5. Operating theatre availability

5.1. Introduction

In this section first some definitions will be presented. Next the operating theatre availability model will be presented. Finally a model for determining the amount for time to be set aside for emergency surgery will be presented.

Availability of operating theatre capacity depends on the simultaneous availability of several resources, e.g. an operating theatre, an anaesthetist, a surgeon and OR-nursing staff. In this paper we will assume that operating time is allocated. This means that the management of the operation facilities is held responsible for the availability of all resources needed. When planning the admission of patients only this available time has to be considered. The problems caused by this approach can be solved on the day the procedures take place by means of the sequence in which they are performed.

Available operating time can be divided into change and cleaning time on the one hand and aggregate operating time on the other. Aggregate operating time can be further decomposed (e.g. initiation of sedation, net operating time etc.). Since only the availability of resources concerns us, only aggregate operating time will be looked at. Classification of patients on the basis of operating time was already discussed above. Another problem is classification of the time between operations. The data showed that this time differed between specialists. However, these differences were small compared to the total length of a session. A fixed time to account for each switch proved to provide satisfactory results.

5.2. The operating theatre availability model

We will look at the predicted length of a planned session consisting of several procedures. Basis of the model is the expected length and variance of the procedure per group. If this infor-

mation is known, then for each planned procedure the expected mean value and variance of the operating time is known. Adding to this a factor for each planned switch between procedures it is now no problem to calculate the total expected time of the planned session. This does not suffice for planning purposes. Information on overflow probabilities is needed to support admission planning. For this, information on the variance of the total session time is required.

If the lengths of the different procedures in a single session can be considered to be mutually independent, then calculation of the variance of the session time is straightforward. However, this independence is not certain. It is for instance quite possible that time lost during a procedure is caught up during the next procedures. This would result in the variance of the session being smaller than the sum of the variances of the parts. The data available were checked to see if independence could be assumed. It was found that the sum of the variances of separate procedures was an adequate predictor of the variance of the entire session. Following this we will in the remainder of this paper assume independence.

Given expected length and variance of a session we now try to determine overflow probabilities. The number of procedures in a session is quite small (between 1 and 5 on average). This number is too small to allow us to invoke a central limit theorem in order to claim that the session time follows an normal distribution. This is confirmed by the data. The approach chosen here was to see if the resulting empirical distribution found for the total session time behaves in a similar way to the normal distribution. That is: is

it possible to find factors f'_α for which:

$$P(x \leq E(x) + f'_\alpha \cdot \delta(x)) = 1 - \alpha, \quad 0 \leq \alpha \leq 1$$

Taking a part of the data to determine these factors, testing them on the remainder of the data and repeating this procedure several times on different partitions of the data resulted in a set of factors which proved usable (Table 2). The factors differ significantly from the factors of the normal distribution. Confidence intervals using this empirical distribution will have to be larger than would have been needed if the distribution had been normal but at least some information on overflow probabilities can in this way be provided.

5.3. Emergency surgery

This model only looks at planned surgery. Up till now emergency surgery was not included. In this paragraph a model will be presented to assist in determining the amount of time to be set aside for emergency surgery. A histogram of the available data on time spent on emergency surgery during normal hours suggests that these data follow an exponential distribution. This is confirmed by a Chi-square test. On this assumption the following model can be constructed based on making explicit the balance between the costs of not using allotted operating time versus the costs of exceeding this time.

Let c_1 be the costs per unit of time of underutilization, c_2 the costs per unit of time of overutilization, $c = c_1/c_2$, $f(x, \lambda)$ the density function of an exponential distribution with parameter λ , $F(x, \lambda)$ the cumulative density func-

Table 2
Empirical factors

α	Factor of normal distribution	Average of empirical factors	Standard deviation of empirical factors
0.200	0.842	0.71	0.04
0.100	1.282	1.34	0.06
0.050	1.645	1.95	0.06
0.025	1.960	2.53	0.07
0.010	2.326	3.41	0.12

tion of $f(x, \lambda)$, m the number of time units set aside for emergency surgery, X the number of time units needed for emergency surgery (a stochastic variable), and $C(X, m)$ the total cost resulting from a choice of m .

If costs of under- and overutilizations vary linearly in time, then for each choice of m the costs are:

$$C(X, m) = \begin{cases} c_1(m - X) & 0 \leq X \leq m, \\ c_2(X - m) & X > m. \end{cases}$$

Expected costs can now be expressed as:

$$E\{C(X, m)\} = \int_0^m c_1(m - z) f(z, \lambda) dz + \int_m^\infty c_2(z - m) f(z, \lambda) dz.$$

Minimizing expected costs is equivalent to minimizing:

$$\begin{aligned} & \frac{E\{C(x, m)\}}{c_2} \\ &= m(c + 1) \int_0^m f(z, \lambda) dz \\ & \quad - (c + 1) \int_0^m z f(z, \lambda) dz - m + E\{x\}. \end{aligned}$$

Differentiation with respect to m and equating the result to 0 gives:

$$\begin{aligned} 0 &= (c + 1) \int_0^m f(z, \lambda) dz + m(c + 1) f(m, \lambda) \\ & \quad - m(c + 1) f(m, \lambda) - 1 \\ \Rightarrow \end{aligned}$$

$$F(m, \lambda) = \frac{1}{c + 1}.$$

Since

$$F(m, \lambda) = 1 - \exp(-m\lambda),$$

the value m for which the expected costs are minimal is:

$$m = -\frac{1}{\lambda} \ln\left(\frac{c}{c + 1}\right).$$

Given information on c (the relative effects of the costs of over- and underutilization of operating facilities) and given the expected value of the

time needed for emergency surgery, it is now possible to calculate the optimal time to be set aside.

6. Nursing staff availability

6.1. Introduction

In this section first some definitions will be given. Next the nursing staff resource availability model will be presented.

If we look at measuring the workload as required by in-patients, we notice (de Vries, 1984) that a distinction can be made between:

1. an amount of work depending on the type of patient,
2. an amount of work depending on the number of patients, regardless of type,
3. an amount of work that has to be done anyway, regardless of patients.

The workload in the first category can be further divided into direct (technical) patient care and other patient related care. Research (de Vries, 1984) shows that nursing staff do not like to postpone direct technical care. When the demand for care increases this means that the other activities will be neglected in favour of this direct care. Work pressure can now be defined as the percentage of total available nursing capacity (expressed in full time staff equivalents) that is spent on direct care. A goal of admission planning is to maintain this percentage within a given margin of a norm percentage. If this norm is set correctly, sufficient time will remain for the other activities.

In determining direct care some workload measurement system has to be used. Many such instruments exist. The instrument we used (Murphy et al., 1978) uses a scoring table as depicted in Table 3, in which four types of patients are distinguished with regard to the care needed:

- I minimal care or self care,
- II average care,
- III more than average care,
- IV continuous care.

On the basis of such a classification instrument it is possible, given the workload connected with

Table 3
Patient classification instrument

Type of patient	I	II	III	IV
independent	()			
help bathing		()	()	
partial help posture		()	()	
total help posture			()	()
partial help feeding		()	()	
total help feeding			()	
infusion		()	()	()
observation 1–2 hour			()	()
constant observation				()
(weighing factors)	(v)	(v)		
total			0.5	

I – minimal care or self care; II – average care; III – more than average care; IV – continuous care.

each category, to determine the workload in working hours caused by each of these types of patients on average.

6.2. The nursing staff capacity availability model

This model is similar to the bed availability model. By extrapolating from the time of the admission decision, day t , a prediction of the situation on a day $t + y$, will be obtained. This extrapolation will have to take into account:

1. patients in hospital on day t who will still be present on day $t + y$,
2. planned admissions during the days $t + 1, \dots, t + y - 1$ who are still in hospital on day $t + y$,
3. emergency admissions during the days $t + 1, \dots, t + y$ who are still in hospital on day $t + y$.

Taking into account emergency admissions on day $t + y$ is in effect setting aside capacity for these patients. Each factor will now be looked at more closely:

6.2.1. Patients in hospital

The bed availability model showed that the probability of a patient from length-of-stay category g still being in hospital on day $t + y$, given that the patient was admitted on day $t - a$, equals:

$$G_g(a, y) = \frac{1 - F_g(a + y)}{1 - F_g(a + 1) - F_g(a + b) + F_g(a + b - 1)}$$

if day $t + b$, $2 \leq b \leq y$, is a sunday. Otherwise

$$G_g(a, y) = \frac{1 - F_g(a + y)}{1 - F_g(a + 1)}.$$

Let p_{gi} be the probability that a patient from group g belongs to workload category i , $1 \leq i \leq 4$, and let k_i be the workload associated with category i .

The expected workload caused by this patient equals:

$$\sum_{j=1}^4 G_g(a, y) \cdot p_{gi} \cdot k_i$$

while the variance equals:

$$\sum_{j=1}^4 G_g(a, y) \cdot p_{gi} \cdot k_i^2 - \left(\sum_{j=1}^4 G_g(a, y) \cdot p_{gi} \cdot k_i \right)^2.$$

Since the workload requirements of the patients in hospital are mutually independent, the total expectation and variance of the workload on day $t + y$ caused by patients present at day t can now be determined by summation.

6.2.2. Planned admissions

The probability of a patient from length-of-stay category g who was admitted on day $t + i$, $1 \leq i \leq y - 1$, still being in hospital on day $t + y$ is $(1 - F_g(y - i))$. Expected workload and variance can now be calculated as described above.

6.2.3. Emergency admissions

This number of patients follows a Poisson distribution with parameter:

$$\lambda = \sum_{y=1}^4 (\lambda_{NEA}(t + i) \cdot (1 - F_g(y - i))).$$

Given that the workload of each of these patients can be seen as the result of a sampling from an empirical function, this sum follows a Poisson 'stopped' distribution. Douglas (1980) proves that for such a distribution the expected value is:

$$\lambda = \sum_{y=1}^4 p_{NEA} k_i$$

and the variance is:

$$\lambda = \sum_{y=1}^4 p_{\text{NEA}} k_i^2,$$

where p_{NEA} is the probability that an emergency admission falls in workload category i .

Expectation and variance of the total workload caused by the patients in hospital on day $t + y$ can now be calculated by summation. Workload is determined by the sum of a number of independent stochastic variables. The total number of parts in this sum is sufficiently large to assume, quoting the Lindeberg–Feller version of the central limit theorem, that workload follows a normal distribution. Since we have determined how to calculate the parameters of this distribution it is now possible to provide confidence intervals for work pressure.

7. Practical experience with the model

7.1. Introduction

A prototype of a decision support system for admission planning was developed. The aim of this decision support system is to provide the admission planner (whomever that may be) with all of the quantifiable information required to make admission decisions for one specialism or a group of specialisms using the same resources. The decision support system developed uses the models described in the previous sections to make predictions regarding the availability of capacity in the future.

The decision support system has been implemented in two orthopaedic and one gynaecological department of three different hospitals for the purpose of evaluating whether:

- the prediction models described previously are useful in practice,
- the system provides the admission planner with all the quantifiable information to make admission decisions, and
- the system supports the admission planner in such a way that he is able to improve the achievement of the admission planning goals.

In this paper we focus primarily on the question whether the prediction models are applicable in practice. A further description of this research can be found in Groot (1993). To answer this question, we investigated whether:

- the assumptions on which the classification systems and the prediction models rely were valid in the three situations studied,
- the data required as input for the prediction models were available and easy to gather, and
- the predictions made on the basis of these models were accurate and reliable enough to use for admission planning purposes.

The results of each of these evaluations are presented subsequently in the next sections.

7.2. Adjustments to the prediction models

The classification systems underlying the prediction models are based upon the data from two large Dutch hospitals. The prediction models are also based upon insights gained in these two hospitals. When the classification systems and prediction models are used in other hospitals it is to be expected that slight adjustments are required. To determine which adjustments are required it is necessary to evaluate whether the assumptions underlying the classification systems and the prediction models are also valid in other hospitals.

In this section an overview is presented of the adjustments made to the classification systems and the prediction models in three surgical specialisms of three Dutch hospitals. Adjustments to the classification systems or the prediction models were made whenever the assumptions on which these classification systems and prediction models rely were not valid in one or more of the hospitals in which the decision support system was implemented.

With regard to the classification systems two adjustments are made. Firstly, in all three hospitals the classification of patients, in such a way that the number of bed-days used within a class is sufficiently similar, is primarily based upon the type of operation instead of upon the preliminary diagnosis. The reason for this adjustment was the

same in all three cases. In all these hospitals the type of operation was entered on the admission form and/or the waiting list form and the patient's diagnosis was not. In addition it proved to be difficult to translate a given type of operation into the corresponding preliminary diagnosis.

Secondly the classification of patients in such a way that the required operation room time within a class is sufficiently similar is not only based upon the type of operation, but also upon the surgeon who performs the operation. This adjustment led to more homogeneous classes of patients. This adjustment could be made in all three cases since it was always known which surgeon would perform a scheduled operation (this was not the case in the two large Dutch hospitals since both hospitals had specialist training facilities).

With regard to the prediction models also two adjustments are made. In two of the hospitals it was decided not to reserve beds for emergency patients. In one of the hospitals this decision was made since an admission stop for emergency patients was declared whenever all beds were occupied or already reserved for elective patients. In the other hospital this decision was made due to the fact that extra beds were available on some occasions since these beds were not taken into account in the calculation of the available bed capacity. The effect of such a decision is that a prediction of the number of emergency patients does not have to be taken into account in the bed availability model.

In all three of the hospitals it was necessary to predict the number of occupied beds not only separate for males and females, but also for a number of different wards in which the patients could be admitted. This adjustment was necessary since the introduction of short-stay and long-stay units meant it might not be possible to admit a patient in a ward in which his specialism had beds available.

As indicated above, the need for adjusting the classification systems and the prediction models is dependent upon the way in which the hospital and the specialism is organized. The adjustments made to both the classification systems and the prediction models affect the performance of the

prediction models. This section presents an estimation of the effect of each adjustment on the performance of the corresponding prediction model.

Using the type of operation instead of the diagnosis as the basis for length of stay predictions can slightly improve the performance of the bed availability model. Data from one hospital were used to estimate the differences in performance between predictions based upon the type of operation and based upon the diagnosis. Initial analyses of the variance of the length of stay based upon the type of operation and based upon the diagnosis showed no significant difference between the two approaches. The mean weighted variance per patient (over a total of 1107 patients) for predictions on the basis of diagnosis was 56.8. The mean weighted variance per patient for predictions on the basis of operation was 55.1. However, when the upper and lower 5% of the data samples in each group were removed, the mean weighted variance of the length of stay for the predictions based upon the type of operation was considerably smaller (14.4) than the mean weighted variance of the length of stay for the predictions based upon the diagnosis (18.7). For these last calculations we used the data for 991 patients out of the total number of 1107 patients.

Predicting the required operation room time not only based upon the type of operation, but also upon the surgeon who performs the operation leads to a smaller variance within each class of patients. A smaller variance within each class of patients leads to a smaller overall variance and thus to better predictions. To conclude, this adjustment improves the performance of the operating room availability model.

The effect of not reserving beds for emergency patients is difficult to estimate. The arrival of emergency patients in both hospitals can no longer be modelled as a Poisson process. The specialism in one hospital has the possibility of placing emergency patients in other wards in case no beds are available in their own ward. The specialism in the other hospital also has this opportunity, but in addition declares an admission stop in case all of the hospital beds are occupied. However, still a number of emergency

Table 4
Results of predictions three days ahead, using a theoretical overflow of 5%

Specialism	Men				Women			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Orthopaedics 1	7.3	0.1	6.6	0.93	13.5	0.7	1.6	0.98
Orthopaedics 2	4.5	0.2	5.0	0.95	13.3	0.2	3.3	0.97
Gynaecology	0.0	0.0	0.0	0.00	9.6	0.1	4.9	0.95

(1) Mean of realized bed occupancy.

(2) Prediction error.

(3) Realized overflow percentage with a theoretical overflow value of 5%.

(4) Realized efficiency with a theoretical overflow value of 5 %.

patients are admitted at their own ward. These patients are not taken into account in the bed availability model. This will cause the actual bed availability to deviate from the predicted bed availability. It is not known whether this deviation is larger than the deviation that would occur in case beds were reserved for emergency patients using a Poisson model.

7.3. Information gathering

To be able to use the prediction models in a hospital data must be available regarding:

- the total availability of beds per gender per ward or per gender per specialism,
- the total availability of nursing capacity per ward or per specialism,
- the total availability of operating theatre capacity per day of the week per specialist or per specialism,
- the age, gender, diagnosis, operation, specialist, specialism and ward of each patient,
- the day of operation for each patient,
- historical data regarding the length of stay for every group of patients with a given operation, a given gender and within a given age group,
- historical data regarding the duration of an operation for every specialist and every group of patients,
- historical data regarding the nursing workload for every group of patients with a given operation,
- historical data on the expected number of emergency patients per day of the week,

- historical data regarding the capacity needs for emergency patients (length of stay, operation time and nursing capacity).

The information gathering process met with some problems. Part of these problems stemmed from the fact that the required information was not yet available in the hospital. For example, in some hospitals:

- the day of operation was not registered,
- data regarding the duration of an operation were not available, and/or
- data regarding the nursing workload for a given patient was not present.

The missing information has to be retrieved either by hand or automatically. In case the retrieval of information in this way is too time-consuming, nurses or specialists could estimate the duration of an operation or the nursing workload required for a patient with a given diagnosis.

Another problem was caused by the fact that the resource allocation does not always take place in the same detail as is required in the decision support system. For instance, in most hospitals a constant number of beds is allocated to a given specialism for a period of one year, but the number of beds is not divided over males and females during the same length of time. The number of available beds per gender differs from day to day and depends upon the gender of the patients in hospital and the configuration of patients on the waiting list. Another example is the fact that in some cases specialisms make use of the same ward, but the nursing capacity is allocated to a ward instead of to the individual specialisms.

7.4. Performance of the prediction models

This section determines whether the predictions made on the basis of the prediction models described in Section 4Section 5Section 6 are accurate and reliable enough to use for admission planning purposes. All the changes in the patient data and the capacity data were registered by the decision support system to provide a basis for evaluating the performance of the prediction models. Using this data and a computer simulation model, it was possible to compare the actual utilization of the resources with the predictions of the resource utilization.

7.4.1. The bed availability model

Predictions of the bed availability for 1 to 7 days ahead were made during a period of two months. These predictions were compared with the actual bed availability in order to determine the performance of the bed availability model. Table 4 shows the performance of the bed availability model for the three specialisms.

Efficiency is defined here as the fraction of the predicted number of available beds which were actually available. In this calculation it is assumed that the total number of beds is equal to the number of occupied beds on day 0. As compared to the efficiency calculated by Kusters (1988), the efficiency calculated here will tend to be lower.

Comparing the results in Table 1 and the results in Table 4 it can be stated that the realized overflow percentage is generally higher in Table 4 and the realized efficiency is generally lower. This means that the bed availability model performs worse in the case where resource groups are labelled by hospital personnel, real admissions have to be allocated to one of the resource groups and these resource groups are used as the basis to make bed availability predictions. This outcome was expected since:

- data of more than a year old were used for the predictions of the length of stay of each patient belonging to a certain resource group, and
- errors could be made in allocating patients to a certain resource group.

The performance of the bed availability model can be increased by using a system in which the

Table 5

The performance of the operating theatre availability model

Specialism	(1)	(2)	(3)	(4)
Orthopaedics 1	30	4.0	38.5	0.94
Gynaecology	51	8.6	33.1	–

(1) Number of predicted operating programs.

(2) Average prediction error (in minutes).

(3) Standard deviation prediction error (in minutes).

(4) Coefficient of correlation.

actual length of stay of a recently discharged patient is added to a databank and used to adjust the cumulative length of stay function of this resource group. In that case the data used is always up to date.

There remains the question whether these results are good enough to use the bed availability model for admission planning purposes. The figures from Table 4 show that the realized overflow percentage indeed is less than 5% in 4 of the 5 cases. The realized efficiency is at least 0.95 in 4 of the 5 cases. These figures still seem reliable enough to use for admission planning purposes.

7.4.2. The operating theatre availability model

Predictions were made for a number of operating programs in order to determine the performance of the operating theatre availability model. Table 5 presents the results of the comparison of these predictions with the actual length of the operating program for two specialisms.

Table 5 shows that the average prediction error of the operating theatre availability model is very small. Also the coefficient of correlation is very high. The operating theatre availability model is obviously performing quite well.

Table 6

Distribution of the predictions of the nursing capacity over the five categories ($N = 49$)

	%
excessively high	0
too high	10
good	76
too low	14
excessively low	0

Table 7

Results of the performance measurements of orthopaedics 1

Performance indicator	Measurement:	
	First	Second
Mean occupancy of the operating time	81.3%	95.3%
Standard deviation of the occupancy of the operating time	18.9%	12.0%
Mean occupancy of the beds	80.1%	76.1%
Standard deviation of the occupancy of the beds	6.9%	14.1%
Number of emergency admissions in the orthopaedic ward	2	13
Number of emergency admissions in the ward of another specialism	1	0
Number of patients with an appointment made 3 or more days in advance	3	84
Number of patients with an appointment made less than 3 days in advance	6	–
Number of patients without an appointment given notice of their admission three or more days prior to the actual admission date	0	–
Number of patients without an appointment given notice of their admission less than three days prior to the actual admission date	103	55

7.4.3. The nursing staff availability model

The nursing staff availability model was used in only one hospital. In this hospital it proved to be very difficult to compare the outcome of the nursing staff availability model with the actual nursing staff availability since the actual nursing workload was not measured. However, in order to be able to test the predictions made by the nursing staff availability model, the head of the ward was confronted with the predictions made

by the system and was asked to classify each prediction in one of five categories ranging from excessively high to excessively low. The results of this classification are presented in Table 6.

7.5. Performance measurements

In Section 7.4 we have stated that the availability models seem to perform satisfactorily. In this section we will determine whether using these

Table 8

Results of the performance measurements of gynaecology

Performance indicator	Measurement	
	First	Second
Average occupancy of the operating capacity	67.5%	77.9%
Standard deviation of the occupancy of the operating capacity	49.0%	36.4%
Average occupancy of the beds	83.6%	81.0%
Standard deviation of the occupancy of the beds	18.0%	22.1%
Percentage emergency admissions admitted in their own ward	100%	100%
Number of patient transfers required	1	2

models can improve the performance of admission planning. Therefore a working group of hospital personnel involved in the admission planning process has determined a set of performance indicators. These performance indicators have been measured twice during a period of a month. The first measurement period represents the performance of the admission planning before using the decision support system (and the availability models). The second measurement period represents the performance of the admission planning when the decision support system is used. Table 7 shows the results of both measurements for orthopaedics 1. Table 8 shows the results of both measurements for gynaecology.

Both in orthopaedics 1 and in gynaecology the occupancy of the operating capacity and thus the throughput of patients has increased after the implementation of the decision support system. Whether this increase in occupancy can be attributed solely to the implementation of the decision support system however remains a big question. As can be seen in both Tables 7 and 8 the increase in the occupancy of the operating capacity has been accompanied by a decrease in the occupancy of the beds. For orthopaedics 1 we have determined that the increase in operating room occupancy accompanied with a decrease in the bed occupancy is not due to a change in the type of patients admitted into the hospital. Although the number of patients treated in orthopaedics 1 has increased from 117 to 139, the frequency with which each operation occurs has not changed. Other factors have played a role in this process. In Table 7 we can also see that the introduction of the decision support system improved the service given to the patients. All emergency patients could be admitted in the orthopaedic ward and more patients could be given an appointment made three or more days before the actual admission date.

Although the question whether the increase of the operating capacity (and the increase in the number of treated patients) can be attributed solely to the implementation of the decision support system cannot be answered it is obvious that such a big increase in the occupancy of the operating capacity is not only due to external factors.

Therefore we can state that using the availability models can contribute to a better achievement of the admission planning goals.

8. Conclusions

In this paper a number of models for predicting resource availability were developed. On the basis of this model a decision support system was designed. This model was tested in three different hospital situations. When evaluating the effect of such a DSS approach a number of different aspects will have to be looked at.

8.1. *The accuracy of the underlying models.*

The accuracy of the models was shown to be sufficiently accurate. The transferred quite easily over different hospitals although, as shown, depending upon the actual situation in which the classification systems and prediction models are used it was necessary to make some minor adjustments.

8.2. *The availability of the data required.*

The models do require historical data. When designing the models care was taken to use only information that would be not too difficult to obtain. Still, it is sometimes difficult to gather and is often already quite old (one to two years). When the information is available, the predictions made are generally quite well. Using more up-to-date information could further improve the performance of the prediction models.

8.3. *The effectiveness of the information in the actual working situation*

Using these predictions in a decision support system for admission planning did lead to improvements in the admission planning goals. OR utilisation was improved while bed occupancy did not suffer. No information on nursing workload is available since the hospitals participating did not use a workload measurement system. On the

whole it may be stated the models provided useful information.

8.4. The acceptance of the model by the staff involved.

A key question in introducing such a model, especially in a professional organisation, is whether or not it will be used. In two of the three test environments the systems was, after a while, accepted. The information was used as the basis for admission decisions. The decisions themselves were of course taken by an admission planned together with the physicians. The DSS only provides information of a limited number of aspects and for instance does not take into account a factor such as case mix. The DSS is not intended to actually make decisions.

In the third environment the system was in the end not used. The reason for this was that the prototype of the DSS which was used only provided information at a single specialism level, while the admission planner in this environment required a more flexible approach. This could not be provided by the system being tested, but adaptation of the system at this point is possible.

All in all it seems that the type of support offered will be acceptable in this environment.

References

- Briggs, G.P. (1971), In-patient admission scheduling – Application to a nursing service, Doctoral Dissertation, University of Michigan.
- de Haas, G. (1984), *Hospital Information Model*, Nationaal Ziekenhuis Instituut, Utrecht, Netherlands.
- de Vries, G. (1984), Evenwicht in zorgvraag en zorgaanbod, (Balance in the supply and demand of hospital care), Ph.D. Thesis, Eindhoven University of Technology (in Dutch).
- Douglas, J.B. (1980), *Analysis with Standard Contagious Distributions*, International Co-operative Publishing House, Fairland, MD.
- Feller, W. (1968), *An Introduction to Probability Theory and Its Applications*, Wiley, New York.
- Groot, P.M.A. (1993), *Decision Support for Admission Planning under Multiple Resource Constraints*, Ph.D. Thesis, Eindhoven University of Technology, The Netherlands.
- Gustavson, D.H. (1968), "Length of stay: prediction and evaluation", *Health Services Research* 3/1, 12–34.
- Handyside, A.J., and Morris, D. (1967), "Simulation of bedside occupancy", *Health Services Research* 2, 287–297.
- Kahneman, D., Stovic, P., and Tversky, A. (1982), *Judgement under Uncertainty: Heuristics and Bias*, Cambridge University Press.
- Kusters, R.J. (1988), Opnameplanning in algemene ziekenhuizen, (Admission planning in general hospitals), Ph.D. Thesis, Eindhoven University of Technology, Eindhoven (in Dutch).
- Leske, M.C., Sorensen, A.S., and Zimmer, J.G. (1978), "Discrepancies between admission and discharge diagnoses in a university hospital", *Medical Care* 16/9, 740–748.
- Mintzberg, H. (1983), *Structure in Fives – Designing Effective Organizations*, Prentice-Hall, Englewood Cliffs, NJ.
- Murphy, L.N., Dunlap, M.S., Williams, M.A., and McAthie, M. (1978), Methods for studying nurse staffing in a patient unit, DHEW publication HRA 78-3, Washington, DC.
- Nederstigt, P. (1985), Diagnostic Related Groups, Ph.D. Thesis, Katholic University Brabant, Tilburg, Netherlands.
- Newell, D.J. (1954), "Provision of emergency beds in hospitals", *British Journal of Preventive and Social Medicine* 8, 77–80.
- Rubinstein, L.S. (1977), "Computerized hospital inpatient admissions scheduling system: a model", Paper presented at the ORSA/TIMS Conference, Las Vegas.
- Warner, D.H. (1976), "Estimating patient discharge from hospitals using both historical and physician supplied estimates combined in a cost/accuracy analysis", *Medical Care* 14/7, 590–602.