Chapter 1

Introduction

The rising cost of health care is forcing hospitals to make better use of existing facilities and to justify new acquisitions. As a result, hospital administrators are interested in predicting bed requirements and studying the effects of various management policies such as restricted admissions, early discharge programs, and resource reallocation. When determining a hospital's bed requirements, hospital managers must always balance the desire for improved utilization with the need to provide a "high level" of service to patients. The tools available to aid in this decision making process include rules of thumb, analytic models, and simulation models. Maternity hospitals in particular are good candidates for models since they are usually self contained and treatment has well defined stages.

Rules of thumb are the first method used to predict hospital bed requirements. These rules simply use past experience to dictate the number of beds needed by a given population. This method results in very crude estimates that ignore both the individual nature of each hospital, and the effects of varying management policies.

Analytic models use a stochastic process to represent the hospital, and describe patient movements and resource utilization. These models generally fall into 3 classes: simple probabilistic models, queuing models, and Markov models.

Probabilistic arrival models (Cowan [7], Slutsky [28], Swartzman [29]) are concerned only with predicting admission demand. Both Cowan and Slutsky estimated the arrival load at maternity hospitals assuming a Poisson arrival distribution. Such probabilistic
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models do not take into account the effects of varying admission policies. However, such
models may be useful to predict input levels for more detailed models.

Queuing models, (Young [36], Shonick [27], Milliken [19], Weiss et al. [35], Thompson
et al. [31]), assume that a hospital is a single service unit. As a result, queuing models,
like probabilistic models, fail to take into account the progression of patients through
the various sections of a hospital. Also, these models do not consider a patient’s diag-
nosis, nor do they have a mechanism for dealing with finite capacity or with overflow
situations. However, queuing models can be effective for studying certain aspects of a
hospital, such as the patient arrival process, in isolation from the workings of the whole
hospital. Queuing models of maternity hospitals include Milliken et al. who predicted
the utilization of delivery rooms.

Markov models are developed with the underlying assumption that the movement of
patients from state to state is only dependent on the current state, and not on any past
history. Markov models include, Thomas [30], Pendercast et al. [21], and Lane et al. [18].
The basic Markov assumption that a patient’s past history has no effect is inappropriate
for most hospital systems (Fetter & Thompson [11]). However, coronary and maternity
services may be exceptions due to their well defined treatment phases (Weiss et al. [15],
[34], Thomas [30]). Markov models ignore many of the intricacy of a hospital functioning.
Semi-Markov models are similar to Markov models, but allow the time between state
to changes to be a random variable. Using a semi-Markov model, Kao [16] was able to
simplify Thomas’ model. Similar models include those by Kao [17], Weiss, Cohen, and
Hershey [15], [34]. Semi-Markov models of maternity hospitals include Weiss et al. [34].

Analytic models produce closed form solutions and can be effective tools for man-
agement. However, in most cases to achieve this form of solution many simplifying
assumptions must be made. Analytic models ignore the interactions among services by
assuming infinite capacity. Also, analytic models usually do not have enough procedural
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detail in terms of patient categories and admission/discharge policies. In many cases this simplification results in models that are not applicable, or are unable to simulate the effects of changing a particular management policy of interest.

Computer simulations allow much more detail than analytic models. They can accurately model complex real-world decision processes, and easily estimate the performance of an existing system under projected operating conditions.

The first computer simulation of a hospital is attributed to Fetter & Thompson [32], [11], [33], [12]. This series of influential papers includes models of a maternity suite, an outpatient clinic, a surgical pavilion, and a model of a whole hospital. These models were developed to study the effects of increasing the number of patients, shortening length of stay, the relationship between size and costs, and the economic implications of single rooms. The models are quite simple in nature. Patients are pre-assigned paths through the hospital, and holding times are determined only as a function of the path and the present node. In addition, these models fail to differentiate patients by diagnosis. Although they can detect the incidence of blocked transfers due to overflow situations, there is no mechanism to handle such transfers.

Other models developed around the same time include those by Barr & Oddie [1], who studied bed distribution and admission policies, Fischer [13], who simulated two maternity hospitals to study the effect of dual appointments, Goldman [14], who studied bed allocation policy, Robinson [24], who looked at scheduling admissions, Beaver [2], who looked at the effects of early discharges, Duchessi [8], who predicted the cost impact of patient load and/or service mix changes, and Rising et al. [23] who modeled an outpatient clinic. Like the Fetter & Thompson simulations all of these models make many simplifying assumptions and do not consider the effect of blocked transfers or admissions waiting, going elsewhere, or preempting another patient. Early computer simulations of obstetric hospitals include Fisher [13], Barr & Oddie [1], Beaver [2], and
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Fetter & Thompson [32],[11]. Many of these early models suffer the same drawbacks as analytic models. They either fail to classify patients ([1],[2],[11],[32]) or do not handle overflow ([13]). Also, none of the models deal adequately with special admissions and discharges.

As well as these models, tools to aid the creation of models have been developed. Fetter & Mills [10] created a special simulation language, HOSPSIM, to simplify the programming of blocked transfer policies. However, there is no reported use of this capability analysing the impact of finite hospital capacity. Raz et al. [22] created DRUMS, a simulation tool that forecasts the daily demand for various resources in the hospital based on a projection of the patient volume and the proportion of patients with a similar diagnosis, but fails to take into account the intricacies of a particular hospital.

Two recent more sophisticated simulation models are Cohen et al. [5], and Dumas [9]. Dumas modeled a large multi-purpose hospital. He showed that the interactions among services in terms of overflows has a significant effect on the optimal bed allocation. Dumas' model also showed the effects of severely restricting off-service placements. However, Dumas assumes that unless originally misplaced patients stay in their initial assigned bed. This is not applicable to the progressive patient care setting of a maternity hospital. In addition, restricting off-service placements is not feasible in the case of non-elective medical care such as obstetrics. The paper by Cohen et al. provides a methodology for modeling progressive patient care hospitals. Cohen et al. assume that transfers and length of stay depend only on the current state, and the patient category unless capacity is reached. They provide a simple illustrative model that simulates the recovery process of coronary patients. Both these models are quite detailed, but are difficult to generalize for other hospitals.

This paper develops a model of a maternity hospital in the framework described by Cohen et al. However, to accurately model a maternity hospital a number of extensions
were required. First, because of the well defined stages of obstetric treatment, patients were classified according to more than one criterion. As a patient moves from one stage of treatment to another the classification that governs the transfers and length of stay (LOS) also changes. Second, some of the length of stay calculations reflected the time of day. This was necessary to simulate the staggered discharge distribution that results from the vast majority of patients leaving the hospital between 11 a.m. and 3 p.m.