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Faculty of Engineering, Science and Mathematics

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Simulation and Optimization of Healthcare Workforce Need

by

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ABSTRACT

FACULTY OF ENGINEERING, SCIENCE AND MATHEMATICS

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The healthcare needs of the UK population are increasingly more demanding as a consequence of demographic changes and improvements in technologies and treatments. As a result, there is an increasing need for efficiency within the healthcare service, and within that, a need for improved planning. One particular area of current concern is workforce planning. This thesis considers the issue of predicting workforce need and the corresponding skill-mix. Three projects are presented, which between them illustrate the use of different OR techniques to assist with the modelling of workforce need. They cover two important healthcare settings: inpatients and intermediate care. Two of the projects demonstrate different ways of combining simulation with mathematical programming, in both cases enhancing the solution given by the simulation alone.

The first project considers the question of how many permanent nurses a hospital should employ. Demand for the different nurses is generated by a Discrete Event Simulation (DES) and a stochastic program then evaluates the optimal number of Whole Time Equivalents (WTEs) to employ.

The second project considers the capacity needed for a redesigned provision of intermediate care services at a rehabilitation hospital. Intermediate care supports the early discharge from, and admission avoidance to, an acute hospital setting. A DES model is presented which enabled analysis of patient flows to evaluate bed and staffing needs.

The third project again considers intermediate care, looking at the types and skills of the workforce required within a rehabilitation team. A Monte Carlo simulation generates a demand for each of a number of different patient interventions. A linear program then optimizes the composition of the team, based on the skills of the different members of staff.

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DECLARATION OF AUTHORSHIP

I, Naomi Helen Powell, declare that the thesis entitled

Simulation and Optimization of Healthcare Workforce Need

and the work presented in it are my own. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- none of this work has been published before submission.

Signed: [redacted]

Date: ..19th...June 2006.......

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Chapter 1

Introduction

1.1 Introduction

This chapter introduces the work contained in the thesis. This PhD was funded by an Industrial CASE award from the Engineering and Physical Sciences Research Council (EPSRC), with the Hampshire and the Isle of Wight Workforce Development Confederation as the industrial sponsor. The industrial sponsor and the general problem area are introduced followed by general research objectives for the thesis. These research objectives were explored through three projects which are then introduced, setting the scene and describing the motivating needs of the real life situations.

1.2 Hampshire & Isle of Wight Workforce Development Confederation

Workforce Development Confederations (WDCs) are partnership organisations aimed at increasing the skills of people who work in health and social care. On 1 April 2002, the 27 confederations within England, of which Hampshire & Isle of Wight (H&IoW) is one, were created. H&IoW WDC is coterminous with H&IoW Strategic Health Authority who rely on the WDC to develop the workforce strategy as part of its overall strategic plan for the NHS in H&IoW.

The main functions of the WDC are to plan the NHS workforce, to commission education and training, to engage in partnerships, and to assure the quality and value for money of its programmes of work and investments.

Each function is broken down into several sub-functions, the first of which (planning the NHS workforce) is broken down as follows:

- develop a strategic vision for the NHS workforce;
- design or redesign working processes and jobs;
- collect and analyse workforce data;
- predict future staff numbers;
- plan the supply of skilled people to the NHS.

Essentially the NHS needs a workforce which has the right number of staff deployed in the right places and working to the maximum of their ability.

Over 80,000 people in H&IoW work in health and social services with around 35,000 employed in the 18 NHS organisations across the region. This makes the NHS the largest employer in the region, employing 4.6% of the economically active population. Around £90 million was spent by the WDC in 2002/03 on supporting training and education for NHS staff.

The South East England Development Agency estimates a need for the health and social care workforce to increase in number by 10% by 2011. At the same time, an aging population means that the NHS will need to employ a greater percentage of the economically active population. Together, this creates challenges and a need to develop career opportunities and ways of working to recruit, retain and develop the necessary workforce.

There is a need for effective workforce planning in healthcare because:

- Training professional staff has high costs and long lead times;
- The size of the healthcare workforce means that it must employ a significant proportion of the economically active population;
- There are constraints on working across professional boundaries, so not only the total size of the workforce, but also the component staff groups must be planned.

Soon after its creation, H&IoW WDC identified the need to provide a workforce planning tool as essential to improving workforce planning capability. It soon became apparent to the WDC, as it did to Wren (2005), that one tool was not sufficient for the variety of planning problems presenting themselves within H&IoW. Planning that had been done prior to the creation of the WDC had largely involved messy spreadsheet models which, in the WDC's own words, provide false assurances about workforce planning because of their deterministic nature.

H&IoW WDC produced a three year strategic plan (Hampshire and Isle of Wight Workforce Development Confederation, 2003) for 2003/04 – 2005/06 from which most of the above information in this section is summarised. The WDC was relatively shortlived in itself, having recently become a directorate of the Strategic Health Authority and thus it is now known as the Workforce Development Directorate.

1.3 The need for research

As has been described above, there is a need for accurate and reliable workforce planning within the NHS, not least because of the large number of staff and therefore large sums of money involved. The awareness by the WDC of the need to develop and research different tools for workforce planning led to the decision for them to sponsor a PhD, the results of which are presented in this thesis. The Director of Workforce Planning at the WDC suggested that a number of projects, based on real-life problems, should be undertaken with a view to identifying any common themes and approaches that became apparent. In total three projects were completed, in two different healthcare settings: hospital inpatients and Intermediate Care.

1.3.1 Review of the literature

The literature (reviewed in Chapter 2) contains several examples of successful applications of OR techniques to healthcare settings. Within this, the examples which have considered the workforce have mostly considered the problem concerning the scheduling (or rostering) of nurses. The few examples that have considered nursing workforce planning have used simplistic methods and have not examined, in particular, the level of detail that is required in order to take into account the inherent variability in patient demand. Hurst (2002a) discussed five methods that are used for nursing workforce planning in practice. These methods are not identical to the examples in the literature where OR techniques have been applied to the problem that it poses the question as to whether OR can be used to model, and to improve on, current nursing workforce planning methods.

Within the literature, the need to take into account the variation in patient demand is apparent, as evidenced by the many examples of stochastic techniques such as simulation. Competing with this is the need to provide managers with a decisive answer and hence the appeal (and array of examples) of optimization techniques which are deterministic in nature. Whilst the benefits of individual approaches are shown in the literature, there is no evidence to suggest that anyone has tried combining approaches for the problem of nursing workforce planning, which raises the question as to whether this can be done and if so, whether it offers any additional benefit to that of using the techniques separately.

Intermediate Care is a relatively new area (or way of working) within the health service which has been identified as a key area within The NHS Plan, published by the Department of Health (2000b). Intermediate Care differs from acute hospital care mainly in the location of where care is provided - i.e. in a patient's home, or at a Day Hospital as well as in a bedded (but non-acute) ward. However, it also differs in terms of the change in emphasis of the staff involved (e.g. more therapists and fewer doctors) since the patients are sufficiently stable from a medical perspective, that the main focus is on rehabilitation, rather than improving medical health.

As a result of its newness, there are many recent examples of Randomised Controlled Trials and other methods of appraisal in this area as the NHS, and various providers within it, seek to evaluate the services. However, there are few examples of OR being applied to Intermediate Care services and within that, no substantial quantitative results and no evidence of any modelling of workforce planning.

1.3.2 Overall aim

The overall aim of the PhD is to use OR techniques to help healthcare professionals and managers make better informed decisions when planning their workforce. The gaps identified by the literature review and mentioned in the above subsection will be explored with two overall research objectives as discussed in the subsections below. As well as these overall objectives, each project had its own research objectives which are listed at the beginning of the relevant chapters (Chapters 3, 4 and 5).

1.3.3 Research Objectives

1.3.3.1 To compare modelling workforce planning in two different healthcare settings

The healthcare workforce is large and varied as a result of the wide range of types of care provided to patients in different healthcare settings. The different projects allow a comparison to be made between healthcare workforce planning in two different settings with a view to identifying any common themes and approaches. The literature will also be a source to find out what healthcare workforce planning methods exist and how they could be improved. Any common factors that contribute to an accurate (as possible) method of workforce planning including the associated skill mix will be explored.

1.3.3.2 To explore which OR techniques are suitable for different healthcare workforce planning problems

The literature (see Section 1.3.1 and Chapter 2) reveals that a wide range of OR techniques have been used to solve healthcare problems, however few have been used to tackle the problem of healthcare workforce planning. The literature will be examined to learn from previous models with a view to applying the lessons learned to the problem of healthcare workforce planning. Different factors may determine which OR technique is best used to solve a particular problem and these will be explored. An investigation will also be conducted into whether using a combination of existing methodologies (a hybrid approach) provides additional benefit over using just one.

1.4 Introduction to the projects

As mentioned above, this thesis contains work carried out on three projects. Working and researching on more than one project allows experiences gained in one project to be applied to another as well as allowing a general overview of the subject area to be acquired. The projects cover two different healthcare settings: inpatients and Intermediate Care. By carrying out projects in different settings, common or generalisable themes and approaches should become more apparent and validation given to any methodologies which work in both settings; or conversely evidence to suggest why they may be inappropriate in one or the other.

The two projects set in the area of Intermediate Care share a common subset of healthcare professionals as well as general healthcare issues. The earlier project provides a basis on which the latter one can build, as the project area offers familiarity, and ways of working with the healthcare professionals are already established.

The projects roughly happened one after the other and are presented in this thesis in chronological order. Each project has required a number of meetings with relevant healthcare personnel to gain understanding and information about the project. The following subsections introduce each of the projects, setting the scene and illustrating the motivation behind the real-life problem which needed solving.

1.4.1 Inpatient workforce capacity model

Working with the Royal Berkshire and Battle Hospitals (RBBH) Trust, Harper (2002a,b) developed a simulation model (Prompt) of an inpatient speciality, which allowed exploration of bed capacities and theatre scheduling, as well as some preliminary work on workforce planning. Prompt was well received by the hospital and they were keen to develop the workforce planning module further.

With assistance from Andre Costa, a visitor to the School of Mathematics, Harper had begun to rebuild Prompt in Visual Basic. It was shortly after this that I became involved. Hampshire & Isle of Wight WDC were aware of the development of Prompt and were keen to explore the possibility of a better workforce element within it, and also to see if Prompt could be used for hospitals within their patch[1]. I took on the role of communicating and meeting with the nurses to ensure that the model was meeting their needs. The staff at RBBH were keen to develop the Acuity-Quality method (explained later in Section 3.4) of calculating workforce need, as well as to group the patients into care similar, and clinically meaningful groups.

We wanted to compare the results from the Acuity-Quality method and detailed patient grouping with a simpler method (Occupied Bed - also explained in Section 3.4), and with fewer groups. Depending on the results of the comparison, this would then justify (or not) the extra time spent by the staff at RBBH on developing the Acuity-Quality method and grouping of patients.

In order to facilitate the comparison, in parallel with the redevelopment of Prompt, I built a prototype model in Simul8. The structure of both Prompt and the Simul8 model was informed through meetings both with key nursing staff and with the

[1]Following the development with RBBH, Prompt was successfully introduced to Portsmouth Hospitals Trust, for which I prepared training materials and a user guide.

director of HR, David Foden. Prompt was developed and used for communication with the nurses, once we were sure about the level of detail to include.

The Simul8 model allowed for exploration of the possibilities of combining the simulation with a stochastic program in order to evaluate the optimal number of nurses to employ. The inspiration and motivation for this came from observing the interpretation of the simulation results by the nursing staff and knowledge that the average number of occupied beds underestimates the actual number of beds needed (Harper and Shahani, 2002).

This work is reported in Chapter 3.

1.4.2 Mount Hospital reprovision

The Mount Hospital reprovision project was concerned with looking at different ways of providing the care currently provided to patients within an Intermediate Care setting, hence the coining of the term 'reprovision'. The Mount Hospital currently provides non-acute healthcare through two Inpatient Wards, a Day Hospital, a Community Rehabilitation Team and Community Physiotherapy services.

An increasing awareness of the inability of the existing infrastructure to provide the care, which the staff wanted to provide for the patients, led to the decision to look at reproviding the services currently provided at the Mount Hospital. In effect this meant considering providing the services on (or based at) a different site or sites. Although the Mount hospital was located in E&TVS PCT and this is where the majority of patients came from, it also served patients from Mid Hants PCT.

We worked with the service model group who were looking at the practical angle of what the different options for reproviding the services meant in terms of bed and workforce numbers. The service model group reported to the project steering group who in turn reported to the boards of each PCT.

In order to analyse how service requirements would differ in the reprovided system if patient pathways were altered, the service model group carried out three audits to analyse where patients were now, and where they could be. We became involved just before the second audit, and were able to use the results of the audit in order to analyse the new patient pathways and capacity levels. A Discrete Event Simulation model was built which was validated by modelling the current system. This was then adapted and used to look at various scenarios for the reprovided system, and the corresponding impact on bed numbers and other capacities within the Intermediate Care setting.

This work is reported in Chapter 4.

1.4.3 Intermediate Care Futures

The Intermediate Care Futures project (subtitle: Taking forward the Intermediate Care workforce in Hampshire and the Isle of Wight) aims to bring together the various stakeholders across Hampshire & Isle of Wight to design a workforce model and associated education to provide the future Intermediate Care services. It is spear headed by Jane Barnacle (Intermediate Care Manager, Eastleigh & Test Valley South Primary Care Trust) and Debra Humphris (Director of the Health Care Innovation Unit, University of Southampton) and sponsored by the Hampshire and the Isle of Wight Workforce Development Confederation.

I have supported the project by analysing the types of health and social care interventions provided for the patients and the different types of staff who provide them. In particular, the care provided by two rehab teams in E&TVS PCT has been examined in detail. This has involved consulting historical patient data. This data is in the form of hand-written patient records which contain much patient specific information that, although irrelevant to this project, presents an ethical problem. It has therefore been necessary to obtain approval for the research from the Local Research Ethics Committee (Southampton & South West Hampshire, REC Reference number: 04/Q1702/10) and from Wessex Primary Care Research Network (Reference number MWP/017/04) as well as being issued with an honorary contract from E&TVS PCT.

The results of the Intermediate Care Futures project as a whole, and to which this project contributed, have been used to develop the role of the Associate Practitioner in Intermediate Care, and to develop common learning modules in the area of Intermediate Care for the Foundation Degree in health and social care at the University of Southampton.

This work is reported in Chapter 5.

1.5 Structure of thesis

The thesis is structured as follows. This first chapter provides an introduction by describing the sponsor, general problem area and research objectives, as well as the real-life problem for each of the three projects. Chapter 2 presents a review of the literature, providing an introduction to the NHS and how OR techniques have been used to workforce plan in healthcare. A specific introduction to Intermediate Care and the idiosyncrasies of this area at the interface between health and social care is also given. Chapter 3 describes the work carried out to determine inpatient workforce needs. Chapters 4 and 5 present work carried out in Intermediate Care. Chapter 4 describes the modelling work carried out with the staff at the Mount Hospital who sought to reprovide the existing Intermediate Care services. Chapter 5 describes modelling work, for the Intermediate Care Futures project, to examine the health and social care interventions provided to patients by the Rehabilitation (Rehab) teams, and the resulting workforce needs. Finally, in Chapter 6 conclusions from each of the projects as well as overall are summarised and discussed.

Chapter 2

Literature Review

2.1 Introduction

This chapter reviews the relevant literature concerned with the work in this thesis. Firstly, a brief history of the National Health Service (NHS) is given, which is followed by a look at issues related to workforce planning and historical attempts at planning within the NHS. Then the focus moves to Operational Research techniques applied to healthcare workforce planning and other related literature. The last section focuses on Intermediate Care, firstly looking at what Intermediate Care is, and then looking at attempts which have been made to evaluate Intermediate Care, most of which have involved clinical trials.

2.2 History of the NHS

The National Health Service (NHS) was founded on 5th July 1948, although planning had been in progress for a long time before that date, and indeed for a long time afterwards. 1948 was a time, soon after the end of World War II when there was much public support and co-operation which made the birth of the NHS much easier. This public co-operation has dwindled through the years as society has become much more about the individual, rather than the collective.

Upon creation, the NHS immediately suffered administrative and financial crisis.

Within three years a small charge was introduced for prescriptions and dental checkups. The NHS however, as an institution, became much loved and much criticised. Better management for the NHS was a key task during its teenage years and in the Porritt (1962) report, the separation of the NHS into three parts (Hospitals, General Practice and Local Health Authorities) was criticised by the medical profession who advocated the need for unification. The Salmon (1967) report resulted in the reorganisation of hospital nursing services after detailing recommendations for both senior nursing structures and the status of the nursing profession in hospital management. Medical advances challenged the NHS, as did the plans for re-organisation by different Governments.

The early 1980s brought about the realisation that, because of financial restrictions, the NHS could not do everything that was medically possible. However, the creation of new technologies and methods increased the public's expectations of the health service that could be provided. In 1990, the Conservative Government introduced the culture of an internal market into the NHS; however this was not without fault and was abolished by the Labour Government which came to power in 1997.

Rivett (1998) describes how the NHS has been plagued by lack of money, under staffing, and being treated as a political football since its inception. Numerous reviews have been carried out with recommendations which have barely had time to be implemented before new and different recommendations have been issued. Some recommendations have failed to have any impact at all, due to lack of resources (people and/or money) to implement them. Targets are continually being set for specific areas of the NHS to meet political promises, and although good for the areas in question, this can result in a withdrawal of resources from other, less high profile, areas.

For more details about the history of the NHS, see Rivett (1998) or the information provided on the web by the Department of Health (2005b) from both of which the above was summarised. Rivett (2005) provides online access to the majority of Rivett (1998), as well as providing an additional, contemporary chapter.

2.3 Workforce planning in the NHS

The NHS is the largest single employer in Europe (Department of Health, 2005a) with around one and a quarter million employees (Wanless, 2002). Of these, more than 332,000 nurses, midwives and health visitors make up the biggest staff group (Department of Health, 1999). In this section, we look at current issues concerning nurses and other healthcare workers and then at historical attempts at workforce planning within the NHS.

2.3.1 Current issues

2.3.1.1 The NHS in general

The aims of the NHS are (and always have been) to bring about the highest level of physical and mental health for all citizens, within the resources available, by:

- promoting health and preventing ill-health;
- diagnosing and treating injury and disease;
- caring for those with a long-term illness and disability, who require the services of the NHS.

(Department of Health, 2003)

As medical knowledge and technology have advanced, the NHS has become a victim of its own success, with expectations of the health service rising whilst it has become impractical to do everything that is now medically possible. The NHS has therefore, of necessity, been continually changing and developing.

Recently, the Department of Health (2000b) has put onto paper, in The NHS Plan, a full-scale modernisation process designed to move into reality the core vision of creating a patient-led health service, whilst being committed to keeping the funding principles of the NHS; that of providing quality care that meets the needs of everyone, being free at the point of need, and being based on a patient's clinical need, not their ability to pay. (Department of Health, 2005c)

2.3.1.2 Nursing skill mix

There are nine basic grades of nurses (from Grade A, Auxiliary & Assistants, to Grade I, Nurse Specialists) and within that, many different branches of nursing. Therefore, different nurses will have different skills, although most will share a common core. Getting the right kinds of nurses in the right places is a problem which several papers have considered. Hurst (2002a), discusses five main methods developed over time and used within hospitals, for calculating the numbers and skill mix of nurses needed. These are:

1. Professional judgement (Telford);
2. Nurses per occupied bed;
3. Dependency-activity-quality (acuity-quality);
4. Timed task/activity;
5. Regression-based activity.

Strengths and weaknesses for each of the methods mean that none is wholly superior to the others, and each should be interpreted before being applied to a particular situation. A brief description of the methods and the main strengths and weaknesses are shown in Table 2.1.

In a later paper, Hurst (2005) discusses further his data set on which his assessment of nursing workforce planning is made, but this time looking at the aspect of quality of care. The Dependency-acuity-quality method is the most popular of the five methods listed previously (Waters and Andalo, 2003). Hurst's analysis showed that lower-quality wards tended to have more fluctuating workloads and used more agency and bank nurses. He comments that unfortunately the relationship between temporary staffing and nursing quality is dated, and the topic is worthy of a deeper enquiry.

Table 2.1: Approaches for calculating the number and skill mix of nurses needed

Approach	Description	Strengths	Weaknesses
Professional Judgement (Telford)	Expert healthcare professionals agree an appropriate size and mix for a ward.	• Quick, simple and inexpensive to use; • Easy to update; • Little adjustment for other care groups; • Can deal with new and immeasurable variables easily.	• The relationship between staffing and nursing quality is hard to explain using this method; • Insensitive to changing patient numbers and dependency mixes; • Viewed as too subjective by some managers.
Nurses per occupied bed	The number of nurses needed per occupied bed is aggregated from data collected over time for similar wards.	• Simple; • Formulas use (unique ward) data collected routinely; • Quality is assured by deriving formulae from quality assured wards.	• Formulae are insensitive to dependency changes; • Formulae are costly to update; • Routinely collected data can be error prone; • Poor practice could be replicated if quality assured wards are badly chosen; • Some hidden structures and processes (e.g. nurses doing non-ward based tasks) can be masked by the formulae.

continued on next page

Approach	Description	Strengths	Weaknesses
Dependency-activity-quality (acuity-quality)	The overall time given to each patient in each category is recorded and converted to ratios. The workload is found from these ratios and the average patient mix.	• Local values can be used, or database averages; • Numbers can easily be calculated for different time intervals; • Changing patient numbers and mixes is easy; • Performance indicators are easily derived.	• Complex; • Non-local data may not be acceptable; • Updating data can add to nurses' workload; • Grade-mix proportions derived may not suit the individual ward; • The relationship between nurse activity and nursing quality is complicated.
Timed task/activity	The average time needed for each care activity, for each type of patient is recorded. The total time is then calculated, based on the average patient mix.	• As for acuity-quality (above); and • Easily computerised; • Base information is easily updated.	• As for acuity-quality (above); • More complex than acuity-quality; and • Commercial systems are expensive.
Regression-based	Predict the required number of nurses for a given level of activity made up of a number of independent variables.	• Useful where predictions are possible; • Ease of use across specialities; • Data is easier to collect than some methods.	• Many variables needing statistical analysis initially; • Difficulty of qualitative variables; • Lack of understanding by nurses; • Extrapolating to predict outside the model's observed range may be unsafe.

Aiken et al. (2002) carry out a study based on worker surveys of nurses in the US, UK, Canada and Germany with the conclusion that hospital quality issues are not unique to any country. Duffield (2005) is in the process of carrying out a study to establish the relationship between nursing skill mix and patient outcomes in Australia. The study is due for completion in 2006.

2.3.1.3 Evidence of the need for multiskilling

Many people have considered the need for the role of nurses, and the ways in which they work and are trained, to be changed. Hurst (1999) presents arguments for a multiskilled healthcare workforce and looks at the educational changes needed to facilitate multiskilling education which he summarises as nine principles. He goes on to look at the wider implications, such as the possible need for different pay structures and also the effect of professionals who may be unhappy about the dissolution of professional boundaries.

Masterson (2002) writes that educators and policy-makers, nationally and internationally, have argued that interprofessional education breaks down some of the traditional and unhelpful demarcations between the health and social care professions, facilitating cultural change and promoting successful team-working. She presents a number of arguments for cross-boundary working such as needs-led services requiring shared skills where competence becomes the critical factor, not professional training. This builds on the need to share expertise, pool knowledge and cross traditional boundaries which has been portrayed as not a choice but an essential ingredient of delivering high quality health and social care (Owens et al., 1995).

Buchan and Edwards (2000) claim that the roots of the nursing shortage in the UK come from the NHS reforms which introduced the internal market in the early 1990s. They suggest that a change in skill-mix could help solve this shortage, and that better integration of workforce planning and operational planning at trust level to improve the link between service delivery and staffing requirements is needed.

Li and Li (2000) look at staff planning in an AIDS related clinic in China. They use a goal programming method to analyse whether significant benefits can be gained from cross training workers. The individual goals were to minimise the negative deviation between supply and demand, the underachievement of professional development, the number of new staff members required, overachievement of overtime, staff substitution, and staffing costs. Key parameters for the model were demand (from different types of patients), the initial number of staff members in each category, various costs associated with the staff, overtime limits, target training hours, and the relative efficiency of staff flexibility which they took to have a 10% surcharge when a substitute was used. Experimental design was then used to create a number of scenarios to analyse when, and if, task flexibility would be beneficial. In most cases they found that it was not cost beneficial to use task flexibility because of the relative efficiencies associated with staff flexibility.

2.3.2 Historical attempts at workforce planning

In 1944, in preparation for the start of the NHS, the Inter-Departmental Committee on Medical Schools attempted to estimate medical workforce requirements for the post war period. The Goodenough Report (1944) was produced. It included a number of important observations and recommendations and stressed the interdependence of medical education and the NHS. Estimates for future requirements were based on three scenarios:

(i) The pattern of retirement of doctors would continue as before;

(ii) The future would see an increasing tendency towards retirement after the age of 60;

(iii) there would be a drastic change in the pattern of retirement above the age of 60.

The first of these scenarios was thought to be (and proved to be) highly unlikely since the country was moving from a period of war into a period of peace and for example, those civilian doctors who had remained in practice in the latter years of the war, would not have done so in a time of peace (Parkhouse, 1979).

The British Medical Journal was concerned about the risk of overcrowding the medical profession and suggested decreasing medical school intakes. However the problem was a lack of appreciation for the number of medical immigrants, particularly from Commonwealth countries (Rivett, 1998).

When, in 1955, the Government's actuary department attempted to estimate numbers of doctors needed in Great Britain, their approach was much the same as that in 1944 and needless to say, the results were not much better. In 1957, Willink identified the main determinants of demand [for doctors in the NHS] as population size and structure, economic growth, policy decisions on the desirable pattern of healthcare, and assumptions on recruitment, emigration, retirement and death.

Operational Research has been used in healthcare settings since at least as early as 1958 when it was applied to outpatient departments where waiting times had been a frequent cause of complaint. Ten years later, J. O. F. Davies (a senior administrative medical officer of the Oxford Regional Hospital Board) said, at a conference celebrating twenty years of the NHS, that reviewing clinical performance and taking advantage of operational research and statistics was important. Practice however, is rarely the same as theory, as one operational researcher found when spending the night in a ward in a hospital in Truro. He discovered that when the night nurses came on duty, they moved the sickest patients out of the four-bed bays into the corridor, as there was no time to go into the bays to see how they were (Rivett, 1998).

A strong plea was made in the Lloyds Bank Review, by Peacock and Shannon (1968), for the provision of alternative assumptions for measures of output, and for the possible combinations of different types of manpower (doctors, nurses etc). When unable to come to any conclusion as to how medical workforce planning will need to change in the future, the default plan was to stick with the existing policies, as it was assumed that these would maintain a reasonable balance. This was certainly the approach taken by the Advisory Committee on Medical Manpower Planning in 1982, when despite intensive statistical work, they were unable to reach any conclusions about whether more or fewer doctors would be required over the next 30 years.

Money can play a key part in the NHS. Thus it is no surprise that economists have had a say in workforce planning. Economists tend to decide how to invest money dependent on how much is available, whereas doctors would tend to decide what needs doing and then work out the costs. Klarman (1969) elaborates this point to suggest that neither is profitable in isolation and that a compromise is needed.

Parkhouse (1979), in summarising workforce planning needs for the future, states that "No economic model confined to medical manpower would seem practicable; the economist's aim would have to be a model of the health service as a whole, in which medical manpower featured as one factor. Such a model, if it were feasible and could be continuously brought up to date, would be valuable to set alongside more specific manpower models in order to enable planners and policy makers to draw and progressively modify their conclusions about the place of the doctor, or any other professional worker, amid the numerous 'priorities' demanding their attention."

Maynard and Walker (1995) review the way that medical workforce planning has been carried out in the UK, in particular since the creation of the Medical Manpower Standing Advisory Committee (MMSAC), in 1991. They report how this committee appears to concentrate only on the number of doctors, without considering any pay incentives since the Review Body on Doctors' and Dentists' Remuneration make recommendations on pay. They find this to be somewhat shortsighted and suggest the need for looking at how pay levels affect recruitment of doctors and also, to investigate substitution possibilities, whereby work traditionally done by a doctor is carried out by another health worker.

The Department of Health (2000a) report, "A Health Service of all the Talents: Developing the NHS Workforce", concludes that workforce planning must be done and radical changes are needed. Two years earlier, as reported by Beecham (1998) in the Medicopolitical digest in the British Medical Journal, Dr Paul Flynn, a specialist registrar, told the Junior Doctors Committee that "Workforce planning is a shambles".

There is much in the literature about workforce planning for doctors, much more so than for other health professionals, perhaps because of the length of time needed for the training of doctors. Literature about nurses has tended to concentrate on the scheduling and rota creation aspects, perhaps because nurses have been seen to be more easily replaceable and abundantly available. However times are changing and young women now choose from a wider range of potential occupations (Hemsley-Brown and Foskett, 1999) since nursing is no longer in the privileged position of being one of the few semi-professions open to females (Firby, 1990).

The key points from these historical attempts at workforce planning within the NHS can be summarised as follows:

- Doctors of the future (and present) will not necessarily follow the same career paths as those of the past (and present).
- Changes in immigration and emigration of doctors should not be ignored when considering the numbers of doctors in the UK.
- The workforce cannot be successfully considered in isolation to other areas of the health service.
- Considering individual groups of the workforce only, can lead to biased and misleading results.
- Planning at the micro and macro level must be interlinked.
- Some form of compromise is necessary for almost all planning purposes.
- Appropriate data, available in a suitable quantity is very important for the purposes of modelling the workforce.
- Short-term planning is difficult. Long-term planning is even harder.
- Respect between different areas of the workforce is needed for flexible planning.
- A good rapport between workforce and planners is important.

- Planning for the NHS needs to be separated from politics as much as possible since it is danger of becoming a political battleground.
- Money can play a key role, both in the amount available for the purpose of planning and for the provision of workforce.

2.4 Healthcare modelling

Our attention now turns too look at the use of OR techniques within healthcare modelling, firstly looking at those which have looked at various aspects concerning the healthcare workforce, and then looking at other related literature.

2.4.1 Workforce models

The vast majority of the literature surrounding nursing workforce planning can be roughly divided into three areas; planning the mix between permanent and temporary nursing, nurse rostering and those which consider the career structure of the workforce.

2.4.1.1 Planning the permanent (and temporary) nursing workforce

Workforce planning for nurses cannot be wholly successful without, at the least, consideration of the relationships and support structures between nurses, doctors and ancillary staff. Whilst this may not be possible in the structure of a model, it should be borne in mind when interpreting and using the model. Nurses tend to work in teams, the size and mix of which can, amongst other things, affect patient care and job satisfaction. There are four main things which affect nursing workforce planning, as identified by Hurst (1993). These are educational (e.g. nurses now require a diploma, whereas in the past they did not), clinical (e.g. advances in care techniques), managerial (e.g. the role that nurses play within the wider healthcare setting) and demographic (e.g. the types of people who do and will make up the nursing workforce).

Healthcare from the international and national level down to the local level is reviewed generally in a World Health Organisation workshop paper by O'Brien-Pallas et al. (2001). In the paper, Integrated health human resource planning (IHHRP) is defined as determining the numbers, mix and distribution of health providers that will be required to meet population health needs at some identified point in time. Service planning, on the other hand is defined as short-term planning which aims to ensure that resources for health are allocated and managed in an efficient and effective manner. They suggest that both IHHRP and service planning should be needs based and outcome directed, thus ensuring system efficiency and effectiveness. O'Brien-Pallas et al. go on to look in detail at three approaches to planning nursing resources. The Needs-Based approach avoids the perpetuation of existing inequities and inefficiencies and is based on the assumptions that all healthcare needs can and should be met. The Utilization-Based approach is based on the assumption that the current healthcare is adequate and appropriate and that all trends will continue as currently observed. The Effective Demand-Based approach introduces economic considerations to complement the epidemiological principles of the needs-based approach. O'Brien-Pallas and collaborators have built a dynamic system-based framework for a simulation of healthcare, attempting to combine the best parts of each of the above approaches. No details are, however, given. The paper includes an annotated bibliography of workforce planning at a high level.

The idea of extrapolating techniques traditionally used in the secondary sector to those used in the tertiary sector is implemented by Adenso-Diaz et al. (2002). Two of the main differences between the secondary and tertiary sector, according to them, is that there is generally a strong seasonality in demand and the presence of the customer when the service is delivered in the tertiary sector. With the relationship between capacity levels and the quality level of the service offered in mind, they set out to solve the task of determining staff numbers in order to provide minimum coverage, while guaranteeing an expected level of quality. They propose an alternative solution to dealing with unexpected demands to that presented by Meredith (1992) who suggests the solution can be found by increasing resources, improving the use of resources, modifying the product, modifying demand, and/or not satisfying demand. Instead, a better planning of available resources is suggested using the Delphi methodology, as described below.

Historical data is used to identify activities, estimates of the time to complete those activities, and the average number of activities per customer. This is then used to calculate a theoretical staff level (assuming a homogeneous workforce) for the past months. The Delphi ratio (Δ = real staff/theoretical staff) is calculated and then consolidation of the quality ratios (based on quality indices recorded by, and of interest to, the company) with the Delphi ratios allows for the calculation of the minimum staff for a defined mix of customers. Adenso-Diaz et al. demonstrated the Delphi methodology by applying it to two examples: hospital nursing and restaurant staff.

Kao and Queyranne (1985) present eight linear programming models for budgeting hospital nursing workforce need. The most complex, and hence difficult to solve, model is a two-stage stochastic program with recourse where the first-stage decides the permanent workforce and the second-stage decides the use of overtime and nursing agencies over a 12-period time horizon. The other models are simplifications, in various ways. The smallest time period considered is a month, and the demand for total nursing hours in each period is approximated using a normal distribution whose parameters are derived from an autoregressive integrated moving average (ARIMA). In comparing the models, they find that ignoring the time-varying nature of demand is acceptable so long as demand uncertainty is taken into account.

Brusco et al. (1993) present analysis of a linear programming model, with the objective to minimise labour costs, designed to explicitly determine both FTE (Full Time Equivalent) and supplemental nursing staff resources required, subject to nurse availability. Sadly, the details of the linear program are confined to an unpublished manuscript by Brusco and Showalter. They present a number of cost savings where the linear program is used, but stress that it is designed to supplement, not replace the current staffing process.

Jeang (1994) discusses how the delivery of healthcare services presents a special problem for inventory and capacity planning, since it is impossible to offer a service ahead of time and the inventory option does not exist. To further increase the difficulty, the demand is often uncertain thus requiring any model to be highly flexible and dynamic. Jeang notes that overstaffing and understaffing are impractical, because of the cost, and possible effects on service quality which may arise since extreme demand may occur at any time. Therefore, he proposes that it is better to be conservative in staff planning and let the part-time staff accommodate the fluctuations in demand. He also notes that because full-time staff usually work a set period each week, a decision based on full-time workforce for a budget cycle will not truly reflect the required nursing levels to meet patient demand. Therefore, taking this dependency on weekdays into account, he develops a linear program, whereby the objective is to minimise cost, whilst determining numbers of full time and part time staff and any overtime. The initial program was found to be difficult to solve, a problem which was overcome by making the number of full-time staff a fixed number, rather than a variable. The linear program was then solved for various numbers of full-time staff, and the results compared.

Griffiths et al. (2005) used Discrete Event Simulation (in Simul8) to model the need for rostered and supplementary nurses in an Intensive Care Unit (ICU) of a hospital. They assumed a 1:1 ratio of nurses to patients and no variation in nursing ability. Supplementary nurses were modelled as costing four times as much to employ as a rostered nurse. Data from the year 2000 was used, when the number of rostered nurses per shift was 14. Using the Simul8 model they were able to conclude that in order to minimise costs, 16 nurses should have been rostered per shift. Unsurprisingly, these 16 nurses would have been 'idle' for a greater proportion of time than the 14 nurses. The model was also used to look at a number of scenarios related to patients' Length of Stay, as well as demand in future years.

2.4.1.2 Nurse rostering

There has been much research interest in nurse rostering, and only a brief overview is presented here. The fact that there is still much interest provides evidence to the fact that finding an efficient use of resources for an inherently variable demand is an intrinsically difficult problem. Siferd and Benton (1992) review nurse staffing and scheduling, with a direct look at the role of OR modelling. They predict that there is much potential for OR models to have a big impact and that it will interest researchers for many years to come.

Money plays an important part in the rostering of nurses, whether explicitly, or not. If money were no issue then, assuming no problems with recruitment because pay conditions are right, hospitals could overstaff consistently, thus ensuring that demand will always be met. Research which has explicitly included money, and the process of creating budgets includes Zegeer (1977) and Keeling (1999).

Green (2004) writes that aside from beds, personnel, in particular nurses, form an important measure of hospital capacity. In most hospitals, ratios of patients to nurses are used to determine the number of nurses assigned to a unit. She proceeds to discuss that although there have been many articles demonstrating the use of optimization models to determine nurse staffing, the basic data needed to use such models is often lacking from hospitals, thus impeding their practical use.

A linear program to determine the optimum mix of different staff categories for a hospital medical unit is presented by Bordolai and Weatherby (1999). Cost is minimised subject to constraints of patient demand, and minimum staffing policies. Bordolai and Weatherby further consider the managerial implications of the results and look at how the sensitivity analyses can be used effectively.

A comprehensive annotated bibliography of personnel scheduling and rostering is provided by Ernst et al. (2004a), including a large section on nurses which would make an excellent starting point for anyone interested in looking further into this area. A subset of the same authors (Ernst et al., 2004b) also provide a review of staff scheduling and rostering, looking at the various problem classifications, solution methods and application areas (including healthcare, where they note that nurses in acute hospitals have been the subject of most rostering problems tackled.)

The method of annualising hours (i.e. specifying a total annual number of hours to be worked, which may then be irregularly distributed throughout the year) is one way of dealing with varying levels of demand for workforce. Corominas et al. (2002) describe a mixed integer linear program to solve the problem of scheduling workers across a year as evenly as possible when the annual number of hours to be worked is fixed. The objective function is to minimise the cost of overtime and the cost of temporary workers subject to bounds such as production capacity being greater than demand, weekly working hours (ordinary and overtime) being bounded in number, and holiday weeks being fixed. The initial model (M1) takes a relatively long time to solve and, with infinitely many optimal solutions, is likely to produce a very irregular work profile. Therefore a smoothing model (M2) is applied, bounded by the results to the initial model which solves quickly, producing a smooth result. In order to explore the sensitivity of the computing times to some of the conditions, different models were created and compared.

Dowsland (1998) tackles the problem of allocating nurses to shifts, such that they appear to be allocated evenly, using a tabu search algorithm. This work is then further developed in Dowsland and Thompson (2000) to enable larger (50 nurses) and more complex problems to be solved, by applying knapsack and network models before and after the tabu search to restrict the solution space, and to ensure feasibility. The model for this work has been called CARE (Computer Aided Rostering Environment) and it has been developed into a commercial software package by Gower Optimal Algorithms Ltd., which can be found on the web at www.goweralg.co.uk. An alternative approach to the same problem, which is compared to, and betters the approach of Dowsland (1998) is found in Aickelin and Dowsland (2004). Surprisingly, no direct comparison of Aickelin and Dowsland's work is made with that of Dowsland and Thompson (2000) although it is cited.

Another commercially available package, tackling a slightly different market, was developed by Eveborn (2004) of Optimal Solutions who used vehicle routing with perfect matching to allocate staff to customers in a home care company. Services provided range from cleaning to advanced medical care, and hence staff have a diverse range of skills. The software is called Laps Care and is available at: www.optimalsolutions.se.

Gutjahr and Rauner (in print) used ant colony optimization to assign (temporary) nurses from a central pool, to hospitals over a one month time horizon whilst considering restrictions such as night working rules. The algorithm, depending on the problem, takes between 6 and 45 hours on a Pentium III computer to successfully schedule 30 nurses to 50 hospitals indicating that this type of model is perhaps more suited to long-term, than to short-term planning, although with advances in technology, running the optimization on a more modern computer may significantly decrease the time taken.

2.4.1.3 Career structures of healthcare workforce

Several papers discuss the need to consider the career structure of the workforce when healthcare planning. Whether or not this needs to be taken into account may depend on the scope and size of the particular area of healthcare under consideration.

Rizza et al. (2003) report a study which aims to determine the mix of current endocrinologists, number of trainee endocrinologists, the effects of age and retirement on the endocrinology workforce and the factors which influence the demand for endocrinologists. They created a model which consisted of two major equations: a supply equation and a demand equation. Six scenarios were evaluated using these equations and one scenario was then chosen for further analysis to test the sensitivity of the assumptions. The editor (Kimball, 2003) of the journal in which Rizza et al. (2003)'s paper was published, makes the comment that any workforce forecast is highly dependent on the accuracy of assumptions about the healthcare delivery system, the prevalence of human disease, and the pace of technological advance.

Saliba (1993) describes a System Dynamics model, written in Ithink, to model the promotion process of people through 8 grades in the Australian Public Service, which although not specifically healthcare, has similarities with the healthcare workforce. The Planning, Resourcing, Integrating Staffing Model (PRISM) is based on a conceptual framework with the policy that a model for workforce planning must not only include the organisational requirements, but the career requirements of its people as well. There are four types of people modelled in PRISM, categorised by their attitude towards their career: steady state attitude, maintaining attitude, consolidating attitude, and stepping attitude.

Georgiou and Tsantas (2002) combine a goal programming approach with a semi-markov model to evaluate numbers of people in each grade, as well as trainees, and the flows between grades. The semi-markov model gives the structure for the constraints, whilst the goals of establishing the number of employees required in each grade are to be optimized. Again this example is not specifically healthcare, but has similarities with the healthcare workforce.

Shemin et al. (2002) describe the results of a questionnaire which was sent to thoracic surgeons in order to provide a snapshot of the workforce of that speciality in the US. Whilst they found the analysis useful and proposed that it was done more regularly, they state that predicting the number of surgeons needed in thoracic surgery during the next 10 to 20 years is complex and fraught with potential error, however they do not go so far as to propose a model.

2.4.2 Other relevant literature

We now look at other literature, which although not specifically about workforce, is also of relevance and importance since it is difficult to do workforce planning in isolation because of the interactions between the different aspects of healthcare.

2.4.2.1 Hospital capacity

OR has been used in several instances in capacity planning for hospitals, mostly focusing on a particular problem, rather than an overall view. A variety of different approaches have been used, depending on available data, the modeller's skill, the particular problem, and naturally the appropriateness of the problem to a particular technique.

MacFaul (2001) shows the working through of different scenarios, in different areas within paediatrics, for numbers of consultants and other workforce in an aim to estimate the staffing requirements in order to provide 24/7 care for children. Logical reasoning and expert judgement are used in determining the staffing numbers. The numbers are based on professional opinion and simple arithmetic is used.

Rifai and Pecenka (1990) use the example of maximising profit and minimising idle capacity when determining the optimal combination of surgical patients, in a hospital, to demonstrate the advantages of goal programming over linear programming.

Blake and Carter (2002) used goal programming to look at resource allocation at a hospital in Toronto, Canada, in terms of the mix of cases. Two models are described: one looks at physician allocation in terms of the mix of cases that may be completed; the other calculates the changes in practice (e.g. reductions in Length of Stay) that are necessary to preserve the existing mix and volume of cases. The second model was built, with the knowledge that physicians can often be unwilling to accept any change in case mix. A key benefit of the models was seen in their ability to make allocation decisions explicit.

Adan and Vissers (2002) develop an integer linear programming model which seeks to optimize the patient mix for a speciality, based on the resources (beds, nurses, operating rooms etc...) available. This is an interesting variant (and much more from an economist's viewpoint) on the more common approach of optimizing resources to meet patient demand.

The stochastic nature of many aspects of healthcare, (e.g. Length of Stay, patient demand) suggests that unless modelling a very predictable (and hence deterministic) situation, methods which incorporate this inherent uncertainty into the model should be used where possible. An example of the problems which can be encountered when using deterministic data to model a stochastic variable are illustrated nicely by Harper and Shahani (2002) using the example of bed capacities.

Queuing theory is a candidate method for coping with the stochastic nature of healthcare, and Gorunescu et al. (2002) demonstrate its use in the planning and management of hospital beds. Analytical methods such as queuing theory can quickly become difficult, if not impossible to solve for more complex and realistic problems, so numerical methods such as simulation tend to be more commonly used. A three phase simulation model (Prompt) allowing various scenarios concerning numbers of beds, theatres and to a certain extent, human resources to be examined is illustrated in Harper (2002a). This model allows the use of stochastic, rather than deterministic data, thus better representing the inherent variability in healthcare.

The Department of Health have developed a Bed Capacity Implications Model (BeCIM) to enable hospitals to determine the bed capacity needed to handle a given level of activity. The model is a Discrete Event Simulation with an Excel interface with a function similar to that of Prompt (mentioned above). Bensley (2003) advocates the gold standard of having generic models, such as BeCIM, but acknowledges that local idiosyncrasies mean that this is not always possible. BeCIM allows the use of local data, which goes some way towards adapting the model to the local situation.

Another example of a Discrete Event Simulation model is that of Kumar and Shim (2005) who use it to evaluate the use of resources by building a model in MedModel (ProModel Corporation) of the surgical care process in a hospital. The current situation allowed each operating theatre to either be reserved for a particular surgical discipline, or to be used by different surgical disciplines. One scenario removed the possibility of allocating operating theatres to particular disciplines. This resulted in more efficient use of resources however it also identified a limitation of the simulation approach in that surgeons would not be able to plan their other work commitments as they would not be sufficiently aware in advance of when they would be operating. Therefore a compromise was found by identifying those disciplines which used similar equipment, and making pooled operating theatres available to these 13 (out of 19) disciplines.

Lane et al. (2000) describe the development of a System Dynamics model for an Accident & Emergency (A&E) department so as to allow exploration of the role of the A&E department in the hospital, with a particular focus on the admission process. They argue that although modellers tend to use Discrete Event Simulation in healthcare settings, System Dynamics modeling can play a different role, providing a systemic view of the interactions of patient flow and information, as well as a strategic perspective of the management of the system. The main purpose of the study was to investigate the sensitivity of waiting times to hospital bed numbers however the study showed that it is systemically naive not to monitor a complex system such as A&E using a variety of signals, and indeed elective cancellations were found to be extremely sensitive to bed capacity. The model also found that waiting times were a result of the combination of arrival patterns and the doctors' rosters.

Another example of System Dynamics modelling was carried out by Brailsford et al. (2004) who created a model in Stella which encompassed not only the A&E department, but the whole emergency healthcare system in Nottingham. This allowed various scenarios (such as the effect of cancelling elective surgery on emergency admissions) to be compared and the effect on the relationships between different parts of the system to be examined.

Brailsford et al. also encountered the limitations of System Dynamics models when asked to look at the option of streaming different types of patients (by severity of illness) in A&E. However a Discrete Event Simulation model that could be quickly produced was able to answer such questions and thus they found that streaming was effective at helping the hospital meet targets, because the different classes of patients had different targets, however streaming 24/7 was not found to be an efficient use of staff resource utilisation. Instead, a flexible system was suggested whereby streaming was used only when waiting times reached a certain threshold.

2.4.2.2 Structuring healthcare problems

Before you can solve a problem, you need to know what the problem is, and this is much easier said than done for many problems, at any level, within healthcare. Baldwin et al. (2004) write that problem definition *itself* is the main concern in healthcare problems. They continue that there is also a problem with the reliability of healthcare data in particular; for example when predicting long-term effects, the data has to be collected from historical records that may have other influences such as changes in technology or medicine that are not taken into account. Also, less than accurate data may be provided due to anxiety about the possible consequences by the professionals. In order to help with the difficulty of problem definition and also the need for multiple stakeholders to understand and believe the model and the modelling process, Baldwin et al. propose a Modelling Approach that is Participatory Iterative for Understanding (MAPIU). This approach involves the stakeholders in the modelling process from the beginning, in an iterative manner, such that the modelling aids the problem understanding.

Eldabi et al. (1999) suggest that when using simulation in the process of decision making (in their example, looking at the use, or not, of a drug to combat breast cancer), whether or not it provides a specific answer to the problem is of low importance; the real power lies in allowing those with expertise in the problem domain to explore the problem.

Lehaney et al. (1999) state that the health sector may find simulation model resource experiments helpful since they avoid playing with real costs and real lives. They also consider the benefits of simulation in achieving greater understanding of a system as well as the importance of raising important issues early in the development so as not to render the simulations ineffective. They present the process of building a conceptual model, and thence a simulation model of an outpatient clinic as the basis for a discussion about the benefits of Soft Systems Methodology because of its structured approach.

Carter and Blake (2004) have many words of advice to impart with respect to modelling healthcare (in particular they use the example of simulation in an acute-care hospital, however their advice is not limited to this example). Three points in particular are:

- In terms of modelling effort, the model (in this case simulation) may be relatively simple. However data collection, model validation and output analysis may require significant effort.
- Decision making in hospitals is characterised by multiple players. Consulting with, and incorporating the objectives of all decision makers is vital.
- Whilst many processes and procedures are fundamentally similar, regardless of the institution, there are usually enough local quirks to render multi-site "cookie-cutter" models infeasible.

Wren (2005) is leading a National Workforce Planning Tools Project which began by identifying the main elements which make up the planning process: Visioning the future, Modelling the Options, Testing the Options, and Action Planning and Review. It is suggested that strategies are tested against scenarios and then compared to see how well each would cope. This was included on the website at the start of the project in 2003, but has since been reviewed and, has not yet reappeared on the website. However, tools which have been identified to support workforce planning at both strategic and operational levels are listed and described briefly.

2.4.2.3 Regional healthcare needs

Roemer and Roemer (1981) compared healthcare systems and manpower policies in different countries. In particular, they noted that Canada had an exceptionally high ratio of hospital beds to population compared with other countries, but that these beds tended to be filled with patients. Whilst not actually proposing a model, they were led to a similar judgement about the supply of doctors, that is that how ever many doctors were trained, they would always find ways to keep themselves busy.

Riportella-Muller et al. (2000) discuss a Workforce Forum which they formed in order to provide for open discussion and deliberation leading to rational planning for Wisconsin's primary healthcare needs. Seven possible scenarios for the future were considered and evaluated using the Integrated Requirements Model (IRM) version 1.5 software developed by the Bureau of Health Professions which gave an estimate of the number of healthcare providers needed, based on a population's age, location, type of health insurance coverage and utilisation rates. As a result of the forum, 10 recommendations were made. These were broadly about supporting primary provider recruitment initiatives, creating capacity for technical assistance in three to five pilot areas, encouraging interdisciplinary collaboration and creating new training opportunities.

Roos et al. (1996) examine how three resource planning tools (ratio, repatriation and population-needs-based approaches) might be used for deciding how many general surgeons are needed in rural southern Manitoba. The ratio approach assumes that the current ratio of surgeons to population is correct and predicts a need for an additional 7.8 to 14.5 surgeons. The repatriation approach relies on examining the number of procedures that might be performed locally if the appropriate facilities and surgeons were available; it predicts a need for up to 5 additional surgeons. The population-needs-based approach estimates needs based on age structure, health characteristics and existing surgical rates for the population; it predicts a need for 1.7 fewer surgeons. The authors, after careful consideration, conclude that the widely perceived shortage of surgeons may be somewhat overstated.

Benchmarking is advocated by Goodman et al. (1996) as an alternative and improved approach to workforce planning than needs- or demand- based planning. The method of benchmarking which they propose is to examine health plans and communities in order to measure workforce deployment. The selected benchmarks are those that achieve low levels of deployment of clinically active physicians without a measured loss of patient welfare due to a shortage of physicians. The benchmarks are used as a current best estimate of a reasonable physician workforce active in patient care for either public-policy or private-sector planning.

In a report for the Australian Medical Association, Access Economics Pty Ltd (2002) criticises the way the Australian Medical Workforce Advisory Committee (AMWAC) has predicted the number of General Practioners (GPs) needed throughout the country by using the number per population in large rural centres as a benchmark and then applying this to all other situations. In reality, GP use varies greatly between urban and rural Australia, and this method resulted in an underestimation of the numbers of GPs required. A multiple regression model (based on age/gender profile of patients, socio-economic factors, aboriginality, price of GP services, supply of doctors, rurality/remoteness, and state/territory) is proposed to estimate demand for GP services. For supply, they assessed how changes in remuneration might operate to provide positive or negative incentives with regards to the number of hours worked. They found that above a certain threshold (Aus$120 per hour), GPs were reluctant to lose their leisure time. The demand and supply were then combined to assess how many hours and at what rate, GPs would be required to work to meet demand. Some policy implications are then discussed to conclude the report.

Traditional hospital productivity indicators include full-time equivalents per admission and time per procedure, but Connor (1995) argues that these must be supplemented by population-based indicators of hospital labour resources. He carried out multivariate analysis, including Tobit models for each personnel category to find out the significant variables. These results were then used to draw conclusions about increases in Full Time Equivalents (FTEs), compared with interns and residents, whilst considering the elderly population, differences in provision in areas with different income levels, and differences due to population migration.

Lagergren (2005a,b) presents a simulation model (ASIM-III) which, respectively, looks at the retrospective and prospective healthcare needs of older people (over 65 years) in Sweden. The population is divided into subgroups according to age, gender, marital status and degree of ill health. Various (longitudinal) national studies have been used to provide the data as well as extrapolation and assumptions where data is unavailable. This study is a rare example of a model designed to predict healthcare needs that have already happened, rather than just using historical data to predict the future. In most situations this is unnecessary as actual data provides a much better representation. However, as in this case, where data is unavailable, modelling can provide insight into historical happenings. The importance of the prospective model is illustrated by the fact that although the size of the older population has been increasing, service provision has been decreasing. A more complex model (such as ASIM-III) is needed, rather than one which simply extrapolates this forward, since service provision will never become superfluous.

2.4.3 Observations

There are opportunities for every kind of OR technique to make a successful attempt at modelling healthcare capacities, as illustrated by the examples mentioned above. It can also be seen that it is important to get the structure of the model right, to see where simplifications can be made, and where the detail needs to be left in. What is apparent, both from the literature and from the experience gained in the projects presented in this thesis, is that a key part of modelling healthcare workforce is in reaching an appropriate set of compromises:

- A compromise between making no simplifying assumptions, and making too many. If no assumptions are made then either the model is in danger of becoming too large to handle, or of failing to be built at all. However, making too many assumptions in order to build a mathematically convenient model has the danger of being too abstract to be useful for the situation it is supposed to be modelling. The examples where mathematical programming has been used in the literature illustrate this problem nicely.

- A compromise between modelling the whole system and a small part of it. The focus of the model needs to be identified. There are many interactions between the various healthcare systems and processes, none operating as a stand-alone item. Building a model for the entire system can happily give a general overview, however it will inevitably also hide the detail for the smaller parts. However, building a model of one small part without allowing for the interactions with other areas healthcare, although easier, has the potential to produce erroneous conclusions because of misrepresentation of the processes.

- A compromise between creating the best possible model and creating something of practical use. Some of the newest and most appropriate OR software is unfamiliar to people within the healthcare professions, with the additional disadvantage of requiring specialist knowledge and/or being expensive. Sometimes it is possible to create a model either using familiar software and/or with a user-friendly interface which is almost as good, but with the advantage of being trusted and where necessary, able to be used by the healthcare professionals.

Few areas of the literature comment explicitly about the data used in the models presented. Data is collected in abundance in most areas of healthcare, however the suitability, reliability and ease of using this in models is not always as good as one would hope for. Within the NHS, there is currently no uniform method of collecting or storing data (however this will hopefully improve with the introduction of the electronic patient record in the near future). Different sources of data are not necessarily compatible, introducing the potential for error and misrepresentation from the data into the model. Therefore, when modelling healthcare, it is important to be aware of the availability and limitations of the data.

Being aware of the limitations of any model is also key to successful modelling of healthcare. Most of the examples illustrated in the literature represent a particular local situation, and whilst many will be generalisable, a comparison will have to be made between the original and the new situation, assumptions checked, and adaptations made as necessary. Similarly, those models which have been built for a general situation, when applied to a particular, local situation, will need to be checked and adapted as necessary to allow for any differences between the local and the general situation.

As an example of the limitations of a model, benchmarking (or a point of reference) is often used as an easy way of comparing how various healthcare providers are performing. It can also be used to extrapolate from one provider to another, to predict healthcare resource needs where the variability in service provision between providers is small. Where variations exist (e.g. in the population served), blind extrapolation can result in misleading conclusions.

2.5 Intermediate Care

Intermediate Care is a distinct part of the healthcare system with its own idiosyncrasies. Therefore, in this section we consider Intermediate Care separately in order to understand the concepts and issues associated with it, as well as the OR models associated with it.

2.5.1 Definition of Intermediate Care

The healthcare needs of the UK population are ever changing and ever more demanding. Intermediate Care has been developed to try to meet the demands of reduced numbers of acute hospital beds and an aging population. Within the NHS Plan, published by the Department of Health (2000b), Intermediate Care has been identified as a key area. Health and social care services need to develop in order to be able to respond to the needs of the people.

Steiner (1997) notes five factors which have served to revive interest in integrated services and in Intermediate Care in particular.

1. "Seamless care" - a health policy buzzword which has increased in popularity, denoting the concept of delivering the right amount of the right service at the right point in the continuum of care.
2. NHS financial incentives encouraging more economical use of existing services and the development of new options if needed.

3. Medical advances have enabled people to live longer and new medical technologies have made it possible to provide more intensive care in a patient's home.

4. Considerable developmental work has been completed in certain areas of Intermediate Care, thus laying the ground to introduce services more broadly.

5. Overall population aging and the observation that patients aged over 75 use 40% of all UK hospital beds, coupled with the encouragement of shorter average lengths of stay, mean that it has become necessary for providers to develop post-acute treatment options.

In the same publication Steiner discusses the many different definitions of Intermediate Care that exist. The differing views of what constitutes Intermediate Care mean that it is difficult to compare research into Intermediate Care in different parts of the country. Melis et al. (2004) suggest that we should not aim to arrive at a uniform definition of Intermediate Care, as they suggest this to be impossible, but rather to define Intermediate Care for the purpose of scientific appraisal. The definition used for Intermediate Care in the studies in this thesis is the one given by the National Service Framework for Older People (Department of Health, 2001b):

> *"A short period (normally no longer than six weeks) of intensive rehabilitation and treatment to enable patients to return home following hospitalisation, or to prevent admission to long term residential care; or intensive care at home to prevent unnecessary hospital admission."*

Intermediate Care can be delivered to the patient in a number of places:

- In the patient's home;
- At a Day Hospital;
- In a non-acute hospital setting.

Intermediate Care works at the interface between the health and social care services; thus care is delivered to the patient by a number of types of workforce across both health and social care. The main workforce types are:

- Physiotherapists;
- Occupational Therapists;
- Nurses;
- Social Workers;
- Rehabilitation Assistants.

Each individual Intermediate Care scheme, and the services within it, will have its own guidelines and idiosyncrasies to determine which patients will be admitted to the particular service. Steiner (1997) included a review of the literature concerning the many different ways that Intermediate Care has been and is being developed and implemented across the country. A couple of years later, Vaughan and Lathlean (1999) wrote a report based on a survey of existing Intermediate Care schemes across the country. They include detailed studies of 8 schemes, brief details of a further 71 schemes, and there are more which they were unable to include because of space limitations. Those that were included were chosen to illustrate the breadth and depth of Intermediate Care schemes provided. Wade and Lees (2004) identify 12 categories of services which fall within the concept of Intermediate Care, and Lees (2004) looks at these in more detail. One thing that all Intermediate Care services share in common is that all patients should be expected to benefit from the service and be willing to partake in it. Older people form the majority, but not the totality of the recipients of Intermediate Care, and Wade (2004) provides a broad perspective on older people and Intermediate Care.

2.5.2 Evaluations of Intermediate Care services

Whilst there have not been many mathematical, or indeed OR, models built in the area of Intermediate Care, there have been many randomised controlled trials and other attempts to evaluate Intermediate Care services. Lees (2004) found that rapid response teams and community assessment rehabilitation teams tend to be scrutinised from a naturalistic (qualitative/phenomenological) perspective, but randomised controlled trials tend to be regarded as the gold standard, and are commonly used to evaluate nurse-led units and 'hospital-at home' teams.

As Steiner et al. (1998) explain, Intermediate Care requires special thought with respect to evaluation because of its relative newness, range of potential users and position between health and social care. They present five rules of thumb, which although concerned with evaluation, can be adapted to OR models of Intermediate Care, as this is a way of evaluating the system without actually interacting with the system. The rules of thumb are:

- Meeting the appropriate need at the appropriate time.
- Designing the evaluation with the objectives of the Intermediate Care programme clearly in mind.
- Agreeing whose perspective will dominate the evaluation design.
- Consulting as widely as possible, as soon as possible.
- Deciding what *you* want to know - the best evaluations being those that serve something more than an external authority's requirements.

A study involving just under 400 older people was carried out by Brown et al. (2003) in the South West. To one group of people, health and social care were given separately, in the so called 'traditional' way, and to the other group, an integrated care was given. The study hoped to find that an integrated approach was more effective; however there was not enough evidence to suggest any differences between the two approaches. However, the patients much preferred having one point of contact and the speed of response for the group receiving integrated care was quicker.

There can be cultural difficulties in implementing new Intermediate Care services as Ryan-Woolley et al. (2004) found in their evaluation of a Community Rehab Team where they identified three cultural divides:

- between health and social services (e.g. health services view social services as 'bureaucratic')
- between medical staff and nurses/therapists/social workers (e.g. medical consultants were reported to be 'reluctant' to release patients to the Community

Rehab Team)

- between acute adult trust staff and staff working in older people's services. (e.g. a senior hospital doctor thought that nurses in the acute trust were not 'trained in or aware of the rehabilitation needs of patients')

The Intermediate Care needs of people in Sheffield are considered by Enderby and Stevenson (2000) who report on planning work done to establish the need for Intermediate Care services. They found it necessary to create eight patient categories, based on need, into which patients could be placed, as otherwise the discussion with the planning partners was restricted to the current ways of working as they found it difficult to think outside the box. The places (from a list of 19) where a person might receive care in each of the categories were defined (in a theoretical way - no patients were harmed!)

The different approaches to assessing patient need by district nurses and by social workers are discussed by Worth (2001). She found that, as expected, the social worker would take more of an interest in social aspects and the district nurse in health aspects. The outcome of the assessment could result in dilemmas for both types of practitioner. For social workers, this would be in identifying needs which could not be met, and for district nurses, this would be in deciding to meet needs which are not their responsibility. A clear need for more resources and better use of resources is expressed by the social workers in this study who "admitted that assessment could not be needs-led when resources are so limited, and for some [patients], there is little point in conducting a needs-led assessment which raises expectations unreasonably."

An evaluation study of Intermediate Care services in Cheshire was undertaken by Roe et al. (2003). This involved collecting data about clients for a 3-month period, grouping these clients and selecting typical cases, presenting this information to the staff and based on their knowledge, identifying future possible developments to improve the service. No economical evaluation was conducted. Key points that came out of the study were the need for Intermediate Care beds in the north of the area, care to be provided in the evenings and at the weekends, the need to regularly review provision, and to talk to each other.

Alternatives to acute hospital care are discussed by Hensher et al. (1999) who found that there is a lack of detailed studies about the subject. They compare the cost of hospital-at-home for patients with different conditions and conclude that the cost varies between conditions. The conclusion reached is that we should be looking more at bridging the gap between hospital and home, rather than trying to find alternative ways of providing the care that is normally provided in a hospital.

A detailed study was carried out by Hardy et al. (2001) in the Cambridge area of the Rapid Response Community Team (RRCT). Patients were assessed in Accident and Emergency and those that were found to be suitable were sent home under the care of the RRCT, rather than admitted to hospital. A control group of 149 patients from a previous year's data was used for comparison. Results were found to be favourable in terms of cost and beddays saved towards patients going home under the care of the RRCT.

Three hospital-at-home schemes are compared by Corrado (2001). Two were early discharge schemes (Bristol and Kettering) and the third was admission avoidance (Leicester). Both schemes reported reduced costs and increased patient satisfaction. The admission avoidance scheme reported decreased patient Length of Stay, whereas the early discharge schemes reported increased overall patient Length of Stay (time in acute hospital plus time in the hospital-at-home scheme). Corrado concludes that further comparisons are needed, particularly with a view to cost effectiveness. He also suggests that a comparison between hospital-at-home and care in community hospital would be interesting.

A detailed cost analysis is given by Coast et al. (1998) who compare acute hospital with hospital-at-home in the Bristol area. Hospital-at-home was found to be cheaper (mean cost per patient £2516, compared with £3292 in an acute hospital), even when subject to sensitivity analysis.

Wilson et al. (2003) checked the consistency of results during a randomised (patients sent either to home (with support) or to hospital) trial and those once the trial had stopped. The results once the trial had stopped were similar to those found during the trial, except that the hospital-at-home scheme was now operating at full, rather than half, capacity.

A systematic review of the best place of care for older people was carried out by Parker et al. (2000) who looked at 52 (medical) trials which had been conducted and the results recorded. The trials themselves and various outcomes (e.g. mortality, readmission and cost) were compared. Results were vague, but included that specialist rehabilitation reduced mortality compared with 'usual care', and that the sooner patients were discharged from hospital, the less functional deterioration they suffered. Substantial gaps were also highlighted in the literature, particularly that of 'hotel' wards in hospitals and for admission avoidance schemes.

Steiner et al. (2001) compared the quality and patient outcomes of post acute Intermediate Care in an inpatient nurse-led unit with conventional post-acute care in an acute hospital. They found care to be neither better nor worse in nurse-led beds, and that putting patients in the nurse-led unit had the effect of unblocking beds in the community hospital, rather than in the acute setting. Walsh et al. (2005) carry out an economic evaluation of, probably, the same nurse-led unit. In this, they find the nurse-led unit to be neither significantly more nor significantly less expensive than standard care.

The importance of knowing your target group of patients when implementing new Intermediate Care beds is cited by Plochg et al. (2005) who evaluated a low intensity Intermediate Care bed set up. In this particular situation, the cohort of patients using the service were not as expected, and indeed no formal assessment of the size of the target population was made prior to implementing use of the new beds. The assessment procedure was also cited as maybe taking too long, thus removing any possible benefits in reduction in Length of Stay. They propose that the three questions identified by Steiner (2001) for Intermediate Care research must be answered simultaneously. The questions are:

1. Which services are best, for which patients, at which point?

2. Which professionals should be involved, doing what, at which point?

3. What is the bottom line, financially?

2.5.3 Modelling Intermediate Care

Mathematical modelling is not able to offer the qualitative evaluation in terms of feedback that a Randomised Controlled Trial offers, however it does offer the unique situation, of being able to evaluate expected outcomes before deciding whether or not to implement any changes.

Perhaps because of the relative newness of the concept of Intermediate Care within the health service (although some would argue that the same jobs have been done, just under different names for many years), a literature search revealed only one OR model built to specifically evaluate Intermediate Care services. This is reviewed in detail here.

The ICON (Intermediate Care, Organisation and Normalisation) project is an evaluation of Intermediate Care services for older people, based on the Intermediate Care services in Shepway, Kent (Carpenter et al., 2003). The largest part of this project involved testing whether computer simulation could be developed and used to evaluate the impact of Intermediate Care services on the whole system. The project had three key research questions:

1. Do Intermediate Care services reduce the use of hospital beds by older people?

2. Do Intermediate Care services reduce admissions to nursing and residential care homes?

3. Do Intermediate Care services reduce overall costs of care?

Whilst wishing to encompass the whole system, the scope of the simulation model was limited to three Intermediate Care services (Community Assessment & Rehabilitation Team, Day Hospital and Recuperative Care Centre), three rehabilitation wards, four older people's wards and Social Services older people's teams. These were seen as the most significant elements of the healthcare system relevant to Intermediate Care, the remaining services being mainly small-scale and voluntary. Much of the simulation was based on data collected simultaneously at the different healthcare locations, tracking individual patients through the services and assessing them on entry and discharge to a service. This data was analysed statistically, in particular to examine the entry criteria for each service.

Discrete Event Simulation (DES) models were then built (using Simul8), incorporating the services' eligibility criteria within them. Models of the individual healthcare services were built to allow detailed modelling such as daily treatment times and employee resources. A combined DES system model was also constructed separately, with necessary simplifications, representing the services as beds or places and not allowing for patients to move directly from one service to another. The simulation methodology can be summarised as follows:

- Characterise the individual
- Decide (by testing against criteria) whether the individual should go to a hospital or to Intermediate Care
- If the individual goes to a hospital, decide which type of ward. If the individual goes to Intermediate Care, decide which type of service.
- The individual exits the system.

The individual service models were used to examine different scenarios such as the increase of resources, or the use of non-gender specific beds. The combined system model was used to evaluate the effect of increasing the number of beds/places available in each of the services on the rest of the system, and to evaluate different patient referral rules, as well as the provision of new services, such as those for cognitively impaired patients.

In discussing the scope and limitations of the model, the authors note that the presence of extreme pressures on the healthcare services mean that the service entry eligibility criteria (which are key to the structure of the simulation) are often circumvented. This was anticipated when the simulation was being built, however it was decided that the simulation should represent the ultimate goal of the developing Intermediate Care services. These limitations are expected to account for the deviations between the observed and simulated referrals.

Katsaliaki et al. (2005) provide the only other paper demonstrating the use of OR techniques in Intermediate Care. They demonstrate the benefits of using a simulation methodology for evaluating alternative patient care pathways for older people after discharge from hospital. This was done from the perspective of Social Services, who participate in providing Intermediate Care, but also are responsible for long-term care packages. Unfortunately the data was not available in the correct format to allow a quantitative analysis of these pathways.

2.6 Summary

This chapter began with a brief history of the NHS, overview of current issues within the NHS and a look at historical attempts at workforce planning within the NHS. This was followed by a survey of the literature, looking at modelling attempts of various aspects of healthcare: planning the nursing workforce, rostering, career structures, hospital capacities, structuring problems,and regional healthcare needs. Key messages from the literature were then discussed in Section 2.4.3. Successful modelling in healthcare requires reaching a set of compromises, in particular between complexity and usability.

The latter part of the Chapter introduced the concept of Intermediate Care, providing care to patients at the boundary of health and social care. There are few attempts at modelling Intermediate Care in the literature (only one was found), although there have been many Randomised Controlled Trials each evaluating a slightly different variant on the provision that makes up Intermediate Care. The relative newness of Intermediate Care means that the services are often still being developed as they are being evaluated, thus affecting the results of any review.

The literature reveals that there is still a need for OR models in healthcare workforce planning, and in particular for Intermediate Care which is currently growing at a faster rate than that at which it can be evaluated through traditional methods such as randomised controlled trials.

Chapter 3

Modelling of Hospital Inpatient Workforce Needs

3.1 Introduction

This chapter presents work which has been developed with RBBH (Royal Berks and Battle Hospitals Trust). This builds on the work carried out by Harper (2002b) with the development of Prompt, a simulation model to predict bed numbers, operation theatre scheduling and preliminary workforce planning. I have developed a model in Simul8 to examine the level of detail required to model workforce planning in a hospital. The output from this simulation is then fed into a stochastic program in order to calculate the optimal size (and associated skill mix) of the workforce.

3.2 Background

Working with the Royal Berkshire and Battle Hospitals (RBBH) Trust, Harper (2002a,b) developed a simulation model (Prompt), written in Delphi, of an inpatient speciality which allowed exploration of bed capacities and theatre scheduling, as well as some preliminary work on workforce planning. Prompt was well received by the hospital and they were keen to develop the workforce planning module further. The workforce planning module allowed for simplistic patient to workforce ratios to be defined, however these did not allow for any direct or indirect care percentage of working time, nor allowance for leave of any kind.

With assistance from Andre Costa, a visitor to the School of Mathematics, Harper had begun to rebuild Prompt in Visual Basic. It was shortly after this that I became involved. Hampshire & Isle of Wight WDC were aware of the development of Prompt and were keen to explore the possibility of a better workforce element within it, and also to see if Prompt could be used for hospitals within their patch. I took on the role of communicating and meeting with the nurses to ensure that the model was meeting their needs. The staff at RBBH were keen to develop the Acuity-Quality method (explained later in Section 3.4) of calculating workforce need, as well as to group the patients into care similar, and clinically meaningful groups.

We wanted to compare the results from the Acuity-Quality method and detailed patient grouping with a simpler (Occupied Bed - also explained in Section 3.4) method, and with fewer groups. Depending on the results of the comparison, this would then justify (or not) the extra time spent by the staff at RBBH on the Acuity-Quality method and grouping of patients.

In order to facilitate the comparison, in parallel with the redevelopment of Prompt, I built a prototype model in Simul8. The structure of both Prompt and the Simul8 model was informed through meetings with both key nursing staff and with the director of HR, David Foden.

Prompt was developed and used for communication with the nurses, once we were sure about the level of detail to include. The advantages of giving the managers and nurses a stand-alone program which could have a much more developed interface for them to use far outweighed the possibilities of using Simul8 (which might have struggled to cope with the quantity of data). In total, data was collected, and scenarios built, to allow for validation with nine specialities. These were Adult Medicine, Elderly Care, General Surgery, Gynaecology, Urology, ENT, Opthalmology, Orthopaedics and Paediatrics.

The Simul8 model allowed for exploration of the possibilities of combining the simulation with a stochastic program in order to evaluate the optimal number of nurses to employ. The inspiration and motivation for this came from observing the interpretation of the simulation results by the nursing staff and knowledge that the average number of occupied beds underestimates the actual number of beds needed (Harper and Shahani, 2002). This work is also presented in this chapter.

3.3 The Problem

All patients in a hospital need some form of nursing care, irrespective of whether they are emergency or elective, inpatient or outpatient. The nursing care needs will depend on the individual patient's condition. The ability of the nursing staff to meet the needs of the individual patients may depend upon who is rostered on to work. Herein lies the problem that we seek to examine in this chapter. Matching nursing abilities to patient need is a difficult process, as not only do you have to have the right staff working the rights shifts, but you have to employ the right combinations of staff (staff-mix), or else be aware that the balance will have to be made up from temporary staff.

In this chapter, we demonstrate the use of the Simul8 model using data from the Orthopaedics speciality. The model could be easily used by other specialities, since although the parameter values (e.g. number of patients, workforce ratios, Length of Stay) would vary, the structure would be the same.

3.3.1 Research objectives for this chapter

The objectives for this project are:

- To build a simulation model to model bed and nursing needs of patients in an inpatient speciality.
- To compare the Acuity-Quality and Occupied Bed methods of estimating patient need.
- To compare whether dividing patients into similar care groups improves the results of the simulation, compared with treating them as one group.

- To build a stochastic program to take the demand from the simulation model and to optimize this in terms of the number of each type of nurse to employ.

3.4 The Methodology

The developed model uses an approach, not currently found in the literature, of a combination of Discrete Event Simulation and stochastic programming. The simulation aspect is used to model the individual patients through time, and the output from this is the nursing need, for each type of nurse, at each time step of the simulation. The stochastic programming aspect seeks to minimise the cost of employing both permanent and temporary nurses whilst satisfying the demand for each type of nurse in the output from the simulation.

Hurst (2002a) describes five approaches to nursing workforce planning, which are summarised in Table 2.1. In consultation with RBBH, the Acuity-Quality and Occupied Bed methods were chosen to be developed and compared within the model. We used local data and adapted the methods as described by Hurst, to take advantage of our model structure. The definitions used in this chapter are given below.

- **Occupied Bed**: The ratio of nurses to patients is defined for each type of nurse. When the simulation is run, the number of occupied beds (and hence patients) is recorded at each time step. The nursing need is a multiple of the occupied bed numbers.
- **Acuity-Quality**: The patient's Length of Stay is divided into dependency states. For each dependency state, the ratio of nurses to patients for each type of nurse is defined. When the simulation is run, the number of patients in each dependency state at each time step is recorded. The nursing need is calculated by multiplying the number of patients in each dependency state at each time step by the defined ratios.

3.4.1 The Simulation

3.4.1.1 Time-step

The simulation was built in Simul8 with a time-step of 1 day. For most specialities (Intensive Care being an example of an exception), nursing need will vary by time of day. This cannot be accounted for with a time-step of 1 day. However, the nurses at RBBH work in three 8-hour shifts and they agreed that the nursing need for the late and night shifts could be thought of as a certain percentage of the early shift. Using a time-step of less than a day (i.e. an hour, since a time step of 8 hours is not easily possible within Simul8) would significantly increase the simulation time and complexity of the model without a significant benefit in the output. Therefore the time-step of 1 day is used in the simulation to model the early shift on each day, and is scaled appropriately to get the total need for each day.

3.4.1.2 Patient arrivals

There are two main options for modelling patient arrivals in the different patient groups:

1. A separate arrival point for each patient group;
2. One arrival point for all patients, leading into a dummy variable which allocates patients to groups according to historical proportions by day and by month.

In each case, interarrival times for each arrival point are modelled using the exponential distribution, the parameters for which are determined from historical arrivals, by day and by month, for the relevant patients.

The first of these options, whilst maybe initially appearing a more intuitive way to model arrivals has an intrinsic problem under certain conditions in Simul8. The problems arise when arrivals vary greatly by day (and possibly also by month, although that would be a rarer problem), in particular when the interarrival times are greater than the unit time of 1 day. This has the effect of reducing the total number of arrivals since a large interarrival time will impede on the following days by preventing arrivals other than the one scheduled from occurring. As an example, consider patients arriving for an operation where few arrive at the weekend, but many do on Monday. There are no simple, nor obvious ways to avoid this problem.

This problem does not affect the second option since the number of patients for the whole speciality is large enough to ensure small interarrival times by day and by month. This is the option which has been used in the model.

3.4.1.3 Length of Stay

Historical data is used to fit a distribution to the Length of Stay for patients in each group. The Length of Stay is modelled as being made up of up to five different dependency states, as suggested by and employed at RBBH. Expert opinion, on the part of the nurses, is used to define the percentage of their Length of Stay that each type of patient (i.e. from each patient group) spends in each of the five dependency states, with state 5 being the highest dependency and state 1 the lowest. Patients are assumed to begin their Length of Stay in their highest dependency state, and monotonically decrease their dependency state until they leave. This assumption was agreed with the nurses since they felt that this described the vast majority of cases and there was no data available to support any backwards flows. Note that not all patient groups require all five states, in particular, elective patients never enter state 5.

Once the patients have arrived, and passed through the dummy activity allocating them to groups, they pass through another dummy activity which assigns six attributes (labels in Simul8) to each patient, defining the Length of Stay. The first attribute is the total Length of Stay which is sampled from the fitted distribution for each patient group. The remaining five attributes represent the Length of Stay in each of the five dependency states and are calculated from the total Length of Stay using the nurse-defined percentages. Each dependency state is modelled as a separate activity (work centre in Simul8) with the time in each state defining the service time. The time is set equal to zero for states which a patient does not enter.

3.4.1.4 Resources

There are two types of resource within the simulation: beds and nurses. Although the purpose of this model is primarily to be run with unlimited capacity, on the part of the nursing staff, the number of beds available is not unlimited.

Beds can be treated as either one large group, or as several separate groups (wards perhaps). To model beds other than as one large group, requires allocation rules to be defined for each patient groups. In order to keep this simulation as simple as possible, and because validation of staffing numbers is easier at a speciality level than at a ward level, the beds are modelled as one large group.

Beds are allocated to patients when they enter dependency state 5, and are released when the patient leaves dependency state 1. If a bed is not available when a patient arrives, then if they are classified as Emergency they are "Transferred" and leave the system. If they are classified as Elective, they are "Delayed" for an amount of time based on expert opinion before re-entering the system.

Nurses are required as a resource for the Acuity-Quality method, but not the Occupied Bed method (which calculates nursing requirement as a multiple of bed occupancy). Each type of nurse is modelled as a different resource. Nurse to patient ratios are defined in the model for each dependency state so nurses are allocated and released for each dependency state. (It has been necessary to use 1/100th of a nurse as the unit for modelling nursing need, because of the fractional nurse to patient ratios and Simul8's integer constraints). For both methods, the nursing need is given in terms of direct care, where direct care is defined as direct patient contact.

3.4.1.5 Activity Flow Diagram

The activity flow diagram for the simulation is shown in Figure 3.1. The diagram, as it is, illustrates the Acuity-Quality method since both types of resources are shown; the activity flow diagram for the Occupied Bed method is the same, except for the removal of the resources representing the different types of nurse. The diagram also illustrates a flexible number of groups whereby for smaller numbers of groups, the number of patients allocated to the 'extra' groups is set equal to zero.

3.4.2 Conversion to Whole Time Equivalents (WTEs)

The nursing need resulting from the simulation needs to be converted from direct care to Whole Time Equivalents. In consultation with the Director of Human Resources (HR) at RBBH, it was decided to do this by using both an 'indirect care' factor and an 'HR function' factor.

The direct and indirect care needs combine to form the total nursing need for each shift. This is then factored up and summed to give the total need, at which point the HR function and number of hours worked are used to calculate the number of Whole Time Equivalents to employ.

Indirect care is broken down into the following categories, each of which is defined in terms of the proportion of a shift:

- Relaxation time - e.g. toilet breaks.
- Supervisory time - e.g. experienced staff supervising less experienced staff.
- Break time - meal and coffee breaks.
- Other - to allow for anything not included in the above.

The HR function is broken down into the following categories, each of which is defined in terms of the proportion of a year:

- Absence - leave through illness;

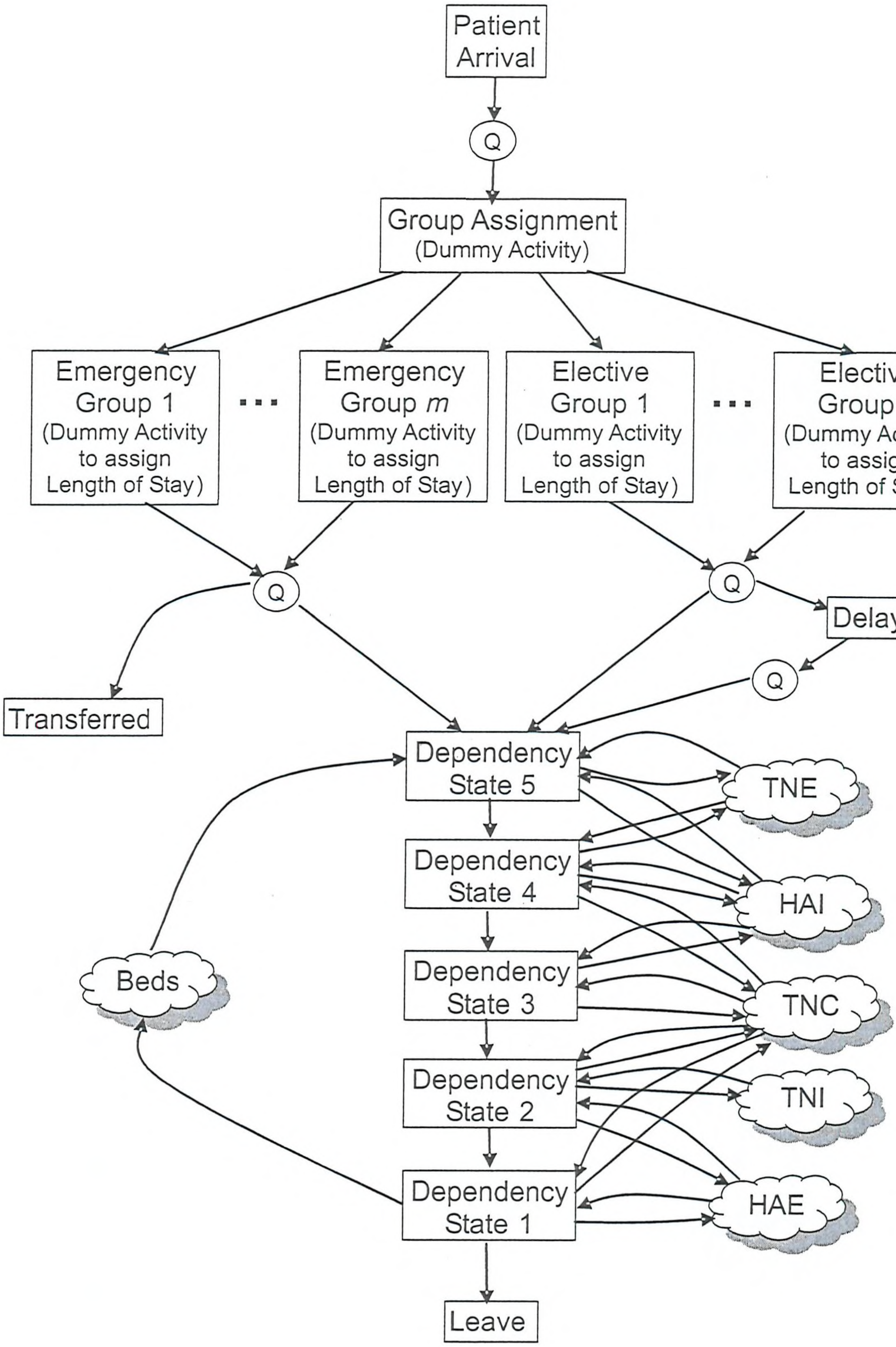

Figure 3.1: Activity Flow Diagram of the Simulation

- Annual leave - statutory holiday leave;
- Other leave - any leave not previously covered.

A working week of 37.5 hours (including meal breaks) is assumed for all nurses, and we assume that each day is divided into three shifts, each of eight hours.

The simulation gives the direct care needs for the early shift. The late and night shifts have been defined as needing 20% less care. Hence the direct care needs for the early shift need to be multiplied by a factor of 2.6 to give the total direct care needs for the day.

Thus, if we let the direct care needed on the early shift be x, and the proportion of indirect time be y, then the total care need per day, taking into account the indirect care time is:

$$\text{Total care per day} = \frac{2.6x}{(1-y)}$$

Letting h be the HR function proportion, then the total number of WTEs needed in employment is:

$$\text{Number of WTEs to employ} = (1+h)7 \times \frac{8}{37.5} \times \frac{2.6x}{(1-y)}$$

Note: 7 days in the week, 8 hours in a shift, 1 WTE works 37.5 hours per week.

If either the indirect care, or HR function proportions are different for the different types of nurse, it is necessary to convert the demand for each type of nurse into Whole Time Equivalents before performing the stochastic program. Otherwise, it is possible to perform this conversion after the stochastic program, since multiplying the right hand side of each of the constraints by a positive constant is equivalent to multiplying the objective function by the same constant. Proof that this is equivalent is given in Appendix A.

3.4.3 The Stochastic Program

In order to determine the optimal number of nurses (and the associated skill-mix) to employ, one approach might be to run the simulation for a number of scenarios, with a different level of resources (nurses) for each scenario. The respective results could then be analysed. Whilst this approach would take into account the availability of the different nurses, the respective costs associated with each type of nurse would not be considered (although the costs could be calculated at the end). We wanted to take a more multi-dimensional approach than was available using simulation alone, and hence this section describes a stochastic program which takes the demand for the different types of nurses over the year and evaluates the optimal number to be employed on a permanent basis, and how many temporary (or bank) nurses should be used. Since the nursing need is highly variable, a stochastic program is appropriate.

For the stochastic program defined below, 30 runs of the simulation, each lasting a year, provide the nursing demand for the 30 different scenarios. These 30 runs/scenarios have identical input parameters and thus are equally likely[1]. Thirty runs and hence scenarios were chosen because the average results of the simulation showed no improved accuracy when more runs were performed and also because it was a compromise between providing a range of demand for the stochastic program and keeping the stochastic program to a manageable size.

3.4.3.1 Definitions

Nine types of staff are considered within the stochastic program. Permanent nurses (both full and part time) can be considered in terms of Whole Time Equivalents (WTE). The care provided by the nurses is thus amalgamated and considered as a whole, rather than modelling each nurse's individual hours separately. We consider 5 types of permanent nurses (as defined and employed at RBBH), which in increasing skill level are:

[1]Alternatively, 30 runs of the simulation with different input parameters for some/all of the runs could provide the nursing demand for the different scenarios. This would then require associated probabilities of the likelihood of each of the different input parameters to be defined.

- Healthcare Assistant Inexperienced (HAI)
- Healthcare Assistant Experienced (HAE)
- Trained Nurse Inexperienced (TNI)
- Trained Nurse Competent (TNC)
- Trained Nurse Experienced (TNE)

When the permanent staff are not able to meet the demand, temporary nurses are used. We consider four types of temporary nurse. There are two agencies which temporary nurses can belong to: NHS Professionals, an internal agency, and external agencies. Within each agency, nurses are considered at two levels of competency: Trained Nurse (denoted by the subscript T in the formulation) and Healthcare Assistant (denoted by the subscript H in the formulation).

We define the variables:
Let x_j be the number of WTE staff of type j , $j = 1, \ldots, 5$. (5 is the most competent)
Let n_{iks} be the number of staff from NHS Professionals needed on day i for staff type k, for scenario s, $i = 1, \ldots, 365, k = T, H, s = 1, \ldots, 30$.
Let a_{iks} be the number of staff from external agencies needed on day i for staff type k, for scenario s, $i = 1, \ldots, 365, k = T, H, s = 1, \ldots, 30$.

Secondly, we define the constants.
Let d_{ijs} be the demand on day i, for nurse type j, for scenario s, $i = 1, \ldots, 365, j = 1, \ldots, 5, s = 1, \ldots, 30$.
Let c_j be the annual salary per WTE nurse of type $j = 1, \ldots, 5$.
Let g_k be the daily wage for nurses from NHS Professionals, $k = T, H$.
Let h_k be the daily wage for nurses from external agencies, $k = T, H$.

Whilst it may be true, for example, that a TNC is a TNC when she/he is working with patients with whom she/he is familiar, and in an environment with which she/he is familiar; it is likely that her/his work will not be at its most efficient when employed in an unfamiliar situation. No numeric evidence to support this has been found in the literature, however the Audit Commission (2001) report "Brief Encounters" says that "A common view ... is that bank and agency staff provide patient care of a poorer quality, or behave in ways that may be considered less professional, than those in permanent posts ... The circumstances in which [those working on a temporary basis] are appointed and carry out their duties are also sometimes less than ideal ... Of course this may also happen to bank staff and to substantive post holders temporarily re-deployed to unfamiliar areas. These circumstances all increase the risks of something going wrong and the likelihood of patients receiving poorer care than they would otherwise get." In order to model this within the stochastic program, we define the following constant:

Let e be the efficiency ratio for the temporary nursing staff (when $e = 1$, temporary nursing staff are as efficient as permanent staff)

The rate payable to NHS Professionals is always less than that of the external agencies. However, staff from NHS Professionals are not always available and sometimes the external agencies have to be used. Since we can assume no difference in standard of care between agency staff, clearly an optimal solution will always chose staff with the lesser cost. We therefore make an assumption about the percentage of time that staff from NHS Professionals are available. After consultation with NHS staff, an initial figure of 70% was agreed upon. (i.e. NHS Professionals staff are available 70% of the time.)

We can therefore remove one of the variables by setting:

$$a_{iks} = \frac{3n_{iks}}{7}$$

Finally we formulate the stochastic program as a combination of an objective and constraints. In this formulation the need for the temporary staff, n_{iks}, are the recourse variables. Each scenario happens with probability p_s: for the example in this chapter, $p_s = \frac{1}{30}$ since there are 30 scenarios and we assume that each scenario is equally likely because there is no difference in input parameters.

3.4.3.2 Formulation

The objective is to minimise costs and the constraints ensure that the demand for each level of nursing care is met, allowing for a nurse with a higher competency level to be used as a substitute for a nurse with a lower competency level but not *vice versa*. The formulation is as follows.

$$\text{Minimise} \sum_{j=1}^{5} c_j x_j + \sum_{i=1}^{365} \sum_{s=1}^{30} p_s \sum_{k=T,H} (g_k + \frac{3h_k}{7}) n_{iks}$$

Subject to:

$$\begin{aligned}
x_5 + \frac{10 n_{iT_s} e}{7} &\geq d_{i5s} \\
x_4 + x_5 + \frac{10 n_{iT_s} e}{7} &\geq d_{i5s} + d_{i4s} \\
x_3 + x_4 + x_5 + \frac{10 n_{iT_s} e}{7} &\geq d_{i5s} + d_{i4s} + d_{i3s} \\
x_2 + x_3 + x_4 + x_5 + \frac{10 n_{iT_s} e}{7} + \frac{10 n_{iH_s} e}{7} &\geq d_{i5s} + d_{i4s} + d_{i3s} + d_{i2s} \\
x_1 + x_2 + x_3 + x_4 + x_5 + \frac{10 n_{iT_s} e}{7} + \frac{10 n_{iH_s} e}{7} &\geq d_{i5s} + d_{i4s} + d_{i3s} + d_{i2s} + d_{i1s} \\
&\quad \text{for } i = 1, \ldots, 365 \\
&\quad \text{for } s = 1, \ldots, 30 \\
x_j &\geq 0 \\
n_{iks} &\geq 0 \\
\text{for} \quad & i = 1, \ldots, 365 \\
& j = 1, \ldots, 5 \\
& k = T, H \\
& s = 1, \ldots, 30
\end{aligned}$$

The optimization software used was Xpress-MP.

3.5 The Data

The data for the model has been provided by RBBH who have also provided some helpful comments in the structuring of the model.

3.5.1 Nurses

In the UK, nurses are categorised according to Grades A to I, with Grade A being the least competent and lowly paid, through to Grade I being the most competent and highly paid. RBBH has developed its own, simplified set of categories (at five levels) for nurses, based on competencies, and it was this that they proposed (and we accepted) we should use for the model. The five levels, and their equivalent Grades, are:

- TNE (Trained Nurse Experienced): Grades F, G, H, I;
- TNC (Trained Nurse Competent): Grades D, E;
- TNI (Trained Nurse Inexperienced): Grade C;
- HAE (Healthcare Assistant Experienced): Grade B;
- HAI (Healthcare Assistant Inexperienced): Grade A.

3.5.2 Patients

RBBH provided us with an anonymised set of data for all inpatient episodes at the hospital, from which we were able to group the patients according to speciality. Note that for each patient episode, the patient is assigned to one consultant, and if the patient changes consultant then that episode ends and a new one begins. Thus the number of episodes is greater than or equal to the number of patients. Since we are unable to match patient episodes belonging to the same patient, we model patient episodes, and therefore all future references to 'patient' are shorthand for 'patient episode'. This should not affect any conclusions since the workload remains the same, but should be borne in mind, if any changes in patient numbers are modelled. In such a case it may be advantageous to find out, for example, the average number of episodes per patient. The RBBH database contains the date of admission and discharge for each patient (episode) from which we are able to calculate a Length of Stay for each patient.

The staff at RBBH were keen to divide the patients in each speciality into clinically meaningful, and care similar groups, (based on workforce needs). This was a very time consuming job as it involved a senior nurse grouping a list of several hundred (in some cases) procedure or diagnostic codes. Once the codes were grouped, we could then extract the relevant patients from the database (which contained the codes) to:

- Calculate the number of patients in each group.
- Fit a distribution to the Length of Stay for patients in the group.
- Determine an arrival profile by month and by day for patients in that group.

For each patient group, it was also necessary to use the expert opinion of the senior nurse(s) to determine the percentage of the Length of Stay that each patient would spend in each of 5 dependency states. Since these 5 dependency states are used at RBBH, this was easier than a new concept would have been.

The groupings for the orthopaedics speciality, consisting of 9 emergency groups, and 8 elective groups, are shown below.

- **Emergency A**: Fractured neck of femur and major joint replacements;
- **Emergency B**: Spinal procedures;
- **Emergency C**: Small closed reductions of fractures and primary repairs of tendons and nerves;
- **Emergency D**: Primary open reductions of fractures;
- **Emergency E**: Intravenous therapy;
- **Emergency F**: Major closed reductions of fractures;
- **Emergency G**: Minor procedures;
- **Emergency X**: Other procedures;
- **Emergency N**: Non surgical treatment;
- **Elective A**: Hip and knee replacements;
- **Elective B**: Other major joints;
- **Elective C**: Minor joints;

- **Elective D**: Decompressions and spinal fusions;
- **Elective E**: Discectomies;
- **Elective F**: Hand surgery including carpal tunnel and treatment of fractures and epidural injection;
- **Elective X**: Other procedures;
- **Elective N**: Non surgical treatment.

In section 3.6.3 this grouping for the orthopaedics speciality is compared with that of just dividing the patients into emergency and elective groups, and that of treating all orthopaedic patients as one group. In order to allow for a valid comparison between different groupings, we have collected the data for the most complicated grouping (the 17 groups as identified above) which can then be aggregated into other groups, using beddays to weight the different groups. Note that beddays is a commonly used hospital statistic and is equal to the sum of the number of days in (normally) a year that each bed in the hospital/speciality/ward has been occupied.

The percentage of Length of Stay (LoS) spent in each dependency state, for each group, and the total annual number of patients, average Length of Stay and beddays can be seen in Table 3.1. Table 3.2 shows the distributions fitted to the Length of Stay for each group. These were fitted using a specially designed statistical analysis program called Apollo as developed by (Harper, 2002a)[2]. Note that for this orthopaedics speciality, all the fitted distributions happen to be lognormal. This is not so for every speciality; the best fit was selected from the following distributions: Exponential, Gamma, Lognormal, Normal and Weibull.

Table 3.3 shows the arrival profiles by month and Table 3.4 by day, as determined by Apollo from the hospital data. The data when the patients are divided into two

[2] Apollo uses a simplex optimizing algorithm AS47 (Nelder and Mead, 1965; O'Neil, 1971) for estimating the parameters of a chosen distribution. The parameters are estimated by minimising the χ^2 value since this is asymptotically equivalent to the maximum likelihood function (Jones, 1997). A comparison of different classification algorithms, including that used by Apollo, can be found in Harper (2005).

groups (All Emergencies and All Electives) and for when the patients are treated as one large group (All Patients) are also shown in these tables. The data for these groupings has been taken from the raw data, except for that of the percentages of time in each dependency state which has been calculated as a weighted average of the 17 groups, using beddays as the weight.

Table 3.1: Percentage of time spent in each dependency state for Orthopaedics patients

Description	Dependencies(% of LoS)					Annual No. of Patients	Av. LoS	Bed days
	1	2	3	4	5			
Emergency A	12	29	29	28	2	327	24.5	8012
Emergency B	6	20	34	27	13	19	19.6	372
Emergency C	55		45			686	3.3	2264
Emergency D	16	24	36	24		391	7.2	2815
Emergency E	4	16	80			65	9.6	624
Emergency F	5	16	24	40	15	234	18.9	4423
Emergency G	50		50			199	4.3	856
Emergency X	17	22	61			272	8.0	216
Emergency N	14	57	29			894	5.4	4741
Elective A	40	26	17	17		653	10.2	6661
Elective B	40		30	30		41	6.6	271
Elective C	36	43	21			76	2.7	206
Elective D	23	22	22	33		90	8.4	756
Elective E	5	19	38	38		81	4.4	357
Elective F	50		50			338	2.1	710
Elective X	34	33	33			1070	2.3	2461
Elective N	25	25	50			135	3.7	500
All Emergencies	17	27	35	18	3	3087	8.6	26282
All Electives	36	25	25	13		2484	4.8	11919
All Patients	23	26	32	17	2	5571	6.9	38201

3.5.3 Beds

The orthopaedics speciality contains 109 beds which are divided into 6 wards. The beds are either designated as 'emergency' (80 beds), or as 'elective' (29 beds), although in practice these boundaries are not strict. Nearly all of the beds (apart from a small number that are ring-fenced) can (and often do) contain outliers from other specialities, most notably adult medicine, and in the same way, some of the orthopaedic patients will be outliers in beds belonging to other specialities. In the

Table 3.2: Distributions fitted to Length of Stay for Orthopaedics patients

Patient Group	Distribution	Mean	Standard Deviation
Emergency A	Lognormal	24.5	36.0
Emergency B	Lognormal	19.6	18.8
Emergency C	Lognormal	3.3	10.2
Emergency D	Lognormal	7.2	14.6
Emergency E	Lognormal	9.6	31.0
Emergency F	Lognormal	18.8	23.2
Emergency G	Lognormal	4.3	14.3
Emergency X	Lognormal	8.0	23.9
Emergency N	Lognormal	5.5	20.9
Elective A	Lognormal	10.1	6.9
Elective B	Lognormal	6.6	9.1
Elective C	Lognormal	2.6	2.5
Elective D	Lognormal	8.4	8.3
Elective E	Lognormal	4.4	2.9
Elective F	Lognormal	2.0	3.6
Elective X	Lognormal	2.3	3.3
Elective N	Lognormal	3.7	13.4
All Emergencies	Lognormal	8.6	28.8
All Electives	Lognormal	4.8	9.4
All Patients	Lognormal	6.8	19.6

Table 3.3: Orthopaedics arrival profiles by month

Patient Group	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Emergency A	29	32	21	25	22	31	25	24	32	25	31	30
Emergency B	3	1	2	2	1	1	1	2	1	2	2	1
Emergency C	42	47	57	65	64	67	82	63	76	44	41	38
Emergency D	28	33	26	29	25	33	52	41	34	33	25	32
Emergency E	4	4	3	6	5	4	9	7	5	11	2	5
Emergency F	15	23	17	22	21	10	23	18	25	20	16	24
Emergency G	20	7	14	16	14	16	23	19	22	20	12	16
Emergency X	19	17	28	24	25	21	33	18	23	29	17	18
Emergency N	74	62	79	91	52	78	75	64	71	81	87	80
Elective A	72	57	53	48	42	47	46	53	57	68	62	48
Elective B	6	2	6	6	6	3	3	1	3	2	1	2
Elective C	6	3	5	9	2	5	9	11	9	7	6	4
Elective D	7	9	7	5	8	7	9	3	6	10	12	7
Elective E	8	7	13	3	8	4	7	4	6	7	9	5
Elective F	30	32	32	23	30	28	26	25	29	32	28	23
Elective X	100	106	111	86	89	60	71	84	98	88	95	82
Elective N	5	13	17	8	11	5	18	10	11	14	13	10
All Emergencies	234	226	247	280	229	261	323	256	289	265	233	244
All Electives	234	229	244	188	196	159	189	191	219	228	226	181
All Patients	468	455	491	468	425	420	512	447	508	493	459	425

historical data for the financial year 2002/03, 17.8% of the orthopaedics patients were outliers and 17.5% of the patients in the orthopaedics beds were outliers from

Table 3.4: Orthopaedics arrival profiles by day

Patient Group	Mon	Tues	Wed	Thurs	Fri	Sat	Sun
Emergency A	42	53	47	55	54	36	40
Emergency B	3	6	5	2	1	1	1
Emergency C	107	113	102	82	84	106	92
Emergency D	53	53	60	66	69	39	51
Emergency E	10	8	11	12	12	2	10
Emergency F	40	27	35	34	34	32	32
Emergency G	31	33	31	27	39	19	19
Emergency X	39	40	48	53	46	24	22
Emergency N	128	133	141	117	122	125	128
Elective A	78	170	147	156	25	6	71
Elective B	19	2	1	7	6	1	5
Elective C	37	14	6	5	3	3	8
Elective D	1	11	52	20	4	1	1
Elective E	1	11	27	24	14	1	3
Elective F	105	74	50	38	23	10	38
Elective X	326	204	158	164	99	14	105
Elective N	29	25	22	30	11	2	16
All Emergencies	453	466	480	448	461	384	395
All Electives	596	511	463	444	185	38	247
All Patients	1049	977	943	892	646	422	642

other specialities. Since these approximately cancel each other out, we make the assumption that we can 'ignore' the other specialities. We model the beds as two groups - emergency beds and elective beds. Whilst patients will ideally find a bed in their respective bed group if possible, they will not be excluded from the other bed group if it is their only possibility for a bed.

3.5.4 Nurses

Nurse to patient ratios are defined in terms of direct care needs for patients, based on an early shift. The nurses at RBBH chose this way of defining the ratios themselves, but it is also the way used by Hurst (2002a) which suggests that it is a sensible and valid approach. There are 3 shifts per day, of which the early shift is the busiest. The staff at RBBH agreed that the late and night shifts only require 80% of the staffing needs of the early shift.

For the Acuity-Quality method, the staff at RBBH defined the nurse to patient ratios for each dependency state in terms of how many patients in a particular state each nurse could care for, as in Table 3.5. At first glance, some of these numbers may appear quite curious, for example patients in the highest dependency states require both the most competent (TNC) and least competent (HAI) nurses. On questioning, the nurses explained that this is because the most competent nurse will lead on the care, but will require an assistant for which the least competent nurse is suitable. Patients in lower dependency states can be cared for by the TNC, TNI and HAE. The TNI appears to be able to care for patients little more than the HAE and HAI which the staff felt accurately represented real life. In practice, nurses tend to be treated as a TNI for only a short period of time, soon progressing to the TNC category.

For the model we need the inverse of this, i.e. how much of each type of nurse each patient needs, and this is shown in Table 3.6. Thus, for example, 1 TNE can care for 32 patients in dependency state 4 and this equates to each patient in dependency state 4 needing 0.03 of a TNE.

Table 3.5: Nurse to patient care ratios

Nurse Category	Patient Dependencies				
	1	2	3	4	5
TNE				1:32	1:2
TNC	1:40	1:32	1:5	1:6	
TNI		1:10			
HAE	1:24	1:32			
HAI			1:12	1:4	1:10

Table 3.6: Patient to nurse care ratios

Nurse Category	Patient Dependencies				
	1	2	3	4	5
TNE				0.03	0.50
TNC	0.03	0.03	0.20	0.17	
TNI		0.10			
HAE	0.04	0.03			
HAI			0.08	0.25	0.10

We convert these Acuity-Quality ratios into ratios suitable for the Occupied Bed method by taking a weighted average, again using beddays as the weights. These ratios are shown in Table 3.7.

Table 3.7: Ratios for the Occupied Bed method

Category	Patient to Nurse Ratio
TNE	0.01
TNC	0.11
TNI	0.03
HAE	0.02
HAI	0.07

3.5.5 Indirect care and HR function values

As described in section 3.4.2, the indirect care and HR function values need to be defined in order to convert the direct care results from the simulation to Whole Time Equivalents. The indirect care and HR function values, defined by the HR director of RBBH, are shown in Tables 3.8 and 3.9 respectively. Note that the indirect care values for TNEs are different to that for the other types of nurses because they spend more of their time in a supervisory role. This means that the conversion to Whole Time Equivalents must be completed before performing the stochastic program.

Table 3.8: Parameters concerning indirect time

Category	% of Shift (All but TNE)	% of Shift (TNE)
Relaxation	5	5
Supervisory	0	10
Break	6.25	6.25
Other	0	0
Total	**11.25**	**21.25**

Table 3.9: Parameters concerning the HR function

Category	% of year
Absence	4
Annual Leave	16
Other Leave	0
Total	**20**

3.5.6 Costs

The salary paid to a nurse depends, as in many jobs, not only on what grade they are employed at but also how long they have been working and/or in post. Table 3.10 shows the average cost for each type of nurse.

Table 3.10: Costs for permanent nurses

Category	Annual cost (WTE salary)
TNE	£28087
TNC	£19372
TNI	£15514
HAE	£13549
HAE	£11528

In a similar way, costs for temporary staff vary, though not so much. NHS Professional staff are less expensive than the agency staff, but different agencies charge different rates. Costs are calculated per hour. Table 3.11 shows the average costs which we have used.

Table 3.11: Costs for temporary nurses

Category	Hourly cost (wage)
NHS Professionals (Trained Nurses)	£14.11
NHS Professionals (Health Care Assistants)	£8.63
Agency (Trained Nurses)	£20.69
Agency (Health Care Assistant)	£12.65

3.6 Results from the Simulation

3.6.1 Validation

The model can be validated at two levels; that of the patients, and that of the nurses. We begin with the patients.

3.6.1.1 Patients

Table 3.12 compares the annual number of patients in the simulation with the historical number of patients, by patient group. The model is accepted as validating the annual number of patients since the historical number of patients is contained within the 95% confidence interval for each group except for group Elective B where the historical number is very slightly larger than the upper confidence interval.

Table 3.12: Annual patient numbers

Patient Group	Historical	Simulation	
		Mean	95% Conf. Interval
Emergency A	327	326.7	(320.0, 333.3)
Emergency B	19	18.1	(16.7, 19.5)
Emergency C	686	682.7	(674.0, 691.4)
Emergency D	391	388.5	(381.2, 395.7)
Emergency E	65	63.4	(60.7, 66.1)
Emergency F	234	236.1	(230.3, 242.0)
Emergency G	199	201.4	(196.8, 206.1)
Emergency X	272	278.3	(271.0, 285.6)
Emergency N	894	900.3	(887.8, 912.8)
Elective A	653	655.3	(648.4, 662.3)
Elective B	41	38.9	(36.9, 40.9)
Elective C	76	74.9	(71.3, 78.5)
Elective D	90	89.6	(85.9, 93.3)
Elective E	81	82.1	(78.7, 85.6)
Elective F	338	337.8	(331.7, 343.9)
Elective X	1070	1060.3	(1050.7, 1070.0)
Elective N	135	134.1	(129.3, 138.9)
All Emergencies	3087	3087.8	(3065.2, 3110.4)
All Electives	2484	2473.5	(2460.9, 2486.1)
All Patients	5571	5580.9	(5555.4, 5606.4)

The average Length of Stay for each patient group can also be validated against historical numbers. These are compared in Table 3.13. Except for the group Emergency N where the historical number is slightly smaller than the lower confidence interval, the historical average Length of Stay is contained within the 95% confidence interval for each patient group. The group, Emergency N, contains patients who do not require surgical treatment. This group is more heterogeneous than some of the other groups, and thus the fitted distribution to the Length of Stay may not be as good a fit as for some of the more homogeneous groups (the fitted mean is contained within the confidence interval). The model is accepted as validating the Lengths of Stay.

Table 3.13: Patient Length of Stay

Patient Group	Historical	Simulation	
		Mean	95% Conf. Interval
Emergency A	24.5	24.5	(23.6, 25.3)
Emergency B	19.6	19.4	(18.1, 20.8)
Emergency C	3.3	3.3	(3.2, 3.4)
Emergency D	7.2	7.2	(7.0, 7.5)
Emergency E	9.6	9.1	(8.3, 9.9)
Emergency F	18.9	19.0	(18.5, 19.5)
Emergency G	4.3	4.4	(4.1, 4.7)
Emergency X	8.0	8.1	(7.7, 8.5)
Emergency N	5.4	5.7	(5.5, 5.9)
Elective A	10.2	10.1	(10.0, 10.2)
Elective B	6.6	6.4	(5.8, 7.0)
Elective C	2.7	2.6	(2.5, 2.8)
Elective D	8.4	8.5	(8.2, 8.9)
Elective E	4.4	4.3	(4.2, 4.5)
Elective F	2.1	2.0	(2.0, 2.1)
Elective X	2.3	2.3	(2.2, 2.3)
Elective N	3.7	3.6	(3.3, 3.8)
All Emergencies	8.6	8.6	(8.4, 8.7)
All Electives	4.8	4.7	(4.6, 4.8)
All Patients	6.9	6.8	(6.7, 6.9)

3.6.1.2 Nurses

Table 3.14 shows the direct care time results from the simulation for the early shift, with the 95% confidence intervals. Results for both the Occupied Bed and Acuity-Quality methods are shown, although any differences between these are discussed later in section 3.6.2. The results shown are those for when the patients are divided into 2 groups: Emergency and Elective patients.

The next step is to add in the time for indirect care to obtain the number and mix of nurses needed on the early shift. Table 3.15 presents the results for the early shift when time for indirect care is added, using the values for indirect care time, as in section 3.5.5, of $y = 21.25\%$ for the TNEs and $y = 11.25\%$ for the other nursing categories.

Table 3.14: Direct care results for the early shift from the simulation

Nurse Category	Occupied Bed Method		Acuity-Quality Method	
	Mean	95% Conf. Interval	Mean	95% Conf. Interval
TNE	1.01	(1.00, 1.03)	1.64	(1.61, 1.67)
TNC	11.14	(11.00, 11.28)	10.77	(10.62, 10.91)
TNI	3.04	(3.00, 3.08)	2.69	(2.65, 2.72)
HAE	2.03	(2.00, 2.05)	1.74	(1.72, 1.76)
HAI	7.09	(7.00, 7.18)	6.98	(6.88, 7.08)
Total	24.31	(24.00, 24.61)	23.81	(23.49, 24.13)

Table 3.15: Early shift (direct & indirect) care results from the simulation

Nurse Category	Occupied Bed Method	Acuity-Quality Method
TNE	1.28	2.08
TNC	12.55	12.14
TNI	3.43	3.03
HAE	2.29	1.96
HAI	7.99	7.86
Total	27.39	26.83

This was thought to be representative by the nursing staff and both the nursing and HR staff were satisfied that the model served the required purpose.

We would like to be able to compare these numbers with the equivalents generated using the method as proposed by Hurst (2002a), and available as a spreadsheet (Hurst, 2002b). Since Hurst's numbers are only available as Whole Time Equivalents, conversion of our simulation results is necessary and this is carried out as detailed in section 3.4.2, using the HR function values defined in section 3.5.5. Table 3.16 contains both the results from this conversion, Hurst's values and the establishment figures from RBBH. This table also shows the percentage of each type of nurse given by each of the methods. Hurst's values were calculated using the default ratios for orthopaedics in the published spreadsheet, and using the average number of occupied beds (91) from the simulation results. The Occupied Bed and Acuity-Quality methods, using Hurst's spreadsheet, give exactly the same results.

The figures in the table vary across nursing categories for the different methods.

Table 3.16: WTE results from the simulation

Nurse Category	Occupied Bed Method		Acuity-Quality Method		Hurst Values		RBBH Establishment	
TNE	6.0	4.7%	9.7	7.8%	11.2	10.7%	14.0	12.8%
TNC	58.5	45.8%	56.5	45.2%	56.1	53.8%	63.3	57.7%
TNI	16.0	12.5%	14.1	11.3%	14.5	13.9%	0.3	0.0%
HAE	10.7	8.4%	9.1	7.3%	11.0	10.5%	2.7	2.5%
HAI	37.2	29.2%	36.6	29.3%	11.5	11.0%	29.5	26.9%
Total	127.6	100%	125.0	100%	104.3	100%	109.7	100%

Overall, the simulation results appear to be higher than Hurst's values, and the RBBH establishment figures, however this is not exactly surprising since the nursing staff defined the ratios themselves. The ratios could be easily adjusted.

One key difference could be because of the way in which the numbers were calculated. The difference being that our method used a bottom-up approach to define nurse-patient ratios, whereas Hurst's method used more of a top-down approach. Using a bottom-up approach can, potentially be more accurate since it removes an element of subjectiveness and the need to rely on assumptions which is necessary with a top-down planning approach. The establishment figures at RBBH would also be considered as a top-down approach. Another difference between our method and Hurst's method is that Hurst used averages to, effectively, create national figures. Using local data allows for any local case-mix idiosyncrasies and necessary practices to be considered. It should be noted that Hurst suggests that local data may be used where it is available.

What is of interest in comparing the methods is the difference in skill mix given by the different methods, as shown by the percentages in Table 3.16. This illustrates that the current RBBH staff-mix is not well aligned to the simulation results. In particular, the RBBH establishment numbers for TNIs and HAEs are very low whereas the numbers for TNCs are high. These results identify the potential for breaking down the traditional demarcations between different nursing categories, and the realisation that actually, a highly qualified professional is not needed for most of the jobs, in a similar way to that which is discussed in Chapter 5 for Intermediate Care.

The hospital staff were satisfied enough with the validity of the model to take control of the model. We were content to let this happen, as we were sure that, with a small amount of minor adjustments, the model would satisfactorily represent real life. Handing over the model to the staff to carry out the final validation was a good way of allowing them to take ownership of the model. It also allowed them to become familiar with the model whilst working with numbers that could be compared with historic data, rather than beginning with analysing possible future scenarios. Whilst the results for the current situation, presented here, were not able to be validated as accurately as we would have hoped for, for the purposes of the experiments detailed below, we can make relative comparisons.

3.6.2 Occupied Bed method versus Acuity-Quality method

An initial glance at Tables 3.15 and 3.16 suggests that there is a small difference between the results given by the Occupied Bed and Acuity-Quality methods. This section seeks to determine whether this difference is statistically significant or not, by carrying out some χ^2 tests. The null hypothesis for each test is that there is no difference between the methods, and the alternative hypothesis is that there is a difference.

Since the Occupied Bed and Acuity-Quality ratios are applied to the same simulation runs, the difference between the total nursing need given by the two methods can be compared directly. The test is conducted separately for each of the 30 runs of the simulation. For each test, there are 365 degrees of freedom and a corresponding critical χ^2 value of 410 at the 95% level. The test statistics for the runs ranged from 28 to 54, thus indicating that the null hypothesis should not be rejected. Although these test results relate only to the 30 specific runs, the alternative hypothesis is rejected by such a large margin that the general conclusion can be drawn that, in most cases, there is no difference between the Occupied Bed and Acuity-Quality methods when considering the total number of nurses required.

The second test considers the nursing need for different types of nurses. We are unable to carry out this test on a day by day basis for each run (as above) since the need for some types of nurse is less than 5 on some days, which would invalidate the χ^2 test. Instead, we sum up the need for each nurse in each month for each run. The χ^2 test is carried out by comparing the monthly need, given by each of the methods, across each of the 30 runs. For these tests, there are 30 degrees of freedom, and a corresponding critical χ^2 value of 43.8 at the 95% level (and 50.8 at the 90% level).

Table 3.17 shows the test statistics for each month, for each type of nurse. Also included in the table are the test statistics for all nurses, by month, and the test statistics when considering the total need over the whole year, for each nurse type.

Whilst most of the test statistics suggest acceptance of the null hypothesis, there are enough that do not suggest this to infer that there is evidence to suggest that the two methods give different results, and therefore that the null hypothesis should be rejected. The null hypothesis is rejected the least for nurse types TNC and HAI. These have patient to nurse ratios defined for, respectively, 4 and 3 out of the 5 dependency states, which is more than for any of the other nurse types, perhaps suggesting that the need for these types of nurse are slightly less dependent on the patient case-mix.

It is impossible to say whether or not conclusions can be generalised across all specialities, hospitals, and all possible patient to nurse ratios. However the results for the orthopaedics speciality suggest that the Occupied Bed and Acuity-Quality methods give similar results when considering the total nursing need, but give slightly differing results when considering nursing need by type of nurse. Discussions with nursing staff at RBBH suggested that the Acuity-Quality method gave sensible staffing levels and skill mixes.

Table 3.17: χ^2 test statistics comparing demand for different nursing categories

Month	TNE	TNC	TNI	HAE	HAI	All nurses
Jan	170.1	28.8	56.8	46.2	25.0	36.3
Feb	176.9	33.5	44.4	35.5	23.0	33.3
Mar	216.6	34.5	59.2	36.7	30.6	45.4
Apr	280.4	20.9	55.0	51.8	23.7	22.8
May	185.7	25.9	39.0	41.0	22.3	30.7
Jun	218.6	22.4	52.8	49.8	24.4	23.3
Jul	392.7	9.0	57.4	68.7	13.5	9.8
Aug	225.6	15.7	53.4	61.9	24.3	20.9
Sep	325.0	20.7	64.4	64.1	24.9	23.4
Oct	189.2	22.3	59.1	46.0	23.0	27.5
Nov	190.4	30.0	58.2	42.7	35.7	43.5
Dec	183.2	32.0	45.6	43.0	37.9	40.2
Whole year	2618.2	148.4	507.3	520.2	31.6	126.1

3.6.3 To group or not to group

This section examines the difference between the results given when the patients are divided into different numbers of patient groups. The nursing staff at RBBH thought to a certain extent, that a positive correlation exists between the number of patient groups and increased accuracy. For them, the thought of treating such a heterogeneous range of patients, in a homogeneous way (by being in the same group) was a dubious prospect. However, since the arrival profiles and Lengths of Stay are modelled stochastically, and fitted to all the patients in the group, we were less dubious and decided to experiment with the number of patient groups.

Within the orthopaedics speciality, three obvious groupings presented themselves: the nineteen groups, as defined by the nurses; two groups, separating the emergency patients from the elective patients; and one group. Whatever the outcome of the experiment, it must be stated that there is a definite benefit to separating patients into different groups where the different groups require different patient pathways within the model. For example, if particular beds are ring-fenced for patients with a particular condition, then those patients should be modelled separately. Table 3.18 shows the results from the simulation, for direct care, for each of the groupings.

Table 3.18: Direct care results for the different numbers of patient groups

Nurse Category	One Group		Two Groups		Nineteen Groups	
	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.
TNE	1.7	(1.7, 1.7)	1.6	(1.6, 1.7)	1.7	(1.6, 1.7)
TNC	10.9	(10.8, 11.0)	10.8	(10.6, 10.9)	10.7	(10.6, 10.8)
TNI	2.7	(2.7, 2.7)	2.7	(2.7, 2.7)	2.7	(2.6, 2.7)
HAE	1.7	(1.7, 1.8)	1.7	(1.7, 1.8)	1.7	(1.7, 1.7)
HAI	7.1	(7.0, 7.2)	7.0	(6.9, 7.1)	7.0	(6.9, 7.1)
All Nurses	24.0	(23.8, 24.3)	23.8	(23.5, 24.1)	23.8	(23.5, 24.0)
Beds	101.8	(100.7, 103.0)	101.3	(100.0, 102.5)	100.5	(99.5, 101.4)

The confidence intervals for each resource overlap between each of the different groupings suggesting that the null hypothesis should not be rejected. In order to investigate further, we looked at the average demand for beds, for each month. The results are shown in Table 3.19 and show that the confidence intervals for the bed numbers overlap for each month, suggesting that there are no significant differences in the bed numbers due to the number of patient groups.

Table 3.19: Average monthly bed need for the different numbers of patient groups

Month	One Group		Two Groups		Nineteen Groups	
	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.
Apr	106.6	(104.7, 108.4)	108.5	(106.5, 110.5)	105.9	(103.9, 107.9)
May	98.6	(96.0, 101.1)	98.7	(96.5, 100.9)	95.8	(93.3, 98.3)
Jun	98.2	(96.0, 100.3)	97.8	(95.9, 99.8)	95.1	(93.2, 97.0)
Jul	100.8	(98.4, 103.2)	100.9	(98.3, 103.5)	97.9	(95.8, 99.9)
Aug	99.3	(96.6, 102.0)	100.4	(97.6, 103.2)	97.9	(95.8, 100.1)
Sep	107.0	(104.7, 109.4)	107.3	(104.9, 109.7)	104.7	(102.6, 106.9)
Oct	106.4	(103.9, 108.9)	105.9	(103.1, 108.6)	105.6	(103.1, 108.0)
Nov	102.7	(100.3, 105.0)	101.3	(99.1, 103.5)	101.4	(99.0, 103.8)
Dec	96.2	(94.0, 98.5)	95.2	(92.6, 97.8)	96.6	(94.0, 99.2)
Jan	95.4	(93.1, 97.7)	94.5	(92.1, 97.0)	97.6	(94.9, 100.4)
Feb	102.9	(100.6, 105.2)	100.9	(98.3, 103.6)	104.1	(101.6, 106.6)
Mar	107.6	(105.1, 110.0)	104.0	(101.4, 106.5)	103.0	(100.3, 105.6)

Next we compare the total monthly demand for each type of nurse, across the different groupings, using the χ^2 test as in table 3.17. No easy conclusions can be drawn from the results since there was no uniform pattern as to when the null hypothesis should be rejected. Whilst it was rejected more for comparisons involving the nineteen groups, it was not accepted for each comparison between one and two groups. Similarly there was no obvious pattern as to acceptance or rejection of the null hypothesis due to the type of nurse. As a summary, the sum of the χ^2 values for each type of nurse, for each comparison of the number of groups are shown in Table 3.20. The sums are smallest, for each type of nurse, in the comparison between one group and two groups, suggesting that the difference between n and $n + m$ groups will be most significant for large values of m. The number of groups (and hence an upper limit for the value of m) should be based on clinically meaningful groups so that the associated demand profiles and workforce needs (ratios) are similar within the group.

Table 3.20: Sum of χ^2 test values comparing the total monthly nursing need for the different numbers of patient groups

Nurse Type	Comparison of Numbers of Groups		
	1 and 2	1 and 19	2 and 19
TNE	267.3	850.4	1052.7
TNC	301.0	568.7	644.4
TNI	326.7	384.8	414.6
HAE	116.7	144.1	137.7
HAI	259.7	705.3	824.2
All Nurses	444.1	1159.1	1395.6

These results suggest, in a similar way to those of the previous section, that when planning is carried out at an aggregated level, then less detail is required within the model. However, when planning at a more detailed level, for example, by month, more detailed modelling is required since the differences between the patient groups become more significant and hence a larger number of patient groups (i.e. a larger value of m) is appropriate.

3.7 Results from the stochastic program

The stochastic program was run using the demand for nursing need produced by the simulation when using the Acuity-Quality method. An efficiency of 0.9 (or 90%) for the temporary staff was assumed initially, and the need for temporary staff was assumed to be fulfilled by nurses from NHS Professionals 70% of the time, and from external agencies for the remainder.

Firstly we compare the results from the stochastic program with the results in Table 3.16 to see whether the stochastic program makes a difference to the number of nurses to employ as opposed to taking the average results using the Acuity-Quality method from the simulation. These results are compared in Table 3.21 which also contains some of the results from Table 3.16 for comparison.

Table 3.21: WTE results from the stochastic program

Nurse Category	Acuity-Quality Method	Stochastic Program	RBBH Establishment
TNE	9.7	13.9	14.0
TNC	56.5	60.5	63.3
TNI	14.1	16.1	0.3
HAE	9.1	9.2	2.7
HAI	36.6	40.5	29.5
Total	125.0	140.2	109.7

The total number of nurses suggested by the stochastic program is 12% higher than that given by the Acuity-Quality method. The number of TNEs suggested by the stochastic program is similar to the RBBH establishment value.

These results suggest that in order to minimise expenditure, a hospital should employ more nurses than the average expected demand would indicate.

3.7.1 Comparison of different rates of efficiency for the temporary staff

The stochastic program was run for differing levels of efficiency of the temporary staff to see the effect that this had on the permanent members of staff. The results are shown in Table 3.22.

These results suggest there will always be a need to rely on temporary nursing staff to meet peaks in demand, since the number of permanent staff needed when the efficiency of the temporary staff is set to zero (so effectively, they do not exist) is significantly more than for the other results. Looking at the higher (and more realistic) levels of efficiency for the temporary staff, an almost linear relationship exists. The relationship between the optimal number of permanent staff and the efficiency of the temporary staff is illustrated in Figure 3.2. A decrease in efficiency

Table 3.22: Comparisons of WTEs for differing levels of temporary nurse efficiency

Efficiency	TNE	TNC	TNI	HAE	HAI	Total Staff
0%	44.2	95.9	19.6	13.7	68.8	242.3
10%	22.3	71.1	18.5	11.2	49.5	172.5
20%	19.7	68.1	18.0	10.6	46.7	163.0
30%	18.5	65.8	17.5	10.0	45.3	157.1
40%	17.2	64.9	17.0	9.8	44.0	152.8
50%	16.5	63.6	16.8	9.5	43.1	149.6
60%	15.9	62.6	16.4	9.6	42.3	146.7
70%	14.9	62.0	16.4	9.3	41.7	144.3
80%	14.3	61.4	16.1	9.4	41.0	142.1
90%	13.9	60.5	16.1	9.2	40.5	140.2
100%	13.5	60.0	15.8	9.3	39.9	138.4

of the temporary staff by 10% suggests that costs are minimised if the total number of permanent staff is increased by two.

Figure 3.2: The relationship between temporary staff efficiency and the total number of permanent staff

3.7.2 Comparison of results from the stochastic program when combined with the Acuity-Quality and Occupied Bed methods

All the results concerning the stochastic program shown previously have used the demand for nurses given by the Acuity-Quality results from the simulation. We now look at the results when the stochastic program is used to optimize the nursing demand given by the Occupied Bed method. These results are shown in Table 3.23. The difference between the results given by the stochastic program and the simulation is less when considering the nursing need given by the Occupied Bed method to that given by the Acuity-Quality method. The increase in the total number of nurses to employ, from the simulation to the stochastic program, using the Occupied Bed method is 6.7%, compared to 12.1% for the Acuity-Quality method.

Table 3.23: Comparison of optimizing the nursing need created by the different methods

Nurse	Acuity-Quality method		Occupied Bed method	
Category	Simulation	Stoch. Program	Simulation	Stoch. Program
TNE	9.7	13.9	6.0	6.0
TNC	56.5	60.5	58.5	61.6
TNI	14.1	16.1	16.0	18.1
HAE	9.1	9.2	10.7	10.2
HAI	36.6	40.5	37.2	40.2
Total	125.0	140.2	127.6	136.1

3.8 Conclusion

There were two main parts to the work in this chapter. The first part used a Discrete Event Simulation model to look at the level of complexity required when planning nursing requirements in an inpatient setting. The second part took the demand output from this DES model and used it within a stochastic program to calculate the optimal number of nurses to employ.

We consider first the work concerning only the DES model. Two levels of complexity were examined: that of comparing two methods for calculating workforce need, and the other of looking at the benefits of dividing the patients into homogeneous groups. The methods for calculating nursing workforce need were based on standard Acuity-Quality and Occupied Bed methods as described by Hurst (2002a). Our aim in comparing the methods was to see if there was any benefit in using one approach over the other, particularly as the Acuity-Quality method requires much more data (and therefore time and effort) to inform it. Our conclusion is that when planning at an overall level, there is little difference between the numbers given by each method. However, when planning at a more detailed level (e.g. by month, by skill mix) then the Acuity-Quality method is better able to pick up the variability and subtlety due to seasonality and/or case-mix and/or other local issues.

Similar conclusions were reached about the number of patient groups needed. When planning at an overall level, a small number of patient groups (or just one) is sufficient. However, when planning at a more detailed level, using more groups allows the variability and/or seasonality of the different types of patients to be picked up. As always, it should be borne in mind that the experiments involving greater levels of detail are more time intensive and a balance should be sought between the time available and the level of detail required.

There were differences between our results and those given by Hurst's methods. This included not only the overall numbers, but also the skill-mix within. Hurst used a top-down method to calculate average workforce ratios at a national level, whereas we used a bottom-up approach which could potentially be more accurate since it is less subjective to the status quo.

The stochastic program was used to evaluate the optimal number of nurses, and the associated skill-mix, to employ on a permanent basis, whilst satisfying the nursing need (by day and type of nurse) given by the DES model. The results suggest that the optimal number of permanent nurses to employ, when taking the need for temporary staff into account, is greater than that given by the average results from the simulation (around 12% when using the Acuity-Quality method, and 7% when using the Occupied Bed method). Further experiments suggest that this depends on the efficiency of the temporary nurses, and that a decrease in efficiency of the temporary nurses by 10% roughly increases the optimal number of permanent nurses to employ by two.

That the optimal number of nurses to employ is greater than the average number of nurses needed seems intuitively right. Harper and Shahani (2002) illustrate the relationship between bed occupancy and refusal rates, whereby as bed occupancy increases, the refusal rate increases. Nurses are unlike beds in that whereas the ratio of beds to patients remains fixed (at 1:1), the ratio of nurses to patients can be forced to vary since it is not (in most cases) a fixed constraint. It is also easier to increase the number of nurses available (through the use of temporary staff), than it is to increase the number of beds. The stochastic program suggests that employing the average number of nurses needed may result in a higher overall cost than if more nurses had been employed. This higher overall cost relies on the nurse to patient ratios remaining constant. Theoretically, in most circumstances they could change, however as a result the nurses may experience increased pressure and the patients may experience a lower quality of care.

Combining the stochastic program with the DES was found to be an effective way to evaluate the optimal number of permanent nurses to employ. The stochastic program allowed relative costs of the different nurses to be considered which would not have been possible simply through repeated iterations of the DES. The Discrete Event Simulation presented here took 10 minutes to run, and the stochastic program 1.5 hours to run using a computer with a pentium 4 processor, a CPU of 1.6 GHz and 256MB of RAM.

3.9 Summary

This chapter has demonstrated the use of a Discrete Event Simulation model and stochastic programming to evaluate nursing workforce need. The DES model was used to examine the level of complexity needed, by comparing two methods for calculating workforce need, as well as looking at the benefits of dividing the patients into homogeneous groups. The general conclusion from these experiments was that the level of complexity required in the model depends on the level of detail at which the results are required. The output from the DES was fed into the stochastic program which optimized the number of nurses to employ, subject to relative costs. The results from the stochastic program suggested employing a greater number of nurses than that given by the average results from the simulation. The combination of a DES and a stochastic program was found to be much more effective than using each singularly.

Chapter 4

Modelling for the Reprovision of Intermediate Care Services

4.1 Introduction

This chapter contains work carried out for the Mount Hospital reprovision[1] project in Eastleigh & Test Valley South Primary Care Trust (PCT). The Mount Hospital, based in Eastleigh, Hampshire, provides Intermediate Care services in a variety of formats to the local population. An increasing awareness of the inability of the existing infrastructure to provide the care, which the staff wanted to provide for the patients, led to the decision to look at reproviding the services currently provided at the Mount Hospital. In effect this meant considering providing the services on (or based at) a different site or sites. Although the Mount hospital was situated in E& TVS PCT and this is where the majority of patients came from, it also served patients from Mid Hants PCT. We worked with the service model group who were looking at the practical angle of what the different options for reproviding the services meant in terms of bed and workforce numbers. The service model group reported to the project steering group who in return reported to the boards of each PCT.

In order to analyse how service requirements would differ in the reprovided system if patient pathways were altered, the service model group carried out three audits

[1]Reprovision is a word coined by the staff working on the project with the meaning that they are looking at different ways of providing the care that is currently provided.

to analyse where patients were now, and where they could be. We became involved just before the second audit, and were able to use the results of the audit in order to analyse the new patient pathways and capacity levels. Each audit encompassed more patients than the previous audit, and indeed the third audit was the only one to encompass all potential candidates for the services provided at the Mount.

A Discrete Event Simulation model was built which was validated by modelling the current system. This was then adapted and used to look at various scenarios for the reprovided system, and the corresponding impact on bed numbers and other capacities within the Intermediate Care setting.

The timescales for this project were quite short (a few months) as the results were needed in order to inform decisions before the public consultation. This meant that detailed data collection was not possible and the best had to be made of that which was available. A large amount of time connected with this project has been spent explaining the results and process to a largely unmathematically-minded project team who nonetheless have been enthusiastic about the outcomes.

4.1.1 Research objectives for this chapter

The objectives for this project were:

- To build a Discrete Event Simulation model of the current Intermediate Care provision.
- To use this model to evaluate the consequences of providing the Intermediate Care services in a new way to the current set of patients, and to an increased set of patients for whom care is not currently provided. Particular reference should be made to bed numbers.
- To increase understanding of how the current system operates.

4.2 The Current system

The current Intermediate Care provision at the Mount Hospital site is composed of a number of services:

- Rehabilitation wards
- Community Rehab Team
    - Preventing Dependency Team[2]
    - Community Physio
- Day Hospital

Patients may use just one of the services, or they may move from one service to another, as their care needs change and develop. However, at any one point in time patients will only be using one of these services.

Data was collected about each service, and analysed to discover from where the patients were referred and to where the patients were discharged. A distribution to represent Length of Stay in each service was fitted using Apollo (Harper, 2002a). Other idiosyncrasies of the individual services which either needed modelling, or needed to be included as an assumption were also noted. Care was required in interpreting the data due to its varying quality and quantity, as is apparent in the results of the analysis presented below.

4.2.1 Rehabilitation wards

Admission and discharge dates (from which Length of Stay can be calculated) as well as discharge destination were acquired from the ward log books for 2003.

[2]This team provides rehabilitation to patients in their own homes in response to a crisis situation where admission to an acute hospital is best avoided or to facilitate discharge from either the acute hospital, or the rehabilitation wards.

Admissions

The total number of patients admitted into the Rehabilitation wards in 2003 was 248. Almost all of the patients' routes into the wards were from an Acute Hospital. As shown in Figure 4.1, there is no evidence of a consistent pattern of admissions (seasonality) during a year. Thus we have assumed that demand fluctuates around an average arrival rate across the year in the model.

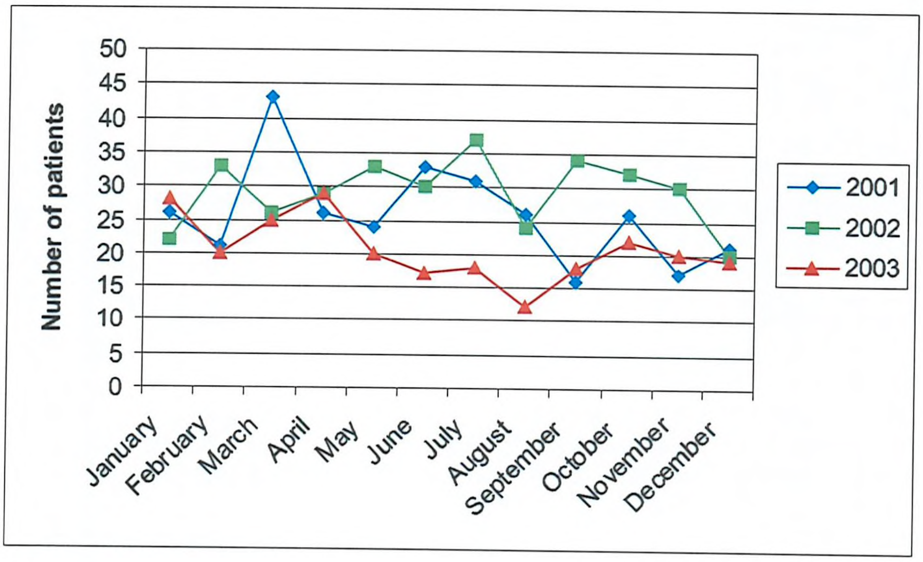

Figure 4.1: Admissions to the rehabilitation wards by month

Discharge Destination

The percentage of patients being discharged to each destination is shown below. This is calculated from data for 194 patients.

Destination	*Number*	*Percentage*
Home or Nursing Home	138	71.1%
Acute Hospital	42	21.6%
Death	14	7.2%

Length of Stay

The Length of Stay for 187 patients was used to fit a distribution. These patients had a mean Length of Stay of 32.4 days with a minimum of 3 and a maximum of 326 days. Using Apollo, the best fit to this data was found to be a Lognormal distribution with mean 3.19 and standard deviation 0.76 (absolute mean 32.4 and standard deviation 28.9). The graph in Figure 4.2 shows a plot of frequency of patients against Length of Stay, together with the fitted distribution. For clarity, this graph excludes the outlying patient with a Length of Stay of 326 days.

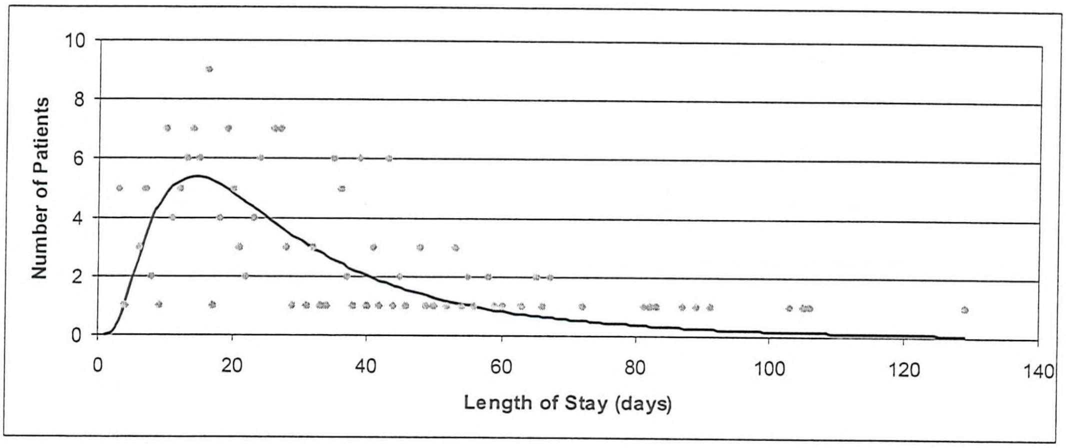

Figure 4.2: Length of Stay in the rehabilitation wards

Other

There are 38 beds across 2 wards. However for 2003, (since April) 12 beds have been closed and the wards have not been segregated. We chose to model the beds as a single ward, containing 26 beds.

4.2.2 Community Rehab Team : Preventing Dependency Team

Admission and discharge dates, Length of Stay, source of referral and destination after discharge were obtained from the summary spreadsheets for 2003. This provided data for 352 patients. A further 82 patients were assessed by the Preventing Dependency Team (PDT) (taking a minimum of one hour direct contact plus administration time), but received no further care.

Admissions

Admissions, by source of referral are shown below.

From	*Number*	*Percentage*
Community	258	73.3%
Acute	70	19.9%
Mount	18	5.1%
Day Hospital	1	0.3%
A&E	5	1.4%

Discharge Destination

Discharges, by destination are shown below.

To	*Number*	*Percentage*
Home (or Nursing Home)	232	65.9%
Day Hospital	51	14.5%
Mount Wards	2	0.6%
Acute Hospital	33	9.4%
Community Physio	19	5.4%
Death	15	4.3%

Length of Stay

The Length of Stay for 352 patients was used to fit a distribution. These patients had a mean Length of Stay of 18.2 days with a minimum of 1 and a maximum of 112 days. Using Apollo, the best fit to this data was found to be a Gamma distribution with shape 1.38 and scale 13.12. The graph in Figure 4.3 below shows a plot of frequency of patients against Length of Stay, together with the fitted distribution.

Other

The number of visits a patient receives a day varies by patient and by day. However, on average, the caseload (visits per day) can be thought of as 50% of patients receiving 1 visit per day, 25% receiving 2 visits and 25% receiving 3 visits.

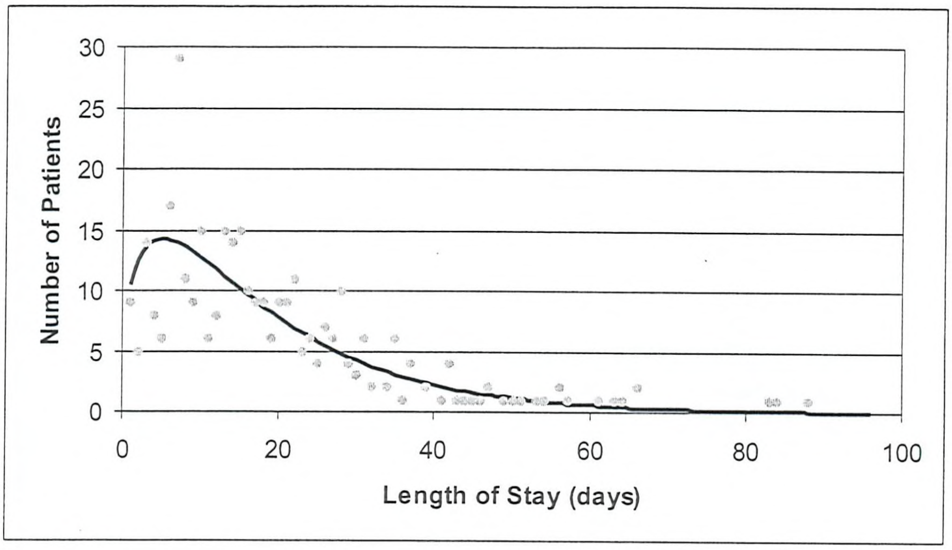

Figure 4.3: Length of Stay with the Preventing Dependency Team

4.2.3 Community Rehab Team : Community Physio

Admission and discharge dates (from which Length of Stay can be calculated) and source of referral were obtained for April-December 2003. There were 369 patients, of which there was complete data (admission and discharge date) for 275 patients.

Admissions

Admissions, by source of referral, calculated from data for 351 patients, are shown below.

From	*Number*	*Percentage*
Community	170	48.4%
Hospital	124	35.3%
Elderly	57	16.2%

Discharge Destination

No information on discharge destination is available. We have assumed that all patients go back to the community.

Length of Stay

The Length of Stay for 275 patients was used to fit a distribution. These patients had a mean Length of Stay of 56.2 days with a minimum of 1 and a maximum of 225 days. Using Apollo, the best fit to this data was found to be a Gamma distribution with shape 0.67 and scale 84.50. However given that 20% of patients spend only one day in the system, we have used a discrete probability profile in the model so as to capture these patients separately and model the probabilities of staying 1,2,3,... days. The graph in Figure 4.4 shows a plot of frequency of patients against Length of Stay, together with the fitted distribution.

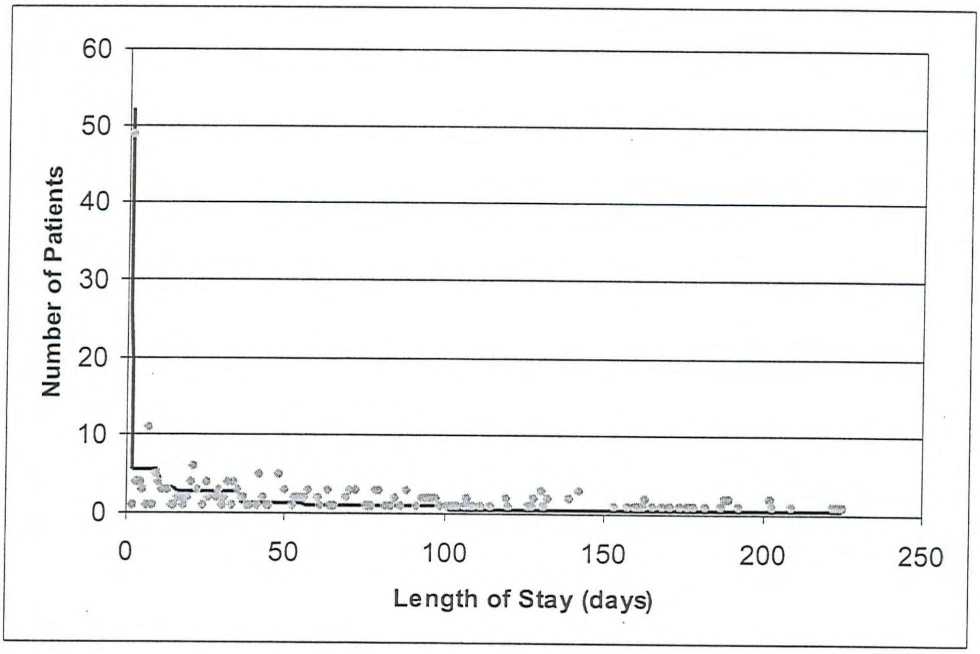

Figure 4.4: Length of Stay with Community Physio

Other

For the financial year 2003/2004, 484 patients were seen, of which 335 (69.2%) were prevention of admission or supported discharge. The current caseload (frequency of visits) is highly variable but is on average, 1.13 visits per week. The number of Community Physio referrals from hospital were known, however it is unknown whether this differentiates between the acute hospital and the Mount Hospital. Since we are unable to obtain more accurate data, it is assumed that all patients requiring Community Physio will step up from the community.

4.2.4 Day Hospital

Data for the Day Hospital was very limited. The admission and discharge information are based on expert knowledge, whilst the Length of Stay information is based on a representative sample of 50 patients.

Admissions

In April to July 2003 (4 months) 136 referrals were made of which 84 attended the Day Hospital. The Day Hospital staff were unable to provide the source of referral for their patients. Therefore, we assume that all patients come from the community, apart from the 14.5% who step down from the PDT (as inferred from the PDT discharge data). In practice, patients will step down from both the Rehab wards and the acute hospital to the Day Hospital.

Discharge Destination

The Day Hospital staff were unable to provide the discharge destination for their patients, however they thought that almost all patients return to the community. Therefore, we assume that all patients are discharged to the community.

Length of Stay

Length of Stay was found from a sample of 50 patients from 2003 thought to be representative by the staff nurse. Although not an ideal way to collect data about Length of Stay, this was the only available option. The mean Length of Stay was 90.7 days with a minimum of 63 and a maximum of 252 days. Note that the modal Length of Stay is 70 days. Using Apollo, the best fit to this data was found to be a Lognormal distribution with mean 4.32 and standard deviation 0.61 (absolute mean 90.7 and standard deviation 60.9). The graph in figure 4.5 shows a plot of frequency of patients against Length of Stay, together with the fitted distribution.

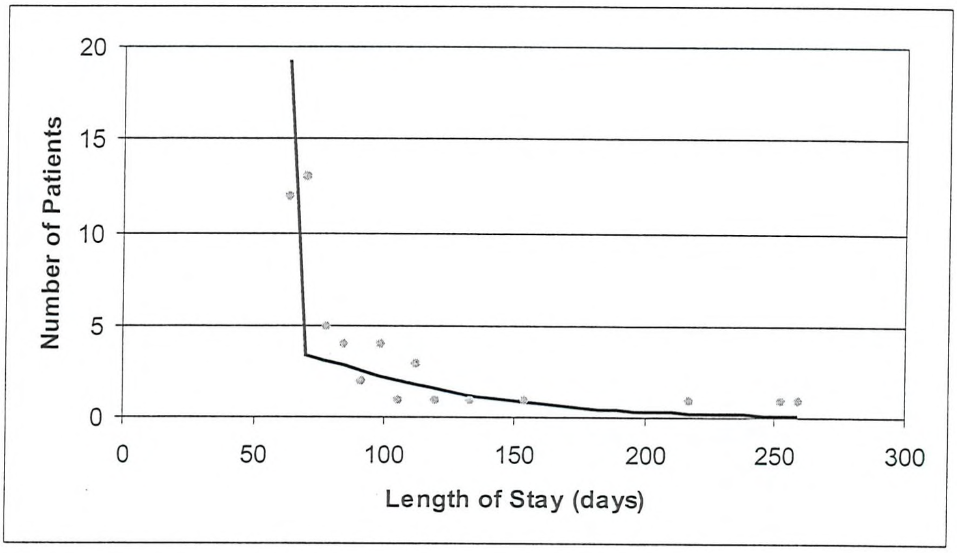

Figure 4.5: Length of Stay in the Day Hospital

Other

The Day Hospital operates from Monday to Friday. It has a capacity of 14 patients visiting the hospital per day and 6 outreach visits per afternoon (a total of 100 available "sessions" per week). Most patients attend the hospital once a week. Data was only available for the inreach patients and so only these have been included in the model. However, the Day Hospital staff see an average of 156 patients per year as outreach. Their capacity for outreach is 6 "visits" per day, 5 days per week. (Note, this "visit" may just be a telephone call.) The Day Hospital staff see an additional 8-10 patients per month on top of inreach and outreach patients, i.e. an average of 108 patients per year, who have a completed assessment where either no input is given, either because they refused to attend, or because they were signposted elsewhere.

4.2.5 Flows of patients at the Mount Hospital

The data for the individual sections was combined, and where possible the services were linked together resulting in the diagram shown in Figure 4.6. The Levels on the diagram indicate services which were directly related to those used in the Audit (see Section 4.3 below). This diagram was used as a basis for discussion with the

Mount Hospital staff to validate the different analyses and assumptions. The staff were satisfied that the diagram represented the current system.

4.2.6 The Simulation model

A Discrete Event Simulation (DES) model was built in Simul8 to model the current system. The Rehabilitation wards (beds), PDT, Day Hospital and Community Physio were each modelled as separate activities, with an associated time sampled from the distribution fitted to the available Length of Stay data for each respective service. These Length of Stay distributions are detailed and illustrated above, in the analysis of each service. The model was run for a period of 365 days, with a step time of 1 day.

The data analysis encompassed two types of patients: Step Down patients who are moving to a lower level of care, and Step Up patients who are moving to a higher level of care. All patients going to the beds are Step Down, those going to the PDT are either Step Up or Step Down, and those going to the Day Hospital and Community Physio are Step Up. All Step Down and Step Up patients were combined to, respectively, create Step Down and Step Up arrival points. Discussions with the Mount Hospital staff, and analysis of the data where possible, revealed little or no seasonality, therefore it was assumed that arrivals were distributed evenly thoughout the year. Interarrival times were modelled using an exponential distribution with an average equal to the simulation time (365 days) divided by the annual number of patients 'arriving' at each point.

Two exit points were modelled, as the service model group were interested in whether the patients were discharged out of the system completely, or whether they needed admission to an acute hospital.

All flows of patients out of an activity or arrival point were determined by percentages calculated from the data analysis. All activity times (Lengths of Stay) are sampled at the point at which patients enter that activity and thus are not depen-

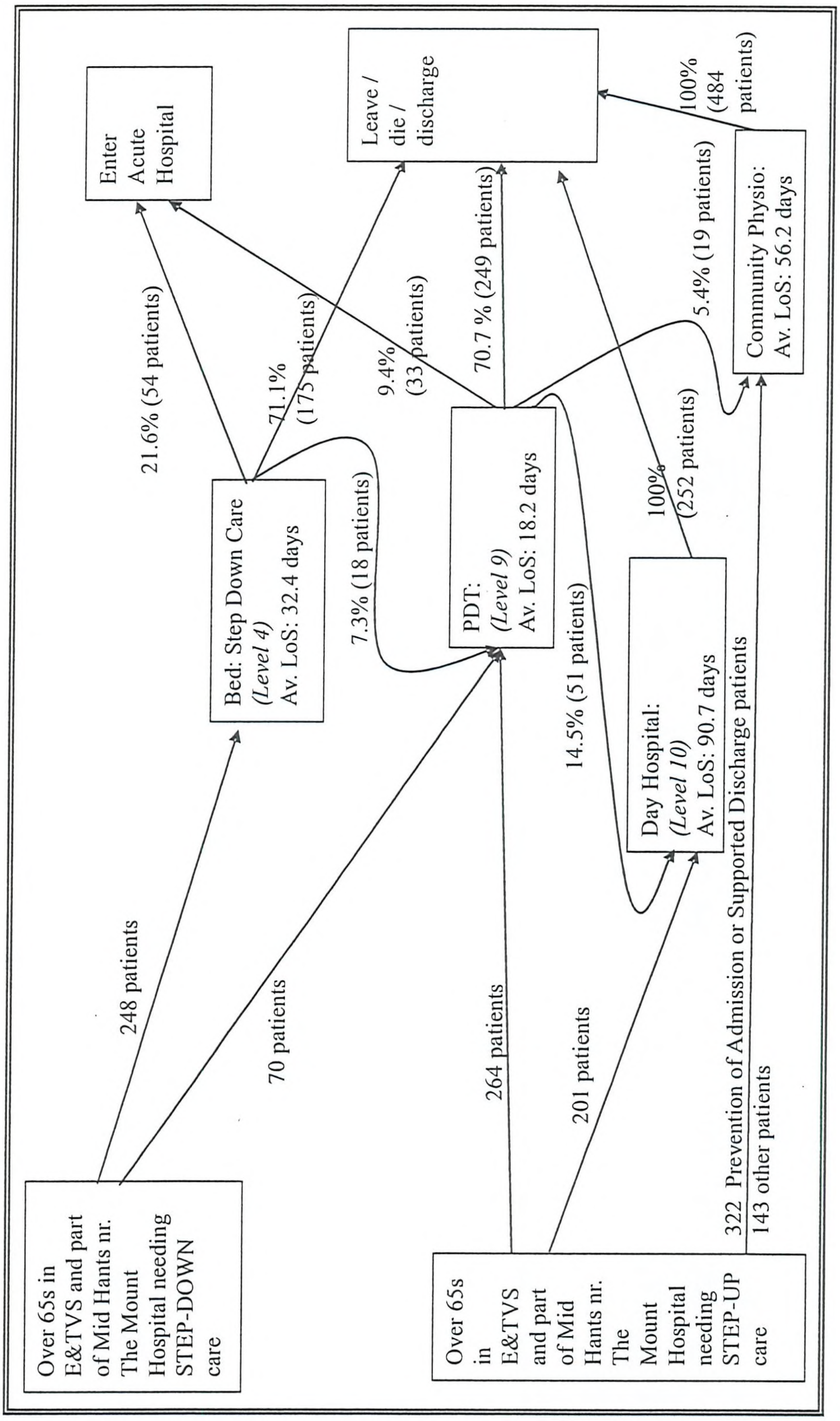

Figure 4.6: Annual flows of patients through the Intermediate Care services at the Mount Hospital

dent on the arrival route of the patient, i.e. whether they have come from another activity within the system, or whether they are new to the system.

It was not necessary to use any resources within the model since none of the activities shared resources, and the capacity of each activity could be constrained.

Figure 4.7 shows the Simul8 model and Figure 4.8 shows the associated activity flow diagram.

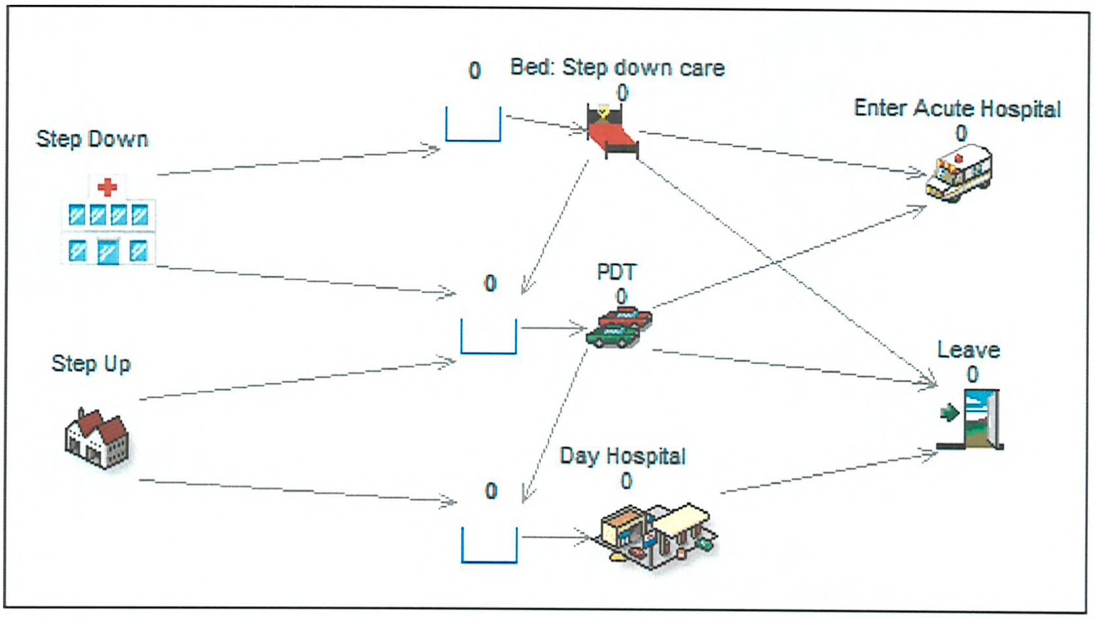

Figure 4.7: The Simul8 model of current Intermediate Care services provided at the Mount Hospital

4.2.7 Results and validation

The results of 100 runs are shown in Table 4.1. These results compare well with the observed data: the 95% confidence intervals contain the observed data. Thus the model of the current Intermediate Care provision at the Mount Hospital is considered validated, and the process of modelling less well-defined services can begin.

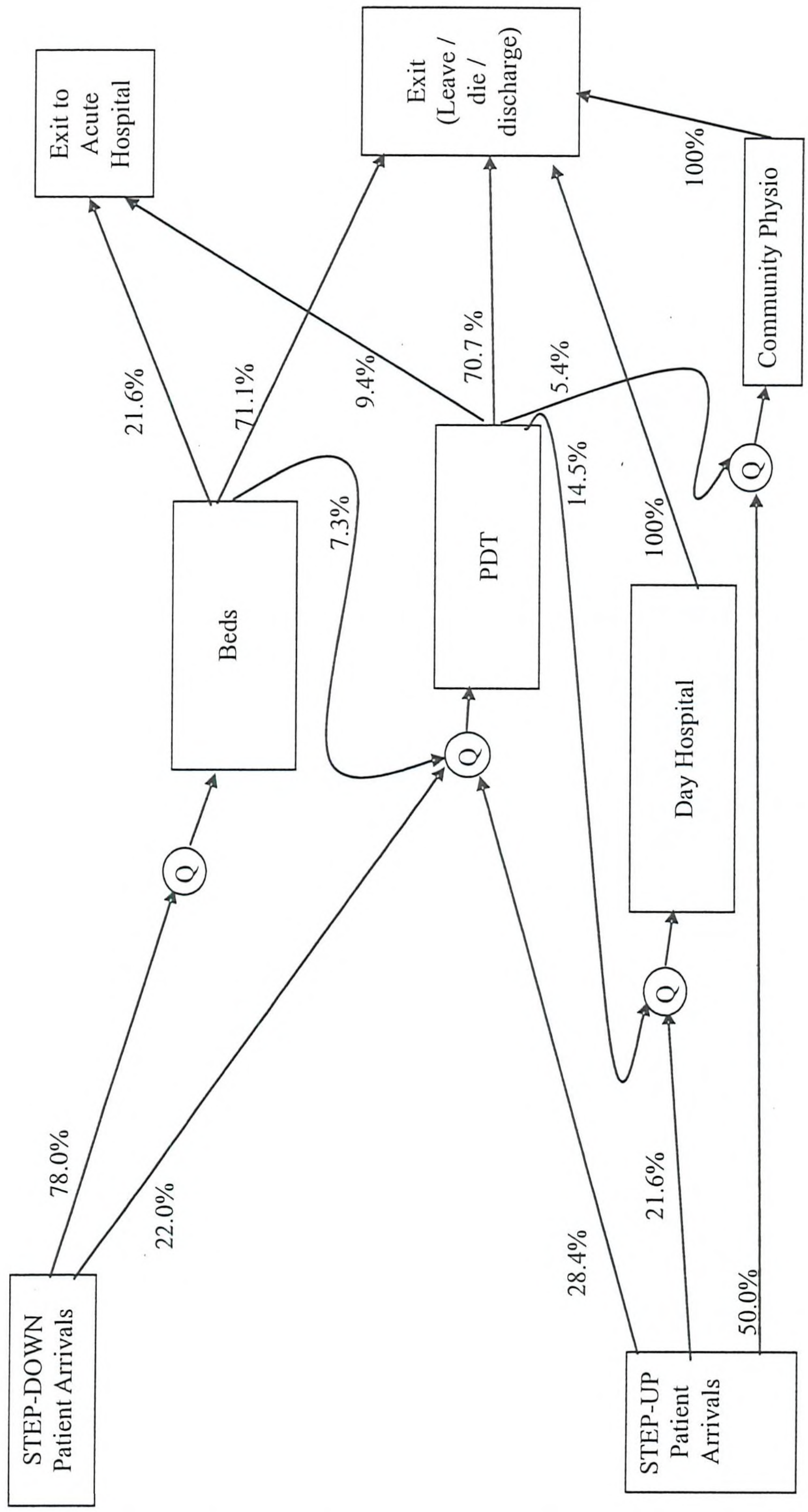

Figure 4.8: Activity Flow Diagram for the Discrete Event Simulation model of current Intermediate Care services provided at the Mount Hospital

Table 4.1: Results from the DES model for the Intermediate Care services at the Mount Hospital

Indicator	Result (95% CI)	Observed Data*
Day Hospital		
Annual number attended (inreach)	253 (250, 256)	252
Community Rehab Team (PDT)		
Annual number seen	440 (432, 448)	434
Average daily occupancy (numbers, patients in system per day)	17.7 (16.1, 19.3)	
Average daily capacity (visits, based on patient visits per day)	31.0 (28.1, 32.7)	
Community Rehab Team (Community Physio)		
Annual number seen	498(478, 512)	484
Average daily occupancy (numbers, patients in system per day)	53.2 (49.2, 57.2)	
Average daily capacity (visits, based on patient visits per day)	8.8 (8.0, 9.4)	
Rehabilitation wards		
Annual number attended	245 (238, 260)	248
Average occupancy (assuming 26 beds)	90.9% (89.1%, 92.7%)	
Average waiting time for admission	5.7 days (3.0, 8.4)	
Average number waiting for admission	3.9 (2.1, 5.9)	

**Observed data shown where available*

4.3 The Audits

4.3.1 Who was audited?

Three audits of the patients who use the Mount Hospital have been conducted. Each audit has encompassed different numbers of patients. The first audit collected information about the inpatients at the Mount Hospital whereas the third audit collected information about all patients using the Mount Hospital facilities and all patients, aged 65 or over, in Royal Hampshire County Hospital (RHCH, the local acute hospital) who lived in the geographical area serviced by the Mount Hospital. The second audit was similar to the third, differing in that fewer patients in RHCH were audited. Table 4.2 summarises the audits in terms of patient numbers.

Table 4.2: The distribution of audited patients amongst places of care

Place of care	Jul 2003	Feb 2004	May 2004	Total
Day Hospital	0	5	40	45
PDT	0	6	32	38
Rehabilitation wards	26	15	22	63
RHCH	0	49	88	137
Total	26	75	182	283

4.3.2 The Levels

As reported by Enderby and Stevenson (2000) from a situation in Sheffield, where Intermediate Care services were being reviewed with a view to offering care more appropriate to a patient's needs, when they focused on existing services their thinking was constrained. Rather, they needed to consider the patients' needs and where they might best be met. In a similar way the levels used in the audit are outside the current provision, although they can be related back, thus allowing thoughts not to be confined to what currently is available.

The third audit introduced a way of classifying the patients according to one of 13 levels. This audit involved retrospective classification of patients in the previous two audits. The levels, as described by the Mount Hospital staff, can be seen in Table 4.3, where Level 1 represents the highest level of care needed, and Level 11 the lowest, with Levels 5C and Level 6B taking the total number of levels up to 13. Patients were also classified as being either Step Up or Step Down.

Step Up: Moving to an increasing level of care need.

Step Down: Moving to a decreasing level of care need.

In practice, it was found that the staff had been over enthusiastic when defining the levels. Patients in Levels 1 and 2 need the care provided in an acute hospital and hence are not considered for the Intermediate Care provision. No-one in the audits entered levels 6B, 7 or 8 so these were not able to be modelled. No difference was found in terms of modelling between levels 3, 4 and 5 except that the staff wanted to analyse the difference if level 3 patients were provided for in their services or not.

Table 4.3: Descriptions of the levels in the reprovided system at the Mount Hospital

Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
Hospital Acute Care	24 Hour General Nursing Care Intensive and continuous (24/7) Rehabilitation needs met via full Multidisciplinary Team Medically Sub Acute Some Acute Nursing Needs met on site. e.g. IVI; IVI Antibiotics; Blood Transfusions; oxygen therapy; Nebuliser therapy. Immediate 24 Hour Medical Assessment 24 Hour access to diagnostics Able to sustain rehabilitation through any medical instability	24 Hour General Nursing Care Intensive and continuous (24/7) Rehabilitation needs met via full Multidisciplinary Team Medically Sub Acute Some Acute Nursing Needs met on site. e.g. IVI; IVI Antibiotics; Blood Transfusions; oxygen therapy; Nebuliser therapy. 24 Hour Medical Assessment on call 24 Hour access to diagnostics Able to sustain rehabilitation through any medical instability	24 Hour General Nursing Care Intensive and continuous (24/7) Rehabilitation needs met via full Multidisciplinary Team Medically stable Some acute nursing needs e.g oxygen therapy; Nebuliser therapy. Daily medical Services with night on-call	< 24 Hour General Care Maintenance Rehabilitation via full Multidisciplinary Team Night Care Needs Psychological Needs remain Or **Level C** Community/R.R. 3 or 4/day visits with re-enablement approach with any night time needs. Important where managing continence at night is new issue May be appropriate for an interdependent couple	24 Hour or less General and/or Nursing Care No Rehabilitation Needs Awaiting Further Services e.g Home Adaptation Further Surgery Nursing or Rest Home SS Package of Care **Level B** Community/R.R 1-3 visits day PDT can provide care where some rehab needs present as well, though start date for ongoing care should be available.	Social Services Residential Care < 24 Hour General Care Night Care Needs Psychological Needs remain Awaiting Further Services e.g Home Adaptation PDT Not appropriate, patient should be in Rehab bed or they may de-skill. SS Package of Care

continued on next page

Level 8	Level 9	Level 10	Level 11
4/day Rehabilitation visits from PDT/R.R As Level 9 but may involve night time activities or concerns re med or fluid intake. e.g. Getting into bed; Prompting and supplying fluids. May include night re-enablement	R.R/Requires ongoing rehab with 1, 2 or 3 activities each day in order to complete the task appropriately and safely, e.g. Washing and Dressing; Undressing; Stair climbing; Meal or snack preparation; Medication prompting; Exercise programme; Mobility progression; Specific transfer practice.	Require 1, 2 or 3 visits each week: Rehabilitation provided by multidisplinary team. May be in patients home or at the Day Hospital. Access to exercise class and falls prevention education. May require access to the extended MD team, including SALT, Dietician etc. Benefit from getting out of own home for rehabilitation, this may include access to specialist equipment.	Require 1 visit a week: Ongoing confidence building, education and seated exercise class provided by multidisciplinary team. Benefit from getting out of own home with a view to sampling longer term day centre service.
Assumptions: any existing care package will be continued. Client may have a continence aid to manage at night time.	More dependent patients can be managed where there is another carer available. Consider intensity of district nursing service.		

4.3.3 Summary of audit results

Two approaches to reallocating the patients were given in the audit:

- If the patient were to be moved tomorrow, what level would they be?
- If the patient were to enter the system again, at what level would they enter?

The second of these questions has provided the main basis for the model as it seeks to take patients through the reprovided system for one year. Tables 4.4 and 4.5 summarise the results of reallocating patients.

Table 4.4: Patient numbers and levels if patients were to be transferred to the reprovided system tomorrow

Daily Patient Numbers	Level										Total
	One	Two	Three	Four	Five	Five C	Eight	Nine	Ten	Eleven	
Day Hospital	-	-	-	-	-	-	-	-	25.8	14.2	40.0
PDT	-	-	-	-	1.9	-	0.5	14.1	1.0	0.5	18.0
Rehab wards	0.7	0.7	7.7	5.9	3.8	-	0.4	2.8	-	-	22.0
RHCH	61.1	3.2	4.5	10.3	4.5	1.9	0.6	1.9	-	-	88.0
Total	61.8	3.9	12.2	16.2	10.2	1.9	1.5	18.9	26.8	14.7	168.0

Table 4.5: Patient numbers and levels if patients were to enter the system again, this time in the reprovided way

Annual Patient Numbers	Level									
	One	Two	Three	Four	Five	Five C	Eight	Nine	Ten	Eleven
Day Hospital	-	-	-	-	-	-	-	-	246.5	5.5
PDT	-	-	-	9.2	-	-	-	278.1	55.6	9.2
Rehab wards (step-up)	-	7.9	31.5	35.4	11.8	7.9	-	3.9	-	-
Rehab wards (step-down)	-	-	-	149.6	-	-	-	-	-	-
RHCH (step-up)	-	51.0	135.0	51.0	-	35.0	-	16.0	-	-
RHCH (other)	2041.0	-	-	-	-	-	-	-	-	-
Total	2041.0	58.9	166.5	245.2	11.8	42.9	-	298.0	302.1	14.7

4.3.4 Distribution of patients between PCTs

The Mount Hospital's services exist for the care of patients in E&TVS PCT and also for those patients in Mid Hants PCT who live geographically nearby. Since the third audit encompassed all patients in RHCH who were over 65, who lived in the relevant geographical area, we can analyse the percentage of patients from Mid Hants and from E&TVS. A graph showing the number of patients from each PCT is shown in Figure 4.9. This equates to a percentage of Mid Hants patients (from the right geographical area for the Mount) of 36.4% in the Mount, 26.4% in RHCH

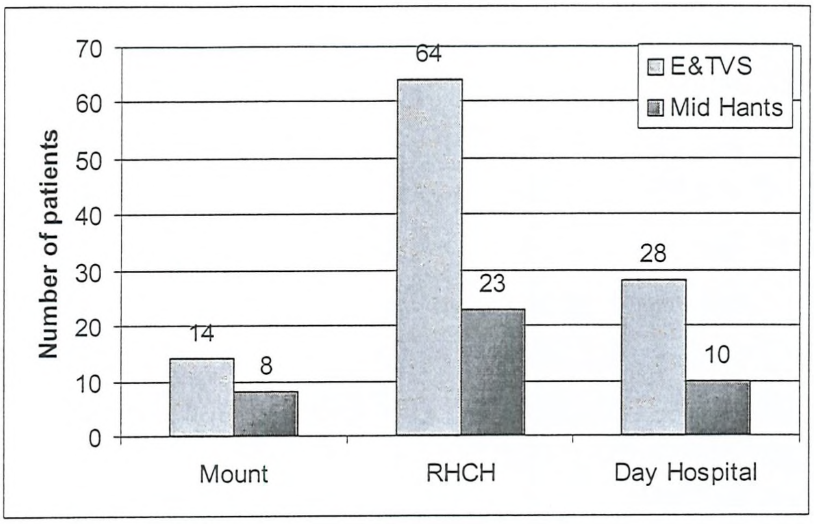

Figure 4.9: Graph to show the distribution of patients between PCTs

and 26.3% in the Day Hospital. For the calculations we needed, we have used a proportion of 30% of patients coming from Mid Hants PCT. This is a figure derived from the PCT, based on their observations over the past 3 years, not on the results found in the audits, however it is similar to using a proportion based on all the patients audited.

4.4 Modelling the reprovided system

The Discrete Event Simulation model of the current system was adapted to model the proposed, reprovided system. This happened through the addition of more activities to represent the 'new' services, and through additional patient flows to represent the expected interactions between the services. It was necessary to make assumptions about lengths of stay for the new services, and patient pathways between the activities. These are detailed below.

4.4.1 Length of Stay

Table 4.6 shows the estimated Length of Stay in the various levels in the reprovided system. These are based on current data, audit data and on discussions with staff, about how these might change in the reprovided system. The mean Length of Stay

Table 4.6: Estimated distributions for Length of Stay in the reprovided system

Level	Mean	Distribution	Parameters	Reason
Three, Four and Five	32.4	Lognormal	Mean 32.4, S.D. 28.9	Same as current Rehab wards.
Five C	2.0	Fixed	2.0	48 hour intervention at home.
Eight	25.2	Lognormal	Mean 25.2, S.D. 0.60	Same as level Nine, but with a mean of 7 days more.
Nine	18.2	Gamma	Shape 1.38, Scale 13.12	Same as current PDT.
Ten	90.7	Lognormal	Mean 90.7, S.D. 60.9	Same as current Day Hospital.
Eleven	14	Lognormal	Mean 14.07, S.D. 9.45	Same as level Ten but with a mean of 14 days.
Community Physio	56.2	Gamma	Shape 0.67, Scale 84.5	Same as current Community Physio.

is presented together with the estimate for the statistical distribution that was used in the simulation model.

4.4.2 Patient pathways

In order to model the flow of patients, some initial assumptions have been necessary where there was limited data; these have been based on discussions with appropriate staff to reflect the nature of the proposed reprovided system.

- Patients will not move between Levels 3, 4 and 5.
- Patients will not move between Levels 8 and 9.
- Patients will not move from Levels 8 and 9 to Level 11.
- All patients entering Level 5C will progress to Level 8 (40%) or Level 9 (60%).
- In the current system, 9.4% of PDT patients step up to an acute hospital. In the reprovided system, 50% of these (i.e. 4.7% of total patients in Levels 8 and 9) will step up to Step-Up beds, the other 50% will still step-up to an acute hospital.
- In the current system, 7.3% of the Rehab wards patients step down from the

wards to the PDT. It is assumed that this number of patients will continue to step down in this way. However, the aim is to step patients down more quickly (i.e. with greater care needs) and thus we will assume that 40% (i.e. 2.9% of total patients in beds) of these patients will step down to Level 8, whilst the remainder (4.4%) will step down to Level 9.

- In the current system, 70 patients step down from RHCH to the PDT. It is assumed that this number of patients will continue to step down in this way. However, the aim is to step patients down more quickly and thus we will assume that 20% (i.e. 14 patients in RHCH) of these patients will step down to Level 8, whilst the remainder (56 patients) will step down to Level 9.
- Patients will not move from Levels 3, 4 and 5 to Levels 10 or 11. In practice this might happen, but since we have no data to show the percentage of patients who would do this, any patients will be included in the patients stepping up directly to Levels 10 and 11.

The number of patients entering the system is based on the audit data which looked at where a patient would enter the system in the reprovided model (See Table 4.5). The audit data showed that nobody would enter Level 8 directly from the community. However this is not thought to be reflective of the true picture by staff, therefore the service model group suggested that 10% (i.e. 30 patients) of the 298 step-up patients for Level 9 will instead go to Level 8.

One of the key aims in the reprovided system is to capture some patients directly into the Intermediate Care system, rather than letting them go into the acute hospital first. Not all the patients audited in the hospital were suitable candidates for the Intermediate Care (IC) beds, and not all the patients who should currently step down from the hospital, are able to. Conditional probability was used to calculate this unmet demand as follows.

Patients from the acute wards go either to the Step Down beds, or to the Community Rehab team. The current data shows that 70 patients currently step down from the acute wards to the Community Rehab team and it is assumed that this number will not change. 248 patients currently step down from the acute wards to the IC beds. However from the data, 25 out of 63 of these could have stepped up so 38 out of 63 were 'true' Step Down patients. If the IC beds are catering for all the demand that exists, then the number of patients stepping down from the acute wards to the IC beds in the reprovided system will be equal to the current number of 'true' Step Down patients. i.e. $\frac{38}{63} \times 248 = 149.6$ patients.

However, if there is unmet demand then the number would be higher and can be calculated using conditional probability. We want to know the proportion of step down patients in the acute wards who will step down to the IC beds. We use w to represent the annual number of patients in the local acute hospital, who, by age and place of residence, are potential candidates for the Intermediate Care services.

P (Going to IC Beds | Step Down)

$$
\begin{aligned}
&= \frac{\text{P (Going to IC beds and Step Down)}}{\text{P(Step Down)}} \\
&= \frac{\text{P (Step Down | Gone to IC beds)} \times \text{P (Gone to IC Beds)}}{\text{P (Step Down)}} \\
&= \frac{\frac{38}{63} \times \frac{248}{w}}{\frac{120}{137}} \\
&= \frac{170.8}{w}
\end{aligned}
$$

We used this number of 170.8 patients per year in the simulation model. This equates to an unmet demand of roughly 20 patients per year, which would seem realistic and will also give a conservative estimate on the bed numbers.

Based on the data collected during the three audits, and the assumptions above, new patient pathways were constructed and these can be seen in Figure 4.10 and the associated Simul8 model in Figure 4.11.

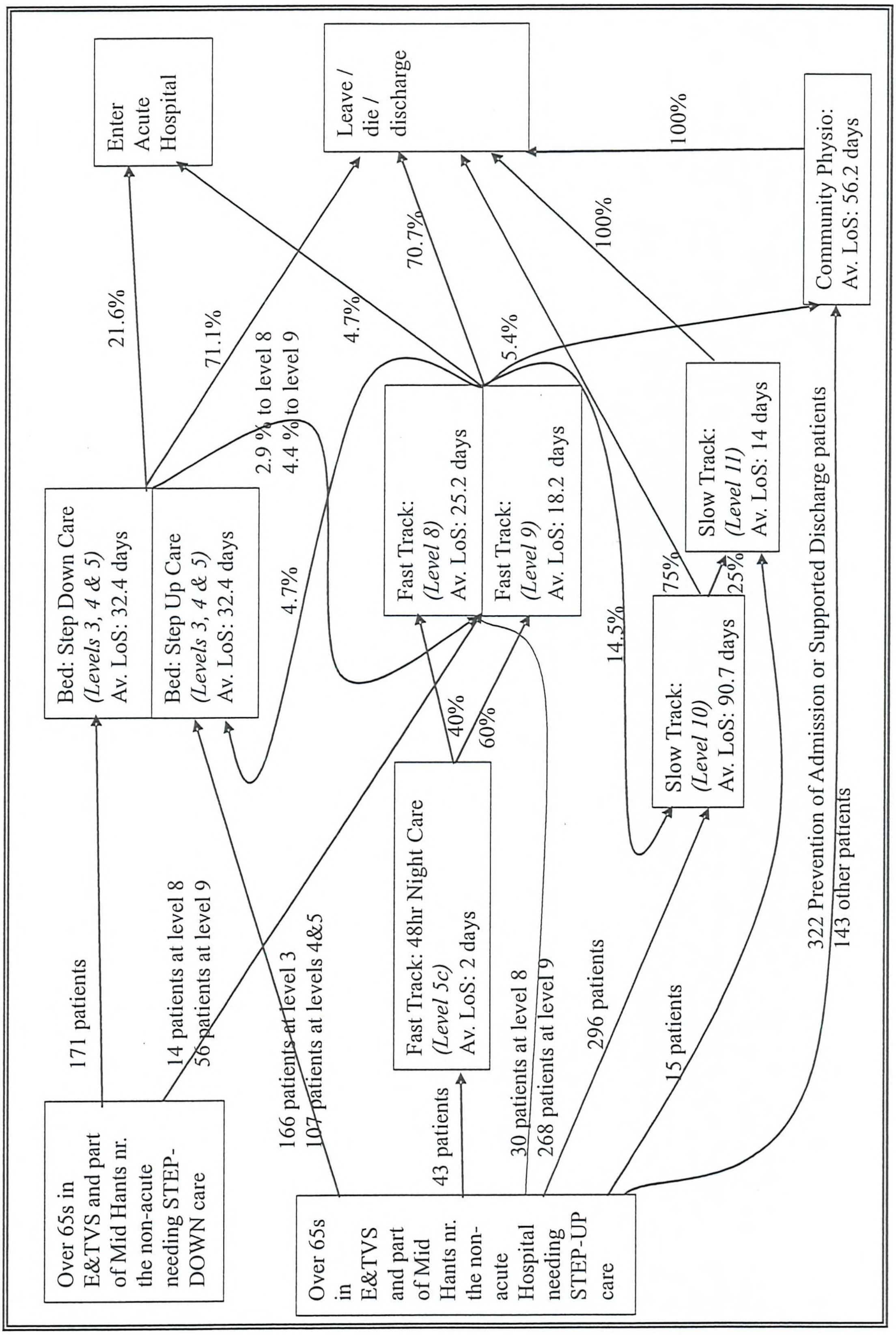

Figure 4.10: Estimated flows of patients through the reprovided Intermediate Care services at the Mount Hospital

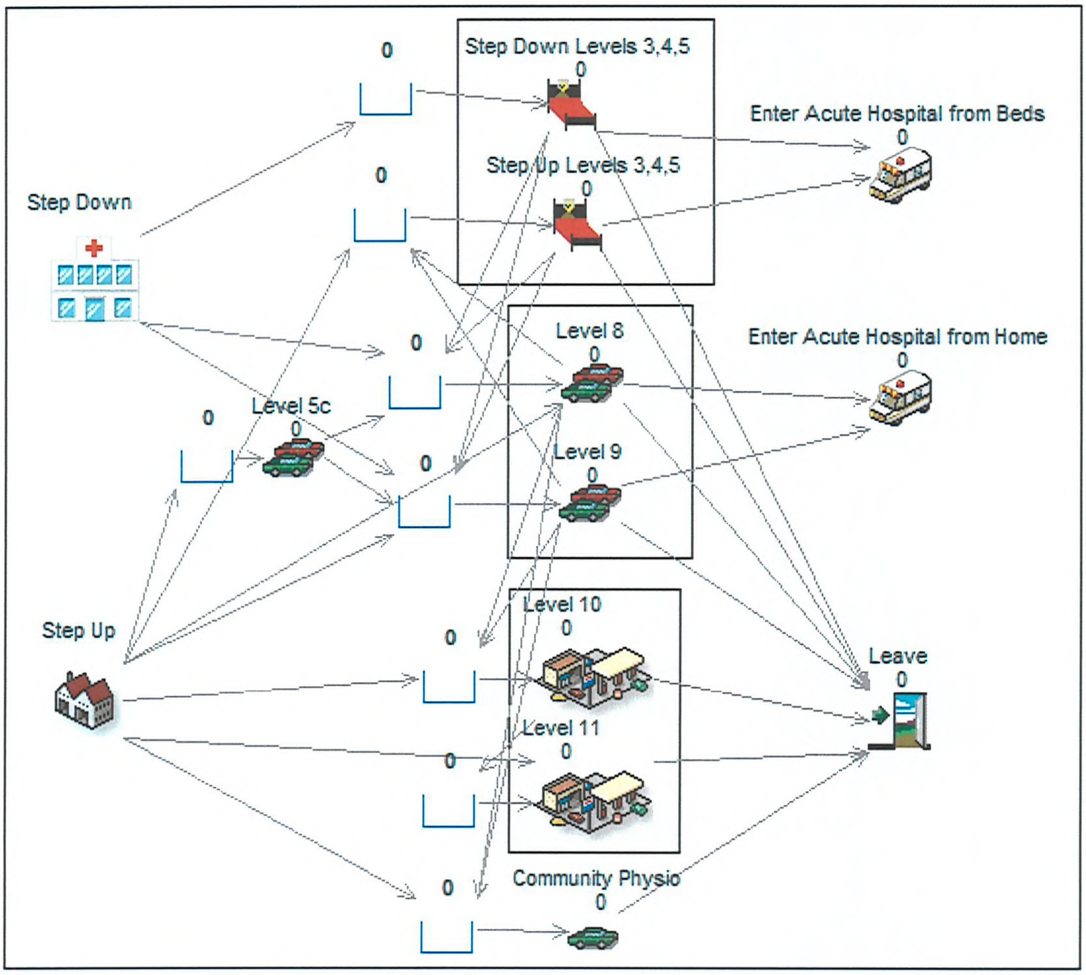

Figure 4.11: The Simul8 model of the Reprovided Intermediate Care services provided at the Mount Hospital

4.5 Results and recommendations for the reprovided system

Running the DES model with unlimited capacity gives the results shown in Table 4.7. The results for each of the individual parts of the system are now examined in turn.

Table 4.7: Results for the reprovided system with unlimited capacity

Place of Care	Indicator	Results (with 95% CI)
Step Down beds (Levels 4 & 5)	Annual number admitted Average daily occupancy (number of patients)	218 (216, 221) 19.6 (19.3, 20.0)
Step Up beds (Levels 4 & 5)	Annual number admitted Average daily occupancy (number of patients)	125 (123, 127) 11.3 (11.1, 11.5)
Level 5c	Annual number seen Average daily occupancy (patients in system per day)	43 (42, 44) 0.24 (0.23, 0.25)
Level 8	Annual number seen Average daily occupancy (patients in system per day)	71 (70, 73) 4.9 (4.8, 5.0)
Level 9	Annual number seen Average daily occupancy (patients in system per day)	366 (363, 370) 18.2 (18.0, 18.4)
Community Physio	Annual number seen Average daily occupancy (patients in system per day)	488 (483, 492) 76.0 (75.1, 76.8)
Level 10	Annual number attended	360 (356, 363)
Level 11	Annual number attended	105 (103, 107)

4.5.1 Non-acute beds (Levels 4 and 5)

For the modelling, we assumed ringfenced beds of Step Down and Step Up patients, since this is what was requested. However, in reality this would not be strictly enforced. The results in Table 4.7 give average results when capacity is unlimited. Of course, this average number will not be achieved all of the time, and the number of beds provided must strike a balance between cost (of having extra beds) and acceptable waiting times. Figure 4.12 shows graphs of average waiting time against number of beds. These graphs show that around 22 Step Down and 13 Step Up beds give reasonable results, with average occupancy rates of 89% and 86% respectively.

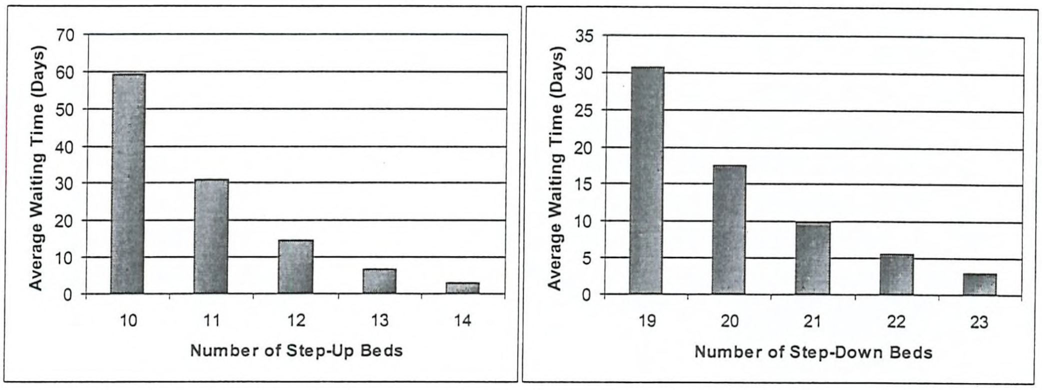

Figure 4.12: The relationship between the number of beds and waiting time (without level 3)

4.5.2 Non-acute beds (Levels *3*, 4 and 5)

One particular scenario which we were requested to examine was that of providing beds at Level 3 compared with not doing so. Table 4.8 shows the relevant results when Level 3 is provided. Again, this average number will not be achieved all of the time, and the number of beds provided must strike a balance between the cost (of having extra beds) and acceptable waiting times. The graphs in Figure 4.13 show that around 17 Step Down and 28 Step Up beds give reasonable results, with average occupancy rates of 87% and 82% respectively.

Table 4.8: Results for the reprovided system with unlimited capacity

Place of Care	Indicator	Results (with 95% CI)
Step Down beds (Levels 3, 4 & 5)	Annual number admitted Average daily occupancy (number of patients)	169 (166, 172) 14.9 (14.6, 15.2)
Step Up beds (Levels 3, 4 & 5)	Annual number admitted Average daily occupancy (number of patients)	293 (290, 297) 26.1 (25.7, 26.5)

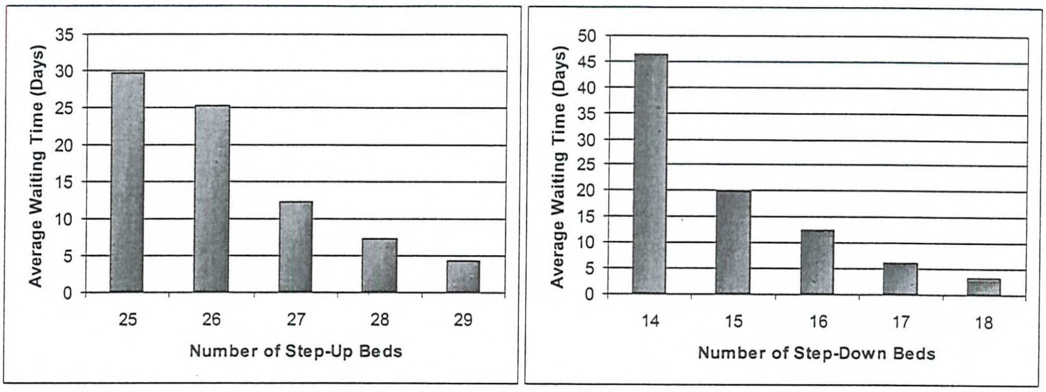

Figure 4.13: The relationship between the number of beds and waiting time (with level 3)

4.5.3 Bed-day savings

We examined bed-day savings for both with and without Level 3 care provision. Based on historical data, we used an average Length of Stay of 41.1 days in the acute hospital.

4.5.3.1 Without Level 3

The model predicts that 102 patients could avoid admission, which could be equivalent to bed-day savings of $102 \times 41.1 = 4192$ bed-days or 11.5 acute inpatient beds a year. Currently, some patients from the Intermediate Care services require admission to an acute hospital. With increased numbers in the equivalent categories in the reprovided system, it is anticipated that admissions of this sort will increase, in proportion to that which currently happens.

The model predicts that the increase in acute admissions from the Intermediate Care service would be 8 patients. Thus, the audit data predicts that the reprovided system will save $102 - 8 = 94$ acute inpatient admissions, or 3863 bed-days or 10.6 acute inpatient beds per year.

4.5.3.2 Level 3

In a similar way, we can model the extra bedday savings if beds at Level 3 are provided. An additional 166 patients a year could avoid admission, with an increase in acute admissions from the Intermediate Care setting of 36 patients. This would result in an additional number of bed-days saved of 5343 bed-days or 14.6 acute inpatient beds per year.

4.5.3.3 Discussion

Providing Step Up beds at Level 3 as well as at Levels 4 and 5 requires an extra 10 beds in the Intermediate Care setting. However 14.6 additional acute inpatient beds would be saved which would result in an overall financial saving since acute inpatient beds are more expensive than Intermediate Care inpatient beds.

4.5.4 Community Rehab Team (Fast Track)

Level 9 is equivalent to the current service provision, and Levels 5c and 8 are new. The annual patient numbers in the predicted model are 480, compared with the current figure of 352, however 43 of these are at Level 5c and 71 at Level 8. Level 9 patients require an average of 1.75 visits per day, whereas Levels 5c and 8 require 4 visits per day and Level 5c requires the addition of night care. Thus the predicted increase in patient numbers (which influences the number of professional staff needed) is 36%, but the increase in visits per day (which influences the number of Rehab Assistants needed) is 71%.

4.5.5 Community Rehab Team (Slow Track)

Level 10 is equivalent to current Day Hospital provision, Level 11 is new and Community Physio remains unchanged. The model predicts an increase from 40 to 90 patients a week which is manageable within the current staffing levels, since the Day Hospital is running below full capacity (mainly due to patient transport restrictions).

4.5.6 Other Considerations

Length of Stay and the effect of an increasingly elderly population were two things which we were asked to consider with respect to bed numbers. It can be noted that, looking into the future, any potential bed savings from a reduction in Length of Stay, may be outweighed by predicted increases in the size of the elderly population, and thus any plans to reduce the number of beds should be considered carefully.

4.5.6.1 Reductions in Length of Stay

It is hoped that, due to the optimized patient pathways, the reprovided model will result in a reduced Length of Stay for the patients. We considered the resulting bed needs when the average Length of Stay was reduced. For the Step Up beds, this can be seen in Table 4.9 and for the Step Down beds, in Table 4.10.

4.5.6.2 Increases in the size of the elderly population

Predicted increases in the size of the elderly population are a 6.2% rise in the over 75s and a 15.2% rise in the over 85s between 2001 and 2008 (E&TVS and Mid Hampshire PCTs, 2004). We considered the resulting bed needs when the Intermediate Care needs grew in line with the lower population increase of 6.2%. This can be seen in the columns for 2008 in Tables 4.9 and 4.10.

Table 4.9: Step Up beds: The effect of reductions in Length of Stay, and of increases in the population

LoS reduction (%)	Average LoS	Beds (2004)	Beds (2008)
0	32.4	13.2	13.9
5	30.8	12.6	13.3
10	29.2	12.1	12.7
15	27.5	11.5	12.1
20	25.9	10.9	11.5
25	24.3	10.4	10.9
30	22.7	9.8	10.3
35	21.1	9.3	9.8
40	19.4	8.7	9.1

Table 4.10: Step Down beds: The effect of reductions in Length of Stay, and of increases in the population

LoS reduction (%)	Average LoS	Beds (2004)	Beds (2008)
0	32.4	23.0	24.4
5	30.8	21.8	23.2
10	29.2	20.7	22.0
15	27.5	19.5	20.7
20	25.9	18.4	19.5
25	24.3	17.2	18.3
30	22.7	16.1	17.1
35	21.1	15.0	15.9
40	19.4	13.8	14.7

4.6 Summary

In this chapter, a Discrete Event Simulation model was built to model local Intermediate Care services, with a view to helping capacity decisions within the process of reprovision of the current services. Several scenarios were run illustrating that capacity is very much dependent on the types of patients cared for, as well as where they are cared for, within those services. Data collection provided a valuable part of the process, not only for building the simulation model, but also for increasing understanding of how the reprovided system should look. As a particular example, the process of carrying out the audits, and discussing the distinctions between patients helped the Intermediate Care staff to identify the difference between providing a realistic, improved service and a more ambitious 'gold' service. The gold service, however good it might be to aim for in theory, needed considerably more financial input than was available.

The results from this work informed the service model group on a way forward to plan the proposed Intermediate Care facilities. There was much political sensitivity to the closure of the Mount Hospital and it attracted much local press. The benefit of this study is that it provided the service model group with quantitative predictions on beds and workforce capacities under various possible future provisions of service. The results were presented at public meetings, and the steering group are themselves using our findings to help form policy.

The work in this chapter is necessarily less substantial than in Chapters 3 and 5 since the timescale did not permit a more comprehensive study. There is also less of a focus on workforce and more on general capacity in this chapter. This is partly because of the timescales and partly because workforce was not seen as a priority for the service model group - bed numbers would dictate the size of any buildings in the reprovided system whereas the workforce numbers were seen as more flexible. For both Day Hospital and inpatient provision, the staff were happy to workforce plan in ways in which they were familiar once the number of patients was known. Because of the timing and numbers involved, there was seen to be no benefit to do this within the model. For the one area of provision where more detailed workforce planning might have been most needed, there was no appropriate data available, as well as an awareness that the work with the Intermediate Care Futures project reported in Chapter 5, would supersede any work done in this area.

Chapter 5

Modelling the Intermediate Care Workforce

5.1 Introduction

This chapter contains work carried out for the Intermediate Care Futures project which is supported/sponsored by the Hampshire and Isle of Wight Workforce Development Confederation (WDC) and the Community Rehabilitation teams in Eastleigh and Test Valley South Primary Care Trust (E&TVS PCT). In order to capture details about patient visits, a database was built, into which members of the Intermediate Care rehab teams entered relevant information from paper patient notes. A model, based in Excel, was built combining a Monte Carlo simulation aspect, to create a demand for workforce need based on the historical interventions from the database, with a Linear Programming aspect designed to optimize the composition of the rehab team, based on the skills of the different members of the workforce.

5.2 The Problem

The Intermediate Care Futures project (subtitle: Taking forward the Intermediate Care workforce in Hampshire and the Isle of Wight) is hosted by E&TVS PCT with the aims of bringing together the various stakeholders across the region to design a workforce model[1] and associated education to provide the future Intermediate Care

[1]Model here refers to a way of working, not to a mathematical model.

services. Underpinning the work is a commitment to multi-professional working and inter-professional learning, encouraging individuals and teams 'to learn with, from and about each other'. (Barnacle and Humphris, 2003)

Intermediate Care covers a wide range of services with an almost as wide range of definitions; a background to Intermediate Care and associated literature can be found in Chapter 2. As stated in Section 2.5.1 the definition of Intermediate Care used in this project is: "A short period (normally no longer than six weeks) of intensive rehabilitation and treatment to enable patients to return home following hospitalisation, or to prevent admission to long term residential care; or intensive care at home to prevent hospital admission." (Department of Health, 2001b)

The Intermediate Care workforce is made up of staff from a range of professions who work together to give care to the patient. As Intermediate Care services are developed, it is anticipated that the traditional boundaries between professions will be broken down as coordinated, multidisciplinary community-based teams are developed (Carpenter et al., 2002). Vaughan et al. (1999) summarise a discussion (without distinct conclusions) held at a seminar to discuss the question "If we could start again, would we reinvent doctors, nurses and therapists, or would a different type of healthcare worker be better suited to the needs of patients within the Intermediate Care environment?"

As identified in Wanless (2002), the way that staff are used can be considered to be more important than the number of staff employed. There is a need for the workforce to be developed in such a way that it meets the future demands of Intermediate Care. The Department of Health (2001a) report on Intermediate Care contains guidance that NHS organisations and councils should: "...identify the skills needed to provide high-quality Intermediate Care and to work in cross-disciplinary teams, and the implications for training and development, skill-mix and recruitment. Workforce planning for Intermediate Care covering the NHS, social care and independent sector should form an integral part of joint investment/implementation plans for older people's services ...".

Within the WDC's strategic plan (Hampshire and Isle of Wight Workforce Development Confederation, 2003), there is a promise that workforce planning will take into consideration 'new roles, new working practice and new ways of training'. Two of the WDC's strategic themes are 'Modernising Learning' and 'Planning the Workforce'.

5.2.1 Research objectives for this chapter

This project has concentrated on looking at the care of patients in their own homes by a rehabilitation team who make visits to the patients as and when needed. In particular the work carried out by two rehabilitation teams (Eastleigh and Romsey) has been examined in detail to explore the types of health and social care interventions provided, and by which professionals, for patients with a range of conditions. The main objectives were to look at:

- The common set of skills required by all staff to optimize contact time with patients;
- Predicting future workforce requirements for Intermediate Care; and
- What the optimal combination of the different staff types for the team is.

5.2.2 What this work was not about

This project was about looking at the way the team are working at the moment, and looking for ways to improve their ways of working. We did not consider the ethical issue of whether it was right that care should be provided outside of a hospital situation and any issues concerned with quality of care that this might invoke. This has been covered in the literature by Petch (2003), Parker et al. (2000), Coast et al. (1998), Hardy et al. (2001), and Steiner et al. (2001) amongst others. In particular, Petch (2003) provides a broad review covering both the literature and some direct testimony, of older people's attitudes towards, and experiences within, Intermediate Care.

5.3 The Data

The Intermediate Care Futures project covers the whole of Hampshire and the Isle of Wight, and whilst a wealth of data was theoretically available, the reality was that patient notes were handwritten, confidential and needed to be interpreted by someone in the field. It was infeasible to acquire data for all of the rehab teams, so we were allocated two teams (Eastleigh and Romsey) in Eastleigh & Test Valley South PCT to concentrate on modelling. It was necessary to obtain approval for the research from the Local Research Ethics Committee (Southampton & South West Hampshire, REC Reference number: 04/Q1702/10) and from Wessex Primary Care Research Network (Reference number MWP/017/04).

A database was designed in Microsoft Access into which the Rehab teams could enter required information from historical patient notes. Information was collected at three levels: that of the patient, that of visits to the patient, and that of the interventions given at each visit. Figure 5.1 contains a screen shot of the database.

Data collected at the patient level was:

- Admission Date (to the care of the rehab team);
- Discharge Date (from the care of the rehab team);
- Patient Group (from a selection of 11 as defined by the rehab teams);
- Post Code (minus the last two letters, e.g. SO17 1);
- Place of Referral (i.e. where the patient came from);
- Discharge Destination (i.e. where the patient left to);
- Additional Comments.

Data collected at the visit level was:

- Date (of visit);
- Time (length of visit, rounded to 15 minutes, as this is how it is recorded by the teams);
- Staff Type 1 (the profession of the rehab team member making the visit);

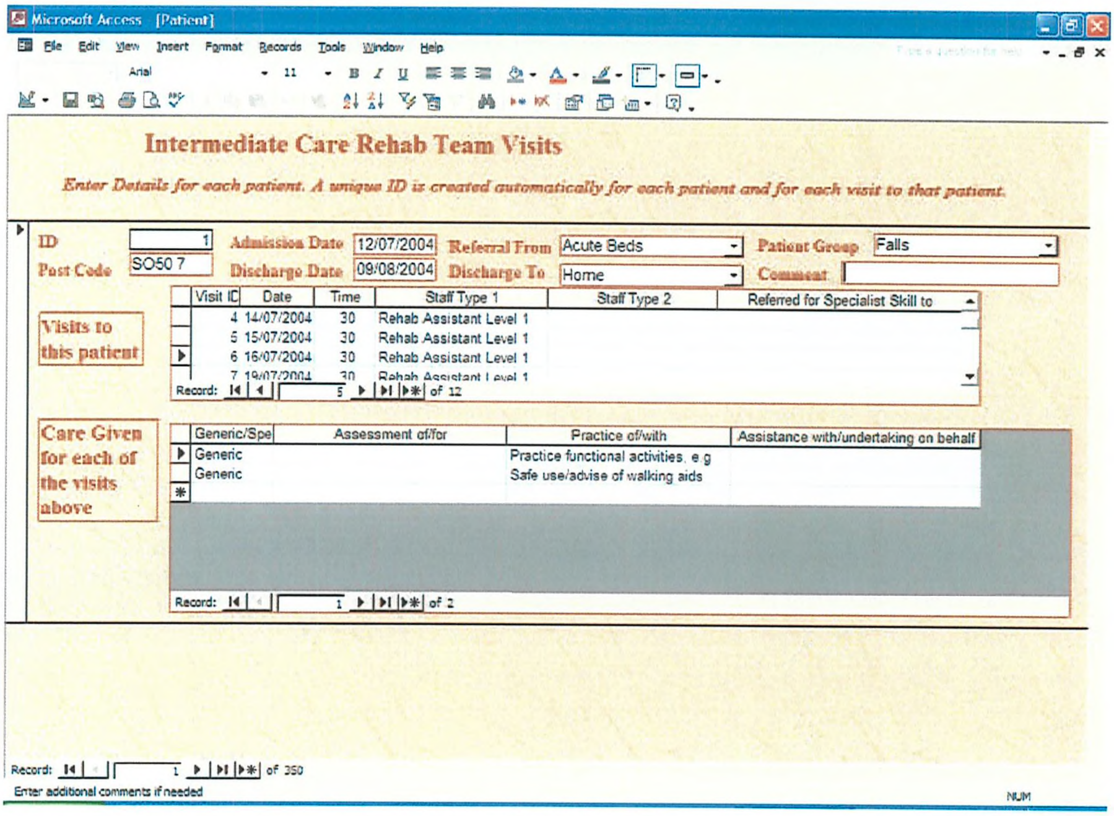

Figure 5.1: Screenshot of the database for patient visits

- Staff Type 2 (for occasions where two rehab team members are present);
- Whether the patient was referred for a Specialist skill.

Data collected at the interventions level was:

- Generic/Specific (a way of gauging the complexity level of the intervention);
- Intervention(s), broken down into three sub-categories of interventions:
  - Assessment of/for;
  - Practice of/with;
  - Assistance with/undertaking on behalf.

5.3.1 Limitations of the data

Each rehab team sees around 700 patients each year. It was felt to be infeasible to collect data from every single patient seen by the team, since it took approximately ten minutes to enter each patient's details into the database. Data for 350 patients was collected from the Eastleigh team and for 200 patients from the Romsey team.

The patient notes to be entered in the database were selected in order from the filing cabinet in the team office. Thus no random selection was performed. Whilst this is not a statistical method of selecting patients, it was one which the Rehab team staff understood (and were happy with) so it would be followed. There is no evidence to suggest that names determine susceptibility to certain illnesses or conditions. We assume that this subset of patient notes is representative of the whole set of patients.

Whilst it would have been useful to collect information about the time spent on each individual intervention during each visit (in the cases where more than one intervention was carried out), this was not possible from the historical data. Times for interventions can vary depending on the patient, time of day, and member of staff. We looked at three approaches for modellng the individual intervention times, which are discussed briefly in Section 5.4.6 and in more detail in Appendix B.

5.3.2 Other uses of the data

The database has allowed for some interesting statistical analysis, as well as providing data for the model. When designing the database, a decision was made to not only collect information pertinent to the model, but also any easily available and possibly useful information as well (such as Post Code and Place of Referral) with a view to analysing these results separately. Appendix C contains a summary of the interesting and informative results from these 'side analyses'.

5.4 The Model

5.4.1 Model requirements

The sponsors of the project were keen to be left with a model which they could use themselves to analyse different staffing combinations and which they could update as and when more data becomes available.

The model users want to be able to:

- Look at the effect on overall team composition when:
    - the skills of the different workforce are varied;
    - the patient mix is varied.
- Look at the statistical analyses carried out when building the model, to analyse various aspects of current practice.

5.4.2 Modelling approaches

A number of modelling approaches were explored, bearing in mind the model requirements in Section 5.4.1. The first approaches focused on modelling daily requirements, however these were abandoned in favour of a more strategic, annual approach. The approaches, and the reasons why they were not explored further, are described briefly below.

Discrete Event Simulation was the first approach to be tried since this can be very user-friendly and a relatively easy concept for non-ORers to grasp. An experimental model was built using Simul8 (chosen primarily because of its availability within the university and low costs, should the client wish to buy the software themselves). The patients were modeled as entities, with patients within each patient group having their own 'entry point'. The interventions were modeled as activities, each with a dedicated resource representing actual intervention utilisation (multiplied by 100 due to integer constraints on resource numbers). Using the batching feature in Simul8, the patients simultaneously visited each intervention which their patient group required and stayed there for a Length of Stay sampled from a distribution and fixed to the patient as an attribute. Resource usage was based on average need per day.

This approach failed because too much detail was being modelled, meaning that the number of objects needed made the Simul8 file unworkable. Whilst the option of trying alternative software (which would need to be purchased) to Simul8 was not completely ignored, the extra insight into the problem which was gained through this modelling meant that we wanted to try some other approaches which may be better suited to the data and the users.

An alternative approach using simulation was considered with a view to modelling the inter-visit times. However, this required the assumption that the number of visits was correct which is something that the Intermediate Care staff want to question. This was also prone to the same problem as the first attempt concerning the number of simulation objects needed.

A variation on the first approach was to use Simul8 to model patients' Length of Stay in the system, and to output the number of patients in each patient group for each day of the year. This was fed into Excel where average ratios were used to calculate the corresponding intervention needs. Aside from the shortcomings of the memory in Excel which was having difficulty coping with all the calculations, this approach inspired the idea of a Monte Carlo simulation in Excel, thus negating the need for any specialist software.

The final approach, reported in the rest of this chapter, builds on the experience of the earlier approaches. Monte Carlo simulation, using Excel's random number generator and the inverse transform method, generates confidence intervals for intervention demand, based on stochastic inputs to patient numbers and intervention times. This demand then feeds a Linear Program, solved by Solver (a default Excel add-in), which is run several times in several configurations to give confidence intervals of demand for the different types of workforce. This is explained in more detail in the following sections, beginning with some necessary assumptions.

A Stochastic Program, as for the inpatient work in Chapter 3, could have been an alternative approach to running the Linear Program several times, however this would require more advanced software than Solver, and would make it much less user-friendly as well as considerably more expensive for the 'customer'.

5.4.3 Modelling assumptions

Modelling any real-life situation invariably requires some assumptions to be made as it is not possible, nor sensible to model every aspect of real life. The assumptions listed here were discussed and agreed with members of the rehab teams and the IC Futures Project.

- There is no difference in the duration, nor in the quality, of an intervention dependent on which particular member of staff carries out the intervention, provided that they are known to be 'competent'[2] in the appropriate skills.
- Whether a patient needs an intervention at the Generic or Specific level is not dependent on which patient group the patient belongs to.
- The proportion of patients (in each rehab team) in the database in each patient group is representative of the proportions in the whole group of patients visited by the rehab team.
- The data from both teams can be joined together to aggregate patient need for interventions.
- Where more than one intervention is carried out in a visit, the interventions are carried out independently of one another. (In real life, it might be the case that interventions overlap, but for the model, we assume that they do not.)
- There is no seasonality for patient arrivals. (In practice, there may be, but we do not have, and cannot obtain, the data to model this - the few instances we have seen, suggest that there are slight lows during holiday seasons, which corresponds with when more staff want to take leave.)
- Where two members of Staff make a visit, we can model this as two separate visits
- Interventions, as described in the database account for the direct care (i.e. direct patient contact) part of a member of staff's work. Indirect care, as well as leave must be factored in.

[2] Here we use the word competent to refer to whether a member of staff has the necessary ability or knowledge (Dictionary, 2004). This is slightly different to much of the literature, particularly in the fields of psychology and management where competence has three main and distinct sub-concepts: knowledge, skill and aptitude (Haspelagh and Delesie, 2006)

- The historical interventions for each patient were appropriate.
- We do not seek to model the actual visits made to the patients, just the interventions, since if we were to model the visits then we would be making the assumption that the interventions were optimally distributed between the visits, with the optimal competencies of the different members of staff. As an example, consider the case where a patient needs a set of interventions when staff member A visits. Staff member A can carry out all the interventions except intervention x which necessitates a separate visit from staff member B. However, if staff member A were trained in intervention x (which may not always be possible), then the separate visit from staff member B would not be necessary.

5.4.4 Model inputs

There are five types of input for the model, some derived from historical data (such as the database) and some from discussions with the staff. The inputs are discussed, in turn, below.

5.4.4.1 Annual number in each patient group

The patients are divided into eleven patient groups which were devised by the rehab team staff, to be clinically meaningful, and to have similar care needs. The proportion of patients in each group in the model is based on the proportions from the database. The annual number of patients is taken from historical data for the team, and is modelled stochastically, as described in more detail in section 5.4.6.

5.4.4.2 Average Intervention need per patient

The average intervention need per patient is the total amount of each intervention that the average patient will need, in each patient group. For each patient group, and intervention, the total number of interventions given is found from the database. This is then divided by the size of the patient group to give the average patient need for each intervention. Note that this average is for the total needs of the patient, not for the daily needs.

Whilst it is certainly true that one patient's need for a certain intervention will differ from another's, we have chosen to keep the model simple by using an average, rather than a stochastic variable. A patient's need for many of the interventions will, in many cases, be intrinsically linked to their Length of Stay, which is not included in the model since the model is not concerned with the daily fluctuations which this would influence. Another reason for using the average is that if we were to make the need a variable, then we would need over 700 variables (11 patient groups, 68 interventions) which would significantly increase the upkeep of the model.

5.4.4.3 Percentage of time each Intervention is Specific

The interventions can be considered at two levels, a Generic (easier) level, and a Specific (harder) level. Note that Generic, in this instance, does not necessarily mean 'able to be done by all team members'. Following discussion with the rehab team staff, we have established that the level of intervention which an individual patient requires does not depend on the patient group. Therefore the proportion of time each intervention is required at the Specific level is calculated over all occurrences of that intervention in the database. Whilst there is the potential to make this proportion stochastic, for similar reasons to that above for the intervention needs, we have chosen not to, basing it instead on averages from the historical data.

5.4.4.4 Time (in minutes) for each Intervention

The time needed for each intervention is not necessarily the same as the time for each visit, since a visit may contain more than one intervention. The patient notes, and hence the database contains only the times for each visit. Although we are unable to calculate an average time for each intervention, it is clear from examining the data that the time can vary considerably (by 30/45 minutes) for different visits, and/or patients. Therefore time is modelled stochastically, and section 5.4.6 contains more details about the method by which this is done.

5.4.4.5 Staff competencies, by Staff type, by Generic/Specific

For the purposes of our model, we define staff competency as whether a member of staff has the necessary ability or knowledge to carry out an intervention[3]. There will be some interventions which a member of staff can carry out at both Specific and Generic levels, others at just the Generic level, and some not at all.

Whilst, in an extreme version of the model, it would be possible to model each member of staff separately, a more general model was wanted, considering staff types, not individuals. Members of the rehab team used their expert opinion to define the various competencies of the different staff types. For reasons stated in section 5.5.5, this was preferable to using the historic set of competencies from the database.

5.4.5 Model overview

Figure 5.2 shows an overview of the model structure. Each input described in the previous section is shown, with a dotted border indicating those which are modelled stochastically. The Monte Carlo simulation (dotted double border), Conversion to Whole Time Equivalents and Linear Program (solid double border) are discussed in more detail in Sections 5.4.6, 5.4.7 and 5.4.8 respectively.

[3]See Footnote 2

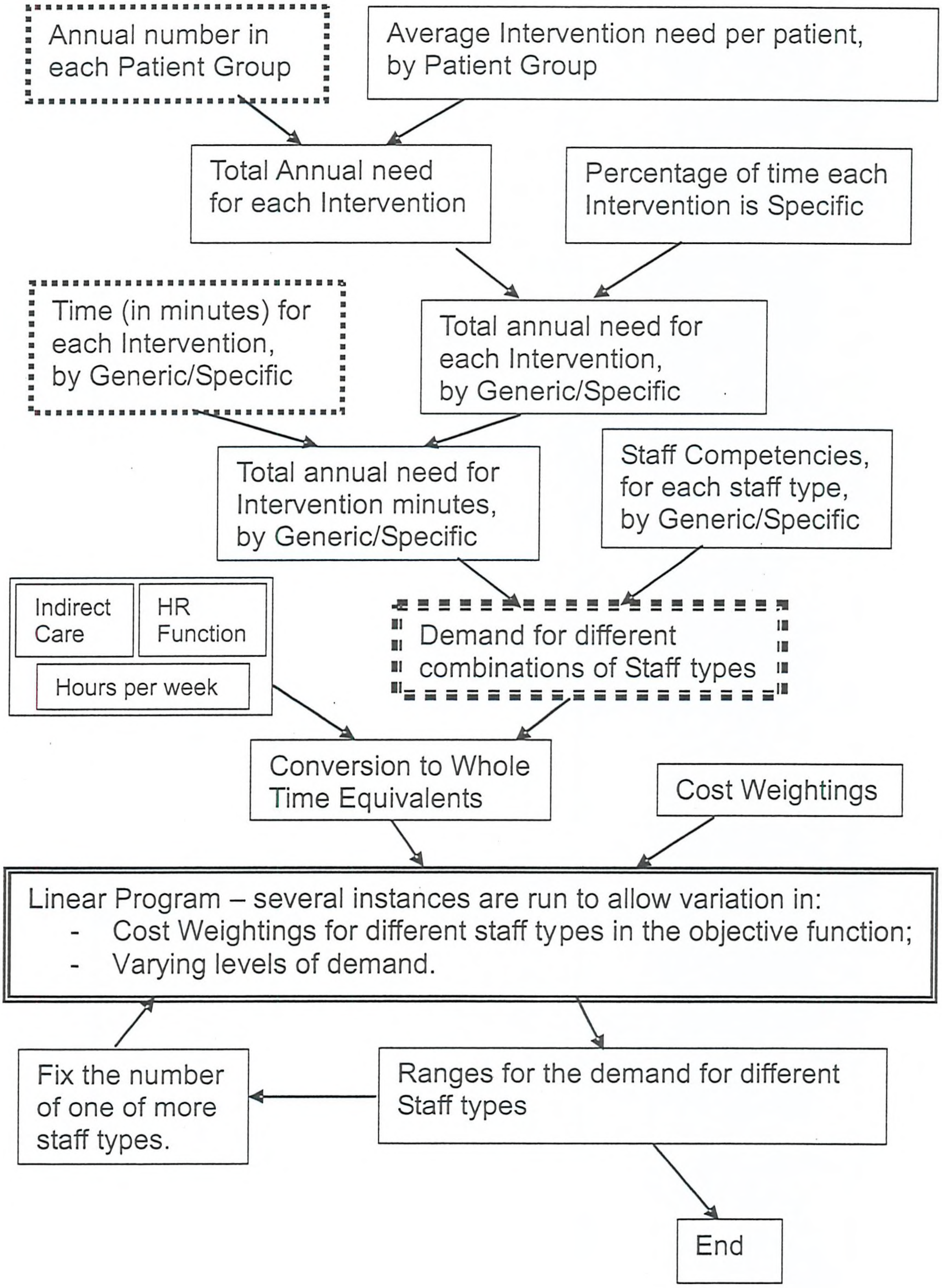

Figure 5.2: Overview of the model structure

5.4.6 Monte Carlo simulation

The Monte Carlo simulation is fed by the inputs discussed previously and shown in Figure 5.2. The two stochastic inputs are discussed below, and then the simulation is explained.

5.4.6.1 Annual number in each patient group

Historical data is used to model the annual number of all patients, and to model the proportion of patients in each patient group. There are two sets of data to be considered. The first is the data in the database which has been grouped into patient groups but which does not contain a complete year's worth of data. The second is a complete year's worth of data, containing arrival and discharge dates, however the patients are not divided into patient groups[4].

Ideally, to model the annual number of all patients, we would like several years worth of data. However, data is available for only one year, and the rehab team's service is changing and expanding (including seeing new types of patient) so that any more 'historical' data may not represent the current provision. Therefore, to model the arrivals stochastically, we group the arrivals by month and take a 3-month moving average (since caseload is determined by Length of Stay as well as date of admission). From this, the minimum, average and maximum annual numbers are calculated by, respectively, multiplying the minimum, average and maximum of the moving averages by 12. A triangular distribution can then be fitted, for which the parameters are the minimum, maximum and median. We felt it was better to calculate the median from the mean, rather than directly from the data, the details of which can be found in Appendix D.

Since complete data for different years and months for different patient groups is not available, the proportions in each patient group are determined by the database

[4]When we carried out a trial asking the staff to group the patients based only on the information available in the summary data, rather than the whole patient notes, there were severe compatibility problems (described in Section 5.5.1.1) with the database data, so we decided not to pursue this further.

and are therefore not stochastic (although it is possible for the user to change them for sensitivity analysis).

5.4.6.2 Time (in minutes) for each Intervention

Just as the time for each visit varies, so does the time needed for each intervention. Ideally, we would like team members to record the time spent on each intervention over a large number of visits, to which we could then fit a distribution. However, this is infeasible since the number of interventions, and rarity of some of them means that the 'large number' would have to be very large indeed, and would impinge significantly on staff working time.

Instead, the data available contains the time for each visit, rounded to the nearest 15 minutes. We have looked at three ways of fitting a distribution for each intervention to this data. The method we have chosen for the model requires the assumption that time is spent evenly between all interventions carried out during a visit. This gives a sample of times for each intervention to which a distribution can then be fitted. We have chosen to fit a triangular distribution (more details about this distribution can be found in Appendix D) because of its simplicity, ease of understanding and ability to be fitted by non-specialists. The other methods which were experimented with (an MLE approach, and an ANOVA approach) are detailed in Appendix B, along with a comparison between them.

5.4.6.3 The Simulation

The Monte Carlo simulation used in the model works as follows. In each run of the simulation, new random numbers are generated using Excel's random number generator. The inverse transform method is used to turn the random numbers into annual numbers of patients, and times for each intervention, based on the fitted triangular distributions. The outputs of the simulation are the demand, in intervention minutes, for each combination of the types of workforce, according to their shared, or unique competencies. The number of simulation runs can be changed, but for all the results shown here, 100 runs were used. This was compared with more runs, and no significant differences found in the results.

5.4.7 Conversion to Whole Time Equivalents

As has been mentioned previously, the intervention times give only the time needed for direct patient care. In considering the number of staff to employ, in terms of Whole Time Equivalents (WTE), time spent in indirect care (e.g. paperwork, travel, phone calls, training, meetings), as well as various types of leave (annual, sick etc) need to be factored in.

For the professional members of Staff, for each x minutes spent in direct care with the patient, they spend another x minutes in indirect care back in the office after the visit, as confirmed by the Eastleigh rehab team manager. We do not have data for the travelling time (always by car), however an educated guess was made by the rehab staff of 15 minutes per journey. From the database, we know that the average time for a visit is about 40 minutes. For Rehab Assistants, the paperwork is written up at the patient's home and so more of their time is classed as direct care, and they can carry out visits back to back where necessary/possible. The frequency of meetings and trainings varies by staff member.

For the model, we have used a direct care percentage of 20% for professional staff, and 40% for junior staff (Rehab Assistants). These may be considered to be conservative estimates, and so section 5.6.2 shows the results when the model was run using different values for the direct care percentages.

The statutory number of hours worked by each member of staff currently varies according to their profession. Therapists work 36 hour weeks, and Social Workers 37 hour weeks, whereas Nurses and Rehab Assistants work 37.5 hour weeks. Many of the team members work part-time, however by calculating workforce needs in terms of WTEs, we do not need to consider the part-time workers separately. As with the work in Chapter 3, we allow a factor, which we call the HR function (Human Resources function), of 20% to allow for annual, sick, study and other types of leave.

The calculation to turn direct intervention minutes into WTEs is as follows.

$$\text{WTEs to Employ} = \frac{\text{Direct intervention time}}{60 \times \text{Direct care percentage}} \times \frac{1 + \text{HR function}}{52 \times \text{Hours worked per week}}$$

The reverse of this calculation (i.e. to turn WTEs into direct intervention minutes) is:

$$\text{Direct intervention time} = \frac{\text{WTEs to employ} \times 60 \times \text{Direct care percentage} \times 52 \times \text{Hours worked per week}}{1 + \text{HR function}}$$

5.4.8 Linear Program

With the demand for the different combinations of staff given by the simulation, and the conversion to Whole Time Equivalents complete, linear programming is used to optimize the team mix. A single, simple formulation, as described below, is used to minimise a cost function subject to satisfying demand for the different staffing combinations. It is necessary to introduce a new type of staff, the Temporary worker, to ensure that a feasible solution to the linear program will always exist. The following abbreviations are used to indicate the different types of staff:

P: Physiotherapists (Physios)
O: Occupational Therapists
N: Nurses
M: Mental Health Nurses
S: Social Workers
2: Rehab Assistants Level 2
1: Rehab Assistants Level 1
T: Temporary Worker

We now define the variables and constants for the Linear Program.

Let $K = \{P, O, N, M, S, 2, 1, T\}$ be the set of staff types and
Let K_i be a subset of K where $1 \leq i \leq 21$

Note: Not all possible subsets of K are used. The subsets are defined explicitly where they are used.

For each $j \in K$,

Let x_{ij} be the number of intervention minutes contributed by staff type j to subset K_i.

Let c_j be the unit cost of staff type j.

Let h_j be the conversion factor to convert intervention minutes to WTEs for staff type j.

Let d_{K_i} be the demand for intervention minutes for the set of staff types K_i

The objective is to minimise

$$\sum_{j \in K} c_j h_j \sum_{i=1}^{21} x_{ij}$$

$$\begin{aligned} \text{Subject to} \quad \sum_{j \in K_i} x_{ij} &\geq d_{K_i} \quad && \text{for } i = 1, \ldots, 21; \\ x_{ij} &\geq 0 && \text{for each } j \in K, i = 1, \ldots, 21. \end{aligned}$$

Another way of thinking about the x_{ij} is that it is the contribution, in intervention minutes, of staff type j to meeting the demand for the set of staff types in subset K_i. Each of the professional staff types will, in practice, command a different salary, however we did not want the linear program to be in a position whereby it was suggesting that one staff type should dominate the team because that staff type is very slightly better value for money because they cost either slightly less and/or work slightly longer hours. Therefore we have four levels of cost which are not true costs, but which relate to each other; the levels are that of the professional staff, the Rehab Assistants Level 2, the Rehab Assistants Level 1 and the temporary worker. In this modelling situation, we do not differentiate between different types of temporary worker, thus assuming the temporary worker to be competent at every intervention, (in practice the temporary worker would not always be the same person).

Several instances of the Linear Program are run using the above formulation as follows. Three levels of demand are evaluated; the median and the first and third quartiles. Each instance contains different costs for the professional staff in such a way that the maximum and minimum need for each staff type can be established for each of the three levels of demand, (since for example, when the cost for Physios is highest, this will give the minimum number of Physios needed). The cost for the Temporary worker remains higher than any of the other costs for all instances of the Linear Program. The costs for the Rehab Assistants remain constant for all instances with $c_T \geq c_j \geq c_2 \geq c_1$ for all $c_j \in K \backslash \{T, 2, 1\}$.

The Linear Program therefore outputs maximum and minimum levels for each staff type for each level of demand, and the numbers for each staff type are dependent on the numbers for the other staff types. This is useful, but to make the model even more useful, there is the opportunity to fix the values for one or more staff types and to re-optimize the Linear Program to see the effect this has on the other staff types. To do this, we choose staff type j to be fixed and let f_j be the fixed number of staff type j. Then the constraint: $h_j x_j = f_j$ can be included in the linear program. This can be repeated for as many staff types as desired.

5.5 Validation (modelling the current situation)

5.5.1 Annual patient numbers

5.5.1.1 By patient group

The number of patients in each patient group in the database, for each of the rehab teams is shown in Table 5.1. The paper records from which the patients were sampled for the database are kept for 2-3 years. Both the rehab teams keep electronic summary records of all patients in a spreadsheet which includes information about their presenting condition. From this, easily accessible data, they were asked to classify all patients from one financial year (744 patients from Eastleigh and 887 patients from Romsey) into each of the patient groups. This information is also shown in Table 5.1.

Table 5.1: Patient numbers by patient group

Patient Group	In Database		Recorded Annual Number	
	Eastleigh	Romsey	Eastleigh	Romsey
Breakdown in home situation	71	10	38	20
CVA	14	11	46	28
Elective Orthopaedics	27	35	106	98
Falls	93	37	97	177
Medical (multipathology)	69	35	204	112
Musculoskeletal	28	30	120	224
Neuro	11	6	43	62
Palliative Care	7	10	4	7
Respiratory	3	3	13	18
Surgical	0	12	0	0
Trauma	27	12	73	54
Unknown	0	0	0	87
Column Total	350	201	744	887

By comparing the numbers, we can see that there is much ambiguity in categorising the patients into groups. Perhaps this is because patients sometimes fall into more than one group and the dominant group is not always clear from the presenting condition. For example we see that in the first patient group, Breakdown in home situation, the database for Eastleigh patients contains 71 patients, which would give an expected annual number of 151, but only 38 are categorised as being in this group from the summary records which contain only the presenting condition.

Table 5.2 shows the predicted annual number in each patient group, keeping the total number as recorded, but using the proportions in the database. Also shown is the difference between the recorded and predicted numbers.

Table 5.2: Analysing predicted annual patient group numbers from the database

Patient Group	Predicted annual number (from database)		Difference between predicted and recorded annual numbers	
	Eastleigh	Romsey	Eastleigh	Romsey
Breakdown in home situation	151	47	-113	-27
CVA	30	51	16	-23
Elective Orthopaedics	57	163	49	-65
Falls	198	172	-101	5
Medical (multipathology)	147	163	57	-51
Musculoskeletal	60	140	60	84
Neuro	23	28	20	34
Palliative Care	15	47	-11	-40
Respiratory	6	14	7	4
Surgical	0	56	0	-56
Trauma	57	56	16	113
Column Total	744	937	0	0

Each of the differences between the predicted and recorded patient group numbers is greater than 10, except for the Respiratory group for both Eastleigh and Romsey, and the Falls group for Romsey. The number of patients in the Respiratory group is very small so this accounts for the very small difference in numbers. For the Romsey Falls group, the prediction is quite accurate, perhaps because these patients' details are stored separately to the other groups by the staff at Romsey, so the staff are used to having a 'Falls' group which would help to reduce ambiguity.

A χ^2 test easily concludes that there is evidence to suggest that the predicted patient numbers are not the same as the actual numbers, since the χ^2 statistic is 391 which is much greater than the significant value of 17 at the 95% confidence level and 9 degrees of freedom (The Surgical and Unknown patient groups were not included in the χ^2 test, since these were particular anomalies).

Since the numbers are so different, and following discussions with the PCT, the decision was made to take the total number of patients from the annual summary records, and the proportions of patients in each patient group from the database. This is because we believe the classification of patients into patient groups is more accurate for the patients in the database since the whole patient notes were used, rather than just the presenting condition as for the classification using the summary records. Therefore the annual number in each patient group used in the model are those presented in columns 2 and 3 of Table 5.2.

5.5.1.2 By year

The annual patient data can be used to look at seasonality in patient arrivals as a whole, but not by patient group. The complete year's set of data contains patient arrivals by month, as shown in Table 5.3. Since the number of patients 'on the books' depends not only on a patient's admission date, but also on their Length of Stay, we have used a three month moving average to smooth the data, the values of which are also in Table 5.3. Section 5.4.6.1 explains the use of the three month moving average and Table 5.4 contains the parameters for the fitted triangular distributions

Table 5.3: Annual patient numbers by month

Actual Numbers													
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Eastleigh	65	59	69	46	66	66	67	69	57	59	77	44	744
Romsey	61	59	61	84	83	96	85	78	68	64	74	74	887
Three Month moving Average													
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Eastleigh	56	64	58	60	59	66	67	64	62	64	60	62	744
Romsey	65	60	68	76	88	88	86	77	70	69	71	70	887

Table 5.4: Parameters for the Triangular distribution fitted to annual patient data

Parameter	Eastleigh	Romsey
Mean	744	887
Minimum	$56 \times 12 = 672$	$60 \times 12 = 720$
Maximum	$67 \times 12 = 804$	$88 \times 12 = 1056$

5.5.2 Intervention needs by patient group

In total, 35 Assessment interventions, 11 Assistance interventions and 24 Practice interventions were used to summarise the care given by the Staff to the patients. An Assistance intervention differs from a Practice intervention in that Assistance is generally doing something for the patient, whereas practice is enabling the patient to do something for themselves.

Table 5.5 shows the total amount of each intervention that an average patient from each patient group will need during their stay in Intermediate Care. These figures have been obtained by averaging over all patients (from both rehab teams) in each patient group. Note that for clarity the values are shown to one decimal place, which for some interventions gives the impression that they never happen. For most patient groups, this is untrue - they are just not that common!

Table 5.5: Average patient need for interventions

Number	Intervention	Patient Group										
		A	B	C	D	E	F	G	H	I	J	K
Assessment of/for												
1	ADL Assessment	0.4	0.3	0.4	0.2	0.2	0.2	0.2	0.1	0.0	0.2	0.4
2	ADL equipment	0.8	0.5	0.3	0.6	0.4	0.1	0.1	0.8	0.0	0.4	0.4
3	Assessment of Balance	0.0	0.4	0.2	0.2	0.1	0.2	0.2	0.0	0.0	0.0	0.1
4	Assessment of carers needs	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.0	0.2	0.1
5	Assessment of Medication Use	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
6	Assessment of musculoskeletal and prescription of exercises	0.2	0.6	1.3	0.4	0.3	0.8	0.2	0.1	0.0	0.4	0.3
7	Assessment of Outdoor Mobility/Stairs/Steps	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.0	0.2	0.1	0.1
8	Assessment of Prothesis Use	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	Assessment of wound	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5
10	Basic Nutritional Assessment	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.3	0.0	0.2
11	Basic Walking aids	0.1	0.1	0.2	0.2	0.0	0.1	0.0	0.1	0.0	0.1	0.1
12	Care Requirements/support	0.5	0.2	0.1	0.3	0.3	0.1	0.2	0.3	0.2	0.5	0.8
13	Clinical Reasoning	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
14	Cognitive assessment	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1
15	Complex aids & equipment (e.g. pulpit frame)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.0
16	Continence assessment	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0
17	Depression assessment	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0
18	Discharge Visit	0.6	0.6	0.9	0.6	0.4	0.6	0.8	0.6	0.5	0.4	0.9
19	Documentation	0.0	0.2	0.2	0.1	0.1	0.2	0.3	0.0	0.0	0.1	0.4
20	Drug history and compliance	0.1	0.2	0.0	0.3	0.0	0.1	0.0	0.0	0.0	0.0	0.2
21	Falls Assessment	0.1	0.0	0.0	0.2	0.0	0.1	0.1	0.0	0.0	0.0	0.0
22	Hip Protectors	0.1	0.2	0.4	0.2	0.2	0.4	0.6	0.1	0.0	0.1	0.3
23	History taking	0.6	1.0	0.6	0.9	0.5	0.6	0.9	0.5	0.5	0.4	0.4
24	Mobility/Gait Assessment	0.0	0.4	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0
25	Neuro Assessment	0.1	0.4	0.3	0.1	0.2	0.1	0.4	0.2	0.2	0.2	0.4
26	PADL Assessment	0.7	0.8	0.3	0.5	0.4	0.2	0.3	0.4	0.5	0.5	0.2

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Number	Intervention	Patient Group										
		A	B	C	D	E	F	G	H	I	J	K
27	Possible future health requirements	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.2	0.1	0.2
28	Pressure Area Assessment	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0
29	Problems with feet	0.1	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.1	0.0
30	Risk Assessment	1.0	1.0	0.5	1.0	1.0	0.3	0.4	0.6	0.8	0.8	0.9
31	S.A.P.	1.9	0.6	0.8	1.4	1.6	0.7	0.5	1.1	1.2	1.2	0.2
32	Signposing/referring on	0.2	0.2	0.4	0.4	0.3	0.2	0.0	0.1	0.3	0.3	0.0
33	Simple adaptions	0.4	0.5	0.1	0.7	0.6	0.1	0.0	0.2	0.2	0.2	0.3
34	Urinalysis/BP/BM/Temp	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
35	Venesection/Phlebotomy	0.4	0.3	0.4	0.2	0.2	0.2	0.2	0.1	0.0	0.2	0.4
Assistance with/for												
36	Care Provision	1.5	0.3	0.4	0.4	1.2	0.6	0.0	0.8	0.2	2.7	0.1
37	Documentation	1.6	0.4	0.4	0.4	1.0	0.5	0.0	0.5	0.3	1.7	0.4
38	Ensure eating/nutritional intake	0.3	0.2	0.2	0.3	0.2	0.1	0.2	0.1	0.0	0.2	0.1
39	Environmental checks	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.2	0.0	0.1	0.0
40	Foot Care	0.2	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.3
41	Full Care/DADL	0.5	0.3	0.1	0.4	0.4	0.0	0.2	0.8	0.3	2.2	1.5
42	Full Care/PADL	0.0	0.2	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
43	Passive movements	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.1
44	Pick up prescription	0.4	0.1	0.3	0.2	0.3	1.1	0.1	0.4	0.0	0.4	0.1
45	Putting on Appliances	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1
46	Shopping	1.5	0.3	0.4	0.4	1.2	0.6	0.0	0.8	0.2	2.7	0.1
Practice of/with												
47	Advice on care/equipment provision	0.7	0.3	0.3	0.5	0.3	0.3	0.2	0.6	0.0	0.5	0.0
48	Balance exercises and re-education	0.0	0.3	0.2	0.1	0.0	0.2	0.0	0.0	0.0	0.2	0.0
49	Documentation	0.9	0.5	0.5	1.2	1.0	0.9	0.3	0.2	0.8	1.3	0.0
50	Falls advice/safety monitoring	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.4	0.0	0.2	0.0
51	Foot care	0.3	1.4	0.7	0.5	0.3	0.1	0.2	0.2	0.0	0.2	0.0
52	Gait re-education	0.1	0.1	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.3
53	Health promotion	0.9	0.2	0.1	0.2	0.5	0.1	0.0	0.0	1.7	2.3	0.1

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Number	Intervention	Patient Group										
		A	B	C	D	E	F	G	H	I	J	K
54	Meal planning/monitoring	0.3	0.4	0.0	0.1	0.6	0.1	0.0	0.0	0.0	0.4	0.2
55	Meal Prep	1.8	0.1	0.5	0.7	1.2	0.4	0.1	0.1	2.5	1.5	0.0
56	Monitoring and advice on meds	2.4	1.6	2.5	1.7	2.0	0.7	1.1	1.1	0.5	1.7	0.8
57	Monitoring changes in condition	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
58	Monitoring of care needs	0.0	0.1	0.0	0.0	0.7	0.0	0.0	0.1	0.0	0.1	0.3
59	Monitoring of carer's well being	0.3	0.2	0.1	0.2	0.3	0.0	0.0	0.4	0.0	0.4	0.0
60	Monitoring of continence	0.3	1.1	0.9	0.6	0.7	0.4	0.2	0.1	0.0	0.4	0.3
61	Outdoor mobility/stairs/steps	0.0	0.2	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.0
62	Practice functional activities, e.g. cleaning	0.3	0.7	3.9	1.0	0.3	1.7	2.2	0.9	0.5	1.2	0.6
63	Practice with exercises	0.6	0.8	0.1	0.2	0.9	0.2	0.0	0.1	0.0	1.1	0.7
64	Practice with personal care	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.1
65	Prosthesis use/appliance use	0.1	0.2	0.5	0.2	0.2	0.1	0.1	0.2	0.0	0.2	0.0
66	Safe use of adaptions	0.4	0.4	0.5	0.5	0.5	0.2	0.5	0.2	0.2	0.7	0.5
67	Safe use of equipment	2.0	2.4	2.1	2.7	2.5	1.2	1.2	0.9	1.0	1.5	0.2
68	Safe use/advise of walking aids	1.6	2.2	0.7	2.1	1.5	1.4	0.8	0.9	0.0	2.1	0.3
69	Transfer Practice	0.0	0.0	1.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
70	Wound Care	0.7	0.3	0.3	0.5	0.3	0.3	0.2	0.6	0.0	0.5	0.0

5.5.3 Intervention times

The parameters for the triangular distributions used to model the intervention times, as described in Section 5.4.6 and Appendix B can be seen in Table B.2. Those interventions which were rare enough to not be included in the sub group of interventions to which the parameters were fitted, were modelled using minimum, maximum and median values for the whole of the sub category of interventions to which they belonged. I.e. for an Assessment intervention which did not have parameters fitted, it was modelled using parameters calculated from all the Assessment intervention data in the sub group. Table 5.6 contains these values.

Table 5.6: Average parameters for the interventions not included in the sub group to which parameters were fitted

Intervention Type	Minimum	Maximum	Mean
Assessment interventions (Generic)	5	60	18
Assessment interventions (Specific)	8	120	19
Assistance interventions (Generic)	4	60	15
Assistance interventions (Specific)	10	30	18
Practice interventions (Generic)	4	69	14
Practice interventions (Specific)	10	30	18

5.5.4 Proportions of Generic / Specific Interventions

Each intervention in the database was categorised as being either at a Generic level or a Specific level. Recall that Generic, in this instance, does not necessarily mean 'able to be done by all team members'. The rehab team staff consider some interventions to be mostly generic, and others to be mostly specific. We recorded what they thought the interventions were (column 'Supposed to be') and then compared this with the results from the database. This is shown for each team separately, and combined, in Table 5.7. From the combined data, we see that there are 18 interventions which are supposed to be Specific, but which for more than 50% of recorded instances are Generic. For 12 of these interventions, 75% of the recorded instances are Generic.

Table 5.7: Specific/Generic breakdown for the interventions

Number	Intervention	Supposed to be	Eastleigh %		Romsey %		Combined %	
			Generic	Specific	Generic	Specific	Generic	Specific
Assessment of/for								
1	ADL Assessment	Generic	51.3	48.8	97.6	2.4	67.2	32.8
2	ADL equipment	Generic	72.5	27.5	85.2	14.8	75.4	24.6
3	Assessment of Balance	Specific	15.4	84.6	91.1	8.9	63.4	36.6
4	Assessment of carers needs	Specific	96.9	3.1	87.5	12.5	95.0	5.0
5	Assessment of Medication Use	Specific	28.6	71.4	100.0	0.0	66.7	33.3
6	Assessment of musculoskeletal and prescription of exercises	Specific	11.6	88.4	61.4	38.6	29.0	71.0
7	Assessment of Outdoor Mobility/Stairs/Steps	Generic	43.5	56.5	100.0	0.0	60.0	40.0
8	Assessment of Prothesis Use	Specific	0.0	100.0	40.0	60.0	33.3	66.7
9	Assessment of wound	Specific	90.3	9.7	95.0	5.0	92.2	7.8
10	Basic Nutritional Assessment	Specific	66.7	33.3	100.0	0.0	76.5	23.5
11	Basic Walking aids	Generic	64.9	35.1	91.2	8.8	77.5	22.5
12	Care Requirements/support	Generic	95.9	4.1	87.5	12.5	94.2	5.8
13	Clinical Reasoning	Generic	0.0	100.0	25.0	75.0	16.7	83.3
14	Cognitive assessment	Specific	100.0	0.0	86.7	13.3	87.5	12.5
15	Complex aids & equipment (e.g. pulpit frame)	Specific	22.0	78.0	53.3	46.7	30.4	69.6
16	Continence assessment	Specific	44.4	55.6	100.0	0.0	54.5	45.5
17	Depression assessment	Specific	80.0	20.0	57.1	42.9	63.2	36.8
18	Discharge Visit	Generic	96.1	3.9	95.6	4.4	95.9	4.1
19	Documentation	Generic	75.0	25.0	100.0	0.0	90.0	10.0
20	Drug history and compliance	Specific	78.8	21.2	86.7	13.3	82.5	17.5
21	Falls Assessment	Specific	66.7	33.3	81.5	18.5	74.1	25.9
22	Hip Protectors	Generic	63.3	36.7	100.0	0.0	76.1	23.9
23	History taking	Generic	84.0	16.0	74.4	25.6	80.6	19.4

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Number	Intervention	Supposed to be	Eastleigh %		Romsey %		Combined %	
			Generic	Specific	Generic	Specific	Generic	Specific
24	Mobility/Gait Assessment	Specific	38.5	61.5	85.5	14.5	49.5	50.5
25	Neuro Assessment	Specific	7.1	92.9	20.0	80.0	10.5	89.5
26	PADL Assessment	Generic	44.7	55.3	95.5	4.5	69.2	30.8
27	Possible future health requirements	Generic	82.7	17.3	62.5	37.5	81.9	18.1
28	Pressure Area Assessment	Specific	53.8	46.2	100.0	0.0	73.9	26.1
29	Problems with feet	Specific	80.0	20.0	100.0	0.0	81.8	18.2
30	Risk Assessment	Generic	85.7	14.3	94.1	5.9	90.9	9.1
31	S.A.P.	Generic	100.0	0.0	71.8	28.2	90.4	9.6
32	Signposing/referring on	Generic	77.5	22.5	98.8	1.2	80.3	19.7
33	Simple adaptions	Generic	63.6	36.4	77.1	22.9	68.4	31.6
34	Urinalysis/BP/BM/Temp	Generic	18.8	81.3	98.2	1.8	41.0	59.0
35	Venesection/Phlebotomy	Specific	0.0	100.0	-	-	0.0	100.0
Assistance with/for								
36	Care Provision	Specific	100.0	0.0	100.0	0.0	100.0	0.0
37	Documentation	Generic	66.7	33.3	100.0	0.0	83.3	16.7
38	Ensure eating/nutritional intake	Generic	98.7	1.3	100.0	0.0	99.0	1.0
39	Environmental checks	Generic	72.6	27.4	96.2	3.8	78.8	21.2
40	Foot Care	Specific	87.5	12.5	94.4	5.6	92.3	7.7
41	Full Care/DADL	Generic	100.0	0.0	100.0	0.0	100.0	0.0
42	Full Care/PADL	Generic	100.0	0.0	100.0	0.0	100.0	0.0
43	Passive movements	Specific	100.0	0.0	100.0	0.0	100.0	0.0
44	Pick up prescription	Generic	100.0	0.0	100.0	0.0	100.0	0.0
45	Putting on Appliances	Generic	93.8	6.2	89.7	10.3	93.1	6.9
46	Shopping	Generic	100.0	0.0	100.0	0.0	100.0	0.0
Practice of/with								
47	Advice on care/equipment provision	Generic	87.6	12.4	80.0	20.0	87.4	12.6
48	Balance exercises and re-education	Generic	100.0	0.0	90.2	9.8	91.8	8.2
49	Documentation	Generic	100.0	0.0	100.0	0.0	100.0	0.0
50	Falls advice/safety monitoring	Generic	88.8	11.2	95.2	4.8	89.1	10.9

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Number	Intervention	Supposed to be	Eastleigh %		Romsey %		Combined %	
			Generic	Specific	Generic	Specific	Generic	Specific
51	Foot care	Generic	100.0	0.0	100.0	0.0	100.0	0.0
52	Gait re-education	Generic	90.8	9.2	95.0	5.0	91.6	8.4
53	Health promotion	Generic	51.3	48.7	66.7	33.3	56.7	43.3
54	Meal planning/monitoring	Generic	100.0	0.0	100.0	0.0	100.0	0.0
55	Meal Prep	Generic	98.9	1.1	100.0	0.0	99.2	0.8
56	Monitoring and advice on meds	Specific	88.7	11.3	-	-	88.7	11.3
57	Monitoring changes in condition	Specific	97.0	3.0	91.4	8.6	95.2	4.8
58	Monitoring of care needs	Generic	100.0	0.0	100.0	0.0	100.0	0.0
59	Monitoring of carer's well being	Generic	87.5	12.5	100.0	0.0	98.9	1.1
60	Monitoring of continence	Generic	85.1	14.9	100.0	0.0	85.7	14.3
61	Outdoor mobility/stairs/steps	Generic	98.9	1.1	99.0	1.0	99.0	1.0
62	Practice functional activities, e.g. cleaning	Generic	95.5	4.5	100.0	0.0	96.6	3.4
63	Practice with exercises	Generic	69.4	30.6	93.2	6.8	80.1	19.9
64	Practice with personal care	Generic	100.0	0.0	100.0	0.0	100.0	0.0
65	Prosthesis use/appliance use	Generic	0.0	100.0	74.1	25.9	71.4	28.6
66	Safe use of adaptions	Generic	94.7	5.3	98.4	1.6	97.0	3.0
67	Safe use of equipment	Generic	95.6	4.4	98.9	1.1	96.9	3.1
68	Safe use/advise of walking aids	Generic	97.5	2.5	97.5	2.5	97.5	2.5
69	Transfer Practice	Generic	88.6	11.4	98.7	1.3	89.6	10.4
70	Wound Care	Specific	75.0	25.0	99.1	0.9	98.2	1.8

We have used the combined percentages to calculate the proportion of time an intervention will be Specific or Generic.

5.5.5 Competencies of different members of staff

Different members of staff are able to carry out different interventions according to their profession and/or skill set, as well as whether the intervention needs to be carried out at the Generic or Specific level. Table 5.8 shows which staff members can carry out an intervention if it is Generic (shaded block) or Specific ("Y"). Obviously, the competencies of each staff group will vary not only from rehab team to Rehab Team, but from person to person, however these Tables show the base level of competencies. The same abbreviations as used for the Linear Program in Section 5.4.8 are used to simplify the tables.

An alternative approach could have been to identify the staffing competencies from the database. This was examined, and Table C.6 in Appendix C contains details of who carried out the interventions which occurred more than 85 times in the database. When looking at who did what in the database, it was felt that the competencies were not well defined enough for the model. The model required a definite "Yes" or "No" for each competency, rather than a vague response indicating that a particular member of staff could do it 3% of the time. The rehab staff were not shown any results from the database before being asked to define the competencies and this has proven to be valuable in challenging any preconceptions they have about who can carry out which interventions.

Table 5.8: Who can do the interventions?

Intervention	P	O	N	S	2	1	M
Assessment of/for							
ADL Assessment		Y					
ADL equipment	Y						
Assessment of Balance	Y	Y	Y				Y
Assessment of carers needs				Y			
Assessment of Medication Use			Y				Y
Assessment of musculoskeletal and prescription of exercises	Y						

continued on next page

Intervention	P	O	N	S	2	1	M
Assessment of Outdoor Mobility/Stairs/Steps	Y	Y					
Assessment of Prothesis Use	Y	Y					
Assessment of wound			Y		Y		
Basic Nutritional Assessment			Y				
Basic Walking aids	Y						
Care Requirements/support	Y	Y	Y	Y			Y
Clinical Reasoning	Y	Y	Y				Y
Cognitive assessment		Y					Y
Complex aids & equipment (e.g. pulpit frame)	Y	Y					
Continence assessment			Y				
Depression assessment	Y	Y	Y				Y
Discharge Visit	Y	Y	Y	Y	Y		Y
Drug history and compliance			Y				
Falls Assessment	Y	Y	Y				Y
Hip Protectors	Y	Y	Y		Y		Y
History taking	Y	Y	Y	Y			Y
Mobility/Gait Assessment	Y						
Neuro Assessment	Y						
PADL Assessment		Y					
Possible future health requirements	Y	Y	Y	Y			Y
Pressure Area Assessment		Y	Y				
Problems with feet	Y						
Risk Assessment	Y	Y	Y	Y	Y	Y	Y
S.A.P.	Y	Y	Y				Y
Signposing/referring on	Y	Y	Y	Y	Y	Y	Y
Simple adaptions		Y					
Urinalysis/BP/BM/Temp			Y				
Venesection/Phlebotomy			Y				
Assistance with/for							
Care Provision				Y			
Ensure eating/nutritional intake				Y			Y
Environmental checks							
Foot Care					Y		
Full Care/DADL			Y				
Full Care/PADL			Y				
Passive movements	Y						
Pick up prescription	Y	Y	Y	Y	Y	Y	Y
Putting on Appliances							
Shopping							
Practice of/with							
Advice on care/equipment provision		Y		Y			
Balance exercises and re-education	Y						
Falls advice/safety monitoring	Y	Y	Y				Y
Foot care					Y		
Gait re-education	Y						
Health promotion							
Meal planning/monitoring			Y				
Meal Prep		Y					
Monitoring and advice on meds			Y				Y
Monitoring changes in condition	Y	Y	Y				Y

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Intervention	P	O	N	S	2	1	M
Monitoring of care needs				Y			Y
Monitoring of carer's well being				Y			Y
Monitoring of continence			Y				
Outdoor mobility/stairs/steps	Y						
Practice functional activities, e.g. cleaning		Y					
Practice with exercises	Y						
Practice with personal care		Y					
Prosthesis use/appliance use	Y	Y					
Safe use of adaptions	Y	Y					
Safe use of equipment	Y	Y	Y				Y
Safe use/advise of walking aids	Y						
Transfer Practice	Y						
Wound Care			Y				

5.5.6 Monte Carlo simulation

The results of the Monte Carlo simulation for the median, 1st and 3rd quartile values for the demand (in minutes) for each combination of staff types are shown in Table 5.9 for the Eastleigh team, and Table 5.10 for the Romsey team. Note that these tables do not show the Temporary Worker, T, who is added to each combination of staff before carrying out the optimization, thus ensuring that a feasible solution will always exist, i.e. to allow for times when demand cannot be met by the regular team members.

Table 5.9: Simulation results for the Eastleigh team

K_i	$j \in K_i$	**Median**	**1st Quartile**	**3rd Quartile**
k_1	P	21631	20337	23569
k_2	O	5086	4664	5581
k_3	N	12039	8728	16307
k_4	M	0	0	0
k_5	S	14298	10891	18790
k_6	2	541	491	598
k_7	1	0	0	0
k_8	PO	2701	2362	3122
k_9	ON	638	502	873
k_{10}	OM	697	488	922
k_{11}	OS	775	655	937
k_{12}	NM	14693	11667	16841
k_{13}	NMS	1329	1052	1920
k_{14}	N2	3805	2594	4996
k_{15}	MS	143	124	166
k_{16}	PONM	28520	23246	33401
k_{17}	PONMS	19415	14866	23948
k_{18}	PONMS2	25689	22764	30552
k_{19}	PONM2	65991	50895	86333
k_{20}	PONMS21	126895	113920	139430
k_{21}	PONM21	28468	25820	30846
Total		376437	358077	405004

Table 5.10: Simulation results for the Romsey team

K_i	$j \in K_i$	Median	1st Quartile	3rd Quartile
k_1	P	28422	25874	31971
k_2	O	5667	5123	6551
k_3	N	11255	8166	14583
k_4	M	0	0	0
k_5	S	14115	10055	19056
k_6	2	871	778	985
k_7	1	0	0	0
k_8	PO	2905	2518	3281
k_9	ON	1050	776	1402
k_{10}	OM	830	534	1145
k_{11}	OS	787	642	911
k_{12}	NM	12958	11212	15306
k_{13}	NMS	1529	1052	2138
k_{14}	N2	9584	6951	14596
k_{15}	MS	142	126	161
k_{16}	PONM	29956	26280	35959
k_{17}	PONMS	21581	16969	28774
k_{18}	PONMS2	31567	26131	36639
k_{19}	PONM2	72561	59346	99183
k_{20}	PONMS21	127982	118954	145751
k_{21}	PONM21	32443	29229	37305
Total		415781	387756	463780

5.5.7 Conversion to Whole Time Equivalents

Current indirect care percentages, HR functions and WTE hours worked per week were agreed with clinical staff. These and the resulting values of h_j, can be seen in Table 5.11.

Table 5.11: Values for converting to WTEs

Staff Type	P	O	N	M	S	2	1	T
Direct Care Percentage (%)	20	20	20	20	20	40	40	40
HR function Percentage (for Leave) (%)	20	20	20	20	20	20	20	20
WTE Hours per week (hrs)	36.0	36.0	37.5	37.5	37.0	37.5	37.5	37.5
h_j (values $\times 10^{-5}$)	5.34	5.34	5.13	5.13	5.20	2.28	2.28	2.28

5.5.8 Linear Program

Given the definitions in Table 5.12, the Linear Program is run for 5 different combinations of cost weightings, as shown in Table 5.13, to allow for each of the professional staff to be made cheaper and more expensive relative to the other professional staff. In total 15 optimizations are performed (5 different cost combinations each at 3 demand levels). Recall that the cost weightings for the Rehab Assistants and temporary staff do not change.

Table 5.12: Cost weighting definitions

Staff Type	Cost Weightings	Value
Professional Staff	x	25
Rehab Assistant Level 2	y	17
Rehab Assistant Level 1	z	15
Temporary Staff	t	100

Table 5.13: Cost instances for the Linear Program

Staff Type:	c_P	c_O	c_N	c_M	c_S	c_2	c_1	c_T
Instance 1	$1.1x$	$0.9x$	x	x	x	y	z	t
Instance 2	$0.9x$	$1.1x$	x	x	x	y	z	t
Instance 3	x	x	$1.1x$	$0.9x$	x	y	z	t
Instance 4	x	x	$0.9x$	x	$1.1x$	y	z	t
Instance 5	x	x	x	$1.1x$	$0.9x$	y	z	t

5.5.9 Validation results for Eastleigh

The results from the Linear Program for the Eastleigh rehab team are shown in Table 5.14 where in the average demand column, the min (max) column shows the average need when demand for that staff type is minimised (maximised). The corresponding ranges for the min and max are shown when demand is low and high. For the professional staff, the minimum for each staff type corresponds to when the Linear Program was run with that staff type most expensive, and the maximum when that staff type was cheapest. The cost weightings for the Rehab Assistants were not varied so minima and maxima are not given.

Table 5.14: Results from the Linear Program (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	4.0	1.1	3.5	1.3	4.6
OT	0.3	3.2	0.2	2.7	0.3	3.7
Nurse	0.5	4.0	0.4	3.3	0.7	4.8
Mental Health Nurse	0.0	3.4	0.0	2.8	0.0	4.0
Social Worker	0.8	2.0	0.5	1.6	1.0	2.5
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	2.6		2.0		3.0	
Rehab Assistant Level 1	4.1		3.7		4.5	
Temp	0.0		0.0		0.0	

To make the results more meaningful and to properly validate them, we now need to fix some of the staff types (variables) and see the corresponding effect on the remaining staff types. We start by fixing the number of Mental Health Nurses to be zero, since the Eastleigh team does not currently contain a Mental Health Nurse.

The results are in Table 5.15.

Table 5.15: Results after fixing the number of Mental Health Nurses (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	4.0	1.1	3.5	1.3	4.6
OT	0.3	3.2	0.3	2.7	0.3	3.7
Nurse	1.3	4.0	1.0	3.3	1.6	4.8
Mental Health Nurse	0.0		-	-	-	-
Social Worker	0.8	2.0	0.6	1.6	1.0	2.5

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	2.6	2.0	3.0
Rehab Assistant Level 1	4.1	3.7	4.5
Temp	0.0	0.0	0.0

Next we fix the number of Social Workers to be the current level, of 1.12 WTE. The results are in Table 5.16.

Table 5.16: Results after fixing the number of Social Workers (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	3.8	1.1	3.0	1.3	4.6
OT	0.3	2.9	0.3	2.2	0.3	3.7
Nurse	1.3	3.7	1.0	2.7	1.6	4.7
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	2.6	2.0	3.0
Rehab Assistant Level 1	4.1	3.7	4.5
Temp	0.0	0.0	0.0

Next we fix the number of Nurses to be the current level, of 1.6 WTE. The results are in Table 5.17.

Table 5.17: Results after fixing the number of Nurses (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	3.5	1.1	2.4	1.3	4.6
OT	0.3	2.6	0.3	1.6	0.4	3.7
Nurse	1.6		-	-	-	-
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	2.6	2.0	3.0
Rehab Assistant Level 1	4.1	3.7	4.5
Temp	0.0	0.0	0.0

Next we fix the number of Occupational Therapists to be the current level, of 1.55 WTE. The results are in Table 5.18.

Table 5.18: Results after fixing the number of Occupational Therapists (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.3	2.3	1.1	1.1	3.4	3.4
OT	1.6		-	-	-	-
Nurse	1.6		-	-	-	-
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	2.6		2.0		3.0	
Rehab Assistant Level 1	4.1		3.7		4.5	
Temp	0.0		0.0		0.0	

Next we fix the number of Physiotherapists. The current level is supposed to be 3.19, however there has been a vacant position (1 WTE) for over a year, so our patient data will reflect this, so we fix the current number of Physiotherapists to be 2.19 WTE. The results are in Table 5.19.

Table 5.19: Results after fixing the number of Physiotherapists (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.2		-	-	-	-
OT	1.6		-	-	-	-
Nurse	1.6		-	-	-	-
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	2.6		1.5		3.0	
Rehab Assistant Level 1	4.1		3.7		4.5	
Temp	0.0		0.0		0.4	

Finally, we fix the number of Rehab Assistants Level 1 to be the current level, of 3.00 WTE. The results are in Table 5.20

Table 5.20: Results after fixing the number of Rehab Assistants Level 1 (Eastleigh)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.2		-	-	-	-
OT	1.6		-	-	-	-
Nurse	1.6		-	-	-	-
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.7		2.2		4.6	
Rehab Assistant Level 1	3.0		-		-	
Temp	0.0		0.0		0.4	

The current level of Rehab Assistants Level 2 is 5.4 WTE.

5.5.10 Validation results for Romsey

The results from the Linear Program for the Romsey rehab team are shown in Table 5.21 where in the average column, the min (max) column shows the average need when demand for that staff type is minimised (maximised). The corresponding ranges for the min and max are shown when demand is Low and High. For the professional staff, the minimum for each staff type corresponds to when the Linear Program was run with that staff type most expensive, and the maximum when that staff type was cheapest. The cost weightings for the Rehab Assistants were not varied so minima and maxima are not given.

Table 5.21: Results from the Linear Program (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.6	4.4	1.4	3.8	1.7	5.2
OT	0.3	3.3	0.3	2.8	0.3	4.1
Nurse	0.6	4.0	0.4	3.3	0.8	5.0
Mental Health Nurse	0.0	3.4	0.0	2.9	0.0	4.2
Social Worker	0.7	2.0	0.6	1.6	1.0	2.5
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.0		2.5		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.0	

To make the results more meaningful and to properly validate them, we now need to fix some of the variables and see the corresponding effect on the remaining staff types. We start by fixing the number of Mental Health Nurses to be 0.53, since this is the current provision in the Romsey team. Table 5.22 contains the results.

Table 5.22: Results after fixing the number of Mental Health Nurses (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.6	4.4	1.4	3.8	1.7	5.2
OT	0.3	3.3	0.3	2.8	0.3	4.1
Nurse	0.7	3.5	0.5	2.8	1.1	4.6
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7	2.0	0.6	1.6	1.0	2.5
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.0		2.5		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.0	

Next we fix the number of Social Workers to be the current level, of 0.69 WTE. Table 5.23 contains the results.

Table 5.23: Results after fixing the number of Social Workers (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.6	4.4	1.4	3.8	1.7	5.2
OT	0.3	3.3	0.3	2.7	0.4	4.1
Nurse	0.8	3.5	0.5	2.7	1.2	4.6
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.0		2.5		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.0	

Next we fix the number of Nurses to be the current level, of 1.86 WTE. Table 5.24 contains the results.

Table 5.24: Results after fixing the number of Nurses (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.6	3.4	1.4	2.5	1.7	4.7
OT	0.3	2.2	0.3	1.3	0.4	3.4
Nurse	1.9		-	-	-	-
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.0		2.5		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.1	

Next we fix the number of Occupational Therapists. The current level is supposed to be 2.08, however there has been a vacant position (0.5 WTE) for over a year, so our patient data will reflect this, so we fix the current number of Occupational Therapists to be 1.58 WTE. Table 5.25 contains the results.

Table 5.25: Results after fixing the number of Occupational Therapists (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.2	2.2	1.4	1.4	3.5	3.5
OT	1.6		-	-	-	-
Nurse	1.9		-	-	-	-
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.0		2.5		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.1	

Next we fix the number of Physiotherapists to be the current level of 2.61 WTE. Table 5.26 contains the results.

Table 5.26: Results after fixing the number of Physiotherapists (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.6		-	-	-	-
OT	1.6		-	-	-	-
Nurse	1.9		-	-	-	-
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	2.8		1.8		4.0	
Rehab Assistant Level 1	4.1		3.6		4.6	
Temp	0.0		0.0		0.4	

Finally, we fix the number of Rehab Assistants Level 2 to be the current level, of 3.72 WTE. Table 5.27 contains the results.

Table 5.27: Results after fixing the number of Rehab Assistants Level 2 (Romsey)

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.6		-	-	-	-
OT	1.6		-	-	-	-
Nurse	1.9		-	-	-	-
Mental Health Nurse	0.5		-	-	-	-
Social Worker	0.7		-	-	-	-
	Average Demand		Low Demand		High Demand	
Rehab Assistant Level 2	3.7		-		-	
Rehab Assistant Level 1	3.2		1.6		4.6	
Temp	0.0		0.0		0.6	

The current level of Rehab Assistants Level 1 is 2.67 WTE (But 1 WTE is vacant).

5.5.11 Validation observations

The results for both teams are accepted as being valid. Whilst the numbers do not exactly match the current team sizes, it is difficult, if not impossible to know what the true values should be. We do not know the extent to which positions within the team have been vacant throughout the years covered by the patient data. This may have influenced the number of patients who could be cared for. In terms of resources, people are different to beds. Beds need to be allocated to patients on a one-to-one basis, and it is difficult to increase the number of beds. People, however, are more flexible and will often work to demand, and do overtime where necessary. There is also the possibility of employing temporary staff in times of great need.

5.6 Experiment results

Various different scenarios were examined using the model, and the results are shown in this section. Only the results for the ranges are presented, which gives a general overview of the balance of the different staff. For the results to be more meaningful, they need to be worked through as in Sections 5.5.9 and 5.5.10, however this is not practical without knowing the current shape of the team as different configurations are possible and valid.

5.6.1 Adding a Mental Health Nurse to the Eastleigh team

The Eastleigh team, unlike the Romsey team, does not currently contain a Mental Health Nurse. We look at the effect that adding a Mental Health Nurse to the team would have on the composition of the rest of the team. Fixing the number of Mental Health Nurses to be 1 WTE gives the results in Table 5.28, which should be compared with the results in Table 5.15, when the number of Mental Health Nurses is zero. Adding a Mental Health Nurse has the biggest effect on the demand for the nurses in the team.

Table 5.28: Results when the number of Mental Health Nurses is one WTE

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	3.9	1.1	3.1	1.3	4.6
OT	0.3	3.0	0.2	2.4	0.3	3.7
Nurse	0.5	3.0	0.4	2.3	0.7	3.8
Mental Health Nurse	1.0		-	-	-	-
Social Worker	0.8	2.0	0.5	1.6	1.0	2.5

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	2.6	2.0	3.0
Rehab Assistant Level 1	4.1	3.7	4.5
Temp	0.0	0.0	0.0

5.6.2 Varying the direct care percentage

Much of the staff's working time is spent travelling to and from patients as well as doing paperwork, training and attending meetings. The staff are concerned about the time they actually spend in direct patient care. We looked at what effect changes in the percentage of time spent in Direct Care would have on the staffing numbers.

Table 5.29 shows the range given by the minimum and maximum for the average demand, for the Eastleigh team, for professional staff and Table 5.30 for junior staff.

Table 5.29: Professional staffing numbers when direct care percentages are varied

Direct Care Percentage	10	20	25	30	35	40
Physiotherapist	(2.4, 8.1)	(1.2, 4.0)	(1.0, 3.2)	(0.8, 2.7)	(0.7, 2.3)	(0.6,2.0)
Occupational Therapist	(0.5, 6.4)	(0.3, 3.2)	(0.2, 2.6)	(0.2, 2.1)	(0.2, 1.8)	(0.1,1.6)
Nurse	(1.1, 8.0)	(0.5, 4.0)	(0.4, 3.2)	(0.4, 2.7)	(0.3, 2.3)	(0.3,2.0)
Mental Health Nurse	(0.0, 6.9)	(0.0, 3.4)	(0.0, 2.8)	(0.0, 2.3)	(0.0, 2.0)	(0.0,1.7)
Social Worker	(1.6, 4.0)	(0.8, 2.0)	(0.6, 1.6)	(0.5, 1.3)	(0.4, 1.1)	(0.4,1.0)

Table 5.30: Junior staffing numbers when direct care percentages are varied

Direct Care Percentage	30	40	45	50	55	60
Rehab Assistant Level 2	3.5	2.6	2.3	2.1	1.9	1.8
Rehab Assistant Level 1	5.4	4.1	3.6	3.2	3.0	2.7

5.6.3 Varying the annual number of patients

With an increasing population who could benefit from Intermediate Care, the number of patients cared for by the teams is likely to increase from year to year, but how should the team composition respond? We looked at the effect that changes in the annual number of patients would have on the staffing numbers whilst keeping the direct care percentage at 20% for professional staff and 40% for junior staff. We ran two scenarios, one where the number of Orthopaedic patients doubled, and one where the number of all patients increased by 50%. Table 5.31 contains the results, with the ranges given by the minimum and maximum, for the average demand.

Table 5.31: Results when varying the annual number of patients

Staff Type	Current	Orthopaedic numbers increased by 100%	All patient Numbers increased by 50%
Physiotherapist	(1.2, 4.0)	(1.3, 4.3)	(1.7, 5.7)
Occupational Therapist	(0.3, 3.2)	(0.3, 3.3)	(0.4, 4.5)
Nurse	(0.5, 4.0)	(0.6, 4.1)	(0.9, 5.7)
Mental Health Nurse	(0.0, 3.4)	(0.0, 3.5)	(0.0, 4.8)
Social Worker	(0.8, 2.0)	(0.9, 2.1)	(1.1, 2.7)
Rehab Assistant Level 2	2.6	2.8	3.7
Rehab Assistant Level 1	4.1	4.3	6.0

5.6.4 Varying Intervention abilities

For this scenario, keeping the direct care percentage at 20% for professional staff and 40% for junior staff, and keeping the annual patient numbers constant, staff competencies for some of the intervention abilities were changed. We choose which intervention competencies to change, based on the popular interventions from Table C.6. We chose to change only Generic level skills, and only interventions from the sub sets of Assistance and Practice (since the interventions in the Assessment sub set may have more accountability issues which affect who can do them than the others). The intervention competencies, (at Generic level) which we added were:

- Care Provision: Physio, OT, Nurse, Mental Health Nurse, Social Worker and RA Level 2;
- Falls Advice/Safety monitoring: RA Level 1;
- Monitoring and advice on meds: Physio, OT and RA Level 2;
- Practice with exercises: RA Levels 2 and 1;
- Safe use/advice of walking aids: RA Level 1;
- Transfer Practice: RA Level 2;
- Wound Care: Physio, OT, Mental Health Nurse.

Table 5.32 contains the results.

Table 5.32: Results when changing the intervention abilities

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	3.0	1.1	2.6	1.3	3.5
OT	0.3	2.2	0.2	1.8	0.3	2.7
Nurse	0.5	2.6	0.4	2.0	0.9	3.2
Mental Health Nurse	0.0	1.9	0.0	0.9	0.0	1.5
Social Worker	0.8	2.0	0.5	1.6	1.0	2.5

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	1.9	1.6	2.2
Rehab Assistant Level 1	5.7	5.0	6.5
Temp	0.0	0.0	0.0

5.6.5 Using the MLE Gamma estimates for Intervention times

The results were rerun for the Eastleigh team, this time sampling intervention times from the gamma distributions fitted using the MLE method, as described in Section B. Table 5.33 contains the initial results.

Table 5.33: Results with intervention times modelled using Gamma distributions

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	1.2	3.2	0.9	2.4	1.4	4.0
OT	0.4	2.4	0.3	1.9	0.4	3.1
Nurse	0.3	2.6	0.2	1.9	0.4	3.4
Mental Health Nurse	0.0	2.3	0.0	1.7	0.0	3.0
Social Worker	0.6	1.8	0.5	1.4	0.6	2.1

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	1.7	1.3	2.2
Rehab Assistant Level 1	2.9	2.5	3.3
Temp	0.0	0.0	0.0

The most marked difference seen in these results is in the number of Rehab Assistants which are about one WTE lower for both Level 1s and Level 2s compared with the results in Table 5.14. Fixing the number of professionals to be the same as in the current Eastleigh team, gives the results in Table 5.34.

Table 5.34: Results after fixing the numbers of all the professional staff, with intervention times modelled using Gamma distributions

Staff Type	Average Demand		Low Demand		High Demand	
	Min	Max	Min	Max	Min	Max
Physio	2.2		-	-	-	-
OT	1.6		-	-	-	-
Nurse	1.6		-	-	-	-
Mental Health Nurse	0.0		-	-	-	-
Social Worker	1.1		-	-	-	-

	Average Demand	Low Demand	High Demand
Rehab Assistant Level 2	1.0	0.1	2.0
Rehab Assistant Level 1	2.9	2.5	3.3
Temp	0.0	0.0	0.0

The number of Rehab Assistants is noticeably smaller than for the equivalent results in Section 5.5.9 (An average of 2.6 Level 2s and 4.1 Level 1s). When we showed these to the Intermediate Care staff, they felt that the results in Section 5.5.9 'felt right', whereas these results did not. When comparing the results from each method with the current teams, the results in Section 5.5.9 are much more comparable than those in Table 5.34. Whilst acknowledging that there is inaccuracy in the intervention times, we conclude that making the assumption that the time for a visit can be divided up equally between the interventions which took place in that visit, and then fitting triangular distributions to the resulting sets of data is an acceptable, and the best, method.

5.7 Conclusions

The Intermediate Care staff were pleased with the project and felt that the results seemed intuitively right. They had suspected that many of the interventions performed by the staff did not require the specialist skills of the professional staff, and the statistical analysis alone demonstrates this. In particular:

- Interventions are required, on average, at the Generic level for 86.4% of instances, (this will vary by individual intervention).
- Taking into account intervention time, over 80% of the total time spent by staff carrying out interventions, is spent doing Generic interventions.
- Using the current definitions of staff competences by intervention, and taking into account intervention times, a Rehab Assistant Level 2 can carry out over 60% of the intervention minutes needed.

The model allows different combinations to be experimented with to look at the resulting team composition. For example, the Eastleigh team could contain as few as 1.5 Physios or as many as 4.4 Physios, with the professions represented by the other team members adjusted accordingly. Similar results can be established for the other professions. This can prove particularly valuable if the team is having difficulty recruiting, for example a Physio (in the example of the Eastleigh team, since this has been vacant for some time) or an OT (in the example of the Romsey team, since this has been vacant for some time) because they can see what alternative staff combinations are possible, so long as the minimum demand for each staff type is met.

A new role in Intermediate Care, the Assistant Practitioner, is currently on the drawing board, and the impact of this role on a rehab team could be analysed in advance by adapting this model. Also of interest is the difference between the theoretical competencies shown in Table 5.8, and what happens in real life which is illustrated in Table C.6. For example, the staff suggested that only nurses are able to carry out the intervention "Drug history and Compliance". However in the database, it is provided by Physiotherapists in 66% of occurrences.

5.8 Summary

This chapter has shown how Monte Carlo simulation and repeated instances of a linear program can be combined to give an effective tool for evaluating staffing combinations in an Intermediate Care rehab team, given patient demand for interventions which require a varied skill set.

The model, and accompanying analysis has provided valuable quantitative results which could only previously be guessed at using 'gut' feelings about the way the rehab teams work. These results can be used to change and improve their ways of working. The results suggest that there is much flexibility in the staffing make up of the rehab team. This is primarily because there are many more interventions which require skills which are common to all, or most, team members, rather than being specific to a particular profession. The analysis has also highlighted differences between the theoretical skills of the team members and what happens in reality.

Chapter 6

Conclusions

6.1 Introduction

In this chapter, each of Chapters 2, 3, 4 and 5 is summarised in turn, looking at the methodology that was used, conclusions that were drawn and the potential for future work. This is followed by a look at the overall conclusions that can be drawn, both in terms of the methodologies used, and the different healthcare settings. The chapter concludes with a list of conference papers where elements of the work have been presented.

6.2 Literature Review

There is a large literature on healthcare modelling, but relatively few published studies on healthcare workforce planning. This literature was discussed in Chapter 2 and some common underlying themes were identified. As discussed in section 2.4.3, a prevailing need for compromise was evident:

- A compromise between making no simplifying assumptions, and making too many.
- A compromise between modelling the whole system and a small part of it.
- A compromise between creating the best possible model and creating something of practical use.

Additional to the need for compromise, this section discussed the importance of being aware data limitations and availability, as well as the limitations of the model.

The literature contains several examples of successful applications of OR techniques to healthcare settings. Within this, the examples which have considered the workforce have mostly considered the problem concerning the scheduling (or rostering) of nurses. The few examples that have considered nursing workforce planning have used simplistic methods and have not examined in particular the level of detail that is required in order to take into account the inherent variability in patient demand. Hurst (2002a) discussed five methods that are used for nursing workforce planning in practice. These methods are not identical to the examples in the literature where OR techniques have been applied to the problem. The work in chapter 3 sought, in many ways, to join up the practices and thinking of healthcare professionals with relevant OR methodologies for the purpose of planning the nursing workforce in an acute hospital.

Within the literature, the need to take into account the variation in patient demand is apparent, as evidenced by the many examples of stochastic techniques such as simulation. Competing with this is the need to provide managers with a decisive answer and hence the appeal (and array of examples) of optimization techniques which are deterministic in nature. Whilst the benefits of individual approaches are shown, no evidence was found in the literature to suggest that anyone has tried combining approaches for the problem of nursing workforce planning. This thesis has successfully interfaced simulation and linear programming in two instances with the result, in both cases, of extra benefit to that of using each technique alone.

Intermediate Care is a relatively new area (or way of working) within the health service which has been identified as a key area within The NHS Plan, published by the Department of Health (2000b). Intermediate Care differs from acute hospital care mainly in the location of where care is provided - i.e. in a patient's home, or at a Day Hospital as well as in a bedded (but non-acute) ward. However, it also differs in terms of the change in emphasis of the staff involved (e.g. more therapists and fewer doctors) since the patients are sufficiently stable from a medical perspective that the main focus is on rehabilitation, rather than improving medical health.

As a result of its newness, there are many recent examples of Randomised Controlled Trials and other methods of appraisal in this area as the health service seeks to evaluate the services. However, there are few examples of OR being applied to Intermediate Care services and within that, no substantial quantitative results and no evidence of any modelling of workforce planning in the literature. Two of the projects presented in this thesis considered problems in Intermediate Care, with one considering workforce planning in detail and both giving valuable quantitative results.

6.3 Hospital Inpatient workforce

This summarises the work presented in Chapter 3.

6.3.1 Methodology

A Discrete Event Simulation (DES) model was used to look at the level of complexity required when planning nursing requirements in an inpatient setting. Two levels of complexity were examined: that of comparing two methods for calculating workforce need, and the other of looking at the benefits of dividing the patients into homogeneous groups. In each case, the nursing need (and associated skill mix) was modelled on a daily basis. The second part of this research combined this DES model with a stochastic program to calculate the optimal number of nurses to employ. The demand (in terms of nursing need, by skill mix and by day) was fed into the stochastic program which seeks to minimise cost, whilst satisfying demand and allowing nurses of a higher competency to carry out work requiring a lower competency nurse, but not *vice versa*. Any demand that is unmet by the permanent staff is met by temporary staff. Experiments were run to examine the effect that varying the relative efficiency of the temporary staff had on the optimal number of permanent staff.

6.3.2 Achievement of objectives

A Discrete Event Simulation model was built to model the nursing need in an inpatient speciality. A comparison of the Acuity-Quality and Occupied Bed methods of calculating workforce need suggested that when planning at an overall level, there is little difference between the numbers given by each method. However, when planning at a more detailed level (e.g. by month, by skill mix) then the Acuity-Quality method is better able to pick up the variability and subtlety due to seasonality and/or case-mix and/or other local issues.

Similar conclusions were reached about the number of patient groups needed. When planning at an overall level, a small number of patient groups (or just one) is sufficient. However, when planning at a more detailed level, using more groups allows the variability and/or seasonality of the different types of patients to be picked up. As always, it should be borne in mind that the experiments involving greater levels of detail are more time intensive and a balance should be sought between the time available and the level of detail required.

Also of interest is the consideration that the results given by the methods in this thesis, which employed a bottom-up approach to define the nursing ratios, suggested a different skill-mix to the results given when using the methods in Hurst (2002a,b), which employed a top-down approach to define the nursing ratios. This suggests that perhaps the current nursing skill mix is more 'top heavy' than it needs to be for reasons of nurse competency. The results in this thesis do not take into account accountability which will lie more heavily with the higher qualified nurses.

The stochastic program was used to evaluate the optimal number of nurses, and the associated skill-mix, to employ on a permanent basis, whilst satisfying the nursing need (by day and type of nurse) given by the DES model. The results suggested that the optimal number of permanent nurses to employ, when taking the need for temporary staff into account, is greater than that given by the average results from the simulation (in the case of the Orthopaedics speciality presented, around 12% when using the Acuity-Quality method, and 7% when using the Occupied Bed method). Further experiments suggested that this depends on the efficiency of the temporary nurses, and that a decrease in efficiency of the temporary nurses by 10% roughly increases the optimal number of permanent nurses to employ by two.

Combining the stochastic program with the DES was found to be an effective way to evaluate the optimal number of permanent nurses to employ. The stochastic program allowed relative costs of the different nurses to be considered which would not have been possible simply through repeated iterations of the DES.

The results of the comparison between the Acuity-Quality and Occupied Bed methods, and the different numbers of groups were used to support the development of Prompt. The results concerning the stochastic program were not finalised in time to influence Prompt, however the stochastic program (or a heuristic equivalent - see Section 6.3.3 below) could be incorporated in a future version.

6.3.3 Future work

There are many ways in which the work in Chapter 3 could be extended. The comparison of workforce methods, using the DES model could be extended to include the other three methods, as described by Hurst (2002a). The stochastic program could be extended to include staff on short-term contracts and overtime (although this could be thought of as being a further subset of the temporary nurses). Attempts could be made to incorporate the stochastic program into a more user-friendly model which could be given to the hospital to use. It may be possible to replace the stochastic program with a heuristic which may have a shorter run time and/or require less specialist software.

Another way to extend the stochastic program would be to look at other variables besides cost in the objective function. For example, job satisfaction could be decreased if nurses are frequently expected to do jobs for which they are over-qualified. It may be that nurses are able to work 'harder' for short periods of time as demand dictates and it may be possible to create some kind of elasticity within the model to allow for this, along with a balancing variable to account for levels of stress that this kind of work would induce. The difficult part for much of this modelling would be in quantifying the variables.

It would be interesting to include other types of workforce in the model, for example doctors and staff from the Allied Health Professions. This was discussed in passing with the staff at Royal Berkshire and Battle Hospitals (RBBH) Trust, and it was felt that a different approach would be needed. For example, the relationship between numbers of doctors and numbers of patients is not as well-defined as it is for the relationship between nurses and patients.

The model could be expanded to model the whole hospital including interactions between the different specialities including outpatients and Emergency Departments. Experience gained when collecting the data suggests that this is not a trivial matter, as even within one hospital the same modelling methods are not always appropriate for the different specialities. There is also the problem of keeping a model within a manageable size and/or dividing it into suitable modules, whilst still allowing the interactions between modules.

6.4 Reprovision of Intermediate Care services

This summarises the work presented in Chapter 4.

6.4.1 Methodology

A Discrete Event Simulation model was built to model local Intermediate Care services, with a view to helping capacity decisions within the process of reprovision of the current services. Several scenarios were run; these illustrated that capacity is very much dependent on the types of patients, as well as where they are cared for, within those services. Data collection provided a valuable part of the process, not only for practical purposes of building the simulation model, but also as a way of understanding how the reprovided system should look. As a particular example, the process of carrying out the audits, defining the levels and discussions concerning the distinctions between patients helped the Intermediate Care staff to identify and evaluate the difference between providing a realistic, improved service and a more ambitious 'gold' service.

6.4.2 Achievement of objectives

The results from this work informed the service model group on a way forward to plan the proposed Intermediate Care facilities. There was much political sensitivity to the closure of the Mount Hospital and it attracted much local press. The benefit of this study is that it provided the service model group with quantitative predictions on beds and workforce capacities under various possible future provisions of service. The results were presented at public meetings, and the steering group are themselves using our findings to help form policy.

A Discrete Event Simulation model of the current Intermediate Care provision was successfully built and validated against current patient numbers. Adapting this model to evaluate the consequences of providing the Intermediate Care services in a new way relied heavily on assumptions about the proposed services since there was no other way to obtain the necessary data. This model of the proposed services provided an easy analysis of the difference in provision needed to provide care to the current set of patients, compared with providing the services to an increased set of patients for whom care is not currently provided. In this way, not only understanding of how the current system operates, but also of how the proposed system would operate, was increased.

The work in this chapter is necessarily less substantial than in Chapters 3 and 5 since the timescale did not permit a more comprehensive study. There is also less of a focus on workforce and more on general capacity in this chapter. This is partly because of the timescales and partly because workforce was not seen as a priority for the service model group - bed numbers would dictate the size of any buildings in the reprovided system whereas the workforce numbers were seen as more flexible. For both Day Hospital and inpatient provision, the staff were happy to workforce plan in ways in which they were familiar once the number of patients was known. Because of the timing and numbers involved, there was seen to be no benefit to do this within the model. For the one area of provision where more detailed workforce planning might have been most needed, there was no appropriate data available, as well as an awareness that the work with the Intermediate Care Futures project reported in Chapter 5, would supersede any work done in this area.

6.4.3 Future work

The work in Chapter 4 was very much done to a set timescale. Although the work done to date has made big steps in structuring the problem and producing a useful model, given more time a more detailed data collection and audit of the patients might allow a more refined model of the services provided at the Mount Hospital to be evolved. Since this work was very much about predicting the use of new services, once these new services are in place the actual services could be compared to the predicted services. Another angle which may be useful to explore is the possibility of exploring whether the DES model built of the Mount Hospital can be generalised to other Intermediate Care settings.

6.5 Intermediate Care workforce

This summarises the work presented in Chapter 5.

6.5.1 Methodology

A Monte Carlo simulation and repeated instances of a linear program were interfaced to create an effective tool for evaluating staffing combinations in an Intermediate Care Rehab team, given patient demand for interventions which require a varied skill set. The Monte Carlo simulation allowed interquartile ranges for the demand, in intervention minutes, to be calculated for each intervention, by sampling both the annual number of patients, and the time for each intervention from fitted triangular distributions. Competencies, as defined by the Intermediate Care Staff for the different members of the workforce were then combined with the demand for each intervention to establish a demand for each staffing combination (since the competencies of the workforce overlap for some, but not all interventions).

The demand for the different staffing combinations feeds into the linear program which seeks to minimize the 'cost' of the workforce whilst ensuring that the demand for each staffing combination is met. Several instances of the linear program were run. Three levels of demand were evaluated; the median and the first and third quartiles. Each instance contained different costs for the professional staff in such a way that the maximum and minimum need for each staff type can be established for each of the three levels of demand, (since for example, when the cost for Physios is highest, this will give the minimum number of Physios needed). The costs for the Rehab Assistants remain less than that for the professional staff, and the temporary worker remains the most expensive option.

The numbers for each staff type are dependent on the numbers for the other staff types. Therefore, a facility is provided to fix the number of one (or more) staff types and to rerun the linear programs to see the effect that this has on the other staff types.

Both the Monte Carlo simulation and the Linear Program were implemented in the same Microsoft Excel workbook so as to enable the model to be run without the need for specialist software. The Monte Carlo simulation made use of the standard random number generator and the inverse transform method. The linear program used the Excel add-in, Solver.

6.5.2 Achievement of objectives

The Intermediate Care staff were pleased with the project and felt that the results seemed intuitively right. They had suspected that many of the interventions performed by the staff did not require the specialist skills of the professional staff, and the statistical analysis alone demonstrates this. In particular:

- Interventions are required, on average, at the Generic level for 86.4% of instances (this will vary by individual intervention).
- Taking into account intervention time, over 80% of the total time spent by staff carrying out interventions, is spent doing Generic interventions.
- Using the current definitions of staff competencies by intervention, and taking into account intervention times, A Rehab Assistant Level 2 can carry out over 60% of the intervention minutes needed.

A list of common interventions was created, and from this the set of common skills required by all staff can be determined, in order to optimize contact time with patients.

Several inputs for the model can be changed to allow evaluation of different future services. For example, the total number of patients and/or the distribution of patients amongst the different patient groups can be altered and associated workforce requirements calculated.

The results from the model suggest that there is flexibility in the staffing composition within the Rehab team. This is primarily because there are many more interventions which require skills which are common to all, or most, team members, rather than being specific to a particular profession. The analysis behind the model has also highlighted differences between the theoretical skills of the team members and what happens in reality. The model suggests ranges for the number of each type of workforce. For example, the Eastleigh team could contain as few as 1.5, or as many as 4.4 Physios, depending on how many members of the other professions are in the team. The model allows the number of one (or more) types of workforce to be fixed, and the corresponding effect on the other workforce types to be evaluated.

6.5.3 Future work

It was necessary to make several assumptions (in particular, about the time spent on each intervention) in order to build the model. Implementation of a detailed data collection in order to better inform the model, would avoid some of these assumptions having to be made and would hopefully therefore create a better model. This would not be a trivial task. Better, and more data could generally improve the model.

It may be possible to replace the repeated use of a linear program with a heuristic which would better allow the possibility of extending and enlarging the model since it would not be restricted by the problem sizes which Solver can solve.

There is the potential to build a similar model to inform workforce planning in a different healthcare setting. Or perhaps for the same healthcare professionals within an inpatient setting.

6.6 Overview

The three projects presented in this chapter have illustrated the use of different OR techniques for modelling different healthcare situations. Different solution methods were needed because slightly different questions were posed by the different projects, however there was also some commonality present and similarity between approaches taken.

6.6.1 Methodology

There are two fundamental approaches to solving real life problems using OR techniques. One way is to start with a technique and then to find real life problems with appropriate specifications. The other way is to start with the real life problem and then to decide on the most appropriate technique(s) to solve it as best you can. This thesis has taken the latter approach.

Three real life problems have been presented, and solutions have been found using a variety of techniques: Monte Carlo simulation, Discrete Event Simulation, Linear Programming and Stochastic Programming. Each of the problems focussed on a different, but related aspect of healthcare workforce planning. One project (Chapter 4) looked at the capacity (in terms of beds and workforce) for Intermediate Care services. The other two projects (Chapters 3 and 5) considered the problem of optimizing the number of workforce to employ, one within an inpatient speciality and the other within an Intermediate Care rehab team.

Healthcare is an intrinsically difficult area to model due to the inherent variability present as a result of the many different illnesses and conditions that patients may have, as well as the many different treatment options which are possible. Thus it is of no surprise that simulation, which allows the use of stochastic parameters as inputs, was an appropriate technique in each of the three projects. Simulation was used to model the patients and their associated workforce (and bed) needs.

For the two projects considering the problem of optimizing the number of workforce to employ, mathematical programming presented itself as an appropriate solution, however this is more typically a deterministic technique. Combining the outputs from the simulation with, in one case stochastic programming, and in the other, repeated instances of a linear program, allowed advantage to be taken of the attractive points of each type of technique: the ability of simulation to model variability, and the ability of mathematical programming to find an optimal solution.

Workforce need in each project was calculated using a bottom-up approach. This required more effort than perhaps a top-down approach would have done, and in the one case where a comparison was possible (Chapter 3) the resulting skill mix was considerably different. A bottom-up approach offers the advantage over a top-down approach of being less subjective to current practice. That is to say that the bottom-up approach is less biased towards the view that a particular type of nurse should carry out a task because they always have done, rather than because they possess the necessary skills.

6.6.2 Achievement of objectives

Overall, each of the projects has given valuable information to the healthcare staff concerned which in itself demonstrates the usefulness and effectiveness of the methodologies used. As well as this, overall conclusions are given below.

6.6.2.1 Comparison of modelling workforce planning in two different healthcare settings

Two different healthcare settings were considered by the three projects. The first looked at the inpatient setting, with the other two looking at Intermediate Care. In the inpatient setting, five established methods, based on expert opinion and averages, for nursing workforce planning exist, as described by Hurst (2002a), however in the Intermediate Care setting there are no such established and documented methods. Thus workforce planning is largely carried out using expert opinion and planning methods based on averages, suggesting an opportunity for the provision of more sophisticated workforce planning in all healthcare settings.

As with any problem, it is important in each setting to have an understanding of the issues and influences connected with the problem. It is also important to work with the model users to ascertain their needs, to validate necessary assumptions and also so that they understand the limitations of any results.

When modelling, the level of detail required depends on what the aim is and how the results will be used. This is particularly illustrated in Chapter 3 with the comparison between the different methods and different sizes of patient groups.

In each project, a bottom-up approach was taken, looking first at the patients and their presenting needs, before converting this into workforce (and bed, in the case of Chapter 4) numbers. This approach was found to work well in each setting since it reduced the levels of bias that may be inherently present in a top-down approach, whilst at the same time being transparent in method. In each case the results challenge the current practice (often derived from a top-down approach), but seem intuitively right to the healthcare professionals.

In Chapters 3 and 5, patient demand was used to model direct patient care (i.e. time spent with the patient) which was then converted into Whole Time Equivalents (WTEs) by adding in indirect and human resources factors (which differed according to the setting). This method was found to be equally successful in each case since the healthcare staff found it easy to either provide data or to make assumptions about the time spent in each type of care.

One area where the different settings differed was in the consideration of skill-mix. In the inpatient setting, the different types of nurses have a hierarchical set of competencies whereby a nurse of a higher competency level can carry out all jobs which only require a nurse of a lower competency level. However in the Intermediate Care setting, whilst the different types of workforce did have some overlapping competencies, the common core was very small. This had the implication that it was better, in the Intermediate Care setting, to go down to the level of the individual interventions that the patients required, whereas in the inpatient setting, this was not so necessary since the hierarchical competencies made the nurse-to-patient ratios easier to define.

6.6.2.2 Exploration of which OR techniques are suitable for different healthcare planning problems

The literature review revealed a wide range of OR techniques applied to various healthcare settings. The models which appear to have had the most impact and to be of the most practical use are those which have been built around the problem. These are often the simpler models. Several OR models have been built to investigate various aspects of the inpatient setting, but none have looked in detail at the issue of nursing workforce planning. The Intermediate Care setting looks much bleaker in terms of OR models with only two models in evidence – both offering valuable qualitative results but minimal quantitative analysis.

The literature illustrated the need to incorporate the inherent variability in patient need in any modelling and this has been taken on board with simulation being applied to each of the projects since this allows stochastic parameters as inputs. This need to embrace the variability is coupled with a need to provide a distinct result as ultimately managers need to decide, for example, how many staff to employ. Simulation is unable to provide this distinct result other than in the form of an average and associated confidence intervals. Therefore optimization was seen as an appropriate tool since this does produce a distinct result.

The models presented in Chapters 3 and 5 interfaced simulation with mathematical programming to take advantage of the stochastic nature of simulation and the deterministic nature of mathematical programming. Although implemented for different reasons, and in different ways, this was found to be successful in both cases and an improvement over the simulation by itself. In both chapters, simulation was used to model patient demand and the resulting workforce need. In Chapter 3, the optimization took into account the relative costs of permanent and temporary staff, with the result that the optimal number of staff to employ is greater than the average need. In Chapter 5, the optimization assisted with interpretation of the simulation results which by themselves suggested many possible feasible solutions.

The appropriateness or not of a particular OR technique to solving a problem depends on what sort of results are required, the intended user and uses, the timescale of the project and the available software. For example, producing results with a confidence interval is of no use if the user actually wants to know how many staff to employ and therefore wants just a 'single number' as a result. Similarly, producing a complicated model requiring specialist software is fine so long as the modeller is producing the results, however this cannot then be easily given to the healthcare staff as they will not have the necessary knowledge to use the model successfully (and may not even have access to the software).

The three modelling tools developed in this thesis each had a different ultimate use.

The first model, in Chapter 3, was used to support the development of the workforce planning aspect of Prompt. The second model, in Chapter 4, was used to support a one-off project. The third model, in Chapter 5, was built with the aim of becoming a usable model by healthcare professionals. The software used in building the different models depended on their ultimate purpose. The first two models were built using specialist software since they were not intended for use by non-specialists. Note that Prompt, which was intended for use by non-specialists, was built as a stand-alone piece of software with particular emphasis on a user-friendly interface. The third model was built using Excel since it was intended for use by non-specialists and Excel is a readily available package, which is familiar, at least at a basic level, to most computer literate people.

Planning at the strategic level requires a different approach to planning at the operational level. For example, Discrete Event Simulation was an appropriate technique to use for the projects in Chapters 3 and 4 since these projects were concerned with the operational level, whereas Monte Carlo Simulation was appropriate for the project in Chapter 5 since this project was at a more strategic level, not requiring the everyday detail that is found in DES modelling.

6.6.2.3 Reflections

As well as conclusions already mentioned above that can be drawn from modelling healthcare workforce planning in the different settings, it is worth reflecting on the experience of the three different projects. For each project, building direct links with the healthcare personnel, through both formal and semi-formal meetings improved understanding of the problem area at an early stage, thus enabling more effective communication. It was also important not to become complacent about knowledge of the area as some of the underlying issues and politics only became apparent later on. Having a direct line of communication reduced the possibilities of misunderstandings through a third party's interpretation.

In each setting it was useful to observe the healthcare staff interpreting the results that were presented to them. In the Mount Reprovision project, these observations suggested improvements to the presentation of the results as the staff were keen to see the exact route of all calculations. In the inpatients project, these observations brought about the desire to interface an optimization technique with the simulation. Discussing the problem and the model with the healthcare staff, and working with them throughout its development, ensured that the model was appropriate for the problem. The laptop provided to me by the School of Mathematics was invaluable for enabling these discussions, as it allowed the model to be taken to the healthcare staff. At the start of the PhD in particular, but also throughout its duration, working with and discussing the work with other OR modellers was also an important learning process.

Working on the different projects in the different settings allowed me to gain a better overview of general workforce planning issues in healthcare than would have been possible with just one in-depth study. Whilst the project in Chapter 4 does not fit so neatly within the overall theme of workforce planning (since it was not possible, nor necessary to do as detailed workforce planning) as in the other two projects, this project was nonetheless valuable. Carrying out this project provided a valuable insight into the Intermediate Care setting and also provided an opportunity to work with some of the staff who were additionally involved in the Intermediate Care Futures Project (Chapter 5). This made the later project easier because a level of trust and recognition had already been formed. The Mount Reprovision project covered a wider range of Intermediate Care than did the Intermediate Care Futures Project, thus allowing a more general overview to be gained before focusing on a more detailed area. The idea of carrying out a smaller project in a new area is therefore something that I would recommend before carrying out a more detailed and longer-term project in that same new area.

Completing the projects in this thesis and finding solutions to real-life problems was a very satisfying process. Extrapolating beyond standard textbook usage of techniques was an exciting and demanding, but also rewarding, experience. The three projects had their similarities but they also had their differences to give an extra bit of interest and stimulation.

6.6.3 Future work

Issues surrounding the planning of the healthcare workforce are not unique to the UK, as the literature, papers at conferences and a visit to the Department of Mechanical and Industrial Engineering at the University of Toronto confirm. Aside from examining the possibilities of generalising the models presented in this thesis to other similar healthcare situations within the UK, another possibly useful research angle would be to see how generalisable they could be to healthcare practice in other countries. It could be anticipated that the success of this would depend on the level of similarity of styles of healthcare provision of the other countries with the UK.

The models presented in this thesis address the planning of the healthcare workforce in an inpatient setting and in Intermediate Care. As has already been discussed (Section 6.3.3) the inpatient model could be extended to include the whole hospital. As a further extension, an overarching model could be created to model the interactions between a whole healthcare region. This would probably require the need for some kind of System Dynamics tool since this considers groups of patients, rather than individuals as in Discrete Event Simulation. System Dynamics would be unable to model the level of detail needed for specific parts of the model and thus the possibilities of combining this with a DES model for the lower levels of detail would need to be investigated. As in this thesis, mathematical programming could be used in conjunction with the DES models (and even maybe the System Dynamics model) to optimize resource usage as appropriate.

6.7 Conference presentations

Throughout the PhD, I have been able to present and discuss aspects of my research with both domestic and international researchers in the field, on a variety of occasions, as listed below.

- The EURO/Informs joint meeting. Istanbul, 7-11 July 2003. *Joint presentation with Paul Harper.*

- The OR Society Simulation Study Group Workshop, Birmingham, 23-24 March 2004. *Poster presentation.*

- UK Simulation Conference, Oxford, 29-31 March 2004. *Presentation and paper in the proceedings:* Powell N.H. & Harper P. R., (2004) Workforce Modelling in Healthcare. in *Proc. UKSIM 2004 (Oxford, UK, April 2004)* Pp 66-69.

- The EURO Working Group of OR applied to Health Services, Stockholm, 27 June - 2 July 2004. *Presentation and paper in the proceedings:* Powell N.H. & Harper P. R., (to appear) Modelling for the Reprovision and Redesign of Intermediate Care services in the UK - a local example. in *Proc. ORAHS 2004 (Stockholm, Sweden, June 2004)*

- Young OR Conference, Bath, 4-6th April 2005. *Presentation.*

- Canada OR Society Conference, Halifax, Canada, 16-18 May 2005. *Presentation.*

- Department of Mechanical and Industrial Engineering, University of Toronto, Canada, 24-27 May 2005. *Seminar and 4 day visit to the department.*

- The EURO Working Group of OR applied to Health Services, Southampton, 31 July - 5 August 2005. *Presentation.*

Appendix A

Optimization Lemma

Consider a Linear Program written in standard form. Multiplying the right hand side of each of the constraints by a positive constant is equivalent to multiplying the objective function by the same constant.

Proof

Consider the standard form of the Linear Program:

$$\begin{aligned} \text{minimise } z &= \mathbf{c}^T\mathbf{x} \\ \text{subject to } A\mathbf{x} &\geq \mathbf{b} \\ \mathbf{x} &\geq 0 \end{aligned} \tag{A.1}$$

where the $m \times n$ matrix A and the vectors $\mathbf{c} \in \Re^n$ and $\mathbf{b} \in \Re^m$ are given constants, $\mathbf{x} \in \Re^n$ is a vector of variables to be determined and z is the value of the objective function.

Let $\mathbf{x}^*$ be an optimal solution to this.

Now consider the Linear Program

$$\begin{aligned} \text{minimise } z &= \mathbf{c}^T\mathbf{x} \\ \text{subject to } A\mathbf{x} &\geq d\mathbf{b} \\ \mathbf{x} &\geq 0 \end{aligned} \tag{A.2}$$

where $A, \mathbf{b}, \mathbf{c}, \mathbf{x}, z$ are as in A.1 and d is a positive constant.

Let $\mathbf{x}' = \frac{1}{d}\mathbf{x}$. This allows A.2 to be rewritten as follows:

$$\begin{aligned} \text{minimise } z &= \mathbf{c}^T d\mathbf{x}' \\ \text{subject to } A d\mathbf{x}' &\geq d\mathbf{b} \\ d\mathbf{x}' &\geq 0 \end{aligned} \tag{A.3}$$

which, since d is positive, simplifies to:

$$\begin{aligned} \text{minimise } z &= \mathbf{c}^T \mathbf{x}' \\ \text{subject to } A\mathbf{x}' &\geq \mathbf{b} \\ \mathbf{x}' &\geq 0 \end{aligned} \tag{A.4}$$

which has an optimal solution when $\mathbf{x}' = \mathbf{x}^*$.

Therefore the optimal value of A.2 is $z = \mathbf{c}^T d\mathbf{x}^*$.

Appendix B

Different Methods for Estimating the Intervention Times

The time for each visit is known, and the interventions which were carried out in each visit are known, however the time spent on each intervention is not known. This Appendix discusses the various methods which have been tried for estimating the time for each intervention. The assumption is made that the time to carry out an intervention does not depend on the member of staff doing the intervention. It is important to remember that:

- The times for each visit are shown to the nearest 15 minutes, with 15 minutes being the smallest recorded time interval.
- The time to carry out an intervention with one patient may be different to that with another patient.

As a data source, a subset of 1004 visits from the database for both Eastleigh and Romsey teams is used. These visits include nearly all the interventions (100 out of 123), and are thought to be a representative sample.

Dividing the time equally between Interventions in a visit and fitting a Triangular Distribution to the resulting data

This method involves creating a set of data points for each intervention, and then fitting a distribution to each set of data points.

In order to create the set of data points, we make the assumption that the time for each visit was distributed evenly between the interventions, thus if a visit took 30 minutes, and 3 interventions were carried out, then each intervention would take 10 minutes [1] .

Once you have the set of data points, a distribution needs to be fitted to them. Through general discussion, we established that the time for an intervention will, like most healthcare data, be asymmetric. Thus we cannot fit symmetric distributions such as the normal or uniform. In the model, we chose to fit the triangular distribution because of its simplicity in use, and in comprehension, by non-specialists. The parameters for the triangular distribution are the mode, minimum and maximum. Note that the mode can be evaluated from the mean, minimum and maximum. This is useful since it makes more sense to get the mean from our data, rather than the mode. More details about the triangular distribution can be found in Appendix D.

ANOVA (Least Squares Estimation)

This method uses the method of least squares, which seeks to find estimates for the vector $\mathbf{b}$ (in this case, $\mathbf{b}_i$ is the time for intervention i) by minimising the sum of

[1] An iterative process was tried for which the first iteration was as described and an average time for each intervention was calculated. The $(i+1)^{\text{th}}$ iteration took the i^{th} average values and used them as weights for dividing up the times for each visit in the next iteration. This resulted in some of the intervention times being iterated down to zero, which is thought to be quite unrealistic, so this idea was not pursued any further.

squares S^2 with respect to b where,

$$S^2 = \sum_{i=1}^{n} e_i^2 = (\mathbf{Y} - \mathbf{X}\mathbf{b})^T(\mathbf{Y} - \mathbf{X}\mathbf{b}).$$

In this case, the vector $\mathbf{Y}$ contains the actual times for the visits. (Y_i is the time for visit i.) The zero-one matrix $\mathbf{X}$ contains details of which interventions were carried out in each visit. So $X_{ij} = 1$ if intervention j was carried out in visit i.

Maximum Likelihood Estimation

Maximum likelihood estimation is a well-known and widely used method of estimation. Given an independent identically distributed random sample $X_1, \ldots, X_n$, the maximum likelihood estimator (MLE) is the value of $\hat{\theta}$ which maximises the likelihood function $L(\theta : x)$. Since the observations are independent, the joint probability density function (pdf) is the product of the individual pdf's. Expressing the joint pdf as a function of θ, given the observations x_i, gives us the likelihood function as below.

$$L(\theta : x) = \prod_{i=1}^{n} f(x_i : \theta)$$

Finding the MLE is an optimization problem, normally solved by numerical iterative methods. Since the logarithmic function is monotonic, the loglikelihood,

$$l(\theta : x) = \ln\left[L(\theta : x)\right] = \sum_{i=1}^{n} \ln\left[f(x_i : \theta)\right]$$

is often used in preference because it is easier to work with, and the same value of $\hat{\theta}$ maximises both $l(\theta : x)$ and $L(\theta : x)$.

Two distributions (Gamma and Inverse Gaussian) were tried as shown below. A method using the Nelder Mead algorithm was used, based on suggestions given by Cheng (2005).

MLE using the Gamma Distribution

The gamma distribution has two parameters: alpha and beta. The alpha can be thought of as the shape of the distribution, and beta as the scale. For the method of maximum likelihood, it is necessary to sum the individual gamma distributions. Whilst the sum of two gamma distributions is not necessarily a gamma distribution, it has the property that if the individual gamma distributions share the same beta, then the resulting sum of these distributions is again a gamma distribution. It doesn't seem too unreasonable an assumption to make that the distribution for each of the intervention times will have the same scale. The pdf for each visit i is:

$$f(y_i, \theta) = \frac{y_i^{\alpha_i - 1} e^{\frac{-y_i}{\beta}}}{\Gamma(\alpha_i)\beta^{\alpha}}$$

Where in this case, y_i is the time for visit i and θ is the vector of parameters to be estimated where $\theta = (\beta, m_1, \ldots, m_p)$ and p is the number of interventions. The mean, μ_i, of the gamma distribution is $\alpha_i\beta$, and the variance is $\alpha_i\beta^2$. So, we can write $\alpha_i = \frac{\mu_i}{\beta}$ where $\mu_i = \sum_{j=1}^{n_i} m_{x(i,j)}$ is the sum of the intervention times in visit i. Here, n_i is the number of visits in visit i, and $x(i,j)$ is the ID of the j^{th} intervention on the i^{th} visit.

MLE using the Inverse Gaussian Distribution

The Inverse Gaussian distribution has three parameters giving a pdf for each visit i of:

$$f(y_i, \mu_i, \lambda_i) = \left(\frac{\lambda_i}{2\pi}\right)^{\frac{1}{2}} y_i^{\frac{-3}{2}} \exp\left[\frac{-\lambda_i(y - \mu_i)^2}{2\mu_i^2 y_i}\right]$$

with mean μ_i , and variance $\frac{\mu_i^3}{\lambda_i}$. The sum of two Inverse Gaussian distributions is not necessarily an Inverse Gaussian distribution. However, the Inverse Gaussian has the property that $\frac{\lambda_i}{\mu_i^2} = \frac{1}{c_i^2}$ for some constant c_i which allows us to simplify the expression for the variance to be

$$\frac{\mu_i^3}{\lambda_i} = \frac{\mu_i^3 c_i^2}{\mu_i^2} = \mu_i c_i^2.$$

so $\lambda_i = \frac{\mu_i^2}{c_i^2}$. Therefore, if for two distributions, $f(y_i, \mu_i, \lambda_i)$ and $f(y_j, \mu_j, \lambda_j)$, $c_i = c_j = c$ then the sum of these distributions is

$$f\left(y_{i+j}, \mu_i + \mu_j, \frac{(\mu_i^2 + \mu_j^2)}{c^2}\right)$$

which is also an Inverse Gaussian distribution.

Comparison of Methods

Table B.1 compares the advantages and disadvantages of each of the methods described previously. It is difficult to evaluate the fit of the data to each distribution, because the true distribution is unknown, and the data is not 'good enough' to perform any kind of goodness of fit test. This is particularly the case because each of the visit times is given in terms of 15 minute intervals, with the smallest value being 15 minutes, and it is the case, that even with the same patient, the same task may take a different time on a different visit. However, by fitting a distribution to the data, as best we can, we hope to be able to capture this stochastic nature, and produce realistic results by making the intervention time a variable with a fitted distribution.

Table B.1: Advantages and disadvantages of the methods for calculating Intervention times

Method	Advantages	Disadvantages
Dividing the Time Equally and Fitting a Triangular Distribution to it	Easily understood and performed by non-specialists. Always gives feasible answers for all interventions. Produces parameters for a triangular distribution for each intervention.	Requires the assumption that the time for a visit can be split equally between the interventions carried out in the visit.
ANOVA	Produces an estimate for the mean for each intervention.	Allows times to be infeasible (negative). Requires the assumption that the errors e_i are independent and normally distributed. Unable to distinguish between two or more interventions if their only occurrence in the data is in the same visit. The data needs pruning to avoid this situation.
MLE using the Gamma Distribution	When it gives answers, they are feasible. Produces parameters for a Gamma distribution for each intervention.	Requires specialist statistical software and/or knowledge. Unable to distinguish between two or more interventions if their only occurrence in the data is in the same visit. The data needs pruning to avoid this situation.
MLE using the Inverse Gaussian Distribution	When it gives answers, they are feasible. Produces parameters for an Inverse Gaussian distribution for each intervention.	Requires specialist statistical software and/or knowledge. Unable to distinguish between two or more interventions if their only occurrence in the data is in the same visit. The data needs pruning to avoid this situation.

Results

Table B.2 shows the results (i.e. the resulting parameter values) for each of the methods, and the corresponding 95 % confidence intervals for the Gamma and Inverse Gaussian distributions, and the minimum and maximum for the triangular distribution. The interventions are referred to by number (as in Tables 5.5 and 5.7), prefixed with an 's' if they are Specific. The frequency column shows the number of times the intervention appeared in the data used to fit the parameters. Note that results are not shown for every intervention, as either the intervention was not carried out in the subset of data used, or it was indistinguishable from other interventions, so was necessarily omitted. Parameters were fitted to 99 interventions in total. Note also that not every intervention is carried out at both the Generic and Specific levels. The fitted beta parameter for the Gamma distributions is 6.73, with a 95% confidence interval of (6.11, 7.35). The fitted c parameter for the Inverse Gaussian distribution is 2.69 with a 95% confidence interval of (2.55, 2.84).

Table B.2: Comparing parameter results for each of the methods

Intervention	Gamma Distribution			Inverse Gaussian Distribution			ANOVA	Triangular Distribution			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI		Mean	Min	Max	
1	6.62	-10.45	23.68	2.76	-15.49	21.01	21.88	14.38	5.63	22.50	3
2	7.13	1.44	12.81	4.12	-0.87	9.11	6.18	17.83	4.29	90.00	34
3	4.76	-7.05	16.56	3.55	-7.19	14.29	4.48	11.64	5.00	22.50	7
4	0.02	-43.71	43.74	0.00	-36.26	36.26	-27.43	6.00	6.00	6.00	1
5	0.02	-45.22	45.26	0.00	-40.90	40.91	-40.77	9.00	9.00	9.00	1
6	43.49	31.10	55.89	41.96	30.83	53.08	43.22	31.36	11.25	60.00	11
7	12.50	1.01	23.99	11.19	-0.67	23.05	12.96	15.91	5.63	45.00	6
10	10.05	-9.44	29.54	11.34	-9.52	32.21	5.50	13.75	11.25	15.00	3
11	0.76	-11.76	13.28	0.07	-12.37	12.51	-2.79	11.04	6.00	20.00	8
12	23.91	18.63	29.19	22.90	18.02	27.77	22.25	23.31	7.50	60.00	32
13	49.67	5.19	94.15	52.94	8.62	97.27	49.43	37.50	37.50	37.50	1
14	30.66	-3.53	64.86	33.32	-0.13	66.78	28.38	22.50	22.50	22.50	1
15	7.93	-14.32	30.19	9.70	-12.52	31.92	5.05	13.50	12.00	15.00	2
16	0.04	-37.52	37.60	0.13	-34.37	34.63	-2.56	11.25	11.25	11.25	1
17	63.35	35.50	91.19	66.53	38.96	94.10	60.00	60.00	60.00	60.00	2
18	17.78	12.17	23.39	16.99	11.82	22.17	16.48	16.36	5.00	30.00	23
19	25.89	3.70	48.07	24.76	2.73	46.78	39.05	19.50	6.00	37.50	3
20	25.72	13.63	37.81	24.97	12.68	37.25	22.36	27.25	15.00	60.00	10
21	17.53	-2.96	38.01	16.53	-3.99	37.04	14.71	19.17	15.00	22.50	3
22	1.16	-18.79	21.11	3.34	-15.24	21.92	9.18	18.00	7.50	33.75	5
23	8.64	2.11	15.16	7.20	0.88	13.51	3.45	15.56	5.00	60.00	26
25	38.48	18.94	58.02	32.05	10.52	53.59	66.94	37.43	5.63	120.00	5
26	15.31	4.57	26.05	15.25	4.64	25.86	13.38	16.69	6.00	30.00	8
27	10.79	-11.36	32.93	11.54	-9.87	32.95	9.96	13.42	9.00	20.00	3
28	0.00	-19.05	19.05	0.00	-16.10	16.10	-9.58	10.42	5.00	15.00	3
29	10.75	-2.54	24.05	11.82	-1.12	24.77	10.37	19.03	7.50	37.50	9
30	38.72	33.71	43.73	39.57	34.43	44.71	37.93	29.18	5.63	90.00	71
31	10.62	6.70	14.54	10.29	6.54	14.04	11.69	14.49	5.00	45.00	69
32	13.38	6.06	20.69	15.30	7.89	22.71	9.48	14.16	6.00	30.00	16
33	7.10	0.47	13.73	7.00	0.67	13.34	3.37	10.63	5.00	22.50	14
35	17.86	15.05	20.68	17.90	15.23	20.57	16.58	16.15	3.75	45.00	83
36	7.38	2.63	12.13	6.68	2.14	11.22	5.58	12.34	3.75	30.00	30
37	7.67	-10.40	25.75	8.58	-9.00	26.15	7.57	14.33	10.00	18.00	3
38	8.65	0.69	16.61	8.64	1.04	16.23	9.82	12.86	6.00	22.50	14
39	22.40	19.22	25.59	22.80	19.78	25.82	20.07	21.21	5.00	60.00	68
40	29.96	24.73	35.18	29.69	24.64	34.75	28.78	26.30	9.00	75.00	40
41	0.01	-28.96	28.98	0.03	-26.98	27.04	0.39	10.00	10.00	10.00	1
42	26.97	16.97	36.98	27.87	18.50	37.24	25.27	23.75	15.00	45.00	8
43	14.62	12.49	16.75	16.34	14.25	18.43	11.49	13.30	5.00	30.00	127
45	11.02	3.76	18.28	10.55	3.66	17.45	10.93	13.73	6.00	30.00	15
46	12.02	3.48	20.57	11.21	2.74	19.68	8.94	15.31	6.00	30.00	12
47	9.51	5.73	13.29	9.65	5.95	13.35	6.05	12.07	5.00	30.00	43
48	21.30	-7.86	50.46	24.83	-3.22	52.87	21.06	15.00	15.00	15.00	1
49	19.57	14.34	24.81	20.73	15.60	25.86	14.62	17.36	8.57	30.00	28
50	0.02	-22.88	22.92	0.03	-21.42	21.48	-0.84	9.50	9.00	10.00	2
51	14.59	9.58	19.60	15.39	10.69	20.10	10.45	13.74	5.00	30.00	19
52	16.39	11.20	21.59	15.31	10.35	20.27	14.70	16.64	4.29	45.00	28
53	13.26	10.55	15.96	13.29	10.68	15.90	11.12	14.27	4.29	30.00	88
54	17.26	14.29	20.24	17.31	14.41	20.21	15.78	16.26	4.29	60.00	111
55	24.53	10.12	38.94	26.08	12.78	39.37	21.73	20.00	15.00	30.00	3
56	3.46	-12.04	18.95	5.84	-9.50	21.18	4.02	15.21	11.25	20.00	6
57	16.33	6.16	26.51	17.62	7.94	27.29	18.44	13.13	7.50	22.50	10
58	14.14	10.58	17.71	13.87	10.35	17.40	11.78	15.60	5.00	45.00	67
59	24.15	17.84	30.46	25.64	19.46	31.81	21.21	20.24	10.00	30.00	21
60	20.74	18.32	23.17	20.79	18.40	23.17	18.12	17.49	4.29	45.00	163
61	21.84	18.91	24.76	21.01	18.20	23.81	20.37	19.53	5.00	60.00	105
62	14.37	4.95	23.79	15.33	6.50	24.16	9.69	12.50	5.00	15.00	4
63	14.60	8.97	20.23	12.52	7.06	17.98	9.54	16.66	5.00	60.00	24
64	16.85	13.19	20.52	16.30	12.75	19.85	13.85	17.81	3.75	90.00	58
65	17.68	15.34	20.02	18.02	15.73	20.30	16.62	16.10	5.00	60.00	179
66	6.28	3.22	9.34	5.46	2.52	8.39	2.46	11.74	3.75	30.00	77
67	0.00	-5.76	5.77	0.00	-5.43	5.43	-0.39	11.56	4.29	22.50	37

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Intervention	Gamma Distribution			Inverse Gaussian Distribution			ANOVA	Triangular Distribution			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI		Mean	Min	Max	
68	16.25	1.04	31.46	11.31	-2.46	25.08	10.15	20.33	6.00	45.00	3
s1	12.60	-15.40	40.59	15.26	-11.58	42.10	11.88	15.00	15.00	15.00	1
s2	30.29	14.55	46.04	32.93	17.36	48.50	27.98	25.60	18.00	30.00	5
s3	12.37	-7.62	32.35	15.64	-4.54	35.82	12.88	15.19	11.25	22.50	4
s6	28.73	22.48	34.98	28.71	22.74	34.68	25.57	25.02	5.00	60.00	31
s9	6.90	-22.78	36.58	8.52	-20.12	37.17	15.13	17.00	9.00	25.00	2
s11	0.00	-62.08	62.08	0.00	-45.10	45.10	-89.33	5.00	5.00	5.00	1
s12	33.32	5.45	61.19	36.03	9.30	62.76	30.00	30.00	30.00	30.00	1
s13	35.13	-4.92	75.17	36.80	-3.72	77.31	20.17	30.00	30.00	30.00	2
s14	5.60	-23.21	34.41	8.27	-19.29	35.83	8.51	10.00	10.00	10.00	1
s15	31.71	18.63	44.80	30.21	17.86	42.55	29.92	30.00	15.00	45.00	7
s16	0.07	-30.65	30.80	0.00	-27.54	27.55	-7.93	15.00	15.00	15.00	1
s18	23.72	-0.53	47.97	25.74	2.50	48.99	17.78	22.50	22.50	22.50	3
s19	22.58	11.61	33.54	22.42	11.94	32.91	25.01	18.75	7.50	45.00	8
s20	1.58	-17.15	20.30	4.08	-13.95	22.12	-2.70	13.13	7.50	15.00	4
s22	13.32	-9.32	35.95	11.31	-13.29	35.91	28.44	19.17	5.00	30.00	3
s23	17.61	7.64	27.58	16.21	6.11	26.31	12.50	18.13	5.00	45.00	13
s24	29.18	10.19	48.17	29.39	10.44	48.33	23.83	30.00	22.50	45.00	3
s26	0.00	-21.08	21.08	0.00	-15.53	15.53	-15.62	11.30	9.00	15.00	5
s27	0.01	-65.66	65.68	0.00	-57.55	57.55	-9.17	11.25	11.25	11.25	1
s29	16.17	-14.51	46.85	17.80	-13.92	49.51	20.26	22.50	15.00	30.00	2
s30	0.01	-24.15	24.17	0.00	-0.02	0.02	34.43	17.50	5.00	30.00	3
s31	47.85	18.53	77.17	47.96	17.07	78.86	50.18	37.50	15.00	60.00	2
s32	35.43	24.74	46.13	35.75	25.38	46.11	32.57	31.67	15.00	60.00	9
s33	24.86	16.02	33.69	24.71	16.02	33.40	27.44	22.15	9.00	120.00	21
s34	48.34	14.23	82.45	51.34	17.97	84.71	45.00	45.00	45.00	45.00	1
s38	0.01	-54.49	54.50	0.00	-50.37	50.38	-32.50	11.25	11.25	11.25	1
s43	18.75	-16.33	53.83	19.62	-15.58	54.82	33.52	21.25	11.25	30.00	3
s47	0.00	-63.70	63.71	0.00	-47.15	47.15	-116.03	5.63	5.63	5.63	1
s50	13.47	-12.53	39.47	14.38	-11.11	39.86	13.25	18.75	15.00	22.50	2
s53	19.03	4.61	33.45	20.20	5.59	34.81	13.22	19.00	15.00	30.00	5
s54	27.05	16.19	37.90	28.66	17.71	39.61	22.55	23.04	15.00	45.00	14
s60	17.34	7.88	26.81	16.98	7.01	26.96	18.40	19.48	5.00	45.00	12
s62	39.46	3.92	75.01	40.16	3.07	77.25	46.14	33.75	30.00	37.50	2
s63	30.66	-3.54	64.86	33.32	-0.13	66.78	28.38	22.50	22.50	22.50	1
s65	11.10	-3.32	25.52	11.97	-3.32	27.27	15.00	10.00	5.00	15.00	2
s68	21.35	-14.48	57.17	22.72	-12.40	57.84	22.45	22.50	22.50	22.50	1

Discussion

The confidence intervals for the Gamma and Inverse Gaussian distributions overlap for each of the interventions, hence there is no evidence to suggest that they are different. The confidence intervals for both the Gamma and the Inverse Gaussian estimates contain the ANOVA estimate for all but eleven of the interventions (1, 25, 43, 49, 51, 60, 66, s11, s26, s30, and s47), although the Gamma, but not the Inverse Gaussian, confidence intervals contains the ANOVA estimate for four of these (1, 49, 51, and s26). Although some of these have a small frequency count in the data set, it is not true of all of them, which suggests that the difference cannot be explained simply by frequency count.

The range for the triangular distribution overlaps with the confidence interval for the Gamma distribution for each intervention, and for all but one (s30) of the confidence intervals for the Inverse Gaussian distribution.

The similarity of these values and the substantial overlapping of confidence intervals and ranges indicates that there is good reason to suggest that the results for the parameter estimates are sensible. The potential for the ANOVA to give negative estimates for some of the interventions (e.g. s11 and s47), yields it slightly inferior to that of the two MLE methods.

Some of the MLE (and ANOVA) estimates are very close to zero, and this is quite unrealistic, since, by definition of being classified as an intervention, the interventions require time and skill which cannot be administered in a second or two.

Adapting the Results

In an attempt to make the MLE results for the Gamma distribution more realistic, we took all interventions which had an average time of less than 5 minutes (i.e. interventions 3, 4, 5, 11, 16, 22, 28, 41, 50, 56, 67, s11, s16, s20, s26, s27, s30, s38, s47) and fixed these to have a duration of 5 minutes, and then reran the Nelder-Mead algorithm to fit the remaining parameters. A comparison of the values before and after are shown in Table B.3. The new fitted beta is 6.93 with a 95% confidence interval of (6.31, 7.54).

Table B.3: Results for the MLE, Gamma method when short Interventions have a fixed time of 5 minutes

Intervention	Gamma Distribution (before)			Gamma Distribution (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
1	6 .62	-10.45	23.68	6.08	-10.35	22.50	3
2	7.13	1.44	12.81	6 .65	1.19	12.10	34
3	4.76	-7.05	16.56	5.00	5.00	5.00	7
4	0.02	-43.71	43.74	5.00	5.00	5.00	1
5	0.02	-45.22	45.26	5.00	5.00	5.00	1
6	43.49	31.10	55.89	42.46	31.80	53.13	11
7	12.50	1.01	23.99	12.15	0.84	23.46	6
10	10.05	-9.44	29.54	9.10	-9.18	27.39	3
11	0.76	-11.76	13.28	5.00	5.00	5.00	8
12	23.91	18.63	29.19	24.12	18.78	29.47	32
13	49.67	5.19	94.15	49.84	4.73	94.94	1
14	30.66	-3.53	64.86	30.80	-3.90	65.50	1
15	7.93	- 14.32	30.19	8.56	- 14.07	31.18	2
16	0.04	-37.52	37.60	5.00	5.00	5.00	1
17	63.35	35.50	91.19	63.44	35.18	91.70	2
18	17.78	12.17	23.39	17.81	12.18	23.44	23
19	25.89	3.70	48.07	21.60	3.70	39.50	3
20	25.72	13.63	37.81	25.69	13.53	37.86	10

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Intervention	Gamma Distribution (before)			Gamma Distribution (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
21	17.53	-2.96	38.01	16.62	-3.57	36.80	3
22	1.16	-18.79	21.11	5.00	5.00	5.00	5
23	8.64	2.11	15.16	8.35	2.88	13.83	26
25	38.48	18.94	58.02	35.50	18.96	52.04	5
26	15.31	4.57	26.05	15.61	4.71	26.51	8
27	10.79	-11.36	32.93	10.87	-10.28	32.02	3
28	0.00	-19.05	19.05	5.00	5.00	5.00	3
29	10.75	-2.54	24.05	9.23	-3.64	22.10	9
30	38.72	33.71	43.73	38.40	33.48	43.31	71
31	10.62	6.70	14.54	10.36	6.49	14.23	69
32	13.38	6.06	20.69	12.92	5.90	19.94	16
33	7.10	0.47	13.73	7.38	0.76	14.00	14
35	17.86	15.05	20.68	18.01	15.16	20.86	83
36	7.38	2.63	12.13	7.45	2.65	12.24	30
37	7.67	-10.40	25.75	8.04	-10.32	26.40	3
38	8.65	0.69	16.61	9.01	0.94	17.08	14
39	22.40	19.22	25.59	22.54	19.32	25.77	68
40	29.96	24.73	35.18	30.00	24.75	35.24	40
41	0.01	-28.96	28.98	5.00	5.00	5.00	1
42	26.97	16.97	36.98	27.14	16.98	37.30	8
43	14.62	12.49	16.75	14.73	12.57	16.88	127
45	11.02	3.76	18.28	11.26	3.88	18.63	15
46	12.02	3.48	20.57	12.36	3.65	21.07	12
47	9.51	5.73	13.29	9.80	5.95	13.65	43
48	21.30	-7.86	50.46	21.05	-8.55	50.65	1
49	19.57	14.34	24.81	19.35	14.11	24.60	28
50	0.02	-22.88	22.92	5.00	5.00	5.00	2
51	14.59	9.58	19.60	14.74	9.65	19.82	19
52	16.39	11.20	21.59	16.00	10.84	21.15	28
53	13.26	10.55	15.96	13.11	10.41	15.81	88
54	17.26	14.29	20.24	16.49	13.67	19.30	111
55	24.53	10.12	38.94	24.54	9.92	39.16	3
56	3.46	- 12.04	18.95	5.00	5.00	5.00	6
57	16.33	6 .16	26.51	16.28	6 .29	26.28	10
58	14.14	10.58	17.71	13.82	10.27	17.38	67
59	24.15	17.84	30.46	24.04	17.72	30.35	21
60	20.74	18.32	23.17	20.07	17.79	22.36	163
61	21.84	18.91	24.76	21.97	19.02	24.93	105
62	14.37	4.95	23.79	14.51	4.93	24.09	4
63	14.60	8.97	20.23	14.48	8.82	20.14	24
64	16.85	13.19	20.52	16.83	13.13	20.53	58
65	17.68	15.34	20.02	17.63	15.28	19.98	179
66	6 .28	3.22	9.34	6 .16	3.11	9.21	77
67	0.00	-5.76	5.77	5.00	5.00	5.00	37
68	16.25	1.04	31.46	16.47	0.99	31.94	3
s1	12.60	- 15.40	40.59	13.36	- 15.04	41.75	1
s2	30.29	14.55	46.04	30.58	14.58	46.58	5
s3	12.37	-7.62	32.35	13.61	- 6 .39	33.62	4
s6	28.73	22.48	34.98	28.64	22.56	34.73	31

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Intervention	Gamma Distribution (before)			Gamma Distribution (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
s9	6 .90	-22.78	36.58	4.56	-23.12	32.25	2
s11	0.00	-62.08	62.08	5.00	5.00	5.00	1
s12	33.32	5.45	61.19	33.41	5.12	61.70	1
s13	35.13	-4.92	75.17	37.27	0.56	73.98	2
s14	5.60	-23.21	34.41	5.92	-23.21	35.05	1
s15	31.71	18.63	44.80	32.28	18.99	45.56	7
s16	0.07	-30.65	30.80	5.00	5.00	5.00	1
s18	23.72	-0.53	47.97	24.44	1.49	47.38	3
s19	22.58	11.61	33.54	21.58	10.99	32.16	8
s20	1.58	-17.15	20.30	5.00	5.00	5.00	4
s22	13.32	-9.32	35.95	7.91	- 12.04	27.85	3
s23	17.61	7.64	27.58	16.54	6 .99	26.09	13
s24	29.18	10.19	48.17	29.35 1	0.07	48.63	3
s26	0.00	-21.08	21.08	5.00	5.00	5.00	5
s27	0.01	-65.66	65.68	5.00	5.00	5.00	1
s29	16.17	- 14.51	46.85	13.76	- 15.91	43.42	2
s30	0.01	-24.15	24.17	5.00	5.00	5.00	3
s31	47.85	18.53 7	7.17	46.03	17.58	74.48	2
s32	35.43	24.74	46.13	35.59	24.74	46.44	9
s33	24.86	16.02	33.69	23.94	15.89	31.98	21
s34	48.34	14.23	82.45	48.41	13.80	83.03	1
s38	0.01	-54.49	54.50	5.00	5.00	5.00	1
s43	18.75	- 16.33	53.83	16.32	-10.23	42.87	3
s47	0.00	-63.70	63.71	5.00	5.00	5.00	1
s50	13.47	-12.53	39.47	12.95	- 13.46	39.37	2
s53	19.03	4.61	33.45	19.85	5.17	34.53	5
s54	27.05	16.19	37.90	28.15	17.24	39.05	14
s60	17.34	7.88	26.81	16.13	7.04	25.21	12
s62	39.46	3.92	75.01	37.97	2.95	72.99	2
s63	30.66	-3.54	64.86	30.80	-3.91	65.50	1
s65	11.10	-3.32	25.52	9.19	-3.35	21.72	2
s68	21.35	-14.48	57.17	20.30	-16.01	56.61	1

Similarly, for the MLE results using the Inverse Gaussian distribution, those times that had an average value of less than 5 minutes (i.e. interventions 1, 2, 3, 4, 5, 11, 16, 22, 28, 41, 50, 67, s11, s16, s20, s26, s27, s30, s38, s47), were fixed to have a duration of 5 minutes and the Nelder-Mead algorithm rerun. The results are in Table B.4 below. The new fitted c is 2.74 with a 95% confidence interval of (2.59, 2.88).

The confidence intervals for the adapted Gamma and Inverse Gaussian distributions overlap for each intervention so there is no evidence to suggest that they are different (the same conclusion as was reached for the two distributions before adaptations.)

Table B.4: Results for the MLE, Inverse Gaussian method when short Interventions have a fixed time of 5 minutes

Intervention	Inv. Gaussian Dist'n (before)			Inv. Gaussian Dist'n (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
1	2.76	-15.49	21.01	5.00	5.00	5.00	3
2	4.12	-0.87	9.11	5.00	5.00	5.00	34
3	3.55	-7.19	14.29	5.00	5.00	5.00	7
4	0.00	-36.26	36.26	5.00	5.00	5.00	1
5	0.00	-40.90	40.91	5.00	5.00	5.00	1
6	41.96	30.83	53.08	41.84	31.93	51.74	11
7	11.19	-0.67	23.05	8.97	-1.06	19.01	6
10	11.34	-9.52	32.21	9.94	-9.20	29.07	3
11	0.07	-12.37	12.51	5.00	5.00	5.00	8
12	22.90	18.02	27.77	23.17	18.27	28.08	32
13	52.94	8.62	97.27	53.16	8.15	98.18	1
14	33.32	-0.13	66.78	33.54	-0.43	67.51	1
15	9.70	-12.52	31.92	9.91	-12.26	32.08	2
16	0.13	-34.37	34.63	5.00	5.00	5.00	1
17	66.53	38.96	94.10	66.73	38.73	94.74	2
18	16.99	11.82	22.17	16.86	11.77	21.95	23
19	24.76	2.73	46.78	18.20	1.96	34.45	3
20	24.97	12.68	37.25	25.30	12.97	37.63	10
21	16.53	-3.99	37.04	15.85	-4.45	36.14	3
22	3.34	-15.24	21.92	5.00	5.00	5.00	5
23	7.20	0.88	13.51	6.41	1.30	11.53	26
25	32.05	10.52	53.59	24.63	9.55	39.70	5
26	15.25	4.64	25.86	15.91	5.15	26.68	8
27	11.54	-9.87	32.95	11.93	-8.81	32.66	3
28	0.00	-16.10	16.10	5.00	5.00	5.00	3
29	11.82	-1.12	24.77	10.44	-1.81	22.69	9
30	39.57	34.43	44.71	38.96	34.15	43.77	71
31	10.29	6.54	14.04	10.07	6.38	13.77	69
32	15.30	7.89	22.71	14.56	7.77	21.34	16
33	7.00	0.67	13.34	8.01	1.88	14.15	14
35	17.90	15.23	20.57	18.14	15.43	20.84	83
36	6.68	2.14	11.22	6.89	2.27	11.51	30
37	8.58	-9.00	26.15	9.33	-8.55	27.20	3
38	8.64	1.04	16.23	9.19	1.49	16.89	14
39	22.80	19.78	25.82	22.78	19.74	25.82	68
40	29.69	24.64	34.75	29.93	24.83	35.03	40
41	0.03	-26.98	27.04	5.00	5.00	5.00	1
42	27.87	18.50	37.24	28.12	18.60	37.63	8
43	16.34	14.25	18.43	16.51	14.40	18.62	127
45	10.55	3.66	17.45	10.92	3.92	17.93	15
46	11.21	2.74	19.68	11.83	3.18	20.48	12
47	9.65	5.95	13.35	10.09	6.33	13.85	43
48	24.83	-3.22	52.87	24.45	-4.05	52.94	1
49	20.73	15.60	25.86	20.52	15.48	25.57	28
50	0.03	-21.42	21.48	5.00	5.00	5.00	2
51	15.39	10.69	20.10	15.61	10.84	20.39	19

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Intervention	Inv. Gaussian Dist'n (before)			Inv. Gaussian Dist'n (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
52	15.31	10.35	20.27	14.14	9.38	18.91	28
53	13.29	10.68	15.90	12.90	10.33	15.48	88
54	17.31	14.41	20.21	16.28	13.54	19.01	111
55	26.08	12.78	39.37	26.15	12.65	39.64	3
56	5.84	-9.50	21.18	6.91	-8.57	22.39	6
57	17.62	7.94	27.29	18.01	8.36	27.67	10
58	13.87	10.35	17.40	13.49	10.00	16.99	67
59	25.64	19.46	31.81	25.50	19.36	31.64	21
60	20.79	18.40	23.17	19.97	17.72	22.22	163
61	21.01	18.20	23.81	21.22	18.39	24.05	105
62	15.33	6.50	24.16	15.58	6.61	24.55	4
63	12.52	7.06	17.98	12.40	6.94	17.85	24
64	16.30	12.75	19.85	16.18	12.61	19.75	58
65	18.02	15.73	20.30	18.03	15.74	20.32	179
66	5.46	2.52	8.39	5.19	2.30	8.07	77
67	0.00	-5.43	5.43	5.00	5.00	5.00	37
68	11.31	-2.46	25.08	11.76	-2.35	25.87	3
s1	15.26	-11.58	42.10	16.30	-10.94	43.54	1
s2	32.93	17.36	48.50	33.48	17.68	49.27	5
s3	15.64	-4.54	35.82	16.36	-3.60	36.32	4
s6	28.71	22.74	34.68	28.81	22.85	34.76	31
s9	8.52	-20.12	37.17	5.85	-20.85	32.54	2
s11	0.00	-45.10	45.10	5.00	5.00	5.00	1
s12	36.03	9.30	62.76	36.27	9.12	63.41	1
s13	36.80	-3.72	77.31	39.18	2.34	76.03	2
s14	8.27	-19.29	35.83	8.40	-19.53	36.33	1
s15	30.21	17.86	42.55	30.34	17.82	42.85	7
s16	0.00	-27.54	27.55	5.00	5.00	5.00	1
s18	25.74	2.50	48.99	26.14	4.34	47.95	3
s19	22.42	11.94	32.91	21.09	11.10	31.08	8
s20	4.08	-13.95	22.12	5.00	5.00	5.00	4
s22	11.31	-13.29	35.91	2.27	-17.38	21.92	3
s23	16.21	6.11	26.31	15.14	5.63	24.64	13
s24	29.39	10.44	48.33	29.79	10.56	49.03	3
s26	0.00	-15.53	15.53	5.00	5.00	5.00	5
s27	0.00	-57.55	57.55	5.00	5.00	5.00	1
s29	17.80	-13.92	49.51	15.47	-15.64	46.58	2
s30	0.00	-0.02	0.02	5.00	5.00	5.00	3
s31	47.96	17.07	78.86	45.56	15.16	75.96	2
s32	35.75	25.38	46.11	38.71	27.70	49.71	9
s33	24.71	16.02	33.40	24.11	16.20	32.02	21
s34	51.34	17.97	84.71	51.59	17.69	85.48	1
s38	0.00	-50.37	50.38	5.00	5.00	5.00	1
s43	19.62	-15.58	54.82	17.23	-7.42	41.89	3
s47	0.00	-47.15	47.15	5.00	5.00	5.00	1
s50	14.38	-11.11	39.86	13.74	-12.14	39.62	2
s53	20.20	5.59	34.81	21.18	6.41	35.95	5
s54	28.66	17.71	39.61	30.49	19.73	41.26	14
s60	16.98	7.01	26.96	15.10	5.75	24.44	12

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Intervention	Inv. Gaussian Dist'n (before)			Inv. Gaussian Dist'n (after)			Freq.
	Average	Low CI	High CI	Average	Low CI	High CI	
s62	40.16	3.07	77.25	38.32	2.09	74.55	2
s63	33.32	-0.13	66.78	33.67	-0.31	67.65	1
s65	11.97	-3.32	27.27	9.03	-3.74	21.81	2
s68	22.72	-12.40	57.84	21.19	-14.38	56.76	1

Appendix C

Extra Results from the Intermediate Care Database

This Appendix contains a selection of the analysis that was carried out using the database which paints a broader picture of the work carried out by the rehab teams, than that provided by the analysis for the model in Chapter 5.

Patient origins and destinations

Discharge destinations for patients arriving from different places of referral are shown for Eastleigh in Table C.1 and for Romsey in Table C.2. Note that for Eastleigh, the number of patients who died is known, and is indicated by the RIP column. For Romsey, the number of patients who died is not known (in the database), so any such patients will be counted in the discharged to home column.

Table C.1: Discharge destinations by place of referral for Eastleigh

EASTLEIGH	**Discharge to:**				
Referral From	A&E	Acute Beds	Care Home	Home	RIP
A&E	0	0	0	4	0
Acute Beds	1	2	3	82	1
Care Home	1	1	5	1	0
Community Beds	0	0	2	21	0
Home	0	0	0	12	0
Primary Care	4	11	12	149	8
Social Services	1	2	2	25	0

Table C.2: Discharge destinations by place of referral for Romsey

ROMSEY	Discharge to:				
Referral From	Acute Beds	Care Home	Community Beds	Home	Social Services
A&E	1	0	0	6	0
Acute Beds	1	0	0	53	0
Care Home	0	8	0	0	0
Community Beds	0	0	0	6	0
Home	0	0	1	22	0
Primary Care	2	1	6	77	0
Social Services	1	0	1	14	1

Patients locations

The maps in Figures C.1 (for Eastleigh) and C.2 (for Romsey) which were created using Streetmap.co.uk (2005) show the spread of the number of visits carried out by each team for the patients in the database. It should be borne in mind that the home postcode of the patient is recorded, and whilst most patients are visited whilst in their own home, or nursing home, some patients will receive visits whilst staying with a relative in the area.

Visits where two members of staff are present

Sometimes it is necessary for two members of staff to visit a patient, either for patient need, training or staff safety. Matrices showing the frequency of different staffing combinations in the database are shown in Tables C.3 (for Eastleigh), and C.4 (for Romsey).

Table C.3: Matrix of Eastleigh staffing combinations

EASTLEIGH	Physiotherapist	Occupational Therapist	Nurse	Rehab Assistant Level 2	Rehab Assistant Level 1
Physiotherapist	-				
Occupational Therapist	26	5			
Nurse	20	22	20		
Social Worker	4	1	11	1	
Rehab Assistant Level 2	11	2	4	6	
Rehab Assistant Level 1	1	7	2	45	17
Mental Health Nurse	-	-	1	-	-

Figure C.1: Map to show the spread of patient visits by the Eastleigh team

Table C.4: Matrix of Romsey staffing combinations

ROMSEY	Occupational Therapist	Physiotherapist	Mental Health Nurse	Nurse	Rehab Assistant Level 2	Rehab Assistant Level 1
Occupational Therapist	1					
Physiotherapist	2	2	1			
Nurse	2	3	3	2		
Rehab Assistant Level 2	2	3	-	15	3	
Rehab Assistant Level 1	1	5	3	14	10	3
Student	2	1	1	2	3	1
Social Worker	-	-	1	-	1	-

Instances when the Patient was referred to a Specialist outside of the Rehab Team

Occasionally, no members of the rehab teams have the specific skill(s) or expertise to carry out an intervention that the patient requires. In such a case, it is necessary

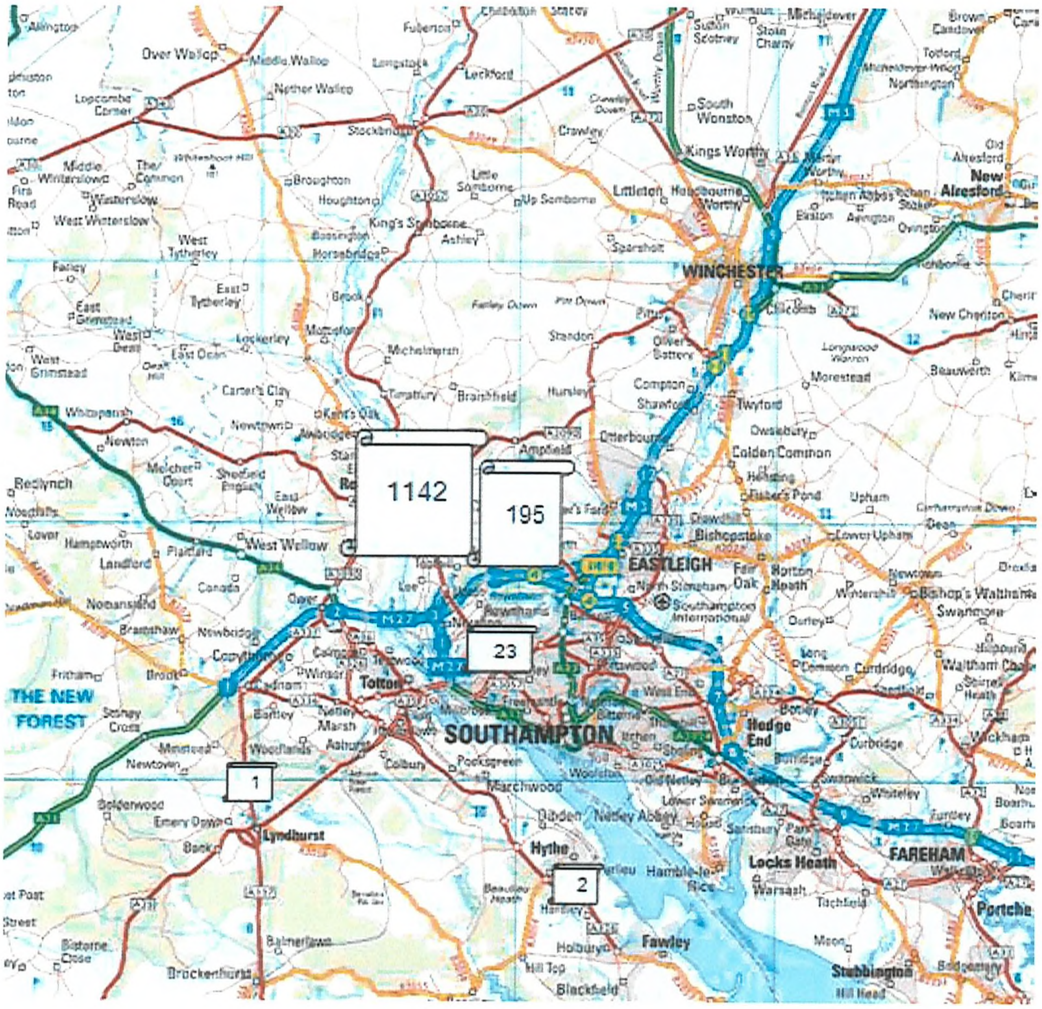

Figure C.2: Map to show the spread of patient visits by the Romsey team

to refer the patient to the appropriate specialist. In the database we have collected data on such referrals, as shown in Table C.5. This information is useful when considering whether or not the rehab team staff should, or could, be trained in the extra skill(s) if appropriate and possible.

Interventions that happen frequently

As would be expected, some interventions happen more frequently than others. Table C.6 shows those interventions which have happened 85 times or more in total (in the database). This shows whether the staff consider the intervention to be Generic or Specific, the total number of occurrences in the database, the percentage of those occurrences which were at the Specific level and the percentage of time the inter-

Table C.5: Frequencies of referrals for specialist skills in the database

Referred for Specialist Skill to	Romsey	Eastleigh	Total
District Nurse	10	35	45
Doctors for Prescribing	1	66	67
GP	27	0	27
Mental Health Team	2	7	9
Podiatrist	1	1	2
Speech and Language Therapist	0	1	1
Technician	16	17	33

vention was carried out by each staff type. It is interesting to compare this with the staff competencies in table 5.8. The Romsey team decided to create a new category of staff - Student, when completing the database. The Student does comparatively few interventions and so for the purposes of analysing the data, the Student has been amalgamated into the Rehab Assistant Level 1.

Particular points of interest (based on this table, using the database data), because of the discrepancy between practice and theory are listed below.

- "Assessment - Drug History and Compliance" is classed as Specific 82.5% of the time, and Nurses or Mental Health Nurses are the only ones who are supposedly able to do this, but 66.3% of the time a Physio has done it.
- "Assessment - Care Requirements/support" is only classed as Specific 5.8% of the time, and when Generic, anyone is meant to be able to do it, however, 67.4% of the time it is carried out by a professional member of staff.
- Two interventions ("Assistance - Care Provision" and "Practice - Monitoring of carer's well being") are supposed to be Specific to a Social Worker, however these were never carried out by the Social Worker, based on the database.
- Assistance interventions where the percentage of time that the intervention is carried out by a professional member of staff is 10% or more greater than the percentage of time that intervention is Specific:
  - Environmental Checks
- Practice interventions where the percentage of time that the intervention is carried out by a professional member of staff is 10% or more greater than the percentage of time that intervention is Specific:

- Advice on care/equipment provision
- Falls advice/safety monitoring
- Meal Prep
- Monitoring and advice on meds
- Monitoring changes in condition
- Monitoring of carer's well being
- Monitoring of continence
- Outdoor mobility/stairs/steps
- Practice with exercises
- Safe use of adaptions
- Safe use of equipment
- Transfer Practice
- Wound Care

Table C.6: More detailed analysis of Interventions that occur more than 85 times in the database

Intervention	Generic/ Specific	Total No. of Interventions	Specific %	Percentage of time Intervention carried out by each type of Staff (%)						
				Physio	OT	Nurse	Social Worker	RA 2	RA 1	Mental Health Nurse
Assessment of/for										
ADL Assessment	Generic	132	32.8	26.5	34.8	21.2	1.5	11.4	3.8	0.8
ADL equipment	Generic	265	24.6	15.8	33.2	27.9	0.4	14.7	6.8	1.1
Assessment of musculoskeletal and prescription of exercises	Specific	220	71.0	75.5	6.8	5.9	-	9.5	1.8	0.5
Care Requirements/support	Generic	171	5.8	13.5	19.9	28.7	3.5	19.9	12.9	1.8
Discharge Visit	Generic	299	4.1	33.1	17.4	22.7	0.7	16.1	7.1	3.0
Drug History and compliance	Specific	95	82.8	66.3	1.1	20.0	-	5.3	5.3	2.1
History taking	Generic	138	19.4	65.2	10.1	15.9	-	4.3	3.6	0.7
Mobility/Gait Assessment	Specific	329	50.5	49.8	18.8	22.5	1.2	4.3	2.1	1.2
PADL Assessment	Generic	87	30.8	13.8	40.2	27.6	1.1	9.2	6.9	1.1
Possible future health requirements	Generic	252	18.1	25.4	21.4	37.7	2.0	10.3	2.4	0.8
S.A.P.	Generic	424	9.6	17.9	26.2	41.5	1.4	5.9	3.3	3.8
Signposing/referring on	Generic	683	19.7	16.3	21.1	26.5	1.0	23.9	11.0	0.3
Simple adaptions	Generic	145	31.6	19.3	40.7	20.7	-	14.5	4.1	0.7
Urinalysis/BP/BM/Temp	Generic	271	59.0	18.8	3.7	59.4	1.5	4.1	10.3	2.2
Assistance with/undertaking on behalf										
Care Provision	Specific	490	0.0	-	0.8	1.8	-	38.4	58.2	0.8
Ensure eating/nutritional intake	Generic	426	1.0	1.6	2.3	6.3	0.2	44.1	44.8	0.5
Environmental checks	Generic	113	21.2	15.0	23.0	16.8	-	25.7	17.7	1.8
Full Care/DADL	Generic	97	0.0	-	1.0	1.0	-	13.4	84.5	-
Full Care/PADL	Generic	268	0.0	1.1	1.1	3.4	-	40.7	53.0	0.7
Putting on Appliances	Generic	256	6.9	9.0	3.1	3.5	-	58.2	25.8	0.4
Practice of/with										
Advice on care/equipment provision	Generic	228	12.6	13.2	21.5	7.9	0.4	36.4	20.6	-
Falls advice/safety monitoring	Generic	492	10.9	10.0	10.8	6.1	-	51.2	21.5	0.4
Gait re-education	Generic	222	8.4	10.8	0.9	3.2	-	72.1	12.7	0.5
Meal planning/monitoring	Generic	279	0.0	0.7	-	2.9	-	47.0	48.7	0.7
Meal Prep	Generic	134	0.8	1.5	3.0	4.5	-	56.7	31.3	3.0
Monitoring and advice on meds	Specific	485	11.3	5.8	4.3	16.1	0.6	38.8	34.2	0.2
Monitoring changes in condition	Specific	967	4.8	16.3	5.0	10.8	0.2	39.9	25.6	2.2
Monitoring of carer's well being	Generic	94	1.1	1.1	2.1	13.8	-	42.6	37.2	3.2
Monitoring of continence	Generic	112	14.3	5.4	6.3	17.9	0.9	38.4	31.3	-
Outdoor mobility/stairs/steps	Generic	302	1.0	6.6	2.0	5.0	-	57.6	27.9	1.0
Practice with exercises	Generic	654	19.9	31.7	2.9	4.7	-	41.6	17.8	1.4
Practice with personal care	Generic	263	0.0	1.9	2.3	2.7	-	43.7	49.0	0.4
Safe use of adaptions	Generic	104	1.6	10.6	11.5	12.5	-	51.0	13.5	1.0
Safe use of equipment	Generic	238	1.1	5.9	12.2	5.0	-	50.4	25.6	0.8
Safe use/advice of walking aids	Generic	1139	2.5	6.0	3.0	2.3	-	61.0	27.2	0.6
Transfer Practice	Generic	863	10.4	11.2	7.5	5.1	0.1	52.6	23.2	0.2
Wound Care	Specific	123	1.8	10.6	-	17.1	-	61.8	8.1	2.4

Appendix D

The Triangular Distribution

The triangular distribution originates from around the middle of the 18th century. As reported in Kotz and van Dorp (2004), recent growth in popularity can be attributed to its use in Monte Carlo simulation and its use in standard uncertainty analysis software, such as @Risk developed by the Palisade Corporation. The triangular distribution is recommended for use when the underlying distribution is unknown, but a minimal value a, some maximal value b and a most likely value m are available. More recently the triangular distribution has been proposed as a substitute for the Beta distribution and Kotz and van Dorp (2004) hope that it becomes apparent that the distribution's 'simplicity' is to a certain extent wrongly perceived. Winston (1994) states that "the triangular distribution has important applications in simulation. It is often used to represent activities for which there are few or no data."

Some important properties are listed below, where a is the minimum value, b is the maximum and m is the mode..

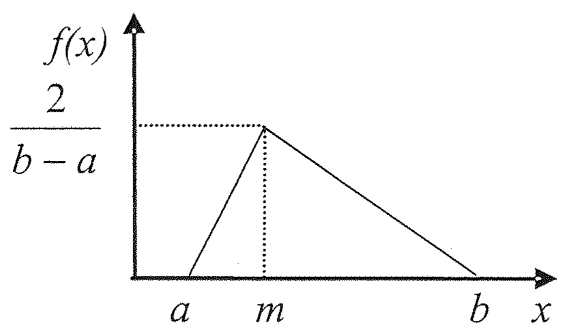

Figure D.1: Graph of the pdf of the triangular distribution

Probability Density Function (pdf)

The pdf is as follows:

$$f(x) = \begin{cases} 0 & , \text{for } x < a \\ \frac{2(x-a)}{(b-a)(m-a)} & , \text{for } a \leq x \leq m \\ \frac{2(b-x)}{(b-a)(b-m)} & , \text{for } m \leq x \leq b \\ 0 & , \text{for } x > b \end{cases}$$

This is illustrated in Figure D.1.

Cumulative Distribution Function (cdf)

The cdf is as follows:

$$F(x) = \begin{cases} 0 & , \text{for } x < a \\ \frac{(x-a)^2}{(b-a)(m-a)} & , \text{for } a \leq x \leq m \\ 1 - \frac{(b-x)^2}{(b-a)(b-m)} & , \text{for } m \leq x \leq b \\ 1 & , \text{for } x > b \end{cases}$$

Generating Random numbers from the Triangular Distribution

Since the cdf can be obtained in the closed form, the inverse transformation method can be used to generate random numbers from the triangular distribution. A random number r, is generated between 0 and 1 and set equal to $F(x)$ from which the corresponding value of x is evaluated, using the equation below. If this is repeated enough times, then the resulting values of x will form a triangular distribution.

$$x = \begin{cases} a + \sqrt{r(b-a)(m-a)} & , \text{for } 0 \leq r \leq F(m) \\ b - \sqrt{(1-r)(b-a)(b-m)} & , \text{for } F(m) \leq r \leq 1 \end{cases}$$

where $F(m) = \frac{m-a}{b-a}$

Calculating the Mean, given the Mode

The mean μ of the triangular distribution is $\mu = \frac{a+m+b}{3}$.

Proof:

$$
\begin{aligned}
E(x) &= \int_a^b x f(x) dx \\
&= \int_a^m \frac{2x(x-a)}{(b-a)(m-a)} dx + \int_m^b \frac{2x(b-x)}{(b-a)(b-m)} dx \\
&= \frac{2}{(b-a)(m-a)} \left[\frac{x^3}{3} - \frac{ax^2}{2} \right]_a^m + \frac{2}{(b-a)(b-m)} \left[\frac{bx^2}{2} - \frac{x^3}{3} \right]_m^b \\
&= \frac{2m^3 - 3am^2 + a^3}{3(b-a)(m-a)} + \frac{2m^3 - 3bm^2 + b^3}{3(b-a)(b-m)} \\
&= \frac{2m^2 - am - a^2}{3(b-a)} + \frac{b^2 + mb - 2m^2}{3(b-a)} \\
&= \frac{-am - a^2 + b^2 + bm}{3(b-a)} \\
&= \frac{(b-a)(m+a+b)}{3(b-a)} \\
&= \frac{a+m+b}{3}
\end{aligned}
$$

Calculating the Mode, given the Mean

Rearranging the above equation gives the mode m of the triangular distribution, when the mean is known:

$$m = 3\mu - a - b$$

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