Modelling waiting lists and waiting times for cardiac surgery operations

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Modelling Waiting Lists and Waiting Times for Cardiac Surgery Operations

By Gareth Greaves

Doctoral Thesis

Submitted in partial fulfilment of the requirements for the award of
Phd of Loughborough University

May 2008

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Dedication

This thesis is dedicated to Joan, Evan and Conor
Acknowledgements

I would like to thank the people who have advised and helped over the duration of the thesis, in particular Ron Summers whose expert guidance and support has proved invaluable. These also include the staff at Glenfield Hospital including Helen Mather, Karen Jack, Teresa Rowley and Dee Cottingham.
Abstract

This study details the creation of two simulation models for a cardiac surgery specialty in a Midlands hospital. The models were designed to help the specialty meet waiting time targets set out by the Government in their NHS Plan.

The first model is a spreadsheet data simulation that gives a general prediction of patients waiting for surgery by time band for up to a year in the future based on previous data.

The study uses the qualitative analysis of interviews and documents to generate the second model. The first part of this model is a qualitative causal loop diagram of the cardiac surgery system. A quantitative ‘Stock & Flow’ model is drawn from this qualitative model which gives detailed predictions of waiting lists and times and other system variables for the cardiac surgery specialty.

The system dynamics model is validated. It can estimate the maximum number of new outpatient attendances the system can support whilst keeping inpatient waiting times below three months for various configurations of theatre time and Cardiac Intensive Care Unit (CICU) beds. The study concludes that CICU beds are a bigger constraint on inpatient waiting times in the cardiac surgery specialty at the hospital than theatre time. Measures to improve waiting times and shorten lists should therefore concentrate on improving patient flow through the CICU, for example more beds in the Unit would enable more patients to be treated. The model can also demonstrate the use of the theory of constraints in managing waiting lists, which is the method used by the NHS Modernisation Agency in their guidance on waiting list management.
Chapter 1: Introduction

1.1 Introduction

The NHS Plan, Department of Health (2000b), described a ten year strategy to improve the services of the National Health Service (NHS). It set out targets for maximum waiting times for surgery. No patient should wait more than six months for an operation by 2005 and no more than three months by 2008 (three months by 2005 for revascularisations). Heart surgery was singled out as a first stage in the process of cutting surgical waiting times and Trusts offering heart surgery had to meet a twelve month maximum wait by April 2002 and nine months by April 2003.

The NHS Plan also set out major reform of the Health Service in return for which a major increase in funding was to be enacted. The Plan described the NHS as a “1940s system operating in a 21st Century World”. Between 2000 and 2005, funding for the NHS was expected to rise by 50% in cash terms and by one third in real terms. (The increase was achieved. In the 2000/01 financial year £45 billion pounds was spent on the NHS, in 2005/06 this had risen to £74.2 billion and is projected to rise to £87.6 billion for 2007/08, sources Department of Health Departmental Reports 2006 and 2007.)

The plan listed some systemic failures of the NHS:

- “a lack of national standards;
- old-fashioned demarcations between staff and barriers between services;
- a lack of clear incentives and levers to improve performance, and,
- over-centralisation and disempowered patients.”

Public Consultation about the Plan showed that the Public wanted “reduced waiting times and high quality care centred on patients”. To this end, the Plan set out targets for maximum waiting times for surgery. The targets were set out in the above paragraphs and are summarised in Table 11 below.
Table 1: Inpatient Waiting Time Targets

<table>
<thead>
<tr>
<th>Target</th>
<th>Target Date</th>
<th>Achieved by Target Date</th>
<th>National Position at March 2007</th>
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<tr>
<td>Heart Surgery 9 month maximum Wait</td>
<td>April 2003</td>
<td>77 patients waiting over 9 months (from a total list of 8,896)</td>
<td>Zero patients waiting over 30 weeks (from a total list of 4,804)</td>
</tr>
<tr>
<td>3 month maximum wait for revascularisation</td>
<td>March 2005</td>
<td>0.006% *</td>
<td>0.14% *</td>
</tr>
<tr>
<td>6 month maximum wait</td>
<td>December 2005</td>
<td>No - 1,008 patients waiting over 6 months (compared to a total list of 784,303)</td>
<td>597 patients waiting over 6 months (compared to a total list of 700,585)</td>
</tr>
<tr>
<td>3 month maximum Wait</td>
<td>Dec 2008</td>
<td>N/A</td>
<td>115,420 waiting more than 3 months</td>
</tr>
</tbody>
</table>

* Data for revascularisations is published by the Healthcare commission and is defined as the number of patients who have been waiting more than six months in the first 11 months of the year beginning in April 2004 or more than three months as at 31st March 2005 for a revascularisation divided by the total number of patients that received a revascularisation between April 2004 and March 2005 (Healthcare Commission, 2005). Less than 0.10% is considered as 'Good'.

To meet the NHS Plan targets, the NHS wanted to increase the funding in existing services, invest in new heart surgery facilities, fund operations in the private sector and utilise extra capacity abroad. There was also to be more flexibility on where patients can be treated. The scheme known as Patient Choice was designed to give patients a choice of four to five hospitals and a date and time of their appointment at the time of referral. This was to be achieved by December 2005 though patients requiring heart surgery were to be given a choice of hospital by April 2005. A new system to utilise any spare capacity in other parts of the UK was to be set up to give the longest waiting patients some choice in their treatment.
By the end of 2005, the NHS Plan suggested that waiting lists should be abolished and replaced with booking systems, giving patients a convenient time to come into hospital and a maximum guaranteed waiting time. Booking systems allow patients to choose the date of their outpatient appointment and the date of their admission if they require inpatient treatment. The NHS Plan (Chapter 12, Sections 16 and 17) suggested that the introduction of booking systems will mean more appropriate outpatient referrals for consultants to work with and more efficient use of clinic slots and theatre time.

The above mentioned booking systems were being introduced through the Department of Health’s combined strategy involving waiting, booking and choice “. . . to give all patients fast and convenient access to health and social care services ..” known as the waiting, booking, choice scheme, Department of Health (2003b). One of the main programmes to achieve this is Choose & Book (Department of Health, 2004a) whereby patients are able to book outpatient appointments and inpatient admission dates (usually via a GP surgery) that are convenient for them. Computer Systems were designed to support this, however many systems were delayed and by the end of 2004 only 63 appointments had been booked using the new system when it should have processed 205,000 (Mathieson, 2007). However, by April 2007, over four million appointments had been booked, Department of Health (2007).

The increase in funding for the NHS came with the condition that services must be improved and if necessary re-designed. The Government’s stated intention is to bring more choice into the healthcare system, abolish waiting lists and make the service as a whole more flexible and responsive to the needs of the patient. The NHS Plan’s aim of increasing capacity and redesigning the way services are offered to patients is seen as the best way to bring down long waits for admissions and appointments. But they are also seen as essential for managing appointments and extending choice for patients.

Glenfield Hospital is one of three hospitals that form part of the University Hospitals of Leicester NHS Trust. Cardiology and cardiac surgery form a major
part of Glenfield Hospital's workload. The Hospital performs about 1,500 heart operations a year (admissions to the cardiothoracic surgery specialty). On average, there will be between 350 and 400 patients on the cardiothoracic surgery waiting lists, at any one time, served by seven cardiothoracic surgeons. Empirical evidence suggests that 31% of admissions for cardiothoracic surgery are classed as emergencies.

Waiting time targets posed a significant number of challenges for Hospital Trusts. These included the best ways to achieve the targets in the timescales set down, deciding if extra elective capacity was needed (and if so, how much) and achieving the targets without disadvantaging other groups of patients or threatening standards of care. The Cardio-Respiratory directorate at Glenfield Hospital decided a model of their processes of care would be best able to answer some of these challenges and help them achieve these targets.

Traditionally the cardio-respiratory directorate in Glenfield Hospital had routinely used simple spreadsheet models on average variables (average additions to list per month, average numbers of operations per month, etc.) to estimate numbers on waiting lists and bed capacities needed to satisfy demand. Now, with the imposition of waiting time targets, managers in the directorate felt they needed a model that could estimate the extra capacity needed to meet these maximum waiting time targets and how quickly the targets could be achieved.

However, it was also concluded that a more systemic model was also needed that could model processes of care in more detail and relate waiting times to the number of beds, theatre time, etc. This systems model would give a better idea of the effects on waiting times and other performance factors of changing policies in the healthcare system. The directorate was also interested in discovering other modelling methods than the simple models they had developed in spreadsheets.
1.2 Background

1.2.1 Rationing Healthcare

Healthcare resources are limited. Demand for healthcare is very high, however, especially in a ‘free’ public service like the NHS which has no price controls. Priorities between patients are determined implicitly, in a process that is invisible to the patient. This hides variation in access between different areas and patients. What principles underlie decisions on both questions and who makes these decisions?

“the rationing of scarce resources at all levels within the NHS has been largely controlled by the medical profession and has been implicit in nature, making no reference to agreed systems or criteria” New and Le Grand (1997)

Deciding who gets treated and what treatments are provided with the available resources leads to a rationing of healthcare. Waiting lists are one element of this rationing. Whose treatment is a priority, whose will be delayed (i.e., enter a waiting list) and whose denied?

As Morgan (1998) pointed out, doctors exist in limits set by Health Authorities in terms of budgeting for certain health priorities. Today’s population is better informed, educated and less acquiescent. Limited resources mean patients are sometimes denied treatment. Implicit rationing cannot sustain the myth that the NHS can do everything for everyone. However, attempts to make rationing more explicit are perceived by the public as a weakening of the comprehensiveness of the service and can lead to controversy. Morgan (1998) recalled the case of ‘Child B’ who was denied treatment for leukaemia by her Health Authority supposedly on the grounds of cost. The case led to a public outcry. The Health Authority decided not to pay for chemotherapy and a bone marrow transplant after similar treatment had already failed to work. A doctor advised the family of ‘Child B’ that there was a 20% chance of success, much higher than had been previously suggested. However, the Health Authority still
refused to pay An anonymous donor came forward to pay for the treatment which at first seemed to work, but, in May 1996, 'Child B' died.

One way in which patients have been prioritised is by making 'time waiting' the criteria for choosing between them, New and Le Grand (1997). Originally the Patients' Charter gave patients the right not to wait longer than two years for inpatient treatment. This target was abolished when the Labour Government of Tony Blair came to power in 1997. Instead they introduced maximum waiting times for surgery starting at twelve months and gradually reducing to three months by 2005/8. In other words, long waits have been given a high priority. Could allocating resources to long waiters who are not seriously ill divert resources from those patients more seriously ill? There is a danger that such a fixed prescriptive system may influence sensible decisions being made in individual cases.

New and Le Grand (1997) suggested some principles to make rationing of healthcare more rational. Rationing should be:

- Explicit – Practices are undertaken openly
- Systematic – Formal ways are used to allocate resources consistently
- Democratic – There is public involvement in the decision making process

The public have perceived treatment on the NHS as being available when needed, never as being rationed. Being open or explicit in rationing policies, therefore, can cause public disquiet even though an implicit rationing has always been a feature of the NHS. Even waiting lists and delays in a GP's waiting room are seen more as 'taking one's turn in the queue', New and Le Grand (1997), rather than as choices being made as to whether to treat a patient. This would not suggest a mismatch between supply and demand. The public will not readily accept an explicit denial that a treatment is worth doing in the first place.
To achieve the new waiting time targets, will consultants need to conform to a common waiting list and treatment policy? If so, there is a need to be more explicit about waiting list policy and rationing to each other and patients. This might lead to public controversy as the Public may view this explicitness as a watering down of the comprehensiveness of the service provided by the NHS.

In the year 2000, the Government, in its NHS Plan, considered the possibility of turning the NHS into a healthcare system that simply provided a core of rationed services, it rejected the idea:

"The issue is not whether the NHS – just like every other public or private health service – has to set priorities and make choices. The issue is how those choices are made. Under the NHS, treatment is based on peoples’ ability to benefit. We are in a period of significant expansion of health service resources. The issue is how to improve decisions about how those expanded resources are used. We can no longer leave to chance decisions about how treatment is provided, how demand is managed, and how costs are driven. National Service Frameworks and the broad priorities set out in this NHS Plan provide the context. The National Institute for Clinical Excellence, supported by its new Citizens Council (see paragraph 10.20) will help the NHS to focus its growing resources on those interventions and treatments that will best improve peoples’ health. By pointing out which treatments are less clinically cost-effective, it will help free up financial headroom for faster uptake of more appropriate and clinically cost-effective interventions. This is the right way to set priorities: not a crudely rationed core service."

Department of Health (2000b), Section 3.32

The National Institute for Clinical Excellence’s (NICE) provides guidance on medicines, medical devices, diagnostic techniques, procedures and the clinical management of specific conditions, NICE (2003). The organisation aims to assess whether treatments are effective and to make sure this information reaches the NHS. Health professionals are expected to take NICE guidelines into account once they are published. NHS organisations have a statutory
obligation to provide funding for treatments and drugs recommended by NICE under its technology appraisals programme (medicines, medical devices, diagnostic techniques and surgical procedures) though only if that treatment is desired by the patient. There is no obligation to fund the other recommendations made by NICE.

NICE was set up to try and stop the ‘postcode’ lottery where access to treatment varies across the country (Butler, 2002). For example, NICE issued guidance on fertility treatment to try and iron out variations of access across the country where some Health Authorities funded it and others did not. NICE formalises the process of deciding what treatments should be provided on the NHS which could be viewed as a way of rationing care. NICE can rule against clinically effective treatments on the basis of their long-term cost to the NHS.

1.2.2 NHS Performance Ratings and Targets

The Commission for Health Improvement (CHI) was the independent regulator of NHS performance. Its work included clinical governance reviews (routine inspections), investigating serious service failures and reporting on key issues such as coronary heart disease. It also published performance ratings such as the NHS star ratings. CHI’s aim was to raise the standard of clinical care in the NHS. CHI’s NHS performance ratings, CHI (2003), put NHS Trusts in one of four categories as shown in Table 1.2.

Acute Trusts were rated against nine key targets set by the Government. Table 1.3 lists these nine targets. The ratings also included a broader set of indicators developed by CHI and the Department of Health, and any recent clinical governance review undertaken by CHI.

23
Table 1.2 Trust Star Ratings

<table>
<thead>
<tr>
<th>Stars</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 Stars</td>
<td>Trusts with the highest levels of performance</td>
</tr>
<tr>
<td>2 Stars</td>
<td>Trusts that are performing well overall but have not quite reached the same consistently high standards</td>
</tr>
<tr>
<td>1 Star</td>
<td>Trusts where there is some cause for concern regarding particular areas</td>
</tr>
<tr>
<td>Zero Stars</td>
<td>Trusts that have shown the poorest levels of performance</td>
</tr>
</tbody>
</table>

In 2003, The University Hospitals of Leicester NHS Trust received a no star rating, down from its two star rating in the last published performance ratings CHI (2003) It failed in two key targets and underachieved on another (Reading, 2003):

- number of inpatients waiting longer than 12 month standard (failed);
- total time in A&E (90% less than four hours) (failed), and,
- A&E emergency admission waits (12 hours) (underachieved)

However in both 2004 and 2005, UHL achieved a three star rating, Healthcare Commission (2004a)

Can these nine key targets (Table 1.3) adequately ‘rate’ a Hospital’s performance? Four Trusts which were being considered for Foundation status lost their three star rating according to Carvel (2003b) Critics of the performance ratings include James Johnson, the chairman of the British Medical Association (BMA) (Carvel, 2003b)

“They measure little more than hospitals’ ability to meet political targets, and take inadequate account of clinical care or factors such as social deprivation.”

The turnaround in UHL’s rating might suggest these targets may not be adequate to differentiate performance amongst hospitals. The targets failed did not take into account clinical care directly, only waiting times for treatment (albeit that long waits for treatment are undesirable) and could be considered
to be political in nature. While a great deal of effort by UHL staff went into achieving this turnaround, the essential difference in the performance in 2003 and 2004 could simply be management attention and not a poorly performing hospital improving dramatically.

Table 13 Nine Key Targets

<table>
<thead>
<tr>
<th>A&amp;E emergency admission waits (12 hours)</th>
<th>Cancelled operations not admitted within 28 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial management</td>
<td>Hospital Cleanliness</td>
</tr>
<tr>
<td>Hospital Cleanliness</td>
<td>Improving working lives</td>
</tr>
<tr>
<td>Number of inpatients waiting longer than the standard</td>
<td></td>
</tr>
<tr>
<td>Number of outpatients waiting longer than the standard</td>
<td></td>
</tr>
<tr>
<td>Total time in A&amp;E</td>
<td>Two week Cancer Waits</td>
</tr>
</tbody>
</table>

On the 30th July 2003 at the Prime Minister’s Press Conference, Professor Michael Barber (Head of the Prime Minister’s Delivery Unit) gave a brief review of the Government’s progress in improving public sector performance (Barber, 2003). One of the areas he talked about was health and the NHS Figures were shown that demonstrated progress to targets of maximum waiting time for elective surgery and waiting time in Accident and Emergency departments. Professor Barber also talked about targets themselves.

“They (targets) are an essential element of managing any large organisation, particularly one spending large amounts of taxpayers’ money. The government’s targets are representations of the real world outcomes that citizens most want to see such as reduced crime, reduced waiting times and so on. They are not substitutes for those real world outcomes, and they enable citizens to hold the government to account.”
In 2006, the Healthcare Commission succeeded the Commission for Health Improvement. It introduced a new inspection regime, the 'annual health check'. The Commission claims the health check "looks at a much broader range of performance than the previous system of star ratings and enables us to paint a more comprehensive picture than ever before of what is happening in healthcare." (Healthcare Commission, 2006, p 5)

Every NHS Body that provides healthcare is assessed annually and rated according to two components: 'quality of services' and 'use of resources'. The Commission measures the performance of NHS Organisations according to standards published by the Department of Health.

These Standards are very broad and cover the following areas:

<table>
<thead>
<tr>
<th>Core &amp; Developmental Standards</th>
<th>Safety</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Clinical and Cost Effectiveness</td>
</tr>
<tr>
<td></td>
<td>Governance</td>
</tr>
<tr>
<td></td>
<td>Patient Focus</td>
</tr>
<tr>
<td></td>
<td>Accessible and Responsive Care</td>
</tr>
<tr>
<td></td>
<td>Care Environment and Amenities</td>
</tr>
<tr>
<td></td>
<td>Public Health</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Existing National Targets</th>
<th>For Example:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Four hour maximum wait in A&amp;E from arrival to admission, transfer or discharge</td>
</tr>
<tr>
<td></td>
<td>Three month maximum wait for revascularisation by March 2005</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>New National Targets</th>
<th>For Example:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>18 Week Target from GP Referral to Hospital Treatment</td>
</tr>
</tbody>
</table>

The Commission's hope is that the assessments will "help people to make informed decisions about their care, promote sharing of information and provide organisations with clearer expectations on standards of performance." (Healthcare Commission, 2006, p 6)
The Audit Commission (1999) gave several reasons why setting standards and targets is important including:

- "focus attention on exactly what kind of service is needed making it clear what level of service is expected,
- help front-line managers to focus effort and resources on priorities, and,
- help the public and service-users to see whether services are being delivered efficiently and effectively and to hold authority members to account for performance"

Targets should:

- "relate to a service objective;
- be achievable but also stretch the organisation;
- have a clear, stable definition so that achievement can be compared over time,
- be easily understood,
- have the commitment of staff;
- be readily measurable, and,
- be honest and unambiguous"

In setting maximum waiting time targets, the Government was trying to set out a measurable, unambiguous indicator of performance that is of concern to the public

1 2 3 'CHD Choice' Pilots

Pilots have been set up to facilitate changes outlined in the NHS Plan. The 'CHD Choice' pilot started in July 2002 and offered patients waiting for heart surgery for more than six months the choice of going to another hospital for quicker treatment. By July 2003, of the 7,262 patients who had waited more than six months for revascularisation, 5,424 were considered eligible for the
scheme. Of these, 5,130 made a choice and 2,549 patients (50% of those offered) opted for treatment at another provider (Patient Choice Trustees, 2003, p 10). This showed that patients were willing to travel for heart surgery to other hospitals meaning that spare capacity in some hospitals might be effectively used to reduce waiting lists in others.

The King’s Fund published an investigation into Patient Choice (Appleby, et al, 2003c). Its main concern was that patient choice could jeopardise access to healthcare. One patient’s choice could mean no treatment for another as some patients choose effective but not cost-effective treatments. The implication was that choice for patients may depend on how articulate or willing to travel they were. While patient choice may lead to greater efficiency in allocating resources it could also lead to less equity as some patients may not be willing to travel or argue their case as effectively as others. There was some concern that patient choice schemes, such as the ‘CHD Choice’ pilot, were merely being used to achieve the Government’s waiting time targets.

1.2.4 ‘Payment by Results’ Funding initiative

A funding system is being introduced so that cash follows the patient to where they are being treated. Known as ‘Payment by Results’ (PbR) it is introduced in a report by the Department of Health (2003a) which described it as a system of paying NHS Trusts for the number of operations they perform adjusted for the complexity of their caseload (known as casemix). This gives incentives for Trusts to perform more work (within agreements set out with Primary Care Trusts) in the knowledge that they will be paid for it. It is also designed to encourage them not to underperform as this would mean funding moving elsewhere. Under the old ‘block’ agreements, activity would have a limited effect on funding. ‘Block’ agreements between health authorities and hospitals ensured a set number of operations in exchange for a certain level of payment. Any over or underperformance by the hospital would not necessarily affect the level of payment received from the Health Authority. These type of agreements left hospitals with little incentive to achieve the set level of operations and considerable financial risk if they over achieved. Paying hospitals according to
what work they have undertaken makes it easier for healthcare commissioners
to move money to other providers of healthcare to make up the shortfall of
activity and achieve waiting time targets

1.2.5 The impact of waiting time targets

Devlin, et al. (2002) argue that waiting time targets are unlikely to help the
Government improve the problem of waiting lists. They list a number of
problems with setting targets for waiting times for elective surgery

Firstly, feedback effects associated with falling waiting times produce results
that tend to increase waiting times. As waiting times fall patients are more likely
to seek publicly funded NHS care (rather than paying to go private). GPs are
more likely to refer patients to consultants and consultants more likely to add
patients on to their waiting lists

Secondly, targets can distort clinical priorities. Patients with less disease
become more of a priority as they approach the waiting time target than sicker
patients who might benefit more from the treatment. Concentrating on certain
targets does not address issues of equity, efficiency and resource allocation.
Meeting a certain target may mean diverting resources from other areas of
care where the health benefits might be greater. A committee of MPs was told
that 25 patients lost all or part of their sight when their follow-up outpatient
appointments were cancelled to make way for new outpatients so that the Trust
in question could meet its outpatient waiting time target (Hencke, 2003).

Thirdly, pressure to meet the targets can result in Trusts mis-reporting or
manipulating the waiting lists. The National Audit Office (NAO) report just such
problems (NAO, 2001a). The NAO's report listed nine NHS Trusts that made
'inappropriate adjustments' to their waiting lists affecting 6,000 patients. The
problems ranged from incorrect procedures followed by junior staff to
deliberate mis-reporting of the figures. A common mis-reporting technique was
to suspend patients from the waiting list temporarily. A patient may be
suspended from the list if they are temporarily unavailable for treatment (e.g
holiday, other medical problems) and they are not counted towards the official waiting list figures.

A report in "The Guardian" on the 5th April 2003, by Carvel (2003c), described the meeting of the maximum wait of 12 months for elective surgery and nine months for a heart operation (NB Heart surgery had a nine month target at this point as it was singled out for the first stage in cutting surgery waiting times). Although 6,700 surgery patients had been waiting more than twelve months at the end of February 2003, only 63 were left by the end of March. Managers had used "every device" to avoid failing the target including paying for private operations. This drop was remarkable given past experience and caused the shadow Health Secretary Liam Fox to remark that "NHS statistics have all the credibility of Enron accounts" (Carvel, 2003c). No patients had been waiting more than nine months for heart surgery by the end of March 2003, the lowest figure since the Government started keeping records in 1998. On the 7th June 2003, Carvel (2003a) reported that those waiting over twelve months for elective surgery had doubled in a month to 134 rather than dropping to zero as expected. The paper also reported the Audit Commission as warning that such results "... were achieved by short-term fixes, diverting resources from long-term investment to modernise the NHS."

One of the NAO's recommendations was to increase monitoring of the way waiting lists are recorded by Trusts, "...there needs to be more checks and balances in the system to help manage such behavioural risks [managers inappropriate adjustments]."

An investigation by the BBC programme Panorama into NHS performance targets (Barclay, 2003) highlighted the consequences of setting targets. The programme showed a Trust, struggling to meet waiting time targets in its Accident & Emergency department, refusing to accept patients from Ambulance paramedics as this would mean that the patient was officially in the Trust's hands and their wait had started. Ambulance crews were forced to look after their patients in an 'ambulance waiting area'. At one time half of the
ambulances in the county were stuck at the Accident & Emergency department leaving the others overworked and overstretched.

The Panorama programme also highlighted the pressure managers were under to achieve targets. A former Trust Chief Executive described certain targets as "P45 targets", meaning they would be sacked if these targets were not achieved.

12.6 The Impact on the Cardio-Respiratory Directorate

In Leicester, long waiting heart surgery patients have been sent to the private sector (Leicester Mercury, 2002a) in a bid to cut waiting times. This helped the Trust to cut its maximum waiting time to twelve months by March 2002 and, it is hoped, will help meet its six month target, UHL NHS Trust Public Relations Office (2002). The Trust has also launched a £10 million bid to increase investment in cardiac services in order to see another four thousand patients a year at Glenfield Hospital (Leicester Mercury, 2002b)

Table 14 Patients waiting for Cardiothoracic Surgery Quarter 1 2002/03 (Department of Health, 2002)

<table>
<thead>
<tr>
<th>Waiting Time (months)</th>
<th>Total</th>
<th>&lt; 3</th>
<th>3-5</th>
<th>6-8</th>
<th>9-11</th>
<th>12-14</th>
<th>15-17</th>
<th>18+</th>
</tr>
</thead>
<tbody>
<tr>
<td>England</td>
<td>11,439</td>
<td>5,152</td>
<td>3,272</td>
<td>1,886</td>
<td>1,073</td>
<td>56</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>100.0%</td>
<td>45.0%</td>
<td>28.6%</td>
<td>16.5%</td>
<td>9.4%</td>
<td>0.5%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>UHL (Glenfield Hospital)</td>
<td>608</td>
<td>240</td>
<td>150</td>
<td>130</td>
<td>88</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>100.0%</td>
<td>39.5%</td>
<td>24.7%</td>
<td>21.4%</td>
<td>14.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The figures in Table 14 show that the University Hospitals of Leicester NHS Trust (UHL) had a higher proportion of patients waiting more than three months for surgery than the England average, 60.5% compared to 55% (Department of Health, 2002)
Table 1.5 shows the same figures, one year on. The figures for England show that the total list had fallen by 27%. While the numbers waiting under three months are unchanged, the number of patients waiting over three months had fallen dramatically. Numbers waiting at UHL for a heart operation fell by 14% and the Trust achieved the nine month waiting time target. Those waiting over six months had fallen from 218 to 40. The distribution of waiting patients is now similar to the national average.

Table 1.5: Patients waiting for Cardiotoracic Surgery Quarter 1 2003/04 (Department of Health, 2002)

<table>
<thead>
<tr>
<th>Waiting Time (months)</th>
<th>Total</th>
<th>&lt; 3</th>
<th>3-5</th>
<th>6-8</th>
<th>9-11</th>
<th>12-14</th>
<th>15-17</th>
<th>18+</th>
</tr>
</thead>
<tbody>
<tr>
<td>England</td>
<td>8,403</td>
<td>5,213</td>
<td>2,431</td>
<td>681</td>
<td>78</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>100.0%</td>
<td>62.0%</td>
<td>28.9%</td>
<td>8.1%</td>
<td>0.9%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>UHL (Glenfield Hospital)</td>
<td>523</td>
<td>327</td>
<td>156</td>
<td>40</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>100.0%</td>
<td>62.5%</td>
<td>29.6%</td>
<td>7.6%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>
1.3 Approaches to Waiting List Management

This section deals with the NHS’s approach to managing waiting lists at a National level since the year 2000.

There are relatively few studies of waiting lists in the literature. A number of factors may have brought this situation about. Firstly many NHS Trusts, Primary Care Trusts (PCTs) and Strategic Health Authorities use the commercial Checklist waiting list model. Secondly most other waiting list models are fairly simple spreadsheet models which their authors would not think important or innovative enough to publish. Lastly, the NHS Modernisation Agency had an emphasis on waiting list management rather than modelling. Harrison (2000) reported the establishment of the National Patients’ Access Team in 1998 by the NHS Modernisation Agency. Their aims regarding waiting lists included:

- providing experienced, practical help for NHS Trusts and Health Authorities to achieve agreed reductions in in-patient, day case, and outpatient waiting

- identifying and disseminating good waiting list and elective care management across the NHS

- supporting NHS staff and patients to re-design and implement improved elective care through, for example, booking systems.

"Harrison (2000)

The Demand Management Group of the NHS Modernisation Agency set out best practice waiting list strategy on its website (NHS Modernisation Agency, 2005b). The Group recommended just one priority queue and one routine queue. They referred to having several priority classes within a waiting list as ‘queues within queues’ and pointed out that they cause problems by increasing the likelihood that patients are admitted out of turn thus increasing maximum waiting times.

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To control waiting times, consultants must control their selection strategy from their waiting list. If patients are seen or admitted out of turn in the queue, this will push up the maximum waiting time, for example figure 1 1 shows two selection strategies applied to the same queue.

The figures below show two queues of equal length, both in terms of size (four patients waiting) and waiting time (four units of time) at the start time, A. Advancing from one time period to the next, e.g. A to A+1, each queue has one patient added and one ‘served’ (or admitted)

Figure 1 1a shows a strategy of selecting patients ‘in-turn’ or the longest waited first (also known as First In First Out or FIFO). Figure 1.1b shows a random strategy of selecting patients from the queue. The ‘in-turn’ strategy results in a constant maximum waiting time of four units whilst the random strategy of figure 1.1b results in a maximum waiting time of seven units. This difference exists despite their arrival and admission rates being the same.

This example brings up the point that it is not always a lack of capacity that produces long waiting times for elective admission, made by Silvester, et al. (2004) in their paper on reducing waiting times for elective admission (The paper includes authors from the NHS Modernisation Agency). They argued that long waits for treatment are mainly caused by a mismatch between demand for the service and the capacity provided to cope with that demand, variation in capacity and demand cause queues

The paper described how applying Goldratt’s theory of constraints can reduce or eliminate queues for healthcare operations. The theory posits that each process has a capacity bottleneck that limits the output level of the system. Variation in the system causes a loss of capacity and an increase in waiting times.
Figure 1.1a: Choose patients ‘in-turn’, i.e. longest waited first

<table>
<thead>
<tr>
<th>Time Waited (Units)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Period</td>
<td>A</td>
<td>A+1 Unit</td>
<td>A+2 Units</td>
<td>A+3 Units</td>
</tr>
</tbody>
</table>

Final Position: Maximum Waiting Time 4 Units

- **Patient Admitted**
- **Patient on Waiting List**
- **New Addition to Waiting List**

Figure 1.1b: Choose patients randomly

<table>
<thead>
<tr>
<th>Time Waited (Units)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Period</td>
<td>A</td>
<td>A+1 Unit</td>
<td>A+2 Units</td>
<td>A+3 Units</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Final Position: Maximum Waiting Time 7 Units

- **Patient Admitted**
- **Patient on Waiting List**
- **New Addition to Waiting**
The Authors point out that waiting lists form very rarely because demand is greater than capacity. More likely is the fact that variation in demand (e.g., referrals for treatment) is not well matched to variation in capacity (e.g., appointments or operations the system is capable of performing). Since wasted capacity (e.g., Patients not turning up, operations cancelled because resources not available) cannot be passed on to some future time whilst unmet demand must be, large variations in either or both will result in patients having to wait longer for treatment.

The Authors list the ways the NHS has managed lists,

- Delaying non-urgent patients so they either get better or go to another provider
- Overbooking of clinic sessions to force urgent patients into a full system

Carving out capacity e.g., ring fencing operating theatre slots for urgent patients. This can worsen the queue and waiting times because slots for urgent patients may not be filled, or could be filled with non-urgent patients seen out of chronological order thus increasing the maximum waiting time. This can lead to increased ‘gaming’ of the system by patients and clinicians.

Waiting List Initiatives are tried out to remove the queue but do not resolve the underlying causes of the queue.

Silvester et al. point out that the NHS would do better to focus instead on improving patient flow by

- Understanding the system
- Simplifying the processes
- Controlling and reducing variation
- Set the capacity appropriately and monitor variation in capacity and demand

The NHS Modernisation Agency produced a series of Management Guides to help in the control of waiting times leading to the possibility of the introduction of the Choose & Book policy. These Guides—‘Initial Validation’ (NHS Modernisation Agency, 2003b), ‘Primary Targeted Lists (PTLs)’ (NHS

A further series of Guides, the Improvement Leaders' Guides, were produced by the NHS Modernisation Agency, that build on these ideas and introduce concepts of systems thinking and process mapping. One such, 'Improving flow' (NHS Modernisation Agency, 2005a), investigated the causes of queues in healthcare settings and suggests improvements to eliminate them.

The Guide explains how to organise a service in which patient waits and delays are eliminated or minimised. The first step to take is to map out the processes involved in the healthcare system. A system will have one step or process slower than the others – the 'rate limiting step' or 'bottleneck'. Queues may build up before this step if patient demand is not matched to its capacity.

'Improving flow' (NHS Modernisation Agency, 2005a) points out that tackling bottlenecks on their own may have implications for other services, shifting the bottleneck elsewhere. Improving flow in an Outpatient clinic may have knock-on effects for the hospital pharmacy. There should be an effort to improve flow over whole systems of care.

The Guide gives details of some techniques that can be used to improve flow, underpinned by the 'Model of Improvement' (see Figure 1.2 below) whereby "... small scale changes are tested and built on gradually to change the larger system" (NHS Modernisation Agency, 2005a).

The Guide also suggests the use of Statistical Process Control to measure the impact of any changes tried out and control any variation in capacity and demand for services.

Most of the ideas running through these guides come from the 'Theory of Constraints' which is most readily demonstrated by the novel 'The Goal' written by Goldratt & Cox (Goldratt and Cox, 1993) and to which the guides refer.
The novel describes the plight of a factory manager, Alex Rogo, who is given just three months to save his underperforming production plant. The plant is losing money, is consistently late with orders and constantly expedites orders causing chaos on the shop floor.

Figure 1.2 The 'Model for Improvement' (From 'Improving Flow' Man Guide)

A chance meeting with his old University mentor, Jonah, forces Alex to think about the real goal of his plant. As Jonah points out the Goal of the plant is not to manufacture items but rather it is to make money from manufacturing, therefore it should only be manufacturing to meet current demand and the company should not try to predict demand merely to keep the plant busy and 'efficient'.

Jonah explains that manufacturing plants are a series of processes where items are constructed and worked on, these items eventually flow through to the process where they are assembled. Some of these processes will be
bottlenecks, that is processes that limit the flow of items through the plant to final assembly. These bottlenecks set the capacity of the system or plant.

The trick is to keep bottlenecks working at full capacity, while non-bottlenecks can have downtime. Non-random variation in the system is reduced so the items flow through the system smoothly with the bottlenecks always having something to work on. Once variation in flow is minimised and the bottlenecks are working at full capacity Alex's team can then predict the time it takes for work to flow through and can give more realistic and lower completion times for orders and so have more satisfied customers. Cutting the batch sizes (the number of items being worked on by a process/machine at one time) further reduces variation by ensuring better flow through the system.

The team are able to use the reduction in variation to predict when to release material on to the shop floor so that enough material is available to keep the bottleneck processes running. They can then predict how much capacity the plant has and the waiting time before any particular order will be completed. With this approach they save the plant and gain promotions within their company.

One of the first bodies to apply ideas behind the Theory of Constraints to healthcare was the Institute of Healthcare Improvement. In their report, 'Optimising Patient Flow' (Institute for Healthcare Improvement, 2003) they describe their program of work with fifty hospitals in the US and UK to improve the flow of patients through an acute hospital. Their idea is to eliminate waits and delays in healthcare by optimising the flow of patients through the hospital. This can be achieved by eliminating any non-random variation in the capacity and demand (patient arrivals) and then matching capacity to demand. The examples given in the report of flow problems in hospitals are diverse and include ambulance diversions (because the hospital’s A&E department is at high capacity), the problems transferring patients from A&E to the rest of the hospital and problems discharging patients out of the hospital. The report also stresses the need to look at the whole system of care and that a patient's timely access to care is part of high quality healthcare.
The Theory of Constraints (ToC) was also used by Umble and Umble (2006) to control waiting times in three NHS Accident & Emergency (A&E) Departments. The paper describes the problem of long waiting in A&E and how Government-set targets for waiting time (maximum four hour wait to be seen and maximum twelve hour wait for admission) were achieved by Trusts.

The Authors used a technique arising from ToC known as buffer management. In manufacturing this aims to control the flow of materials through the system by monitoring its buffers. A buffer is simply the materials needed at a specific location for the process to consume. A buffer is used to protect the process from disruption by scheduling enough time for materials to reach that buffer. Buffer management involves monitoring the actual arrival of materials to the buffer and comparing it to the planned arrival. The causes of any delays can then be investigated and improvements made.

A manufacturing system's work is limited by its constraint resource. ToC suggests the best way to utilise this system is by developing schedules that best use this constraint. Non-constraints are synchronised to support the constraint. Work is realised into the system only as fast as the constraint is able to process it. The Authors admit for an A&E department, controlling the flow of patients into A&E will prove difficult, however they still found some techniques of buffer management could still be applied.

In the case of A&E, this meant dividing a patient's waiting time before being seen into four zones, shown in Table 1.6 below.
Table 1: Waiting Time Zones (before being seen)

<table>
<thead>
<tr>
<th>Colour</th>
<th>Time Period</th>
<th>Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>0-1 hours</td>
<td>Safety zone</td>
</tr>
<tr>
<td>Amber</td>
<td>1-2 hours</td>
<td>Tracking zone</td>
</tr>
<tr>
<td>Red</td>
<td>2-4 hours</td>
<td>Expedite zone</td>
</tr>
<tr>
<td>Black</td>
<td>4+ hours</td>
<td></td>
</tr>
</tbody>
</table>

This system was implemented in the A&E departments with a new information system which recorded the patients, their waiting time and what, if appropriate, was causing any delay. Thus if the patient did fall into the red zone they would already have been tracked and any delays already known about. Every week the information system was used to report on where delays were occurring in the previous week, this report was discussed in a meeting between the various interested parties or stakeholders and any problems acted on. A feedback loop was therefore established – this helped improve staff morale as it shared problems between departments and broke down barriers between staff. The implementation led to an improvement in waiting times in all three A&E departments and to their meeting of Government targets.


The report identified four key criteria of Trusts which were successful in maintaining low waiting lists and times.

- Information Use. Information needed to be reliable, detailed, comparative and continuous (usually daily but sometimes hourly). Successful Trusts could produce waiting times data for individual patients easily, unsuccessful Trusts would not know if they could believe their own waiting list figures. Successful Trusts collated and compared waiting times information at consultant level, discussing variations between consultants was a first step in persuading them to change working practices.
• Organisational focus  Commitment and regular involvement from top management was seen as essential to make progress towards targets. There were a large number of tactics managers used to persuade consultants to own and commit to a strategy of reducing waiting times.

• Capacity. Having the resources to increase capacity was clearly important. Temporary measures to increase capacity in order to meet targets were often seen as essential but wasteful, expensive and prevented the same money being invested in permanent capacity.

• Efficiency of the process. Most Trusts had made use of short bursts of temporary activity to ‘keep up’ on waiting time targets but successful Trusts realised that to sustain this, a sophisticated view of the care process would need to be implemented. Identifying bottlenecks in the system, taking a ‘whole hospital system’ approach and working out the best way of handling the interaction between elective and emergency admissions.

The National Audit Office undertook a review of patient waiting in the NHS (NAO, 2001b). One of the five key ways the NAO identified for improving the management of waiting lists and times was to “Manage the process as a whole” (The other four ways were “GP should refer appropriate patients to consultants”, “Outpatient clinics should operate at optimal capacity”, “Optimise the use of operating theatres” and “Have in place effective discharge arrangements”).

Appleby, et al. (2003a) points tie in with the Theory of Constraints (ToC) approach. Having reliable information made a difference to Umble and Umble (2006)’s application of ToC in their study of A&E departments. Identifying bottlenecks and taking a ‘whole hospital system’ approach chimes with the NHS Modernisation Agency’s preferred way of managing waiting lists (NHS Modernisation Agency, 2005a). Silvester, et al. (2004) also argue that increasing capacity is wasteful and misses the point that it is the healthcare system itself that may need to change.
1.4 Aims and Objectives

The approach to waiting list management described in the last section eschews modelling as a prediction tool and instead relies on experimenting on the real world system. Proudlove, et al. (2007) make this point and suggest it could be partly because of over complicated models with poor modelling objectives. They stress the importance of understanding the generic working of systems in order to improve them. One of the aims of this study is to produce a modelling tool that can be used to assist in the management of waiting lists and waiting times. Such a tool would assist managers in understanding the workings of the cardiac surgery system.

Waiting list modelling in the cardio-respiratory directorate in Glenfield Hospital has routinely used simple spreadsheet models on aggregate variables (additions to list per month, average numbers of operations per month, etc.) to estimate numbers on waiting lists and bed capacities needed. In the systems simulation model to be developed as part of this study, a more dynamic representation of the system variables will allow more information to be gained on the actual status of the waiting lists. Validating the utility of this new information is a further aim of the study.

This study aims to provide usable models that predict waiting times for cardiac surgery in Glenfield Hospital in Leicester. The detailed aims and objectives are set out below.
Aim 1
To describe, explain and predict patient waiting times for cardiac surgery procedures in Glenfield Hospital, Leicester

Objective 1.1
Discover the information that managers and clinicians at the Hospital use to control the cardiac surgery system

Objective 1.2
Identify and compare models and modelling methods used in healthcare settings

Objective 1.3
Identify and assess the range of variables, including funding and management issues which impact on patient waiting times for cardiac surgery procedures

Aim 2
To develop a waiting list model/tool for the use of the stakeholders at the Hospital

Objective 2.1
Design and develop a linking mechanism for information to be accessed directly from the Hospital’s Patient Administration System so that it is conveniently displayed/monitored for managers and clinicians and other stakeholders.

Objective 2.2
Develop a model interface allowing information produced by the model to be displayed optimally

Objective 2.3
Evaluate the final model with stakeholders and suggest recommendations for further work
1.5 Summary

This chapter has given an introduction to the present study into the modelling of waiting lists and waiting times at Glenfield hospital in Leicester. It has described the context in which this study has been undertaken, the NHS plan and the introduction of waiting time targets. It has also investigated some of the techniques currently used for managing waiting lists. Lastly the chapter has stated the study’s aims and objectives.

The next chapter describes the research methods used in the conduct of this study.
Chapter 2: Research Methods

2.1 Introduction

This chapter describes the research methods used in this project, comprising the main methods of data collection, in depth interviews and document analysis. The chapter then moves on to consider modelling methods. This includes the examination of the chosen modelling paradigm.

The modelling process adopted and model validation are described next, followed by a section on the spreadsheet modelling approach adopted. Finally, the system dynamics modelling method, that comprises both its qualitative and quantitative components, is examined in depth. The chapter concludes with a section on why system dynamics has been chosen over other modelling methods to simulate waiting lists in this study.
2.2 Data Collection and its Analysis

2.2.1 Interviews

Bell (1999, p 136) suggests there are various types of interviews depending on how structured they are. Formal interviews are highly structured with the interviewer asking questions with only a limited number of answers that are completed by the interviewer rather like a questionnaire. This format can be analysed quickly though coverage is dependent on design. There is a risk that areas may be omitted due to inappropriate design leading to a situation where the interview may not necessarily stimulate as much discussion and commentary from the interviewee as hoped.

Semi-structured interviews have some general areas for questions defined beforehand in the form of a interview or topic guide which is usually sent to the interviewee prior to the meeting. Interview or topic guides are described in Patton (2002, p 343). These guides list the questions or topics to be examined in the interview and make sure the same areas are covered with each interviewee. The interviewer remains free to build a conversation in an informal style yet remains bounded within a specified subject area. Guides also make sure the interviewer has considered how to spend the limited time available during an interview. Sources for topics to include in the guide include the research literature, the interviewer's knowledge of the area of study and any preliminary work carried out, for example, informal discussions with stakeholders (King, 1994). Probes can also be included to remind the interviewer to explore some areas further. Topic Guides can also be modified through use to include areas that have emerged in interviews.

Unstructured interviews have no formal structure and are more like a general conversation with an interviewee. They will likely produce a great deal of data but are difficult to control and time consuming to analyse. This type of interview is ideal if the researcher does not know much about a subject area and wishes to explore it before perhaps carrying out more structured interviews.
King (1994) lists four steps for using qualitative research interviews, “1. Define the research question; 2. Create the interview guide, 3. Recruit participants, 4. Carry out the interviews.”

To respond to these steps in turn, the aim of the research is to simulate waiting lists and waiting times for cardiac surgery at a specified Hospital. Factors affecting these lists and times must therefore be uncovered. The major resources affecting lists must be identified and also the way in which those resources are managed to accommodate the needs of patients.

A topic guide (King’s Interview Guide) was produced which listed the areas around which the interview would revolve without any specific questions. The topics for the guide were based on the knowledge and prior experience of the researcher and some informal discussions with the stakeholders at the Hospital. It was used to provide a basic structure for the interviews, giving them a semi-structured nature. The guide was sent to the interviewees before the interview so they could familiarise themselves with the interview’s proposed content. The first area, in the topic guide, to be explored was the interviewee’s experience and use of models. The next section covered the patient’s journey through the current system from referral to discharge including how patients were added to the list and how resources were used. Finally, the interviewees were asked if they had any suggestions for the research. The Topic Guide is shown in Appendix 1.

Participants were identified by the General Manager of the cardio-respiratory directorate and recruited from the management based on who would have a good overview of the cardiac surgery system and enough time to spend giving an in-depth interview.

There are many practical issues involved in carrying out interviews. One of these is the phrasing of questions. Leading questions, for example, ‘How unreasonable are Government targets for waiting times?’, are best avoided as
these place the interviewer’s point of view on to the interviewee who may agree from politeness or a desire to please (King, 1994). In the example above, it would be better to say ‘What factors have affected the achievement or otherwise of the Government targets for waiting times?’ and then probe for any feelings about the targets themselves. Telling the interviewee what their answers mean is also to be avoided, again because it imposes the interviewer’s perceptions and view on the interviewee who may not feel able to challenge this view. Another trap to avoid is assuming the answer to a question is so obvious the question need not be asked.

King (1994) advises starting an interview with a straightforward question that the interviewee can handle easily so that both questioner and interviewee can relax and feel they are getting to know each other. More sensitive and difficult questions should be held for later on in the interview. Similarly, an interview should not end on a topic which is difficult or painful. The interview should move towards a more positive topic to complete the meeting.

Interviews do not always go well. Some interviewees can be uncommunicative, only giving short answers to questions. This may be because they are defensive about the subject or want to complete the interview as soon as they can. Making sure the interviewer is asking open questions (that is not “Yes/No” response type questions) and examining the phrasing of the questions would be one way to try and avoid this problem. Being clear with the interviewees about how much time is required and assuring the interviewee about the anonymity of their responses could also solve the uncommunicativeness of interviewees. The opposite problem can also occur, when an interviewee diverges from the topic of interest repeatedly. While some digression can lead on to new areas of interest, an interviewer must try to impose some control on the discussion.

Four interviews were carried out as part of this study, both in Glenfield Hospital, one on the 3rd August 2004 at 10:30AM with the Clinical Audit and Performance Manager, one on the 30th September 2004 at 2 30PM with the Waiting List Co-ordinator, the third on the 22nd June 2005 with the General
Manager of the Cardio-respiratory directorate and the fourth on the 15th July 2005 with the Master Scheduler. Interview notes are attached in Appendix 2. The first two interviews acted as pilots, the topic guide was felt to be valid though some minor adjustments were made as a result.

2.2.2 Limitations of Interviewing

Interviewing is time consuming to carry out, in its preparations (constructing a topic guide), in carrying out interviews (travelling to and from an interview for instance) to analysing the data produced. Interviews are timeing to conduct, both an interviewer and interviewee must hold concentration and attention for long periods. The interviews that took place for this study usually took between one and one and a half hours to conduct.

Interviews produce a large volume of data to analyse and it is easy for a researcher to become ‘bogged’ down in the analysis. King (1994) suggests the researcher should ask themselves if a particular line of analysis is adding to the understanding of the topics that were set out to be studied and if not to ask themselves if it is raising new questions of interest. If the answer is ‘no’ to this question then the line should be abandoned and the researcher should change direction.

Interviewing is a highly flexible research method that can produce data of great depth and, as King (1994) points out, participants are usually comfortable with it. However interviews require careful planning and design.

2.2.3 Document Analysis

Initial information about the cardiac surgery system, the way patients go through this system, and the factors that impact on their waiting times for surgery are to be sought through an examination of documents available in the specific Hospital directorate and from Department of Health (DH) and National Health Service (NHS) documents that apply to all Cardiac Surgery centres.
Organisations will usually have a variety of documentary sources in existence. Forster (1994) points out that documents come in many forms, "company annual reports, public relations (PR) material and press releases; corporate mission statements, policies on rules and procedures". Different documents are aimed at different audiences, from general memos to private or covert correspondence amongst informal groups. Documents describe the way problems are understood in an organisation. They show appropriate behaviours and ways of getting tasks done in the organisation. The advantage of examining documents is that the data are already assembled and collecting them is unobtrusive, busy subjects do not have to give up time to be interviewed or fill in a questionnaire. Performing a document analysis can improve the design of other research methods, e.g., the design of interviews, making the data they collect more targeted and accurate and saving time in their collection. The analysis can be used as another means of triangulating data. It can be compared to the interview data to corroborate it or show up inconsistencies between the two. Documents may be fragmentary. They may not be an accurate record of events or processes and they could be political and subjective. Therefore documents will need to be checked and interpreted carefully. Documents can also be time consuming to access and analyse. Nicolle (2004) reports a change in the University Hospitals of Leicester NHS Trust's (UHL) corporate information system to accommodate a new document management system that enables staff to access corporate policies and procedures. The author hopes that this system can speed up access to documents, throughout the Trust.

The local UHL Waiting List Policy will be analysed as will any National documents that have an impact locally will also be examined. These include the NHS Plan and the National Service Framework for Coronary Heart Disease.
22.4 Content Analysis

It is proposed to analyse the interview notes in ATLAS ti, a program that assists in qualitative analysis. The results of the analysis will provide a more meaningful insight into construction of the simulation and spreadsheet models to be used later in the systems intervention.

The question arises why use qualitative analysis at all, why not simply build models from interpreting the interview data directly, doing the analysis all 'in the head'? A more structured analysis means there is less likelihood of something important being missed. Also, some way has to be found to record how a model has been built from the data, some way of documenting and monitoring the analytical processes involved in forming the model from the underlying interviews. The use of qualitative analysis software aids this process.

Since this research is involved in modelling a specific system, any qualitative analysis carried out must take into account this systems perspective. Patton (2002, p. 119) defines a systems perspective thus:

"Holistic thinking is central to a systems perspective. A system is a whole that is both greater than and different from its parts. Indeed, a system cannot validly be divided into independent parts as discrete entities of inquiry because the effects of the behaviour of the parts on the whole depend on what is happening to the other parts."

Qualitative data can be organised and reported in a number of ways (Patton, 2002, p. 439). Methods vary from storytelling approaches and case studies to analytical framework approaches. Analytical framework approaches include organising qualitative data to describe important processes and issues. This approach is key to describing the system in this research study.

Content Analysis involves finding patterns and themes threaded through the data (Patton, 2002, p. 452). Inductive analysis is the discovery of patterns,
themes and categories in the observed data. Findings come out of the data, through the researcher's dealings with them. There are two ways of performing inductive analysis on qualitative data. The first is to identify and define categories or patterns developed by the people being studied or interviewed, known as indigenous concepts or 'in vivo' coding. The second involves the researcher identifying and defining categories for which the people under study did not have labels, known as sensitising concepts.

Categories are used to form typologies. Typologies are classification systems that divide a concept into parts along a continuum (Patton, 2002, p. 457). An example would be classifying governments along a democratic–authoritarian continuum. Typologies make explicit patterns that appear to exist in the data. They can also be of indigenous (i.e., using the distinctions used by the people being interviewed) or analyst-constructed types.

The next stage is to recognise patterns in the data. Patton (2002, p. 462) goes into some detail describing what he terms the 'mechanical work of analysis.' Essentially this is going through the data and identifying, coding, classifying, and labelling the primary patterns found. The first step of analysis is to develop a coding scheme to produce a framework for organisation of the data. This describes what data have been collected and builds a foundation for the final interpretive step.

King (1994) points out there is no single set of rules for analysing qualitative data though there are common features. He goes on to suggest that familiarisation with the data is an essential first step.

Fielding (1995) describes several issues in choosing an appropriate qualitative software package. These include data entry and storage, coding, annotation, and searching. ATLAS.ti links to text files so 'raw' text does not have to be typed in again. Coding is achieved on-screen visually whilst working through the text. ATLAS.ti has many ways to annotate the data and codes produced. Memos can be produced that link to quotations from the text and/or codes to
document the analysis process. The interface is navigated via a Windows GUI (Graphic User Interface).

ATLAS ti gives the User the ability to create independent quotations. These can be linked together or with codes, memos and even whole documents in a highly flexible network view, a visual way to represent the analysis. The relationships between objects can be specified in the network view and these relationships used as search operators in ATLAS ti’s query tool (Lewins and Silver, 2004, p 11) describe ATLAS ti as offering “great flexibility and provides several different ways of working to suit different purposes.”

NUDIST was also examined as a possible software package to perform the analysis. A disadvantage is that NUDIST insists the User picks a unit of text (a line, sentence or paragraph) to commence coding the document. This means you need to be fairly sure at an early stage of the analysis that an appropriate choice is made (Lewins and Silver, 2004, p 22). However, NUDIST does have a good range of search tools (e.g., Boolean, proximity, cross tabulations) with an easy to use graphical interface.

AnSWR (Analysis Software for Word Based Records) is a free, open source package that can be downloaded from the American Centre for Disease Control (CDC) website (Center for Disease Control, 2004). It was developed by the CDC primarily to manage and analyse large, complex, team based projects using a systems approach to qualitative analysis. However, the interface feels clunky and there seems to be a little ‘distance’ from the raw data compared to ATLAS ti.
2.3 The Modelling Paradigm

2.3.1 What is a Model?

A model is a representation of reality. Reality is frequently too complex for the human mind to understand. One way to deal with this is to "... strip the processes of some of their features, to leave us with models of the original processes" (Morgan, 1984). Understanding the model provides insights into the real world process itself. The modelling process, by definition, must be a simplification otherwise such models are "... as complicated as the real-life systems we wanted to understand in the first place" (Hannon and Ruth, 2001, p 5) and so we may as well experiment with the real system. The process of modelling involves deciding what is relevant and must be included and what is not relevant for the model and can be left out. Deciding what is relevant depends on the aims of the study. Modelling hospital systems with the aim of predicting numbers on the waiting list for a particular specialty will have to model the way waiting patients are allocated operations but not include, for example, the exact position of beds in the wards.

Experimenting with models is easier than with a real-life system. All variables are under the modeller's control and there are no ethical considerations. Changing a real-life system could be expensive and in the case of medical facilities, potentially life threatening. Time is also shortened in a model. Years can be simulated in seconds. Waiting this long to observe all the effects of an experiment with a real-life system is impractical. This time advantage of a model means a great deal of experimentation can be carried out to test the assumptions of structure and process that the model embodies. Experimenting with different assumptions means that many different scenarios of future conditions can be predicted and the effect of decision making can take into account these different possibilities.

Modellers try and validate their models, that is, ensure their models are accurate and produce the same behaviour as the real-life system usually by comparing them with past data or information. Differences between the model...
prediction and real-world practice can invalidate a model and lead to its revision (Hannon and Ruth, 2001, p 9) Validity is also sought from people involved with the real-life system who could be said to ‘know’ it best. They can review the structure of the model to see if there are any obvious discrepancies or errors.

2.3.2 Characteristics of Modelling Methods

What method is best suited to modelling the cardiothoracic surgery system at the Hospital? In other words, what characteristics of modelling methods best fit the current research study?

The model’s workings would have to be transparent if it is to gain widespread acceptance amongst the Clinical Directorate’s clinicians and managers. This would imply that the findings from the model are easy to communicate, in terms of both their outputs and methods. The degree to which the model visualises its description of the system is also crucial to communication. Both clinicians and management would not want to spend time trying to understand a complicated mathematical model in order to ‘validate’ it as an accurate description of the system. This makes ease of validation another key characteristic.

In tandem with ease of communication is ease of use. The model’s interface should be usability tested and any feedback incorporated back into the modelling process. Nielsen (1993) defines usability to have five components. A user interface should be easy to learn, efficient, memorable, with few errors and subjectively satisfying. An interface with these qualities would fit in with the User’s way of doing things more easily and make it easier for him/her to understand and use the model. Awkwardness in using an interface could impede the communication of understanding the model imparts about the system it is representing. A User wants primarily to learn about the system being modelled not learn how to use a frustrating, complicated interface.
Some form of validation of a model is necessary for it to gain acceptance to its intended audience. Pidd describes validation as ensuring "... that the model is wholly adequate and appropriate for the task for which it is intended." (Pidd, 2004, p. 233)

Validation of a model ensures that any predictions, descriptions and explanations of the system's behaviour can be given appropriate weight by the stakeholders involved. Stakeholders will want to take some action with the developed model and so will want to be reassured that the model is an accurate representation of the real system. As Pidd (2004, p. 234) points out, though, problems are not independent of the modellers or their clients. Models are simplifications of real problems or systems and this simplification process is not independent of the modellers. Validation, in the sense of demonstrating that a model is fully correct, is not possible. Pidd regards validation as an "ideal towards which we must strive...". Negative consequences could result from decisions made on the basis of erroneous models, validation of these models does matter.

There are two types of validation defined by Pidd (2004, p. 240). The first is 'black box' validation where the inner structure of the model and the real world system are regarded as unknowns. The output results of the model are compared with the output results of the real system. 'White box' validation is where the structures of both model and real system are compared under the assumption that both are known and understood.

System Dynamics and Discrete Event Simulation models both explicitly define their structure so 'white box' validation could be attempted as well as 'black box'. This will mean that validation of these types of models becomes more complex, however, it could also mean that confidence in these models is increased (though there is no guarantee that the view of the system that is being validated against is correct).

The aim of the current investigation is not only to provide a qualitative description of the Cardiac Operations Waiting List (COWL) system but also...
produce a quantitative model which can generate estimates, for example, of the extra operations required to meet waiting list targets. Qualitative and quantitative modelling are also referred to as 'soft' and 'hard' types of Operational Research respectively. A modelling technique that can provide both these aspects would be very useful.

The research aims to examine the effect changes in policy or structure would have on the COWL system. A modelling method would have to include prediction of the effects of holistic changes to any particular part of the system. Patients have different characteristics that are of interest in the model. They are more likely to be admitted the more sick they are and the longer they have already waited, this phenomenon leads to a heterogeneous patient population. Different modelling techniques are better than others for capturing this 'heterogeneity', the different characteristics affecting the way in which the model develops. Heterogeneous 'entities' with different characteristics or 'attributes' are central to the operation of a discrete event simulation model, for instance, whilst system dynamics models homogenous populations though some software packages can overcome this.

On a more practical level, another consideration in choice of model type is the choice of software available for its execution. Purely mathematical models would have an advantage as they could be programmed via a general purpose spreadsheet. Conversely, methods like System Dynamics need specialist software which could be costly, in terms of learning curve and time for widespread adoption.

The eight characteristics of modelling methods discussed thus far are listed in Table 2.1 below.
These are then used to compare the suitability of four distinct modelling methods: analytical modelling, Markov chains, Discrete event simulation, and System dynamics. Analytical models are those that define their desired output variables in terms of certain input variables via a formula or equation, for instance, certain queuing systems can be have variables like ‘average waiting time’ defined by an equation involving queue arrival and serving rates. A Markov chain is a method which models a system by describing it as being in one of a certain number of defined states with certain probabilities of transferring to another of the defined states. These probabilities depend on the present state and not on how the system reached the present state. Discrete event simulation provides a method of simulating objects or ‘entities’ with characteristics. Entities are either in ‘waiting’ or ‘active’ states. System Dynamics is a simulation method which describes a system in terms of levels and rates and simulates that system via a network of interlinking difference equations. Table 2.2 shows the considered modelling methods compared in terms of the eight characteristics identified as the best fit for the current research.
<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Analytical Models</th>
<th>Markov Chains</th>
<th>Discrete Event Simulation</th>
<th>System Dynamics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transparency</td>
<td>Structure of Model hidden in mathematics so would be quite mysterious to non-experts</td>
<td>Description of states provides some transparency.</td>
<td>Visual description of resource part of model but information structure hidden in control processes.</td>
<td>Resource and Information structure shown visually.</td>
</tr>
<tr>
<td>Ease of Communication</td>
<td>Mathematical nature of model structure complicates communication to non-experts</td>
<td>Visual structure of model eases communication to non-experts</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Interface</td>
<td>N/A</td>
<td>N/A</td>
<td>User interface generally constructed in high level programming language</td>
<td>Can build User Interface quickly in software packages</td>
</tr>
<tr>
<td>Ease of Validation</td>
<td>Structure of model shrouded in mathematics so 'white-box' validation difficult.</td>
<td>Structure of model defined by states that an entity can be found in, so 'white-box' validation possible.</td>
<td>Information structure of model also explicitly shown alongside resource structure so 'white-box' validation possible.</td>
<td></td>
</tr>
<tr>
<td>Quantitative and Qualitative</td>
<td>Quantitative.</td>
<td>Quantitative.</td>
<td>Qualitative and Quantitative.</td>
<td>Qualitative and Quantitative.</td>
</tr>
<tr>
<td>System Wide Effects</td>
<td>Depends on model structure but the more complicated the model the more difficult any equations become to solve.</td>
<td>Depends on model structure but the more complicated the model the slower it will be to execute.</td>
<td>Can assess system wide effects.</td>
<td>Designed with system wide effects in mind</td>
</tr>
<tr>
<td>Heterogeneous Population</td>
<td>Depends on model structure but the larger the number of variables needed to be modelled the more complicated the model becomes.</td>
<td>Models entities with 'attributes'.</td>
<td>Only homogenous population modelled but some software packages can overcome this</td>
<td></td>
</tr>
<tr>
<td>Software</td>
<td>Spreadsheet.</td>
<td>Spreadsheet.</td>
<td>Specialist programs.</td>
<td>Specialist programs.</td>
</tr>
<tr>
<td></td>
<td>Higher level programming languages.</td>
<td>Higher level programming languages.</td>
<td>Higher level programming languages</td>
<td></td>
</tr>
</tbody>
</table>
2.3.3 The Model Process

The process for building the model is taken from Flood and Carson (1993, p 165) and is shown in figure 2.1.

Figure 2.1 Model Building Process (after Flood and Carson 1993; p 165)

- Problem Perception

Once a problem has been identified that requires a model to help solve, the modelling process can move to the Modelling Purpose stage which is made up of the three processes of description, prediction and explanation (Flood and Carson, 1993, p 153)
- Model Purpose
A model's purpose in describing a system must be in terms of conciseness to aid the resultant ease of analysis. In terms of prediction, a model must be able to predict the system's response to a stimulus. The explanatory part of a model is to do with how well it shows the system behaviour and structure depending on one another.

- Model Formulation
Model formulation is the process whereby the model is constructed and begins with the conceptualisation stage. Conceptualisation results in a broad, qualitative model and is usually described by the use of sentences and diagrams. This qualitative model can then be transformed into mathematical equations to form a quantitative model capable of being solved and simulated. This process is termed mathematical realisation or mathematical synthesis (Flood and Carson, 1993, p.165).

- Model Identification
Model identification is the estimation of parameters for the quantitative model. For complex models, this tends to be done iteratively, crudely estimating parameters and then comparing simulated output with observed data. (Flood and Carson, 1993, p.167). The model can then be simulated.

- Laws, Theory and Data
Laws, theory and data relevant to the system being modelled are used at the model formulation and identification stages, influencing conceptualisation, used to formulate relationships between variables and help in identifying the parameters of the model.

- Model Validation
This has two parts Internal Criteria where the model should not have any logical inconsistencies; and External Criteria where the model's output should correspond to any available data (Flood and Carson, 1993, p.167). Model validation is described in more detail in the next sections.
The final result of this process should be a fully validated mathematical model which can be experimented on showing different scenarios of interest to the model's Users

2.3.4 Validity of Research: Internal Validity

Internal Validity assesses the extent to which the model gives an accurate reflection of the real life system being modelled.

Comparing the output of the model to some past data is one way of testing the validity of a model. This means producing a reference mode for the model to see if this mode can be reproduced by the model. Any changes in model structure or policy can then be compared against this reference mode.

However, validity is also a question of gaining the model's Users' confidence in the structure and behaviour of the model and not just reproducing past data. Lane, et al. (2000) discuss the validation of their system dynamics model of an Accident & Emergency (A&E) department. Confidence in their model's validity gradually built up as the model was developed with the system actors. They subjected their model to two types of validation tests, structural-based tests and behaviour-based ones.

Wolstenholme (1990) gives a summary of tests for building confidence in system dynamics models. These are reproduced in Table 2.3 below. This confidence is based on:

- appreciation of the structure of the model,
- the model's general behaviour; and,
- the model's ability to produce accepted responses to set changes.
Table 2.3 Verification Tests of System Dynamics Models (Wolstenholme, 1990, p. 60, also Serman, 1984)

<table>
<thead>
<tr>
<th>Test of model structure</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure Verification</td>
<td>Is the model structure consistent with knowledge of the system?</td>
</tr>
<tr>
<td>Parameter Verification</td>
<td>Are the parameters consistent with knowledge of the system?</td>
</tr>
<tr>
<td>Extreme Conditions</td>
<td>Does each equation make sense when its inputs take on extreme values?</td>
</tr>
<tr>
<td>Boundary Adequacy (Structure)</td>
<td>Are the important concepts for addressing the problem included within the model?</td>
</tr>
<tr>
<td>Dimensional Consistency</td>
<td>Is each equation dimensionally consistent?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test of model behaviour</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Behaviour Reproduction</td>
<td>Does the model generate the symptoms and behaviour modes of the real system?</td>
</tr>
<tr>
<td>Behaviour Anomaly</td>
<td>Does anomalous behaviours arise if an assumption of the model is deleted?</td>
</tr>
<tr>
<td>Family Member</td>
<td>Can the model reproduce the behaviour of other examples of systems in the same class as the model?</td>
</tr>
<tr>
<td>Surprise Behaviour</td>
<td>Does the model point to the existence of a previously unrecognised mode of behaviour of the real system?</td>
</tr>
<tr>
<td>Extreme Policy</td>
<td>Does the model behave properly when subjected to extreme policies or test inputs?</td>
</tr>
<tr>
<td>Boundary Adequacy (Behaviour)</td>
<td>Is the behaviour of the model sensitive to the addition or alteration of structure to represent plausible alternatives?</td>
</tr>
<tr>
<td>Behaviour Sensitivity</td>
<td>Is the behaviour of the model sensitive to plausible variations in parameters?</td>
</tr>
<tr>
<td>Statistical Character</td>
<td>Does the output of the model have the same statistical character as the ‘output’ of the real system?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test of policy implications</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>System Improvement</td>
<td>Is the performance of the real system improved through use of the model?</td>
</tr>
<tr>
<td>Behaviour Prediction</td>
<td>Does the model correctly describe the results of a new policy?</td>
</tr>
<tr>
<td>Boundary Adequacy (Policy)</td>
<td>Are the policy recommendations sensitive to the addition or alteration of structure to represent plausible alternative theories?</td>
</tr>
<tr>
<td>Policy Sensitivity</td>
<td>Are the policy recommendations sensitive to plausible variations in parameters?</td>
</tr>
</tbody>
</table>
2.3.5 Validity of Research: External Validity

External validity refers to the extent to which research can be generalised beyond the current setting. It can refer to population validity (can the research be generalised to a wider population) and ecological validity (can the research be generalised to other settings). One way to interpret this is to ask if the research is generalisable to other Departments with other patient populations.

The British Heart Foundation website (British Heart Foundation, 2005) lists information for people waiting for heart surgery and includes information on their hospital stay. The only major difference to the Cardiac Surgery Department at Glenfield Hospital is in an elective patients progression through the system is they may be admitted a few days before to the ward or they may attend a pre-admission clinic for tests and then be admitted to the ward the night before their admission.

Other differences between Hospital departments will include differences in numbers of consultants and the differing casemix (differences in the fitness of their patients) they face. Consultants will tend to do different numbers of certain operations and some will do more specialised operations (though there could be standards set by a professional body). Emergency rates will be different in different areas. These, on the whole, can be accounted for in the model and would simply mean changing certain parameters and re-validating the model.

Information structure could vary widely amongst Departments. How a Department reacts to rising waiting times and lists will depend on the relationship between its Management and Clinicians. Different targets may be more important to different groups, for example, clinicians will see mortality rates as more important than the size of waiting lists.
2.4 Spreadsheet Models

The initial data model of the cardiac surgery waiting list was developed in the Microsoft Excel spreadsheet program.

Spreadsheet programs are computer programs that assist in providing automatic calculations of linked quantities organised into sheets of cells. Values or formulas are entered into these cells, each cell having a unique reference description which can be used by any other cell, for example, the simplest formula a cell could contain would be a simple reference to another cell e.g. ‘=F3’ where the ‘F’ refers to the sixth column and the ‘3’ refers to the third row. The effect of this formula is simply to take the value in cell ‘F3’ and copy it to the referring cell.

The origins of spreadsheets lie in accounting. A "spread sheet" or spreadsheet is a large sheet of paper with columns and rows that organised data about transactions. It spreads all of the financial data on a single sheet of paper for a person to examine when making a decision (Power, 2004).

Most spreadsheet programs contain a wide ranging set of functions. 'Microsoft Excel' contains functions to sum the values of a range of cells. There are also decision functions like ‘IF’. Programs also usually have advanced statistical and financial functions, and other tools to help in modelling. Operational Research techniques can also be incorporated. Linear programming, where the optimal value of a variable is to be found that fits a system of linear equations, is another popular tool, as are charting options. Programming languages can also be incorporated into spreadsheets to give Users a highly flexible calculating environment.

Albright and Winston (2005, p 20-1) define spreadsheet models as involving inputs, decision variables and outputs. The inputs are fixed (though possibly uncertain), decision variables are the values that can be controlled and outputs are calculated from inputs and decision variables and are the quantities of interest to the modeller. Spreadsheet modelling then becomes the process of
relating inputs and decision variables in formulae in a spreadsheet and obtaining the outputs.

As an example, in the spreadsheet model of waiting lists presented in Chapter 5, the inputs are ‘Additions to the waiting list’ and ‘Number of Leavers’ are inputs, the ‘number of operations’ is a decision variable and the ‘Number of Waiting Patients by months waited’ form the output.

Precision of numbers is a problem for computers. Numbers can always be divided, there is an infinite number of fractions. However computers are digital, they have a finite number of discrete memory locations in which to store numbers. A computer can only store numbers to a certain precision depending on the method used for calculation in its Central Processing Unit.

Spreadsheets written by End Users are prone to errors. Panko (1998) examined several studies that investigated spreadsheet errors, of the 367 spreadsheets examined, 24% had errors. He points out that End Users rarely develop their spreadsheets using methods involved in developing software programs. A guide to spreadsheet modelling best practice, produced by Read and Batson (1999, p 3), introduces the idea of a “Modelling life-cycle” into spreadsheet model development, similar to software development, though they do stress their methodology should be applied flexibly according to the type of model being developed.

Spreadsheets usually hide the formulas they rely on, instead just showing the numbers they calculate. Good documentation is therefore needed to allow a model user to navigate and investigate a model. Read and Batson (1999, p 19) show the need for a specification for a spreadsheet model to make testing easier and more effective, including what the model is supposed to be doing at any point in time. Albright and Winston (2005, p 21) stress the need to design and construct spreadsheet models that are usable and readable. They list several ways to improve readability including.
• “A clear, logical layout to the overall model
• Separation of different parts of a model, possibly across multiple worksheets”

Excel can be used to develop a model because it is a program that is a part of the Microsoft Office Suite and as such is widely available in both the University and Hospital. It has several advanced features, for example, use of statistical and financial functions, link to Visual Basic for applications programming and a well honed development environment. Excel also has easy to use chart facilities and it is easy to develop a User Interface within the spreadsheet.

Microsoft Excel has fifteen digits of precision and can represent numbers as small as $10^{-307}$. Documentation is supported in Excel with features like ‘Comments’ which can be added to individual cells and an auditing tool to identify which cells refer to which. This feature helps in the validation process and provides confidence to the end-users.

2.5 Qualitative Description by System Diagrams

System diagrams are used to describe and conceptualise the system qualitatively. They illustrate relationships between variables and classify them as augmenting (positive or variables influence acts in the same sense as each other) or inhibiting (negative or variables influence acts in the opposite sense). They are used to identify feedback loops. Analysis of such loops brings forward understanding of system behaviour.

Feedback loops influence system behaviour depending on whether they are positive or negative. System diagrams can be used to see if a feedback loop is positive or negative. The net effect of a loop can be obtained by following through the individual influence links. If this net effect is negative, then the loop is negative, if positive then the loop is positive. Negative loops are always target seeking. They produce behaviour that tends to push levels towards
equilibrium values. Figure 2.2 shows the generic structure of a negative loop using one rate and one level using signed digraph diagram conventions.

Figure 2.2: Generic structure of negative loop (based on Flood and Carson, 1993, p. 54)

An example of negative loops include a thermostat in a central heating system shown below in Figure 2.3 (from Wolstenholme, 1990, p. 20). This figure shows an influence diagram in which the rate is the amount of a resource that flows in unit time, levels are the accumulation of rates and auxiliary variables are used to break down the stages in calculating rates from levels, see next section.

Influence diagrams are defined by Flood and Carson (1993, p. 56) as a specific type of signed digraph with strict logical rules for relating the elements. These rules are set out in Table 2.4 below.

Figure 2.3: Thermostat Negative Loop Model

![Thermostat Negative Loop Diagram with Key]

KEY

- Room Temperature Level → Resource Flow
- Heat Input Rate Rate or Auxiliary → Information Link
For the thermostat example above, the policy defining the rate variable is to eliminate the difference between the actual size of the level and a target level (Room Temperature and the Thermostat setting). The rate variable created from the difference is usually divided by a correction time which determines the rate at which a control is implemented. A small correction time gives fast, unstable correction, a large correction time results in slower, more stable correction.

Table 2.4 Rules for Influence Diagrams (from Flood and Carson, 1993, p.56)

<table>
<thead>
<tr>
<th></th>
<th>A Level can only be preceded by a rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>A Level may be followed by an auxiliary or a rate</td>
</tr>
<tr>
<td>3</td>
<td>An auxiliary may be followed by an auxiliary or a rate</td>
</tr>
<tr>
<td>4</td>
<td>A rate must be followed by a level</td>
</tr>
<tr>
<td>5</td>
<td>A level may not directly affect another level</td>
</tr>
</tbody>
</table>

Positive loops result in growth or decline. The processes are self-reinforcing, for example, population growth. A growing population will tend to increase the birth rate which, in turn, will increase the reproducing population (See figure 2.4).

Figure 2.4 Population Growth, an example of Positive Feedback (after Wolstenholme, 1990, p.22)

Diagram:

**KEY**

- Population
- Level
- Resource Flow
- Information Link
A simple waiting list system could be thought of as Patients being added to the list (a level) at a certain Rate of Addition and coming off the list at the admission to hospital rate Figure 2.5 shows just such a simple waiting list system

Figure 2.5. Influence Diagram of simple waiting list system

The polarity of arrows shows in which direction a variable changes another e.g. An *increase* in the admission rate would lead to an *increase* in the number of hospital patients, hence has an augmenting sign (can also be labelled ‘S’), and a *decrease* in the number on the waiting list, hence has an inhibiting sign (can also be labelled ‘O’) Care needs to be taken with polarities in influence diagrams especially with resources that are conserved For instance, Lane (2000) describes an example of a bathtub filling with water where a decrease in the flow rate does not lead to a decrease in the volume of water in the bath A decrease in the admission rate does not necessarily mean a decrease in the number of inpatients, just that the rate of increase slows down Whether this leads to a decrease in the number of inpatients depends on the discharge rate from hospital. Lane (2000) defines link polarities carefully as, “A change in an influencing variable may produce a change in the same direction in the influenced variable, or add to the value of that influenced variable.”

Organisational boundaries can be marked to clarify which organisations control which rate variable in the process, and which departments within organisations control what. A common reason for problems in lengthy processes in large
systems is the number of different organisations controlling different parts of the process. Organisations must integrate their control strategies with adjacent organisations for processes to flow smoothly.

Wolstenholme (1990, p 3) gives a definition of system dynamics as.

"A rigorous method for qualitative description, exploration and analysis of complex systems in terms of their processes, information, organisational boundaries and strategies, which facilitates quantitative simulation modelling and analysis for the design of system structure and control."

Wolstenholme explicitly includes qualitative description in his definition as a starting point. Earlier authors, e.g. Forrester (1961), only define system dynamics in terms of quantitative modelling (see next section). Qualitative System Dynamics (as described in Wolstenholme, 1990) are based on creating influence diagrams, and using these to analyse the system. Diagrams are developed with the individuals who are involved with the system (or system actors) to make their perceptions of the system's structure, strategies and environment explicit. Sharing of perceptions of the system by these individuals can broaden their understanding of the system. Feedback loop structures can be identified by a modular, step by step approach. It also makes the translation of a qualitative model to a quantitative one much easier.

More general system diagrams are described in the description of 'systems thinking' to be found in Senge, et al. (1994). The elements are not strictly defined as rates or levels but in more general concepts. Senge, et al. (1994) do not describe the conversion of these qualitative models into quantitative ones, relying on the qualitative models to describe system behaviour in their visualisation of feedback loops.

Positive and negative loops are two of the system archetypes described in Senge, et al. (1994) though they are labelled reinforcing loop and balancing loop respectively to indicate their behaviour. Other archetypes described
include "Fixes that backfire", "Limits to growth", "Shifting the burden", "Tragedy of the Commons" and "Accidental adversanes"

As can be seen from Figure 2 6, Senge's system diagrams are more informal than Wolstenholme's influence diagrams. The elements are not strictly divided into levels and rates. A snowball running down a hill is used to denote a positive feedback loop and balance scales are used to depict a negative feedback loop. Figure 2 6 shows the "Fixes that backfire" archetype.

Senge et al (1994, p 126) describe problem situations that fit the "Fixes that backfire" archetype. A problem requires speedy resolution and a quick 'fix' is enacted to solve the problem, however, the quick 'fix' has long term consequences that oppose the short term ones and actually aggravate the original problem.

Figure 2 6 "Fixes that backfire" archetype (from Senge et al, 1994, p 126)
There are a number of objections to system archetypes. While they can be useful as an introduction to systems thinking, archetypes can come to be regarded as mere templates which just involve filling in the blanks for the particular situation involved and applying the 'moral' (Senge et al., 1994, p. 178). Another problem with system archetypes is that they can suggest a prediction for the behaviour of the system which is incorrect. It is assumed that once an archetype is fitted to the system in question, the system will behave just as the archetype does but this is not necessarily true.

A third form of qualitative description used in System Dynamics models is the Causal Loop Diagram. These combine the informal concepts found in Senge's System Archetypes with the influence polarities of Influence Diagrams. Unlike System Archetypes, Causal Loop Diagrams do not try and 'fit' a template archetype on to the described situation. They can be used to develop models of less structured problems.

So, for example, the simple waiting list described in figure 2.5 above could be described in a causal loop diagram as in figure 2.7 below.

Figure 2.7  Causal Loop Diagram of simple Waiting List System

- Addition → + Waiting List  - Admission Rate ← - Inpatients Rate

**KEY**

- The negative sign means that the items at the tail and the head of the arrow change in the opposite direction

- The positive sign means that the items at the tail and head of the arrow change in the same direction

(from Roberts, et al., 1983, p.56)
An example of this kind of analysis is the example of road building, given by Roberts, et al. (1983, p 48). Figure 2.8 below describes the road building process in the form of a causal loop diagram.

**Figure 2.8 Causal Loop Diagram of Road Building**

![Causal Loop Diagram of Road Building](image)

NB. The symbol used in the figure above points out a loop in the causal loop diagram. The '+' or '-' defines the loop as either positive or negative, respectively.

The negative loop is a controlling loop and should mean that the number of traffic jams is controlled at a certain level. An increase in the number of traffic jams increases the need for new roads which increases the roads being built. This will result, eventually, in more roads which should decrease the number of traffic jams. While this may well occur at first, the outer positive loop will then come to dominate as more roads increases the attractiveness of driving, encouraging more people on to the roads and an eventual increase in the number of jams again. This will set off another round of road building in a vicious cycle. A good example being the building of the M25 circular route around London. Although originally built as a three lane motorway, its popularity by drivers as a means to expedite their journey without traversing London itself has led to plans to expand it to a six lane motorway, with further lanes in places where there are known bottlenecks.
2.6 System Dynamics (SD)

System dynamics (SD) is a modelling method that aims to provide easy to use tools/models for use by a wide audience, not just the technically adept. It aims to help understanding of the relationship between a system's behaviour over time and its underlying structure and policies. A system's problem behaviour over time is observed and identified. SD can be used to create a valid model of the system which can reproduce current system behaviour. This model can be used to help find improved system behaviour. SD was developed by Jay Forrester at MIT in the 1950s and 1960s as 'Industrial Dynamics' (Forrester, 1961).

Industrial Dynamics (Forrester, 1961, p.13) was described as "the study of the information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies) and time delays (in decisions and actions) interact to influence the success of the enterprise". The subject was interested in the flows of information, money, orders, materials, personnel and capital equipment and the dynamics between them. To represent industrial activity these six flows formed six interconnected networks. Forrester wanted to capture in a single framework the functional areas of management (e.g. marketing, production, capital investment etc.) to give an experimental, quantitative approach to improve the design of company and economic systems.

Forrester developed system dynamics at the Sloan School of Management at the Massachusetts Institute of Technology (MIT). A team of researchers from the school used system dynamics to produce models of future world growth for the Club of Rome report 'Limits to Growth' (Meadows, 1972). This report and its follow up 'Beyond the Limits' (Meadows, et al., 1992) use system dynamics models to argue that the Western World must switch to renewable energy sources and cut down on its use of materials if its standard of living is to be maintained.

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The 'World3' model described in Meadows, et al. (1992) demonstrates that as non-renewable resources run out (oil, minerals) and population increases, more industrial capital must be diverted to find more of these non-renewable resources leaving less industrial output to be spent on consumer goods and services. Also, as population grows, so more food must be obtained from less agricultural land (less agricultural land due to more pollution) The model has a global scale and outputs are variables such as population, industrial output, food, life expectancy, services per person and consumer goods per person. The inputs to the model include the amount of non-renewable resources left on the Earth, conversion rates to renewable forms of technology and pollution rates. Various scenarios are run with differing input values, most end in a global collapse with a collapse in population and living standards. By running the model with constraints on population and industrial growth and more efficient technologies, the authors eventually find a scenario for sustainable living.

SD usually involves computer simulation modelling. It involves quantifying with the system actors the shape of relationships between variables within the model, the values of parameters and the construction of simulation equations and experiments. Relationships can be shown in a number of ways including direct observation, accepted theory, hypothesis, assumption or statistical evidence. SD can also be used to test different ways of information usage in the strategies used to control the system under study. This can give an understanding of how information can be used to improve control and help system actors in identifying information needs and general problem solving abilities. SD has explicit diagramming conventions (Lane, 2000). The first step in constructing a system dynamics model is to conceptualise the system using a Causal Loop Diagram. These diagrams give a broad representation of the feedback structure of the model and are simpler than the fully specified model. Stock and Flow diagrams give much more detail (for instance, distinguishing between a resource stock and an information level) and enable the simulation of a quantitative model. Stock and Flow diagrams also model processes naturally. Wolstenholme (1990, p 11) describes systems as having two basic components: process structure and information structure. These structures can
be represented by two generic building blocks: resource flows and information flows.

2.6.1 Resource Flows and Process Structure

A resource flow is the chain of conversion where a resource is converted between states. It is made up of levels and rates. The basic process in any system is to convert resources between states. Resources could include material, people, cash, patients, etc. A state of a resource is any accumulation of the resource which is relevant to the model. The states are known as system levels or stocks. They are measurable quantities of any resource in a system at any point in time.

The rate at which resources are converted between states is represented by rate variables. They increase or deplete resource levels i.e., they control flows into and out of stocks. They take place instantaneously and so are not directly measurable. Physical flows can be conserved or non-conserved. Conserved resources cannot be lost or gained within the model.

A system's process structure (made up of resource flows of levels and rates) can be represented by pipe diagrams (also called stock/flow diagrams). This type of diagram is shown in Figure 2.9 below which shows a representation of a simple waiting list system first shown in the influence diagram of Figure 2.5.

Figure 2.9. Flow Diagram of simple waiting list system

<table>
<thead>
<tr>
<th>KEY</th>
<th>Level</th>
<th>Information Link</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rate</td>
<td>Resource Flow</td>
</tr>
<tr>
<td></td>
<td>Auxiliary Variable</td>
<td>Source / Sink</td>
</tr>
</tbody>
</table>
2.6.2 Information Flows and Information Structure

In the previous example of the pipe diagram of hospital admissions the rate variables are undefined (no arrows lead into them, no causality has been specified) These are open loop models Creating information structure makes these into closed loop models

In specifying the information structure of the model, two questions must be posed,

1 What levels have a causal effect on the rate?
   The information chosen by the system actors

2 What rules specify the type of effect?
   The strategy by which to use the information.

Information flows link knowledge about levels to rates and specify how rates change in the future to change the resource quantities of the levels. Auxiliary variables are another useful component of system dynamics diagrams. They occur in the steps leading from levels to rates They are not strictly necessary for the model to work but are useful if used in a real life system Figure 2.10 below shows the simple population model with some information structure (Hannon and Ruth, 2001, p.33) In the diagram below the 'Net Births' equals the 'Net Birth Rate' multiplied by the difference between the 'Population' and the 'Target Population' Hannon and Ruth (2001) label this a 'goal seeking' model as the 'Population' stock gravitates towards the value given in the 'Target Population' auxiliary variable.
Quantitative System Dynamics is based on calculus, levels are the integration of rates over a period of time. It uses numerical simulation methods based on simple difference equations. A sequence of numbers is generated by some formula, 

\[ a_n = f(n) \]

\( f(n) \) could be an explicit formula such as 

\[ a_n = \frac{(n+1)}{(n^2 - 1)} \]

However, sometimes \( a_n \) is expressed as a function of other terms in the sequence, for instance 

\[ a_n = a_{n-1} + 3 \]

These functions are known as difference equations (Slaughter, 2000)

For a system dynamics model, difference equations are used to calculate levels and auxiliary variables. For instance, at time point 't', a level has value
'Lt'. To calculate the value of the level at the next time point, 't+1', any in-flowing and out-flowing rates must be calculated and then added or subtracted from the value, 'Lt' as shown in figure 211 below,

Figure 211. System Dynamics Level Calculation

\[ L_{t+1} = L_t + (\text{in-flowing rates}) - (\text{out-flowing rates}) \]

263 Criticisms of System Dynamics

Flood and Jackson (1991) list two main criticisms of system dynamics. The first is from a 'hard' systems perspective and the second from a 'soft' systems viewpoint.

1 System Dynamics does not conform to scientific method

The scientific method works by observing and measuring phenomena in isolation and formulating laws to explain the behaviour of these phenomena and any relationships between them. System behaviour is then explained by aggregating these laws. System Dynamics tries to model the whole of the system even when the relationships between parts of the system are not precisely known. It is felt that constructing the feedback loops of the system's structure to explain behaviour is more important than an exact description of the relationships between parts of the model.

This leads on to the view that system dynamics lacks rigour, is not precise and could ignore theories that already exist between elements in certain phenomenon.

However system dynamics were first developed to analyse complex systems on which data was difficult to collect. A more strict approach to scientific method could render System Dynamics useless.

2 System Dynamics tries to model an external, 'objective' reality without taking into account the subjective nature of the system actors' perceptions.
From a 'soft' systems view the underlying assumption of system dynamics is that an external, 'objective' reality exists that can be modelled. Social systems are more complicated than this, being the construction of humans whose intentions and motivations are an important part of the system's behaviour. System Dynamics cannot deal with this subjectivity and can only produce a distorted model that is influenced by the hidden assumptions and prejudices of the modeller.

This criticism can be answered by arguing that there is an external reality represented in the process structure; patients do go through a process of referral, outpatient appointments, waiting for inpatient treatment (if necessary) and finally surgery. Staffed beds and operating theatres exist and need to be utilised efficiently. The information structure is more at the discretion of the social system operating in the cardiac surgery system. For example, what procedures are followed in deciding who gets an operation if there is a shortage of beds, consultants exercise their clinical judgement and freedom when deciding if a patient goes on the waiting list. Validation of the structure of the model by different types of stakeholder is one answer to try and ensure the model does not reflect the prejudices of one group.

2.7 Choosing System Dynamics over other Modelling Techniques

System Dynamics can be more easily understood and implemented than other modelling techniques by non-technical people. Discrete Event Simulation (DES), for instance, usually requires experts in Operational Research for model development (Davies, et al., 2003). Software packages for system dynamics are highly graphical and easily manipulated and can describe complex networks. They are an aid to communication of the model. Most System Dynamics software packages can be used to build a User interface to the model. Prototype interfaces can be built quickly for User testing and evaluation.
Queuing theory analytical models are only valid under certain conditions or assumptions. Although useful in simple situations, Queuing theory analytical models are more complicated to understand and much more limited than system dynamics models. Compare the queuing theory analytical study by Weiss and McClain (1987) into ‘bed blockers’ (patients delayed in discharge from hospital for non-medical reasons) to the system dynamics study of Wolstenholme (1995) into the same area.

Wolstenholme (1995) investigated the effects of a change in legislation transferring the responsibility for community care of the elderly from the Department of Health to local government social services directorates which had cash limited budgets. The intention was to save money by slowing down the flow of patients into community care. However, as the study showed this had unintended consequences for other parts of the care system especially the healthcare system. By slowing down the flow of patients into the community, beds became blocked in the hospital which decreased the admission rate and caused the waiting list to grow. This, ironically, meant more elderly people waiting for admission to hospital in the community requiring the help of social services. The model developed by Weiss and McClain (1987), in contrast, is more complicated and of much more limited scope. It can only be used to generate scenarios around the discharging of patients from hospital and does not take into account any feedback effects on to admissions into the hospital.

One disadvantage of System Dynamics is that it deals with homogenous populations in contrast to DES in which discrete entities have attributes such as age and gender. This can lead to a proliferation of states (Davies, et al., 2003). For instance, if the modeller was interested in population dynamics, rather than having one level representing population, several levels would have to be created representing each age group and gender. Hannon and Ruth (2001, p 60) describe just such a model. Some System Dynamics software packages have introduced array variables which alleviate this problem to some extent. Hannon and Ruth (2001, p 66) demonstrate the population model using array variables. Anderson, et al. (2002), in their study of CABG patients, use a
feature of the STELLA software known as ‘conveyers’ to keep track of
individual patients with multiple characteristics

System Dynamics also offers both qualitative and quantitative parts
(Wolstenholme, 1990). The quantitative model can be smoothly drawn from the
qualitative, conceptual model. Simulation and System Dynamics are what
That is they trace out the consequences of events and decisions as if we were
looking at the particular system in operation. System Dynamics has causal loop
diagrams, Lane (2000), Discrete Event Simulation has Activity Cycle Diagrams,
Pidd (1992). Mathematical modelling techniques like Queuing theory, Markov
chains and linear programming deal only with quantitative data, they have no
explicit way of describing a system qualitatively. The complexity of the hospital
system requires that both qualitative and quantitative data needs to be
included making system dynamics a much more appropriate approach.

System Dynamics explicitly models the information structure of a system. Van
Ackere and Smith (1999) develop a model of national waiting lists that relies on
‘waiting time’ and ‘perceived waiting time for supply’ that effects the number of
beds. These two variables are shown in the model. The way they effect the
model (the equations that they represent) would only be a ‘click’ away in the
software. Information the modelled process depends on is part of the structure
of the model. The information structure of a System Dynamics model links past
information of levels to future values of rates, contrasting with a Markov chain
where the past history of the process plays no part in determining its future
(Lawrence and Pasternack, 1998). While Discrete Event Simulation use
Activity Cycle Diagrams to describe the physical process entities go through in
a system, they do not model a system’s information structure explicitly. A
Discrete Event Simulation model describes the system’s information structure
in its control mechanisms but this is implicit to the model and would not
normally be shown to the user of a model.

System Dynamics usually requires specialist software, though at least one
study by Worthington (1991), built a basic ‘stock and flow’ model in a
spreadsheets. Models can be built using a high level programming language but this process is time consuming. Analytical models and Markov chains could be built in general purpose spreadsheets.

System Dynamics and Discrete Event Simulation are better at describing the system wide effects of a policy/information change. Markov chains only take into account the present state of the system when generating future states. Although not impossible to model a feedback effect using a Markov chain, the resulting model could well be structurally awkward. Feedback effects add another complication in the use of analytical techniques.

It is felt that system dynamics is the best modelling technique to use in the current research. Its visual nature makes it easier to communicate and validate than the other methods. It has qualitative and quantitative sides and can easily model system wide effects. Although it has difficulties modelling a heterogeneous population, there are techniques in the software packages to overcome this. Specialist software is needed to use system dynamics but such software can be used to build models faster and with greater ease than the development of other models using a different modelling method.

2.8 Triangulation of data

Gill and Johnson (2002, p 229) define triangulation as “The use of different research methods in the same study to collect data so as to check the validity of any findings.”

This research will triangulate the data obtained from interviews with the document analysis and quantitative data from the Patient Administration System (PAS). It is hoped that analysing the PAS will confirm and quantify relationships put forward from the Interview and Document analyses in order to confirm their reliability.
This research will involve developing two models. One in a spreadsheet, the other a system dynamics model. The spreadsheet model is intended to be a broad, aggregate model intended to forecast waiting list sizes over the next few months. The two models will be compared to each other to see if they produce the same general trend in waiting list sizes and waiting times. An exact comparison of numbers will most likely prove to be inappropriate as the system dynamics method tends to be used to demonstrate trends in variables rather than deal with exact predictions.

2.9. Summary

This chapter has described the main research methods used in this study. It has also set out the reasons for using the system dynamics modelling method to simulate waiting lists.

The next chapter examines the literature for healthcare modelling studies, finding out the main methods used to model healthcare systems and why they were used for these purposes.
Chapter 3: Literature Review

3.1 Introduction

This chapter investigates the methods used to model healthcare systems. It seeks to find out why these methods are used and what advantages and disadvantages do they pose.

The most obvious place to start when examining the literature for models of waiting lists and healthcare systems is queuing theory and analytical models. However, the literature showed that most analytic models were limited in scope and hard to solve. In the 1960s and 1970s, Markov chains improved the scope of studies (though still limited) and extended the solubility of some problems but could not model the dynamic and complex nature of some healthcare systems.

The rise in the power of computing in the 1980s and 1990s meant that techniques based on numerical methods became more feasible in the modelling of systems. Simulations became cheap and easy to build and their use was within the grasp of a Manager at his/her desktop. Two methods of simulation became popular in healthcare modelling, Discrete Event Simulation (DES) and System Dynamics (SD). DES studies tend to be operational in nature (Braidsford, et al., 2004; Everett, 2002) while SD studies are more strategic and epidemiological (Bennett, et al., 2005).
3.2 Analytical Techniques and Queuing Theory

A simple way of looking at waiting lists is to model them as queues in which ‘customers’ (patients) arrive who require a ‘service’ (surgery) from ‘servers’ (surgical teams).

French, et al. (1986) list four factors which affect the way a queue operates:

1. The arrival pattern of customers. Customers may arrive completely at random as at a bank or at regular intervals such as goods coming off a production line or they may arrive with some random variation around a regular pattern as in an appointment system at a doctor’s surgery.

2. Service times. The time taken to serve a customer can be fixed or random. The time a teller at a bank takes to serve a customer will depend on what they want, the time for a car to go through an automatic car wash is the same from car to car.

3. The number of servers. There can be many or no servers to serve customers. Traffic lights are red for a certain amount of time i.e. they are serving no one in the queue of cars building up before them whilst other cars in other independent queues go through the junction. There could also be one queue with many servers, each server dealing with the next customer in line.

4. The queue discipline. A server could serve customers as First Come First Served (FCFS) as in a supermarket queue, or Last In First Out (LIFO). Customers may balk when they see the size of a queue and refuse to join it, they are then lost to the system or may come back later. Customers may also renege whilst in a queue, that is they may leave the queue instead of being served because the waiting time has become too long.
Formula can be developed to find certain performance measures of simple queues (like average waiting time, average queue length and the proportion of time a server is serving) if the queues conform to certain assumptions. These assumptions include using certain probability distributions to model the arrival and service processes, no reneging or balking by customers and certain queue disciplines (like FCFS).

Arrivals to queues can be modelled using a random Poisson distribution if they satisfy the three conditions of orderliness, stationarity and independence (Lawrence and Pasternack, 1998). Orderliness is the condition that in any time instant, at most one customer will arrive to the queue. Stationarity is where for a given time frame, the probability that a customer will arrive in a certain time interval is the same for all time intervals of equal length. Independence means that customers arrive independently of one another, an arrival during one time interval does not affect the probability of an arrival in another time interval.

The probability of \( k \) arrivals during a time period of length \( t \) is (Lawrence and Pasternack, 1998)

\[
P(k) = (\lambda t)^k e^{-\lambda t} / k!
\]

where \( \lambda \) is the average arrival rate per time unit
and \( k! \) is \( k*(k-1)*(k-2)*...*1 \)

Service times can be modelled using the exponential probability distribution (Lawrence and Pasternack, 1998). The probability that the service time \( X \), is less than some value \( t \) is given by,

\[
P(X \leq t) = 1 - e^{-\mu t}
\]

where \( \mu \) is the average service rate.
The exponential distribution is known as a memoryless or Markovian distribution. This means that the probability of completing service in a certain time interval is the same no matter how long the customer has already been served or if he/she is about to start service. A customer who has already been served for two minutes is as likely to finish service in the next three minutes as a customer who has just started service. The Poisson distribution also shares this memoryless property (French et al., 1986).

Different types of queue can be denoted using a shorthand notation to refer to different queuing systems easily.

Arrival Process / Service Process / Number of Servers

Common notations for the arrival and service process are shown in Table 3.1 (Lawrence and Pasternack, 1998)

Table 3.1 Meaning of symbols in queue notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>Markovian</td>
<td>Distribution with a memoryless distribution e.g., Poisson distribution for arrivals and an exponential distribution for service times</td>
</tr>
<tr>
<td>D</td>
<td>Deterministic</td>
<td>Arrivals come at a constant rate, service times are constant</td>
</tr>
<tr>
<td>G</td>
<td>General</td>
<td>General probability distribution with a known mean and variance</td>
</tr>
</tbody>
</table>

For example in the M/M/1 queuing system, arrivals follow a Poisson distribution, Service times follow an exponential distribution and there is one server. Average numbers of customers in the M/M/1 queue can be calculated according to,

\[ L_q = \lambda^2 / (\mu (\mu - \lambda)) \]

while the average waiting time in the queue can be obtained from,
\[ W_q = \frac{\lambda}{(\mu(\mu - \lambda))} \]

(Lawrence and Pasternack, 1998)

Other performance measures can be developed for other simple queues, for example M/G/1, M/E_r/1 (\(E_r\) = Erlangian distribution) and M/M/k/F (where \(F\) = upper limit of customers allowed in the queue). These formulae are derived from assuming that the system is in a 'steady-state', that is the service rate is greater than the arrival rate so that the queue does not become infinite in length.

### 3.3 Analytical Healthcare Models

Weiss and McClain (1987), describe a queuing model of 'backup' patients in an acute care hospital. 'Backup' patients are those patients on a ward who no longer require acute medical care but cannot be discharged while they await a placement in a nursing home or for the arrangement of social support services if returning to their own home (NB. In Britain these patients are known as 'bed-blockers'). These Alternate Level Care (ALC) patients use up a sometimes lengthy period of 'administrative days' (i.e. the patient no longer needs medical care but is delayed for administrative reasons) which is costly, in the United States, to the patient or his/her insurers.

The authors analysed a model of ALC patients waiting in a queue to be discharged. Rather than model patient flows from the hospital to individual ALC facilities, transfers to 'extended care' were treated as one aggregate flow enabling the system to be treated as one large queue. This makes the solution easier as it now involved a single server queue rather than a two stage multiple server queue (whose solution would probably involve simulation and the collection of data from a large number of small, disparate organisations). The disadvantage of this simplification is that it cuts down on the amount of analysis that can be performed with the final model. Fewer questions can be posed.
relating to the organisational boundaries between hospitals and lower-level care facilities

The authors' model was based on two assumptions

- ALC patients arrive randomly, according to a Poisson distribution
- ALC patients depart at a rate dependent on the number of ALC patients and the placement process of the hospital

The daily discharge rate of ALC patients is modelled using the following equation,

\[ \mu_n = \alpha + n\mu \quad n \geq n^* + 1 \]

\[ \mu_n = 0 \quad n \leq n^* \]

where '\( \mu_n \)' is the daily discharge rate, '\( n \)' is the number of ALC patients, '\( \alpha \)' is the rate at which placements become available and are offered to the hospital and '\( n^* \)' is the number of 'hard to place' patients.

Using this equation for the service rate, the authors derived expressions for the average number of ALC patients and the variance of the distribution of number of ALC patients in terms of the service and arrival rates and '\( n^* \)' and '\( \alpha \)'

Two different models of ALC service is derived from different values of '\( \alpha \)' and '\( n^* \)'. These are described in Table 3.2 below

The authors collected data from seven hospitals in New York State to test the validity of their model. They found good fits of the data for both the 'saturation' model and the 'restoring force' model. Hospitals' policy towards 'backup' patients would be different according to the type of model that best fitted. A hospital with a 'restoring force' model would best target those patients who are difficult to place. Hospitals facing a 'saturation' model would do best by encouraging more ALC places to be established and offered to the hospital's patients.
Table 3.2: Two different models of ALC service

<table>
<thead>
<tr>
<th>$n^*$</th>
<th>$\alpha$</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>&gt;0</td>
<td>'saturation' model. $\alpha$ is the rate at which openings become available and are offered to the hospital and $\mu$ is the rate at which ALC patients leave without using the placement system. As $n$ increases, the average placement success per patient decreases, the discharge planners must divide their attention between the patients on the ALC status so they become saturated with work.</td>
</tr>
<tr>
<td>$\geq \alpha/\mu$</td>
<td>&lt;0</td>
<td>'restoring force' model. The discharge rate drops to zero when $n$ falls to $n^<em>$. When $n &gt; n^</em>$, the discharge rate increases linearly. The model is an approximation of a non-uniform population of 'normal' and 'hard-to-place' patients. When $n$ is low, the 'hard-to-place' patients are over-represented and the discharge rate per patient approaches zero ($n^*$ becomes an estimate of the 'hard-to-place' patients). There is more pressure on the discharge planning staff to place patients when the ALC census is high and less when the census is low. As the census increases the placement rate per patient increases and vice versa.</td>
</tr>
</tbody>
</table>

The authors’ hoped that their models could be used “to make predictions concerning the impact of various decisions about reimbursement, discharge planning and certification of extended care facilities” (Weiss and McClain, 1987). However, the models are drawn at the level of the hospital. There is no examination of any differences between wards and specialties. A discharge policy based on an analysis at the hospital level may not be appropriate for individual wards and specialties.

Shmueli, et al. (2003) used a queuing model to investigate the different admissions policies of an Intensive Care Unit (ICU). The model used was the 'Erlang-loss' M/M/m/m model which has ‘m’ servers (beds) and a finite size of patients allowed in the system (to a maximum of ‘m’ patients). If the ICU is full a patient is blocked and either tries again later or receives treatment on an ordinary ward. The authors were interested in comparing different admissions policies in terms of the number of lives per year they would save. Three
different policies were examined, these are listed in the following table (Table 3.3).

Table 3.3 Different admission policies to the ICU

<table>
<thead>
<tr>
<th>Admission Policy</th>
<th>Explanation</th>
<th>Expected statistical lives saved per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCFS</td>
<td>First Come First Served.</td>
<td>1004</td>
</tr>
<tr>
<td>FCFS-H</td>
<td>First Come First Served—Hurdle: The patient has to satisfy a minimum potential benefit increase before admission is allowed.</td>
<td>1184</td>
</tr>
<tr>
<td>FCFS-BSH</td>
<td>First Come First Served—Bed Specific Hurdle: The patient has to satisfy a minimum potential benefit increase dependent on the number of available beds before admission is allowed. The hurdle increases as the number of available beds decreases.</td>
<td>1198</td>
</tr>
</tbody>
</table>

They were also interested in looking at the equitableness of these admission policies. Was it fair to block patients because they did not reach a survival benefit threshold? The authors argue that it is. After all, would it be fair to turn away a patient who could benefit greatly from ICU because the Unit is full of patients who will only benefit marginally?

The authors calculated the incremental survival benefits from APACHE II (Acute Physiological And Chronic Health Evaluation) scores in a sample of patients from Hadassah Hospital in Jerusalem. APACHE II scores use factors such as a patient’s age, sex, general acute diagnosis to compare patients level of sickness. As can be seen (Table 3.3) the FCFS-BSH policy does the best but only marginally over the FCFS-H policy. The authors display a graph of what they describe as the 'optimal' bed specific hurdles varying by beds available but give little information as to how they obtained these figures.
Gorunescu, et al. (2002) demonstrated the effect of a holding area for patients waiting to be admitted on to the geriatric ward. They used a queuing model to plan bed allocations in a Hospital's Department of geriatric medicine. The aim of the study was to find out the effect of changing arrival rates, mean length of stay and the number of beds on the probability that the ward and waiting area are full, occupancy level of the ward and the costs associated with patient stays. The model used was a M/PH/c/N where 'PH' is a Phase Type service distribution. This means the servers (the beds in this case) switch between different service phases depending on who has been admitted to the bed. It arises because geriatric patients are a mixture of different types, some need acute medical services, some rehabilitation and other long-term care. Each of these types has a different service time distribution and is modelled using an individual exponential distribution which is then combined into a 'mixed exponential' distribution. The model was assumed to be in a steady state. Data from a London Hospital was used to produce the model and test the five as listed in Table 34 below.

Scenario 4 found there was little point in providing a ten bed waiting area unless there was a certain threshold of staffed beds on the ward. For example, with 140 staffed beds the probability of a patient being rejected for admission decreases from 9% to 6% whilst if there are 155 staffed beds that rejection probability decreases from 3% to 1.5%. The costing in Scenario 5 took into account the cost of refusing admission to patients, the cost of a waiting area and the cost of staffed beds (both occupied and the cost of beds lying idle). At 155 beds, the cost of providing a ten bed waiting area was £172,000 per year.

The model can be used to assess the benefits of providing extra beds to minimise the probability of a patient being rejected when demand increases especially in the Winter months. The strength of this model is that it takes into account different types of patient. Long stay patients reduce the number of available beds so their effect is important to model.
### Table 3.4: Scenarios for model

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Modelled the effect of changing the arrival rate while keeping the average length of stay and bed allocation constant.</td>
</tr>
<tr>
<td>2</td>
<td>Modelled the effect of changing the average length of stay while keeping the arrival rate and bed allocation constant.</td>
</tr>
<tr>
<td>3</td>
<td>Modelled the effect of changing the bed allocation while keeping the average length of stay and the arrival rate constant.</td>
</tr>
<tr>
<td>4</td>
<td>Modelled the effect on bed occupancy of adding a five or ten bed waiting area to Scenario 3.</td>
</tr>
<tr>
<td>5</td>
<td>Costed Scenario 4.</td>
</tr>
</tbody>
</table>

An overview of the various models developed, methods employed and their major findings are given in Table 3.5. All three of the above studies cover small areas of application, an Intensive Care Unit (ICU), a genetric department and 'bed-blockers' in a hospital, usually over one particular boundary either discharging from the ward/hospital or admitting patients to the ward. The areas the models study are limited in scope. This in itself may be reasonable for the aims of the particular studies, however, it means the studies do not take into account other parts of the health and social care systems. Changing policies here in these wards may have problematic consequences elsewhere. For example, in Schmueli et al.'s study, how will referring staff react to an admission policy that, to them, could almost be seen to vary randomly (they won't necessarily know how many empty ICU beds there are)? Weiss and McClain make no attempt to examine the effects that an increase in discharges will have on the local social services. The Gorenescu et al. study may be interesting from a systems viewpoint as it could relieve pressure in the hospital's Accident & Emergency department (assuming their hospital has one) but no attempt has been made to assess this benefit and include it in the evaluation of the various scenarios.
### Table 3.5 Overview of models

<table>
<thead>
<tr>
<th>Authors/Year</th>
<th>Subject</th>
<th>Methods used</th>
<th>Major findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weiss &amp; McClain, 1987</td>
<td>‘Bed-blocking’ patients delayed in discharge from a hospital ward</td>
<td>Analytical queuing model with service rate dependent on the number of patients waiting for discharge and Poisson Arrivals</td>
<td>Examined two different types of the model, ‘saturation’ and ‘restoring force’. Found data from Hospitals fitted both types reasonably well</td>
</tr>
<tr>
<td>Schmueli et al, 2003</td>
<td>Admission policies into an Intensive Care Unit</td>
<td>‘Erlang-loss’ M/M/m/m queuing model</td>
<td>First Come First Served – Bed Specific Hurdle was the admission policy that saved most statistical lives</td>
</tr>
<tr>
<td>Gorunescu et al, 2002</td>
<td>Bed allocations in a genatnic medicine hospital department.</td>
<td>‘Phase type’ M/PH/c/N queuing model</td>
<td>Little point in providing beds in a waiting area unless there was a certain threshold of staffed beds on the ward</td>
</tr>
</tbody>
</table>

Also, all three studies are highly mathematical which could be troublesome in trying to communicate the particular model to various stakeholders and lead them to accept the model and its conclusions. All three depend on developing complex equations using advanced mathematical concepts to model their problems. Whilst these equations are reasonably applied to the areas of study, not all managers and clinicians will have the mathematical skills and knowledge to follow them easily. It will therefore be difficult for them to follow a model’s development unless carefully explained by its developers leading on to problems in acceptance of the model.

All the studies considered here model quantitatively. There is no attempt to provide anything other than a basic qualitative description of the model’s subject. They do not analyse and infer any system behaviour from these qualitative descriptions.

The models did not describe a diverse set of patients. Patients were usually differentiated on one variable alone. Gorunescu et al. (2002) differentiated patients only according to the type of care they needed, Shmueli et al. (2003)
does use several patient characteristics to 'score' their level of sickness but it is the level of sickness that is used in the final model. Weiss and McClain (1987) used a homogenous group of patients delayed in their discharge from hospital. This may not matter if the model is 'fit for purpose' i.e. it answers the questions that the authors posed and further wider effects of the systems under study can be discounted.

3.4 'Black Box' Modelling

This is a type of analytical modelling where no knowledge or assumptions are made about the system being modelled. Equations are developed based purely on observed data relating output variables (measures of interest like waiting times) to input variables (number of patients added to the list for example). The system itself is an unknown 'black box' as shown in figure 3.0 below.

Figure 3.0 A 'Black Box' model

Output variables are related to input variables via a formula. The parameters of this formula are then estimated using the observed data and various mathematical techniques.

Giraldo et al (2000) modelled a surgical waiting list in terms of the number of admission requests (additions to the list), the number of surgical interventions and the mean time for surgery (these last two inputs gave the available time at the operating theatre). They analysed four different kinds of surgery over 24 months of data. The Authors estimated parameters that best fit an equation that modelled the data. They achieved reasonable fits of formula to data, with
mean percentage errors for the different types of surgery of between 2% and 10%. There was no explicit modelling of emergency patients though this will clearly have an effect on the available time at the operating theatres.

The advantages of this kind of modelling is that once developed, the equations can quickly generate predictions of future output variables given certain inputs. The disadvantages are that the 'black box' model is entirely reliant on the observed data in the past to make its predictions, any change in behaviour of the system being modelled would make the model invalid. A lack of internal description of the system makes validation difficult and cannot lead to any insights into how the system can be improved.
3.5 Markov Chains

Many systems can be visualised as occurring in stages. At each stage the system can be determined to be in some state. The numbers residing on a waiting list, for example, are usually calculated at the end of each month. The number of states in a process is either finite or countably infinite. A M/G/1 queuing system (see page 90 for definition) which has no upper limit to the number of people waiting in its queue is an example of a system with a countably infinite number of states.

The probability of a process moving from one state to another is independent of how it came to arrive in its present state. In queuing models the probability of moving from six to five people in the queue does not depend on how the six came to be waiting in the first place (Lawrence and Pasternack, 1998). Systems in which the past history of the process plays no part in determining its future behaviour are known as Markov processes or Markov chains.

Lawrence and Pasternack (1998) list the properties of a Markov process:

- the process consists of a countable number of stages,
- at each stage, the process can be in a countable number of states, and
- the probability of moving from state $i$ at stage $k$ is to state $j$ at stage $k + 1$ is independent of how the process arrived at state $i$.

The probability of moving from state $i$ at stage $k$ is to state $j$ at stage $k + 1$ is denoted by $P_{ij}$ and is known as a transition probability. These probabilities can be written as a transition matrix.

$$
P = \begin{bmatrix}
P_{11} & P_{12} & P_{13} & \cdots & P_{1n} \\
P_{21} & P_{22} & P_{23} & \cdots & P_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
P_{m1} & P_{m2} & P_{m3} & \cdots & P_{mn}
\end{bmatrix}
$$
The state probability, $\pi_i(j)$, is the probability that the process is in state $i$ at stage $j$. The state probabilities at any given stage are given by the state vector which consists of the individual state probabilities,

$$\Pi(j) = [ \pi_1(j) \pi_2(j) \pi_3(j) \ldots \pi_n(j) ]$$

The state probabilities satisfy the following relationship,

$$\Pi(j+1) = \Pi(j) P$$

### 3.6 Healthcare Models based on Markov Chains

Blair and Lawrence (1981) used a Markov chain to describe a system of burn care facilities in New York State. The model was also used to search for the optimal distribution of beds between facilities. Their model describes the effects of having a state-wide referral policy whereby if a burns patient who requires treatment finds that the Burns' Unit they arrive at is full they can be referred to another facility in the State. The patients were assumed to arrive in a Poisson distribution and also to have an exponential service time. The service time is the patient's length of stay in the Burns' Unit. The Unit's beds are the servers. No queues are allowed to form so if a patient finds all beds in the system are full they are lost to the system. This assumption is reasonable if the patients in question move to another Burns' Unit across state borders. If they are held in a lower level acute bed until a Burns' bed becomes free then this may upset the analysis.

The model calculates the probability that a patient can be admitted to a bed in the system and the average occupancy of beds in the system (occupancy is the number of occupied beds divided by the total number of beds). This reflects the two objectives of the analysis, making sure there are enough beds available for all burns patients and finding the most efficient, cost-effective use of those beds.
The second part of the paper describes the model's use in finding the optimum number and distribution of beds between facilities for a specified level of service, in this case a 95% probability that a patient can be admitted to a bed in the system. The optimum number of beds was discovered by treating the system as a whole as a M/G/s/s queue and varying 's' whilst subjecting the queue to the system's aggregate arrival process.

The distribution of beds was discovered by running the model using an optimisation algorithm. The algorithm tried out various configurations of beds with the goal of trying to maximise the minimum level of service amongst the various Burns' Units (the level of service being defined as the individual facility's probability that a burns patient can be admitted to it). The model was designed with experimentation in mind. In their conclusion, the authors state "Health care planning must be a dynamic process and the availability of a descriptive model to answer 'what-if?' questions is a valuable asset."

A Markov chain model was also used by Liu, et al. (1991) to analyse a medical record system in a general hospital in Taiwan. The purpose of the model was to estimate the future storage space and retrieval time for medical records under different disposal policies; how long to keep a patient's medical record after their last visit to the hospital. The longer the time before disposal, the more storage space required and the longer to retrieve a record but less resources spent recreating a returning patient's record. The authors defined the chain's states in terms of the number of months since a patient's last visit. If the patient revisited the hospital, their medical record returned to state zero. If the medical record reached the time to disposal, state 'n' (e.g. n=60 months for a five year disposal policy), then it would remain in state 'n' and if the patient returned a new medical record would be created. A Markov chain was used as the modelling method as a patient's future visit to a hospital depends mostly on the time of his or her last visit and is independent of the times of his or her previous visits. The model demonstrates the overall trade-off of storage space versus re-creation and disposal of medical records. The authors used a formula derived from the transition probabilities to come up with the average time (and variance) that records spent in storage.
A Markov chain was constructed by Shachtman and Hogue (1976) to investigate research data on the consequences of abortion on later pregnancies. Their model consisted of states that described a woman’s reproductive path, being made up of pregnancy states by month, susceptibility to pregnancy by month, reduced susceptibility to pregnancy due either to contraception (which was further sub-divided into types of contraception) or natural infertility and abortion (either induced or spontaneous). All these states were further subdivided into those women whose first pregnancy had ended in abortion, those whose first pregnancy had ended in birth and those who had already had a baby. Thus the model would be able to simulate reproductive behaviour between the group whose first pregnancy had been aborted and the group whose first pregnancy had gone to term. The number of states in the model was large at 79. They calculated transition probabilities based on data from a study of 928 women in Skopje in what then was Yugoslavia in the late 1960s.

Kao (1974) used a semi-Markov chain to model the movements of coronary patients within a hospital (a semi-Markov chain is one in which the transitions between states occurs randomly rather than regularly). The ‘states’ are defined by the care unit in which a patient resides. Patients are admitted to the CCU (Coronary Care Unit) and may then be transferred to other Units like ICU (Intensive Care Unit) or PCCU (post-Coronary Care Unit). There are six transient units like these and three other absorbing states, Death, Discharge Home and ECF (Extended Care Facility). The strength of the model is that it can be used to show the knock on effects of an increase in beds in the hospital’s CCU. Its weaknesses are its assumption that patients require a similar amount of resources per day and a similar amount of time spent in a care unit whatever their condition.

A further example is Kastner and Shachtman (1982) use of a Markov chain to study hospital acquired infections. They defined patients to be in 17 states including primary and secondary infections of four of the main infection sites. They estimated transition probabilities from a US National medical record study.
of 58,000 patients. The questions they asked of their model included how much longer a patient with a hospital-acquired infection stays in hospital compared to a patient without such an infection and how would the length of stay in hospital be influenced by the elimination of certain types of hospital-acquired infections? The answers to such questions combined with information on costs of hospitalisation could be used by health planners to choose between different Infection Control Programs.

Vieira, et al. (2003) model the Mother-to-child transmission (MTCT) of HIV using a discrete event simulation that has a semi-Markov structure (i.e., transitions between states occur randomly). The model has five states, three relating to the three trimesters of pregnancy, one to labour and one to the period after the birth. The authors explore the effect of anti-retroviral treatments and the cessation of breast feeding on the numbers of eventual HIV+ children. To assist the end user Health care planner a highly visual User Interface was built using Visual Basic to give a familiar 'Windows' feel.

Table 3.6 summarises the studies examined in this section. These examples of the uses of Markov Chains show they are flexible enough to be used in a wide variety of settings for several purposes. Liu et al. (1991), Blair and Lawrence (1981), and Kastner and Shachtman (1982) used them for planning services (Medical records storage, Burns Care facilities and the cost of different Infection Control Programs respectively), while Kao (1974) showed the effect of a resource constraint (number of CCU beds in the hospital). Markov Chains demonstrate a solution to multiple queues and queuing networks that go beyond analytical techniques. Fewer assumptions about arrival processes, service times and queue disciplines need to be made.
Table 3.6 Summary of Markov Chain studies

<table>
<thead>
<tr>
<th>Authors/Year</th>
<th>Subject</th>
<th>Methods used</th>
<th>Major findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blair and Lawrence 1981</td>
<td>Burns care facilities in New York State</td>
<td>Markov chain</td>
<td>Found optimal distribution of beds between facilities</td>
</tr>
<tr>
<td>Liu et al. 1991</td>
<td>Medical Record System</td>
<td>Markov chain</td>
<td>Show trade-off between space and disposal of medical records</td>
</tr>
<tr>
<td>Shachtman and Hogue 1976</td>
<td>Consequences of abortion on later pregnancy</td>
<td>Markov chain</td>
<td>Model shows differences in reproductive behaviour between the group whose first pregnancy had been aborted and the group whose first pregnancy had gone to term.</td>
</tr>
<tr>
<td>Kao 1974</td>
<td>Movements of Coronary Care patients within a Hospital</td>
<td>Semi-Markov chain</td>
<td>Shows the knock on effects of increase in CCU beds</td>
</tr>
<tr>
<td>Kastner and Shachtman 1982</td>
<td>Hospital Acquired Infections</td>
<td>Semi-Markov chain</td>
<td>Model costed different infection Control Programs</td>
</tr>
<tr>
<td>Vieira et al. 2003</td>
<td>Mother to Child Transmission of HIV</td>
<td>Discrete Event Simulation with Semi-Markov chain structure</td>
<td>Explore the effect of anti-retrovirals and the cessation of breast feeding on transmission rates</td>
</tr>
</tbody>
</table>

Markov Chains are more explicit in showing the model structure than analytical techniques. The states that the patients can enter must be explicitly defined and transition probabilities between states enumerated. This improvement in transparency gives these models more scope for communication to non-experts and validation. Any validation of the models that do go on centre around generating transition probabilities from historical data and using statistical tests to compare certain parameters with empirical data. Historical data are also used to test some of the Markov model assumptions, for example, to test whether the transition probabilities are stationary from one time period to the next. Kastner and Shachtman (1982), for instance, compare
model prediction and observed length of hospitalisation for patients with a hospital acquired infection.

Markov chains can lead to the creation of large state spaces, for example Shachtman and Hogue (1976) s' chain led to 79 states being defined. This could slow down any analysis being performed and is also complicated to communicate and validate. The large number of states in the model did give rise to a heterogeneous patient population with a wider scope for analysis.

As with analytical techniques, Markov Chains are quantitative models and no explicit analysis of the qualitative description of the modelled system is undertaken.
3.7 Simulation

The analytical solutions to queuing problems discussed above cannot always solve (or the solution is too complex to derive) more complicated real-life modelling problems. If this is the case, then simulation can often be used to produce a working model. French et al. (1986) defines simulation as: "a procedure by which an actual sequence of realisations of chance events, decisions and outcomes may be traced out as if we were actually observing the particular system in operation."

Simulation models evaluate a system numerically over time. "Its purpose is to estimate characteristics for the system" (Lawrence and Pasternack, 1998).

Many analytical techniques use an algorithm to obtain an optimal solution, a simulation traces through events in a simulated system to evaluate each option. There is no guarantee that policies thought to be optimal by reference to the use of a simulation are in fact optimal.

Simulation can model events that occur randomly and can reflect the frequencies of occurrence. Random number mapping can be used to generate events in a simulation. A spreadsheet can be used to generate numbers randomly with a uniform distribution. These are then mapped to a random variable (for example, the number of customer arrivals in a time period) to reflect the distribution of that random variable, see Table 3.7 below.

Table 3.7 Random number mappings

<table>
<thead>
<tr>
<th>Number of customer arrivals</th>
<th>Corresponding random numbers</th>
<th>Probability Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1-10</td>
<td>0.10</td>
</tr>
<tr>
<td>1</td>
<td>11-23</td>
<td>0.13</td>
</tr>
<tr>
<td>2</td>
<td>24-26</td>
<td>0.03</td>
</tr>
<tr>
<td>3</td>
<td>27-45</td>
<td>0.19</td>
</tr>
<tr>
<td>4</td>
<td>46-76</td>
<td>0.31</td>
</tr>
<tr>
<td>5</td>
<td>77-100</td>
<td>0.24</td>
</tr>
</tbody>
</table>
Simulations can be of the 'fixed time' or 'discrete event' types. Variables that describe the system state are evaluated at each time period of the 'fixed time' simulation while, in a 'discrete event' simulation, the variables would only be evaluated when certain events take place. 'Discrete event' simulations can be more efficient when a system state variables do not change often.

Gillow (1976) used the simulation of a queuing system to examine the optimal design of an abortion clinic. Analytical techniques could not be used as the patients' behaviour did not fit the assumptions required for the use of the equations involved in queuing theory. The clinics could not treat anyone over twelve weeks pregnant and these patients would have to be turned away. The process involved investigating the clinic as a network of queues where a patient would wait for counselling, laboratory tests, pre-operation medication and the procedure itself. Simulation was seen as the simplest way to model the system. Two variables were used to denote the configuration of the clinic, the number of counselling rooms and the number of procedure rooms. Three pilot queuing simulations were run for each clinic configuration to guess the average number of patients who could be given abortions daily. These figures were used as a starting point in a 'gradient search' optimisation technique to maximise the abortion clinic's profitability for a given demand and clinic configuration. The profitability was expressed in terms of costs (number of nurses and doctors' hours required for example) and revenues (charge per abortion).

Optimal design of abortion clinics can improve the conditions for the patients e.g., by minimising the time spent waiting before the procedure. It is a complex piece of research, not easily communicated to potential users. It also only deals with two different variables to describe clinic configuration, the number of counselling rooms and the number of procedure rooms. Other variables might be the number of nurses on duty or the maximum allowable overtime hours a doctor can work. Nevertheless, the simulation evaluates different clinic configurations in a way that is just not possible with an analytical model especially with a significant number of reneging patients.
3.8 Discrete Event Simulation

Discrete Event Simulation evaluates the variables that describe a system's state only at those times when certain events take place (Pidd, 1992) The interactions of the modelled entities can be shown in 'activity cycle' diagrams. These diagrams show the life cycle of each entity class (e.g. patients) and displays their interactions. Activity cycle diagrams have just two symbols shown in Figure 3.1

![Activity Cycle Diagram]

Figure 3.1 Symbols used in activity cycle diagrams

A Live State usually involves the interaction of more than one type of entity. The duration of a live state can always be determined in advance e.g. by sampling a service time from a probability distribution.

A Dead State is generally a state where the entity waits for something to happen. Waiting in a queue is a dead state for an entity. Time spent in a queue depends on the duration of the preceding and succeeding live states.

The process-interaction approach to discrete event simulation takes the process of an entity through its life cycle as the basic unit of the simulation. A process is the sequence of activities an entity goes through in its life in the system. A process-based computer simulation must record the progress of each entity through its process. The simulation must also have some way of progressing the entity through its process.

At each time point in the simulation, each existing entity is moved through its process until it is halted by either
- **an unconditional delay** The entity's progress is stopped for a time period which can be determined in advance. The delay depends only on the passage of simulated time.

- **a conditional delay.** The entity's progress is stopped until certain conditions in the simulation are satisfied. A patient will stay on a waiting list until the hospital is ready to admit them.

The points at which an entity is delayed in its process are called re-activation points. The simulation must contain a record of each entity's re-activation time (if known) and its next re-activation point.

Two lists are maintained:

- **Future events list** A list of entities whose progress is unconditionally delayed, whose re-activation time is ahead of the current clock time.

- **Current events list.** A list of entities whose progress has been unconditionally delayed and whose re-activation time is now due. The list also includes entities that are conditionally delayed.

The simulation then operates the following cycle at each clock time:

- **Future events scan** The time of the next event is obtained from the future events list. The simulation's clock is moved to this new time.

- **Move between lists** Entities on the future events list whose re-activation time equals the new clock time are moved to the current events list.

- **Current events scan.** The simulation performs the events on the current event list moving each entity further through its process if conditions allow. Entities that have been moved either complete the process or are halted because of a delay. If the delay is unconditional, the entity is moved to the future events list.
The simulation then runs through as many time steps as the modeller desires to generate the required performance information. Discrete Event Simulation is a very flexible modelling technique though sometimes time consuming to build and run. The next section describes some healthcare models built using Discrete Event Simulation.

3.9 Discrete Event Simulation Healthcare Models

Everett (2002) describes the design of a discrete event simulation model for decision support for the scheduling of patients waiting for elective surgery in Western Australia. The model can be used as an operational tool to match availability and need, as a performance reporting system and as a planning tool comparing the effect of alternative policies.

The main focus of the paper was in examining scheduling efficiency of elective surgery both within and between hospitals. The model can identify inefficiencies in the existing system and explore whether rearranging present resources will improve the service.

An analytical model can be optimised. However, the different stakeholders (patients, doctors and surgeons, administrators, politicians) had widely different ideas of what an optimal solution would be (according to Everett, 2002) and so simulation was chosen as the modelling method. The simulation model was thus used to encourage communication between stakeholders. The Graphical User Interface (GUI) gave more opportunity for stakeholders to participate in its development as it was a visual interface that gave immediate feedback when a User tried to interact with its varous inputs. The design went through iterative criticisms and enhancements from the stakeholders. Everett also extended her knowledge of the model by demonstrating it to stakeholders.

The ‘patients’ are specified by the type of treatment required and their urgency level. Average cases per day for each urgency level and the mean and standard deviation of operating hours and bed days can be specified for each type of treatment. As the simulation progresses patients join the waiting list.
the beginning of each day, the average daily number of each urgency level for each type of treatment is used to generate new patients according to a Poisson distribution. Operating hours and bed days for each patient are randomly generated using a normal distribution (they did not try to fit real data).

There were three hospitals included in the model. Each selected patients daily from the waiting list. Resources for the hospitals can be specified e.g., operating hours and beds. Patients have an expected operation length and patients are selected according to priority and whether the cumulative expected operating time will exceed the budgeted operating time. Budgeted operating theatre time and budgeted bed availability were the limiting resources.

Developing the model highlighted the data requirements and demonstrated this to the stakeholders. It showed the need for detailed historical data. The question of whether the system required more resources could only be answered by asking if the resources already assigned were being used efficiently, which requires detailed historical data on the quantity, timing, and breakdown of demand.

The model could be used operationally in real time, the cases not being generated statistically but read in from a file of real cases (centralised system to schedule the flow of elective surgery patients to appropriate hospitals in a co-ordinated system that, presumably, would be more efficient and fair). The model could be used as a monitoring tool using real historic data to see if waiting times could have been controlled better. It could also have been used in a planning role to look into alternative structures and different deployment of resources e.g., investigate the effect of combining the three hospitals’ waiting list.

Swisher and Jacobson (2002) described the construction of a Discrete Event Simulation model of a Doctors’ out-patient clinic. The model was used to evaluate different operating procedures in the clinic to see if efficiency can be improved (efficiency was defined as increased patient throughput, less waiting.
The simulation model can determine the staffing and physical resources required in a clinical environment. Proposed clinic designs were evaluated using statistical techniques.

Eight distinct patient categories were used. The model analysed operations using arrival and service time distributions based on these categories. Several parameters in the simulation could be changed, including medical staff composition, examination rooms, and registration rooms. The simulation gave decision makers a tool to balance clinic profit and patient satisfaction (based on clinic waiting times).

El-Darzi, et al. (1998) describe a discrete event simulation model of a geriatric inpatient ward. The aim of the study was to assess the benefits of a model that looks at the impact of bed blockage, occupancy, and emptiness on patient flow in a geriatric ward. Patient arrivals were modelled as a Poisson process and if no beds were available, a waiting list would form. However, for the initial purposes of the model, it was assumed that the admission rate would equal the arrival rate. The service mechanism was modelled as three states of care. All patients were first admitted to an acute bed. Most would then be discharged, but others would be transferred to Rehabilitation (medium length care) and then discharged. Some Rehabilitation patients would stay on for long-term care. If no bed was available in the later states, then a queue would form 'upstream' causing a bed blockage e.g., if no Rehabilitation beds were available, then anyone in acute care requiring transfer to Rehabilitation would have to wait.

The first model executed by the authors was the unconstrained model where there was no limit to the number of beds allowed to be occupied and no queues were allowed to form. The authors used statistics from a North London Health District to run their model and compared their results to a BOMPS (Bed Occupancy Modelling and Planning System) flow model. BOMPS is a deterministic model of geriatric bed planning used in several hospitals in the NHS. The two different modelling systems gave similar results in terms of occupied beds.
The basic model introduces queues. The number of beds was set at the average number of occupied beds from the unconstrained model plus some 'emptiness' percentage. Queues form in the Acute and Rehabilitation parts of the system if the next compartment of care has no beds to offer. Patients arriving for admission to find no beds available are rejected. The model was found to be sensitive to small changes in conversion rates (Acute to Rehabilitation and Rehabilitation to Long Term) and lengths of stay.

The model was useful to try out different scenarios and in particular to estimate the average bed 'emptiness' to ensure a 24 hour a day acute bed service. The authors also believe the model to be useful in demonstrating the long-term effects of any radical change in bed configurations.

Davies and Davies (1987) used Discrete Event Simulation to provide a model to generate planning information for managers allocating funds for renal patients requiring kidney transplant. The paper shows an Activity flow diagram for the system these patients go through. New patients arrive randomly and are given characteristics like age, blood group and preferred dialysis by sampling from various distributions (the model used information from the European Dialysis and Transplant Association (EDTA) registry which collects data from 32 countries in Europe, the Middle East and North Africa).

Patients are then put in a queue for either dialysis or CAPD (Continuous Ambulatory Peritoneal Dialysis; patients require several bags of sterile fluids each day). If treatment eventually fails they can have a kidney transplant (if they are suitable). Cadaver kidneys arrive independently of the patients. They also have attributes such as blood group. They are matched to a suitable patient on the transplant waiting list. The compatible patient is removed from the waiting list and they start the transplant treatment. Survival times for both patient and kidney are sampled from distributions. When a patient finishes on any treatment, he/she either 'dies' or queues for another type of treatment.

The authors chose Discrete Event Simulation because...
• It allows the patients' treatment choices to be influenced by their characteristics and their treatment history
• It can realistically describe constraints on treatment availability such as a limited supply of transplant kidneys

The study demonstrated that simulation can be successfully used in a decision support system. Outputs of the model included treatment places used and treatment queue lengths. The model acquired data from the EDTA registry automatically to set patient characteristics to whatever locality requesting such information. Financial costs of treatments were also to be added in a further development to cost different scenarios of treatment provision. The study also allows local health planners access to a robust and credible model without the trouble of extra data collection or model development.

Davies (1994) used a discrete event simulation to describe the treatment system for patients suffering from coronary artery disease. The aim was to provide a description of patient movements from treatment to treatment and the resources they used while undergoing these treatments. Treatments included angiography (diagnostic technique), angioplasty (treatment that unblocks arteries under X-ray) and coronary artery bypass surgery (CABG, heart surgery). The model took into account operating theatre and bed availability.

The model was to be used in costing different policy strategies and possible demand scenarios. As such it had to work on two timescales, the long term survival of patients undergoing treatment and the day to day use of hospital resources.

The model was developed in conjunction with a London Hospital and it demonstrated that the number of cardiology beds was too low causing a bottleneck in the system. A predicted rise in demand would initially make costs rise but this rise would level off as there were not enough beds to meet demand.
An overview of the various models developed, methods employed and their major findings are given in Table 3.8

Simulation is a more flexible modelling approach than analytical techniques. The types of problems attempted are wider ranging. Everett (2002) used her model for planning bed use and operationally as a decision support tool to schedule elective patients. Swisher and Jacobson (2002) simulated an outpatient clinic to improve patient waiting times. Davies (1994) simulated coronary artery disease treatment system for better financial planning. El-Darzi, et al. (1998) modelled a geriatric inpatient ward for better bed configurations and easier patient flow.

Simulation studies tend to be more ambitious and of a larger scope than analytical queuing models. Systems of queues and servers can be realised. Gitlow (1976) modelled an abortion clinic that has several queuing stages. Davies and Davies (1987) modelled the whole system of treatments that renal patients go through in a healthcare system. This involved several waits and simulated patients swapping back and forth between several treatment queues. Davies (1994)'s simulation of the system of healthcare for coronary artery disease modelled two timescales of use in the same model, enabling it to be used for short term financial planning and the long term effects of treatment on patient survival.

Simulation can take into account more effects more easily and realistically than mathematical models. For instance, resource constraints like the supply of kidneys in the Davies and Davies (1987) simulation of system of healthcare for renal patients can be readily included. The study also modelled patients' choices over treatment being influenced by their characteristics (age, blood group etc) and their treatment history, this is hard to achieve in any other way than a simulation.
<table>
<thead>
<tr>
<th>Authors/Year</th>
<th>Subject</th>
<th>Methods used</th>
<th>Major findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gillow (1976)</td>
<td>Abortion Clinic planning.</td>
<td>Simulation of queuing network 'Gradient search' optimisation</td>
<td>Found optimal design of clinic in terms of counselling and treatment rooms</td>
</tr>
<tr>
<td>Everett (2002)</td>
<td>Decision support for the scheduling of patients waiting for elective surgery</td>
<td>Discrete Event Simulation</td>
<td>Model identified scheduling inefficiencies in elective surgery process. Model used to plan services.</td>
</tr>
<tr>
<td>el-Darzi et al (1998)</td>
<td>Bed use and patient flow in a geriatric inpatient ward</td>
<td>Discrete Event Simulation</td>
<td>Estimated the average bed 'emptiness' to ensure a 24 hour a day acute bed service. Demonstrated effects of changes in bed configurations.</td>
</tr>
<tr>
<td>Davies and Davies (1987)</td>
<td>Treatment system for patients suffering from kidney failure</td>
<td>Discrete Event Simulation using Pascal programming language.</td>
<td>Demonstrated simulations’ use in a decision support system. Local health planners able to access model without extra data collection or model development.</td>
</tr>
<tr>
<td>Davies (1994)</td>
<td>Treatment system for patients suffering from coronary artery disease</td>
<td>Discrete Event Simulation using Pascal programming language incorporating POST (Patient Oriented Simulation Technique)</td>
<td>Number of cardiology beds was too low in the Hospital causing a bottleneck in the system. Costed different policy strategies on two different timescales.</td>
</tr>
</tbody>
</table>
A disadvantage of simulation is that they can be time consuming and difficult to set up. The studies by Davies and Davies (1987) and Davies (1994) also both required programming knowledge, though to some extent this has been alleviated by modern visual software environments. Simulations can also take a long time to run.

DES models entities with ‘attributes’, automatically introducing a heterogeneous population. Everett’s patient entities were modelled using ‘priority’, ‘Expected Operating Hours’ and ‘Expected Bed Days’ attributes. Davies and Davies had patient entities with ‘Age’, ‘Blood Group’ and ‘Preferred Dialysis Method’ as attributes. These attributes are important as they can determine the future course of the simulation. Everett’s patients would be treated on the basis of their priority and the contracted hours the hospital had to fill. Davies and Davies’ patients would be matched to a transplant kidney partly by their blood group.

Feedback effects on the system can be modelled in DES. Davies’ model on the healthcare system for coronary artery patients has some being fed back into the system at a later date as they come back for more treatment in following years. Davies and Davies’ model of renal services has patients going back and forth between CAPD and haemodialysis services.

Validation of model structure is now easier to achieve. Stakeholders can view a standard activity diagram made up of live and dead states. Staff were involved at all stages of the model building phase of Davies’ coronary care model. Everett gave extensive presentations on her model to the various interested parties whilst developing the model.
3.10 Petri Nets

Petri nets are another form of discrete event simulation. They are used to model systems, especially systems with independent parts.

A Petri net is made up of four parts, a set of places, a set of transitions, an input function and an output function (Peterson, 1981). The input function specifies which places are inputs to which transitions while the output function specifies which places are outputs to which transitions. This becomes clearer in graph form shown in figure 3.2.

Figure 3.2 A simple Petri net

\[ \text{Place} \]
\[ \text{Transition} \]
\[ \text{Arc} \]

The arc directed from place \( p_1 \) to transition \( t_1 \) means \( p_1 \) is an input place of \( t_1 \). The arc directed from \( t_1 \) to \( p_2 \) means \( p_2 \) is an output place of \( t_1 \). Multiple arcs can exist between a place and a transition (or vice versa), for example, there are two arcs between \( t_2 \) and \( p_1 \) in figure 1.

A marked Petri net is one which has an assignment of tokens made to its places. Numbers and positions of tokens will change during the execution (or simulation) of a Petri net. Figure 3.3 shows the Petri net of Figure 3.2 with a marking.

A Petri net is executed by firing its transitions. A transition is fired by taking tokens from its input places and creating tokens in its output places. A transition can only fire if its input places have each got as many tokens as arcs.
from the place to the transition. If this is the case the transition is said to be enabled.

Figure 3.3 Marked Petri net

![Marked Petri net diagram](image)

When an enabled transition fires, the tokens are removed from the input places (multiple tokens are taken for multiple arcs) and tokens are created in the output places (multiple tokens are created for multiple arcs). For example, the Petri net in figure 2 has two transitions; $t_1$ is not enabled as its one input place ($p_1$) has no tokens. $t_2$, however, is enabled as $p_3$, its input place, has at least one token. Firing $t_2$ will place two tokens in $p_1$ (and remove one token from $p_3$), thus enabling $t_1$.

In order to model systems, Petri nets are used to represent conditions and events (Peterson, 1981). Events are occurrences that take place in the system. They can only occur if certain conditions hold. These are called the preconditions of the event. If the event takes place, then these preconditions may stop holding true and other conditions, post-conditions, may become true. Events can be modelled by transitions and conditions by places. The firing of a transition corresponds to an event taking place. As a demonstration, figure 3.4 shows a Petri net description of the cardiothoracic surgery system at Glenfield Hospital.

T2 represents an 'elective admission' event. The preconditions are a patient waiting on the list, an available consultant (NB This implies an available operating theatre) and a free Cardiac Intensive Care Unit (CICU) bed. The
single post-condition is an occupied CICU bed. Table 3.9 below shows the preconditions and post-conditions for each event.

Figure 3.4 Petri net of Cardiothoracic Surgery System

Several of the events in Figure 3.4 would be enabled at the same time. \( t_1 \) represents an addition to the waiting list and \( t_4 \) a discharge from CICU. The exact sequence of events or firing sequence would be determined by various probability distributions.

Petri nets were used by Hughes et al. (1998) to model patient flow in a surgical specialty. The modelling was performed at two different levels. The first was at a high policy development level to determine the resources needed for the healthcare needs of the patient population in question. The second is at a lower, operational level to assess the most efficient way of scheduling treatments within the resource constraints imposed.
The high level model consisted of patient flows in figure 3.5 below.

Table 3.9: Preconditions and Post-conditions of the Petri net of Figure 3.4

<table>
<thead>
<tr>
<th>Event</th>
<th>Description</th>
<th>Preconditions</th>
<th>Post-Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_1$</td>
<td>Patient enters the Waiting List</td>
<td>Waiting List Addition</td>
<td>Patient on Waiting List</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Waiting List Addition</td>
</tr>
<tr>
<td>$t_2$</td>
<td>Elective Admission</td>
<td>Patient on Waiting List</td>
<td>Occupied CICU bed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Consultant Available</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Free CICU Bed</td>
<td></td>
</tr>
<tr>
<td>$t_3$</td>
<td>Consultant scheduled</td>
<td>Timetable.</td>
<td>Consultant Available</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Timetable</td>
</tr>
<tr>
<td>$t_4$</td>
<td>CICU Discharge</td>
<td>Occupied CICU bed</td>
<td>Free CICU Bed</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Inpatient on Ward</td>
</tr>
</tbody>
</table>

The model comes in two forms, the high level system model where the Petri Net models its Places on, figure 3.5, i.e. the individual units, and the lower level unit model which models each unit in a generic way whilst linking them in a similar way to the first model.

Figure 3.5: High level patient flows in Petri Net Model (Hughes, et al., 1998)
The Petri Net uses 'coloured' tokens which means that different types of tokens flow through the model. These tokens are then attached to different attributes, in the Patient token case a length of stay attribute (whereby transitions are not enabled to fire until a certain token's length of stay has elapsed for the Place they are occupying) and an Admission attribute specifying an arrival rate for origin-Places.

This generic, modular structure and the coloured Petri Net formulation makes the model extensible with an easy addition/removal of units as needed.
3.11 System Dynamics (SD) and Healthcare Systems

Health applications of System Dynamics modelling include epidemiological studies (for example Dangerfield et al. (2001), study of AIDS/HIV and the effect of antiretroviral treatment) as well as the implications of policy changes on healthcare systems (for example Wolstenholme, 1995) study of funding changes to Community Care).

Taylor and Lane's (1998) paper contrasts System Dynamics with Discrete Event Simulation (DES) in the context of health care modelling. They compared the two techniques by the way they deal with modelling complexity. The authors defined complexity to have three dimensions, detail, dynamic, and organisational.

Detail complexity involves the existence of multiple variables which can produce a great number of different effects. It often involves the interaction of patients and resources, for instance, whether and when waiting list patients are admitted to hospital could depend on their age, urgency and the amount of time they have waited and the amount and type of resources available to treat them. Detail complexity usually relates to the system’s physical resources.

Dynamic complexity arises where the consequences of cause and effect relationships are hard to analyse over time. This would include unforeseen side effects of policy changes, differences in short and long term behaviour responses and between local and global responses. Delays and non-linear responses are important factors in this type of complexity.

Organisational complexity involves social factors that effect the system’s operation. It includes factors that are hard to quantify like the quality and value of treatments, the effect of staff morale on treatment and the quality of information.

Taylor and Lane (1998) suggested that SD concentrates on describing dynamic complexity rather than detail complexity and DES concentrates on
modelling detail complexity. They also suggested that organisational complexity is important to SD as it can explicitly model social factors and the distinction between perceived and actual values whilst DES tends to ignore organisational complexity. The authors explored how SD might be used in modelling waiting times for Coronary Heart Disease (CHD) procedures but did not give any detailed model to show how the SD approach might have worked in practice.

Lane et al. (2000) described a system dynamics model of an Accident and Emergency (A & E) department at a London hospital. The model was developed following public concern at long waiting times and other problems at A & E departments leading to a sense of an A & E ‘crisis’.

Several explanations of this ‘crisis’ had been put forward including:

- bed closures in the 1990s,
- bed ‘blocking’ by patients (usually elderly) who are fit to be discharged but need lower level nursing care usually in a home, but no place is available or funds available,
- Government waiting list reduction initiatives, and,
- internal market effect on occupancy rates (no more ‘slack’ in the system).

However, one of the findings of this study was that reductions in bed numbers did not increase waiting times for emergency patients in A & E but rather sharply increases the number of cancelled elective operations. This was because medical staff gave preference to those most in need and an emergency patient will usually be in greater need of medical treatment than those who can safely wait, hence the elective operation was cancelled. The other major finding of the study was that reductions in waiting times could be achieved by “selective augmentation of resources within, and relating to, the A & E unit”.

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They conceptualised the system in terms of the community (where patients originate) and the hospital. The hospital was further split into three sub-types, the A & E department, the management of elective patients and the wards. All three sub-types had an effect on waiting times in A & E for emergency patients.

The authors defined a reference mode: decreasing acute bed capacity increases bed occupancy (number of patients divided by the total number of beds) levels so hospitals can still pull through the same number of patients so the emergency admission rate and A & E waiting times remain unchanged (as mentioned earlier, this reference mode was shown by the model to have an unintended consequence of increasing the number of cancelled elective operations).

A base case simulation was then created using information from historical data and the hospital Bed Manager. This base case represented the system as it was currently running.

Two major factors in the waiting time for emergency A & E patients were identified:

1. Waiting time from registration to completion of A & E doctor consultation. There was a large variation in this waiting time depending on the time of day, due to the fact that the increase in doctors in the midday period was not enough to cope with the midday/early afternoon increase in demand.

2. Waiting time from decision to admit until admission to ward. This was the largest component of patient waiting time. It was caused by the arrival and discharge patterns and the bed turnover interval. The bed turnover interval increases just as more patients arrive in A & E. Also, not enough A&E nurses are available to accompany patients to wards so elective patients step into beds prioritised, in theory, for emergency patients. There is a surge in emergency admissions around 10PM when the bed turnover time decreases and A & E becomes less busy so releasing nurses to accompany patients to the ward.
Model validation was split into two parts, structure based and behaviour based tests. The structure of the model was discussed with the modeller's collaborators in the hospital, as well as inputting extreme values to see how the model reacted.

Behavioural tests involved the use of simulations to reproduce the general trends of already recorded data. However, this data did not exist in some cases and so the performance indicators outputted by the model simulations were put to the hospital collaborators to adjudge valid. No detail was provided of these judgements.

Various policy analyses were tried out with the model including reducing bed capacity compared to the base case and increasing demand in A & E compared to the base case. A 'crisis' day was also simulated where demand 13% above normal levels was input to the model.

Reducing the bed capacity saw elective operation cancellation rates soar, bed occupancy rates virtually unchanged around 95% and waiting times in A & E unchanged as these emergency patients are given priority over elective patients.

The study identified two areas of avoidable delay for A & E patients caused by low doctor capacity in the morning and limited bed availability in the afternoon. It also demonstrated that capacity was insufficient to deal with demand and that the system had "... little room for manoeuvre".

The model was constructed in terms of bed numbers. It was not clear whether the staffing levels of these beds were constant. The NHS has had problems in recent years with nurse recruitment and retention. If nurses could not be found to staff these beds, then this could be a factor in increasing elective operation cancellation rates. A future development in the model was the specific inclusion of bed blocking effects. Again, as for staffing levels above, bed blocking has an effect on availability of acute beds for elective operations. The model's use of
average length of stay in hospital would presumably, have taken into account bed blockers. Nevertheless, the study showed that there are sometimes unintended costs to making efficiencies. In this case, the experience of patients facing cancelled operations (and the future costs for the NHS and the health consequences for those patients) were discounted while looking for health improvements in the ‘wrong’ places.

Brailsford et al (2004) investigated the system of emergency care in the city of Nottingham. Between 1999 and 2001 emergency admissions rose threatening elective admission targets. Managers wished to know why the rise was taking place and what measures would be best to alleviate the problem. The period had seen longer waits in the Accident & Emergency (A & E) department.

System Dynamics was chosen as the modelling method as the study was aiming to represent a large, complex system involving over 600,000 people. The authors wanted to investigate the general system and the relationship between its parts rather than individual pathways and they wanted to identify bottlenecks in the system. Model development was split into three phases, qualitative, quantitative and validation.

The qualitative phase developed a ‘conceptual map’ of the emergency care system which involved thirty interviews of various stakeholders in the system. Useful insights were gained through the development of this map and it was used as the basis for the quantitative model.

The quantitative phase was pursued to enable different experiments with service configuration and demand rates. It was written in the STELLA software program and populated using data from April 2000 to March 2001. Output included the throughput of each ‘front door’ into the system (e.g. Accident & Emergency, NHS Direct telephone advice service etc.) and occupancy rates of the hospital wards involved.

The model was validated by developing it in close cooperation with stakeholders. They could see the internal structure of the model and could...
come to a judgement as to its appropriateness. The output of the quantitative model was also compared to real, observed data.

Various scenarios were tested including maintaining current growth in emergencies with no increase in resources (the 'Doomsday' scenario), reducing emergency admissions for certain patient groups by the use of a Diagnostic and Treatment Centre (DTC) (i.e. patients who were being sent to A & E by GPs just to 'jump' the queue for diagnostic tests) and earlier discharge of the elderly to nursing homes.

The 'Doomsday' scenario would result in a significant decrease of elective admissions for Nottingham's hospitals within five years. Sending a small proportion of emergency patients to a DTC instead would significantly decrease bed occupancy on the wards. Surprisingly, early discharge of the elderly to nursing homes made hardly any difference to bed occupancy rates. These were only a few of the different scenarios that the model could investigate.

The authors lastly built a Discrete Event Simulation (DES) to investigate the 'streaming' of A & E cases. Patients with minor conditions would be streamed off to their own waiting area and dedicated staff, not sharing resources with A & E. They found that streaming was not an efficient use of clinical resources and that an improvement in waiting times for the least urgent patients was at the expense of waiting times for medium urgency patients.

The study indicated the model's usefulness in stimulating debate and discussion. It was also seen as a tool for visualising the whole of the system which was particularly remarked on and noted by the stakeholders.

The decision to model the A & E system using DES seems a little unorthodox (although a perfectly adequate modelling method). The authors took this decision because "...system dynamics does not ideally lend itself to narrowly focussed systems involving resource constrained queuing networks." But this
only makes sense if there was a need to model patients with multiple attributes and only urgency of condition seems to be modelled in the study.

System Dynamics has also been used to model the use of scarce resources in healthcare. Coronary Artery Bypass Grafts (CABGs) use up more healthcare resources than any other single procedure. An American study, Anderson, et al. (2002), developed a system dynamics model that predicts the costs and outcomes of CABG surgery. The model can be used to predict the resource utilisation, costs and outcomes for various patient populations and the effectiveness of policies to contain costs.

Wolstenholme (1995) described a system dynamics model of the boundary between the health service and community care. The model examined the consequences of transferring responsibility for funding community care for the elderly from the Department of Health to Local Authority Social Services Departments (SSD). The new budgets in SSD control were now cash limited. The control of the rate at which elderly people, needing publicly funded community care, passed from the NHS to SSDs.

Figure 3.6 shows the influence diagram for Wolstenholme's model of community care. The balancing loop on the right controls future costs by restricting the inflow of people into community care by reducing hospital discharge rates. Bed blocking within hospitals resulted if discharge rates were reduced which in turn caused a reduction in admission rates and an increase in the waiting list (this takes time). Increased waiting lists meant more elderly people at home requiring community care facilities which further drained the community care budget causing discharge rates to fall further so feeding in on itself in a vicious circle.
The Wolstenholme (1995) model is an example of a systems archetype known as 'fixes that backfire', where a well intentioned policy action results in a chain of reactions that feedback on to itself and undermine the original policy.

Keen (1998) made some criticisms of Wolstenholme's paper on community care. Firstly, he pointed out that Wolstenholme's model omitted consultants' role in influencing admission and discharge rates, the private and voluntary sectors, incorrect representation of the role of informal carers and the limited financial inputs. Secondly, the model only concentrated on resources and did not model other factors such as the quality of care, capacity of different services and equity issues. Thirdly, the influence indicators (the signs on the arrows) in the model appeared overly deterministic. Wolstenholme assumed that increasing the rate of discharge from hospital increased the numbers in residential care but Keen felt that this might be positive or negative as the aim of the new community care policy was to increase the number being cared for in their own homes. Indeed, the direction and magnitude of this flow between hospital and residential care was an indication of the success of the policy. As
a result, Keen felt Wolstenholme's model was at best a weak predictor of future behaviour of the system

Keen (1998) went on to describe a system dynamics model of healthcare services for dementia. His model showed the flow of patients with dementia between hospital, community, and nursing homes. Flows between the levels were based on the available beds in hospital and nursing homes. Mortality factors took patients out of the system from all three levels. The original model included Respite Care but this was integrated with the "Community to Hospital" flow as it was felt to be marginal to the modelling. Thus an elegant, simple model was produced that could simulate the numbers of people with dementia in the system over ten years according to different assumptions.

However, having constructed the model, Keen did not make much use of it. Two scenarios were presented, the first involved an increase in nursing home places of 50% and the second a reduction in hospital beds. The first scenario was interesting as after five years of reducing the numbers living with dementia in the community, the nursing home beds filled up again and the numbers living in the community with dementia again started to rise. This was because the model assumed a 2.5% annual growth rate in the community population. The second scenario, unsurprisingly, saw numbers in the community climb as hospital beds are cut (again the same growth rate was assumed).

System Dynamics has been used to study the epidemiology of disease. Dangerfield, et al. (2001) described a System Dynamics model on the epidemiology of HIV/AIDS and in particular the effect of triple combination antiretroviral therapy, known as HAART (Highly Active Anti-Retroviral Therapy). Since the introduction of this new therapy, new AIDS cases had dropped sharply. Three models were put forward to study the impact of HAART on the incidence of HIV/AIDS. The models tracked a group of patients through the various stages of HIV/AIDS and also whether they were being treated with HAART.
Model 1 assumed a therapy breakdown will move a patient from HAART treatment to HIV Stage 3 while Model 2 assumed a patient will move to the more serious late stage AIDS. Model 3 differentiated patients entering HAART according to the stage of HIV/AIDS reached. HAART may be more effective if started earlier. Various model parameters were estimated by fitting the model to published data on new cases of HIV and AIDS from 1980-2000. Scenarios explored the effect of increased survival time and lower infectivity of HAART patients on HIV incidence and new AIDS cases that HAART will, it is assumed, bring about.

Other scenarios explored include a regression in sexual behaviour by healthier but still infected patients. This could trigger a sharp rise in new HIV infections. The authors concluded there should be no underfunding of health education programmes because people can live with HIV infection.

This study showed the introduction of a new treatment can have undesirable side-effects. Patients staying healthier for longer could trigger a change in behaviour that undermines the benefits of the new treatment. The models also explored the effects of varying the infectivity of HAART patients and the average period of time that HAART treatment is effective. Infectivity was found to be a more significant factor in its effect on new HIV cases.

Van Ackere and Smith (1999) developed a System Dynamics model of national level waiting lists from a macro economic point of view. It assumed that the perceived waiting time (by patients, physicians and managers) for surgery is the main influence on the amount of elective surgery demanded and supplied. The causal loop diagram of their model is shown in figure 3.7, please note that the two parallel lines in the figure (||) represent a time delay before the influence is fully realised, an increase in the "Average Waiting Time" will take time to influence "Resources" and "Demand".

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The model consists of two balancing loops on the demand and supply side. An increase in average waiting time eventually leads to more resources which in turn will cause the average waiting time to decrease. An increase in average waiting time will also eventually cause demand to fall which in turn causes the average waiting time to decrease.

The authors then constructed a more detailed stock and flow diagram in which resources were represented by the number of NHS beds and the demand side by the number of new NHS referrals. The number of patients treated depends on the number of beds available and this influences the true waiting time which in turn influences the perceived waiting time. Perceived waiting time is split in two, one perceived by patients and GPs on the demand side which influences the number of NHS referrals and the other perceived by consultants and hospital management which influences the supply of beds. The way demand and supply varies with their respective perceived waiting times are described by two elasticity functions $\eta_d$ and $\eta_s$.

The authors also attempted to model the effect of the private sector. They assumed that longer perceived waiting times encouraged patients to opt for a private operation and so stimulate the private sector.

Two scenarios were explored, a 2.4% growth in demand per year, corresponding to the expected growth, and a 10% growth in demand, corresponding to a worst case. Both scenarios were simulated over a ten year period. Suppressed demand rose in both scenarios, in the 10% scenario suppressed demand soars. The conclusions drawn from the model are a touch obvious. Is it any surprise that suppressed demand soared when the model
assumed only limited growth in NHS beds and a private sector expansion that the Authors acknowledge cannot be afforded by every patient?

This is a very high level model of waiting lists and, as the authors admit, they did not investigate the 'black boxes' they labelled demand and supply. However they did list some areas of the 'black boxes' for further investigation.

Garcia and Busto (1998) modelled waiting lists in the Spanish Health Service using System Dynamics. They wanted to model the effect on the service of the three main ways of managing waiting lists that existed in Spain.

These are

- Sub-contracting activity. At the start of every year each hospital has to decide how much activity they wish to subcontract to other hospitals. Apart from not being popular with patients the Authors felt this policy was bureaucratic and inflexible.

- "Special Programs". For hospitals with long waiting times for treatment, "Special Programs" were put into operation to extend the working day for medical staff during which they are paid per case for extra work. However this created perverse incentives for medical staff to inflate their waiting lists to boost their incomes.

- Waiting List Validation. Hospitals called patients a set number of times on the telephone to make sure they still wanted or needed to be treated. If there was no answer then the patient is removed from the list. However if this policy was implemented too aggressively (as waiting lists were used to judge the quality of the local health service) it led to patients being wrongly taken off the list.

A Causal Loop Diagram was produced of these three effects working on the inpatient and outpatient waiting lists of the general surgery department of the Authors' local hospital. A part of this diagram showing the surgery "Special Program" is shown in figure 38 below.
The short term effect of the “Special Programs” was to reduce waiting lists however they led to lower productivity in the usual working hours which lengthened the list again and re-established the “Special Program” and boosted the medical staffs’ income.

The Causal Loop Diagram was converted into a quantitative System Dynamics model and the model data compared to observed, historical data. A good fit was found with the model which reproduced the main historical trends of the surgery waiting list.

After performing several simulations the Authors concluded that current policies to manage waiting lists did not affect their long term trend and the political cycle was shorter than the time needed to observe these trends so that these kinds of policies were used as a short term ‘fix’.

Their recommendations included

- Subcontracting work to other hospitals should become more flexible and based on waiting time targets for each department
- “Special Programs” were to be carefully used
- Waiting List validation took place only to improve the quality of the information and not to manipulate waiting lists

Reconfiguration of services have also been modelled using System Dynamics. Taylor and Dangerfield (2005) modelled the effect of shifting cardiac
catheterisation services from more specialist, tertiary level care to more general, secondary level care for low risk patients. This shift in services was done to improve access but it was feared the shift might stimulate demand for the service so choking off access; an unintended consequence. To control this extra demand, there were usually calls for stricter clinical guidelines or more capacity in the service but the Authors’ argued that there may be little point in these interventions if the system’s underlying feedback mechanisms were not understood properly.

The cardiac catheterisation service shifts in two English district general Hospitals were investigated. One had a permanent shift in cardiac catheterisation services from the tertiary centre and the second had only a temporary service at the district level when the tertiary centre was being renovated.

The model is quite complicated, however, the simplified Causal Loop Diagram shown in figure 3.9 below gives the basic feedback structure:

Figure 3.9 Basic Feedback Structure (Taylor and Dangerfield, 2005)
The figure shows three balancing loops (B1, B2 and B3) and three reinforcing loops (R1, R2a and R2b). These are summarised in Table 3.10.

The model tried to capture the growing skills and confidence of junior operators on demand (Loop R1). As their skills increased, the juniors recognised more outpatients in need of investigation so forming a feedback loop in the model.

Table 3.10  Feedback loops indicated in model described in Figure 3.9

<table>
<thead>
<tr>
<th>Reference</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>Balancing loop between cardiac catheterisation waiting list and cardiac catheterisation rate i.e. if the waiting list increases so does the cardiac catheterisation rate to keep the list in check</td>
</tr>
<tr>
<td>B2</td>
<td>Effect of waiting time on demand</td>
</tr>
<tr>
<td>B3</td>
<td>Other Outpatient waiting list removals balancing the Outpatient waiting list</td>
</tr>
<tr>
<td>R1</td>
<td>The skills effect of junior operators on demand for the service.</td>
</tr>
<tr>
<td>R2a &amp; R2b</td>
<td>Knowledge of GPs and patients of the cardiac catheterisation service on demand for cardiac catheterisation investigations and Outpatient appointments respectively.</td>
</tr>
</tbody>
</table>

Parameters were estimated for the model and it was validated by comparing model output to historical data. The model had also been built in close consultation with the various Managers and Consultants at the hospitals involved so a degree of validity already applied. The model reproduced trends in the system's main performance characteristics like 'Average waiting time for a cardiac catheterisation investigation', 'referral rate' and 'Cardiac catheterisation investigation waiting list'.

For each hospital, a base case simulation (which tried to reproduce the real system's modes of behaviour) was generated for comparison with later experiments. Various policy experiments were then carried out to see how services could have been improved. These included simulating different capacities in the system and stricter referral guidelines.

The Authors concluded:
• "Increasing capacity is not necessarily the most effective way of improving access". Their simulation experiments showed the best way of improving access was stricter referral guidelines combined with changes to the targets that drive activity (e.g. a desired list length). This was only true in cases where spare capacity existed (which a service change might throw up).

• "Focusing on isolated events, short-term results and single performance measures can lead to ineffective policies and misleading conclusions" One of the hospitals maintained a waiting time goal but this did not mean the system was pressure free. Whilst the waiting time goal was being maintained, the waiting list rose and the goal was only being achieved by the funding of a rise in activity levels.

Table 3.11 below summarises the studies in this section on System Dynamics healthcare models

The scale of the studies reviewed were generally large. Van Ackere and Smith (1999) studied National waiting lists, Brailsford, et al. (2004) examined the emergency care system of an East Midlands city. The exception to this was Lane, et al. (2000) in which the authors modelled a hospital A&E department. The Van Ackere and Smith (1999) study could be considered too large a scale Problems with waiting lists and times must be solved at a local level and it is unclear how a proposed solution to waiting lists at this level of modelling could be devolved down

There was a qualitative aspect to most of the models examined. Brailsford, et al. (2004) found this to be a very illuminating part of the modelling process, their qualitative model provoked debate and discussion in their stakeholder group. The development of their quantitative model was informed by this first stage. Both Garcia and Busto (1998) and Taylor and Dangerfield (2005) developed extensive, qualitative causal loop diagrams which were analysed and developed into quantitative simulations.
Validation of the structure of the models was undertaken by working with the system stakeholders. Brailsford, et al. (2004) developed their model in close conjunction with Actors in the real system. These Actors could judge whether the structure of the model was appropriate. Lane, et al. (2000) discussed the structure of their model with his collaborators in the Hospital they were working with. Taylor and Dangerfield (2005) developed their models in close collaboration with Managers and Clinicians at their two participating hospitals. This is known as 'white box' validation (Brailsford, et al., 2004) as the validity is tested through the open scrutiny of expert eyes. The internal structure of the model is laid bare. This is opposed to 'black box' validation where the quantitative model's output is compared to real, observed performance data generated by the system. García and Busto (1998), Taylor and Dangerfield (2005), Brailsford, et al. (2004) and Lane, et al. (2000) all subjected their models to 'black box' validation.

The system wide effects of policies were put under scrutiny by the simulations. The effect of a maximum waiting time policy in the Accident & Emergency Department of a London Hospital was shown by Lane, et al. (2000) to have an effect in another part of the system, on elective admissions. Policies put in place by the Spanish Health Service to alleviate long waiting times for elective treatment were actually causing the system to act in a counter-productive manner and were actually having no effect on waiting times as García and Busto (1998) proved in their simulation.

Several of the models were used as a basis for communication between the stakeholders to develop a better understanding of the healthcare systems they were trying to manage and so improve policies designed to deal with them. Brailsford et al. (2004) developed, validated and experimented with their model with several stakeholders who formulated the idea that diverting a small proportion of emergency admissions from the city's hospitals to other care facilities would significantly decrease bed occupancy on the hospitals' wards.

The studies generally modelled homogenous populations though one exception was Anderson, et al. (2002) who used certain functions available on
the STELLA system dynamics modelling software to give their patients certain characteristics

Table 3.11 Summary of System Dynamics studies

<table>
<thead>
<tr>
<th>Authors/Year</th>
<th>Subject</th>
<th>Methods used</th>
<th>Major findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wolstenholme (1995)</td>
<td>Community Care.</td>
<td>System Dynamics.</td>
<td>An increase in bed blocking will result if community care budgets were passed to social services and cash limited.</td>
</tr>
<tr>
<td>Keen (1998)</td>
<td>Community Care.</td>
<td>System Dynamics.</td>
<td>Increase in nursing home places reduces numbers of people with dementia living in the community at first but then numbers rise again as places fill up.</td>
</tr>
<tr>
<td>Braisford et al. (2004)</td>
<td>Emergency care system in the city of Nottingham.</td>
<td>System Dynamics. Discrete Event Simulation.</td>
<td>Diverting a small proportion of emergency admissions from Hospital to other care facilities would significantly decrease bed occupancy on the wards. ‘Streaming’ of A&amp;E cases is not efficient in terms of clinical resources.</td>
</tr>
<tr>
<td>Lane et al. (2000)</td>
<td>Long Waiting Times for admission from an Accident &amp; Emergency Department.</td>
<td>System Dynamics.</td>
<td>Reducing bed numbers increased elective operation cancellations and had little effect on waiting times in A&amp;E (for a ward bed). Two areas of avoidable delay for A&amp;E patients identified.</td>
</tr>
<tr>
<td>Dangerfield et al. (2001)</td>
<td>Effect of new HAART treatment on HIV / AIDS.</td>
<td>Quantitative System Dynamics.</td>
<td>New HIV cases more sensitive to variations in infectivity of HAART patients than the average time to treatment breakdown. Regression in sexual behaviour that could result from new treatment could cause a sharp rise in HIV infections.</td>
</tr>
</tbody>
</table>
Table 3.11 (contd): Summary of System Dynamics studies

<table>
<thead>
<tr>
<th>Authors/Year</th>
<th>Subject</th>
<th>Methods used</th>
<th>Major findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garcia and Busto (1998)</td>
<td>Modelling of waiting list management in the Spanish Health Service</td>
<td>System Dynamics</td>
<td>Measures to combat long waiting lists and times for treatment (in the Spanish Health Service) were having little effect or were counter-productive.</td>
</tr>
<tr>
<td>Taylor and Dangerfield (2005)</td>
<td>Service shifts in cardiac cathetension</td>
<td>System Dynamics</td>
<td>Improving access by reconfiguring services could stimulate demand though improved capacity is not necessarily the best way to deal with this new demand.</td>
</tr>
</tbody>
</table>

3.12 Summary

Since the Second World War there has been an increasing use of Operational Research techniques in healthcare. This has started with analytical models (e.g. Bailey, 1952) and gone on to make use of more visual modelling techniques and simulation like System Dynamics (SD) and Discrete Event Simulation (DES) into the 1980s and 1990s, mostly because of the increase in computing power over this time.

Communication of DES and SD models is easier than analytical or Markov chain models because of their visual nature. Compare Shmueli, et al. (2003)’s mathematical model to the visual SD models developed by Taylor and Dangerfield (2005) to describe a system of cardiac catheter care.

Validation of models has become more explicit in the literature as time has gone on and has developed into a separate activity in model development. The validation of model structure is possible with DES and SD because of the more visual nature of their models. These modelling paradigms increasingly involve stakeholders.

DES and SD bring a qualitative description phase to models especially SD, for which some authors (e.g. Wolstenholme, 1990, or Roberts, et al., 1983) define
an explicit qualitative phase Analytic models have no such clearly defined qualitative stage, Weiss and McClain (1987) mainly describe their model textually with only some reference to basic high level diagrams. These diagrams merely try and describe the model, they are not used to analyse and predict the model's behaviour as a qualitative SD model would offer, for example, García and Busto (1998) analyse their simulation's qualitative model to show the likely behaviour of the model.

SD studies examine system wide effects, SD concentrates on finding feedback loops in the system of resources and information that make up the system's processes. This leads to a better description of what Taylor and Lane (1998) term dynamic and organisational complexity. They describe DES as being better for detail complexity. This may be because DES models heterogeneous populations of entities. This means the model describes each entity or object involved in the simulation via differently valued attributes. A patient entity will have an Age attribute, and a Diagnosis attribute. SD only models homogenous quantities (though can be overcome in specialist software packages). In other words the levels that make up a SD model represent just one concept. The number of patients diagnosed with one disease under forty would be represented by a single quantity in a level. The level of description of entities in analytical models and Markov chains depends on the number of variables modelled though the larger the number of variables the more intractable any solutions to these models become and increases complexity (Shachtman and Hogues' Markov chain had 79 states).

SD and DES models tend to have a larger scope than analytic models, compare Wolstenholme's (1995) SD model to Weiss and McClains' (1987) mathematical models on community care. The first attempts to model the whole system of community care, the other just the admission and discharge process in one hospital. Of course, as Keen's (1998) criticisms of Wolstenholme's model makes clear, more visual simulation models do not necessarily make for better models. SD and DES may make modellers more ambitious but do not necessarily lead to
better models A well presented, elegant analytical model produced by a modelling team that knew its limitations would still be much more useful than a sprawling, badly presented visual simulation. Modellers should know each technique's advantages and limitations and choose according to the modelling situation in front of them.

The next chapter analyses the interview and document data gathered during this study and attempts to summarise it to describe the cardiac surgery system under examination.
Chapter 4: Findings

This chapter will present the findings from the qualitative analysis of the interview data and the document analysis, while Chapters 5 and 6 will demonstrate the design, implementation and evaluation of the models used to simulate waiting lists for cardiac surgery.

4.1 Qualitative Analysis of Interview Data

The interview data were examined using the 'AtlasTi' software and key concepts coded in each interview. Coding involved attaching a word or phrase (i.e., a code) that encapsulated an idea or object to a passage in the text of an interview. For instance, the code 'Managing Waiting Lists' was attached to the following text in Interviewee 1's interview: "She had dabbled in management of waiting lists for the last ten years but as monitoring and reporting on waiting lists rather than actual management". It was also attached to the following text in Interviewee 2's interview: "Consultants manage their lists independently and don't communicate about them." Coding was a time-consuming activity.

Memos were also recorded during the coding and other stages of the qualitative analysis process. Memos are thoughts and comments about the analysis that the researcher can record as the analysis proceeds, for example, one memo recorded was entitled "Multiple Information Systems" and read "16/4/05 - Several systems seem to be in place for recording and communicating data".

Popular codes were identified by the number of occurrences in the texts (the number of occurrences was generated by the 'Atlas Ti' software). The concepts, themes, and relationships surrounding these codes were examined in more detail. Table 4.1 lists the codes.
Table 4.1 Popular Codes from Qualitative Analysis

<table>
<thead>
<tr>
<th>Code</th>
<th>Occurrences</th>
<th>Degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consultants</td>
<td>20</td>
<td>16</td>
</tr>
<tr>
<td>Patients</td>
<td>18</td>
<td>8</td>
</tr>
<tr>
<td>Emergencies and Elective Cancellations</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>CICU (Cardiac Intensive Care Unit)</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Managing Waiting Lists</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>

The instances in the interview text of the codes listed in Table 4.1 were examined. Nearby codes (that appeared in the text) were identified and an assessment made of their relationship to each other. The codes in Table 4.1 were also examined to see how they related to other more distant codes (in terms of the text) and memos that had been recorded during the analysis. This was a highly iterative process. This led on to the production of a ‘network’ view which related different codes, memos and quotations from the text as nodes in a network. Several network views are shown later on in this chapter.

Relationships included those defined in the ‘Atlas Ti’ software, for instance ‘=>’ indicates a causal link between two network nodes, or those that were defined by the User, for instance ‘SEES’ indicates when a person views/meets information/another person. The number of linkages in these network views that a code, memo or quotation accumulates is known as its degree. The degrees of the popular codes in Table 4.1 is shown.

A number of themes appeared whilst coding the data. These are listed in Table 4.2.
<table>
<thead>
<tr>
<th>Theme</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conflict</td>
<td>Conflict between different groups trying to achieve different targets.</td>
</tr>
<tr>
<td>Knock on Effects</td>
<td>An Action in one part of the system may have consequences for entities in another part, e.g., a 28 day cancellation will be brought in before the target is breached even if that admission causes another elective patient to be blocked.</td>
</tr>
</tbody>
</table>

### 4.1.1 Consultants

Figure 4.1 shows the network view constructed around the ‘Consultants’ code.

The first part of the network concerns the process of putting patients on to the waiting list. A Consultant will see the patient in their outpatient clinic and their diagnostic results. Using their knowledge and clinical experience, they will add the patient on to the waiting list if they judge it necessary (N.B. The quotations from the interview notes listed on the networks, e.g., “2.93” and “2.94”, are reproduced in Appendix 3 for clarity).

The memo “Diagnostic Delays” reads, “If there is a delay in getting tests it will delay placing the patient on the waiting list.”

Memos are written at the time of analysis to remind the researcher of a particular idea when examining this part of the data and to help in explaining the final analysis.

The memo “Diagnostic Delays” refers to the possibility that a hidden waiting time may occur at the outpatients stage if there is a delay in performing diagnostic tests.
The second part of Figure 4.1, "Waiting List Leavers" (3.120), simply refers to the fact that patients leave the waiting list for many different reasons and will have to be taken into account in the final simulation model.

The third part of the network, "Scheduling" (2.139 and 3.158), notes the role of the consultant in scheduling their own theatre list. This scheduling can be upset by the arrival of an emergency admission which has priority over elective admissions. Emergencies can therefore result in an elective admission and/or operation being cancelled. Associated with this scheduling of elective admissions is a finite capacity for each consultant in the operating theatre that puts a limit on the number of operations he/she can carry out. The memo "Consultants’ capacity" reads, "Consultants have individual slots in theatre giving them a certain capacity for performing operations.”

The fourth segment of the network, "Managing Waiting Lists" (3.159), points out that Consultants manage their own waiting lists independently and do not communicate the complexity of the cases they have scheduled with the other Consultants of the shared resources (e.g. beds). The 'knock on' effects this has on the system is not evaluated. The memo "Independence" reads, "Consultants manage their lists independently from one another and do not communicate about them.”
Figure 4.1 ‘Consultants’ Code Network View

Key

2.94 – Quotation taken from the interview notes (see Appendix 3)

- Memos
- Codes

Relations (System)

“=>” Causes
“<>” Contradicts
“[]” is part of
“[]” is property of
“==” is associated with

Relations (User Defined)

“+” Increases
“-” Decreases
“Sees” – Views other object
4.1.2 Emergencies and Elective Cancellations

Figure 4.2 shows the network view constructed around the 'Emergencies' and 'Elective Cancellations' codes.

This network view examines the ways emergencies can cause an elective admission to be cancelled in more detail than the 'Consultants' network view. The memo "Emergencies cause Elective Cancellations" reads, "Causation in Consultants Network View explained in this Emergencies and Elective Cancellations Network View".

The first section details the effect Emergency admissions have on "Lengths of Stay" in hospital and "Unoccupied Beds", (Quotations 2.66 and 3.160, please see Appendix 3 for full text of quotations from the interviews). Emergency patients take up beds that could otherwise be used for elective patients and also tend to stay longer so blocking beds. This in turn will tend to increase the surgical waiting list and so increase the number of emergency patients coming in from the waiting list. An increase in the waiting list will also tend to increase waiting time though this will also depend on the selection strategy used to schedule waiting elective patients. A decrease in the number of beds will also tend to increase elective cancellations. Also mentioned here are "Blue Forms". These are generated by emergency patients who were undergoing a catheter procedure when it becomes clear they need immediate surgery.

The second part of the "Emergencies and Elective Cancellations Network View" concerns the effect that emergencies out of office hours have on staff availability for subsequent elective admissions (Quotations 2.2 and 2.88). 'On call' theatre staff need a certain period of rest, if called out, before they can resume work.
Figure 4.2 'Emergencies' and 'Elective Cancellations' Codes Network View

Key
294 - Quotation taken from the Interview notes (see Appendix 3)

- Memos  - Codes

Relations (System)
"=>" Causes
"\" is property of
"==" is associated with
"isa" specific to general concept

Relations (User Defined)
"*" increases
"*" decreases
"Stays" Patient remains in
"IF" object under condition
The third section of the network view shown in Figure 4.2 shows the possible subsequent effects an elective cancellation can have. The memo "Elective Cancellations kept on Ward" reads, "Elective Cancellations can be kept on the ward if they would break the 28 day target if discharged. Hence they cause the number of unoccupied beds to decrease and potentially cause more elective cancellations." The "28 day target" referred to above stipulates that patients whose operations are cancelled on the day of operation must be re-admitted within 28 days.

4.1.3 CICU (Cardiac Intensive Care Unit) and Cardiothoracic Surgery Wards

Figure 4.3 shows the network view constructed around the "CICU" code.

The top section of the "CICU" network view shows the possible pathways a patient could pass through once an inpatient (Quotation 2.146). After an operation, patients will usually go to the CICU to recover though some may instead go to the High Dependency Unit instead (the Unit offers a level of care somewhere between CICU and an ordinary ward, hence beds here are more efficient to run). Patients who go to HDU are the lower risk patients. Patients on HDU can end up in CICU anyway.

The lower half of the network view shows the effect on the cardiac surgery system of another department in the Trust trying to meet its own target (Quotations 3.142 and 3.143). In this case admission time targets in Accident & Emergency (A & E). Patients in A & E who are assessed as needing admission must be admitted to a ward within a certain time otherwise the Trust loses a star rating. If a surgical ward bed is all that is available, then it has to be used. Patients admitted in this way are termed 'bed blockers' and can block discharges from CICU to the ward and also elective admissions.
Figure 4.3 'CICU' Code Network View

Key

2 94 – Quotation taken from the interview notes (see Appendix 3)

- Memos

- Codes

Relations (System)
"==" is associated with

Relations (User Defined)
"TRANS" patient transfers to
4.1.4 Patients

Figure 4.4 shows the ‘Patients’ code network view

Figure 4.4: ‘Patients’ network view

Key

2.94 – Quotation taken from the interview notes (see Appendix 3)

- Memos

- Codes

Relations (System)

"==>" Causes

"==>" is associated with

"isa" specific to general concept

Relations (User Defined)

"TRANS" patient transfers to

"CARE" under care of

"Sees" Views other object

"*" increases

"IF" object under condition

"Stays" Patient remains in
Most of this network view has been seen before in the previous three sections, however here it forms a process that takes a patient through the system.

A patient will be seen in outpatients by a consultant and if further treatment is deemed necessary will be added to the elective waiting list for an operation. Elective patients can have their operations cancelled if there is an emergency admission who needs treatment immediately and who may need the theatre, staff time and / or CICU bed more urgently.

Once admitted patients are transferred to CICU or HDU before going on to the general ward and finally discharge.

4.1.5 Managing Waiting Lists

This section investigates the ‘Managing Waiting Lists’ code to discover the policies and strategies used to manage the waiting list. The ‘Managing Waiting Lists’ network view is shown in Figure 4.5.

The first part of the diagram points out that the reporting of information is part of monitoring and managing waiting lists (Quotations 2.24 and 2.26). This reporting can take various forms, for instance ‘Outpatients’ outcomes are monitored to make sure no one added to the waiting list on the PAS system are missed in the administration (Quotation 3.36).

The first COWL (Cardiac Operations Waiting List Project) spreadsheet model (to be described in Chapter 5) was used to predict the size and waiting times of future waiting lists and to calculate the numbers that should be admitted to hospital to meet a certain waiting times target (Quotations 2.36 and 2.42).
Figure 4.5 'Managing Waiting Lists' network view

- Patient Lists
- TCI Dates
- ~Scheduling
- ~Consultants
- ~Theatre List
- ~Managing Waiting Lists
- ~COWL Mode
- ~Slowness of Model
- ~Contracts
- ~Reporting
- ~Waiting Time
- ~Standards and Targets
- ~Long Waiters
- Outpatients
- 2.37
- 2.38
- 3.30
- 3.32
- 3:112
- 3:119
- 2.42
- 2.36
- 2.26
- 2.106

Key:
- Memos
- Codes

Relations (System)
- "->" Causes
- "=" is associated with
- "[]" is part of
- ""]" is property of

Relations (User Defined)
- "Sees" Views other object
- "-" decreases
- "ALLOC" Allocates

2:36 - Quotation taken from the interview notes (see Appendix 3)
Another common way to manage the waiting lists is to print off reports from the UHL (University Hospitals of Leicester NHS Trust) intranet that list patients waiting for treatment and using these as a basis for getting consultants to allocate TCI (To Come In) dates for the elective patients (Quotations 2 37, 2 38 and 3 30).

One reason to actively manage waiting lists is that they are the subject of several Standards and Targets, some of which will affect the management of the Hospital if not met. An example is the 'Star' ratings. Standards and targets drive the need to monitor and admit long waiting patients before they breach said standards (Quotation 2 106).

4.1.6 Theme Conflict

This section deals with the theme of conflict between Managers and Consultants aiming for different targets. Figure 4.6 demonstrates this theme in a network view.

Consultants want to concentrate on their sicker patients whilst Management want to admit longer waiting patients. Both groups are working to two different sets of targets. Figure 4.6 shows this with 'Long Waiters' and 'Number of deaths after CABG' (N.B. a CABG is a type of surgical procedure, a Coronary Artery Bypass Graft). The memo 'Performance Indicators conflict' reads,

"For example there is a conflict between clinicians aiming for lower deaths after CABG surgery and managers aiming to bring in long waiting patients. What if a waiting CABG patient dies because the operating slot is taken up by a longer waiting patient?"
Figure 4.6 'Conflict' Network View

Key
294 - Quotation taken from the interview notes (see Appendix 3)

- Memos
- Codes

Relations (System)
"-" decreases
"===" is associated with

Relations (User Defined)
"Control" aims to control
4.1.7 Theme: Knock on Effects

This section describes the theme of 'Knock on Effects' in the system of different policies and phenomena. Figure 4.7 shows the network view.

Figure 4.7: 'Knock on Effects' Network View

Key

3 157 – Quotation taken from the interview notes (see Appendix 3)

- Memos
- Codes

Relations (System)
"==" is associated with
"=>" causes

Relations (User Defined)
"IF" object under condition
"TRANS" patient transfers to

"Stays" patient remains in
The network shows the unwanted knock on effects caused by standards and targets. For instance the 28 day target states that a patient whose operation is cancelled on the day of admission must be re-admitted within 28 days to have their operation. However if their operation is again cancelled they must be kept in the hospital until an operation slot becomes free. This will have the effect of blocking beds in the ward which then means a block on moving patients from CICU to the ward and finally a block on operations is possible.

The next section of the network points out the effect of independent scheduling of operations by each of the consultants. This means there is no central point to assess the complexity of cases and no way of knowing how this will effect the future running of the system.

Another block on ward beds is bed blockers from A & E (Accident and Emergency). One of the standards there is a star rating limiting the time a patient can wait in A & E before being admitted to a hospital ward (assuming they have been assessed as needing admission). So a patient will be admitted to whatever hospital bed is available in whatever specialty.
4.2 Document Analysis

This section describes the findings from the document analysis. Several national and local documents pertaining to waiting lists and access to elective care were analysed for common themes. Three main themes emerged:

1. Standards and targets
2. Guidance for waiting list management
3. Patient choice and booking

Table 4.3 below shows the list of documents used.

<table>
<thead>
<tr>
<th>Section</th>
<th>Document</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standards and Targets</td>
<td>The NHS Plan</td>
<td>Department of Health (2000b)</td>
</tr>
<tr>
<td></td>
<td>Standards for Better Health</td>
<td>Department of Health (2004b)</td>
</tr>
<tr>
<td></td>
<td>A First Class Service Quality in the NHS</td>
<td>Department of Health (1998)</td>
</tr>
<tr>
<td></td>
<td>National Service Framework for Coronary Heart Disease</td>
<td>Department of Health (2000a)</td>
</tr>
<tr>
<td></td>
<td>Winning the War on heart Disease: Progress Report 2004 of the NSF for CHD</td>
<td>Department of Health (2004c)</td>
</tr>
<tr>
<td></td>
<td>&quot;Choose &amp; Book&quot; - Patient’s Choice of Hospital and Booked Appointment</td>
<td>Department of Health (2004a)</td>
</tr>
<tr>
<td>Guidance for Waiting List</td>
<td>The NHS Plan</td>
<td>Department of Health (2000b)</td>
</tr>
<tr>
<td></td>
<td>Waiting List Validation: towards a fully booked NHS</td>
<td>NHS Modernisation Agency (2003b)</td>
</tr>
<tr>
<td></td>
<td>Primary Targeting Lists: towards a fully booked NHS</td>
<td>NHS Modernisation Agency (2003a)</td>
</tr>
<tr>
<td></td>
<td>Rapport Online Service Improvement Service</td>
<td>CHD Collaborative (2004)</td>
</tr>
<tr>
<td>Patient Choice and Booking</td>
<td>&quot;Choose &amp; Book&quot; - Patient’s Choice of Hospital and Booked Appointment</td>
<td>Department of Health (2004a)</td>
</tr>
</tbody>
</table>

Local documents were obtained via the Trust’s Document Management System.
4.2.1 Standards and targets

This section sets out some of the main standards and targets for waiting lists and access to elective care.

The NHS Plan (Department of Health, 2000b) set out the Labour Government’s programme of reform and investment in the National Health Service. The document set out its “... purpose and vision to give the people of Britain a health service fit for the 21st century a health service designed around the patient” (Department of Health, 2000b, Executive Summary p10). The NHS Plan called for reform and re-organisation of the way the NHS was run and the way staff worked. In particular it called for a focus on patient centred care, “The NHS has to be redesigned around the needs of the patient” (Department of Health, 2000b, Executive Summary p11).

The Plan listed “a lack of National Standards” (Department of Health, 2000b, Executive Summary p10) as one of the systematic problems of the NHS. This passage stated the consequences of this lack of National Standards, “An absence of clear national standards made planning and deploying resources – including staff numbers and training – more difficult. Health inequalities were compounded by a failure to match provision of services with health needs.” (Department of Health, 2000b, Chapter 2 p30).

The public consultation exercise undertaken for the NHS Plan identified waiting for treatment as one of the public’s chief concerns about the NHS (Department of Health, 2000b, Annex 1, p134). Hence the Plan’s introduction of waiting time targets for elective care. A much more radical aim of the NHS Plan was the idea of introducing booking systems as a replacement to waiting lists (Department of Health, 2000b, p 105, para 12.20). The Plan’s aim with this strategy was to force Hospitals to be more efficient in their scheduling and use of outpatient appointments and theatre sessions (Department of Health, 2000b, p104, para 12.16).
The Plan's main theme was to set out a policy that seeks to devolve operational control of the NHS to the local level and make the organisation more flexible in its workings whilst nationalising quality control by setting out standards of care at a National level for the first time. The Department of Health has set out National Standards for Health and Social Care from 2005 to 2008 in its report 'Standards for Better Health' (Department of Health, 2004b).

"The Department of Health will set national standards, matched by regular inspection of all local health bodies by the Commission for Health Improvement " (NHS Plan, Executive Summary p11). The Healthcare Commission (formerly known as the Commission for Health Improvement) produced a series of performance ratings which compared every NHS Trusts' performance to the main targets set by the Government. The Healthcare Commission admitted that these 'star' ratings "...do not provide a comprehensive picture of every aspect of a NHS organisation's performance", (Healthcare Commission, 2004a). The indicators did not measure or compare outcomes of treatment so they could not be used to identify variations in the quality of care between Trusts. Table 4.4 shows the key indicators used.

A Trust's final 'star' rating was calculated using a 'Balanced Scorecard' approach. The scorecard had three focus areas:

- Clinical focus (including deaths following a heart bypass)
- Patient focus (including cancelled operations and patients waiting longer than standard for revascularisation)
- Capacity and capability (including information governance)

University Hospitals of Leicester NHS Trust (UHL) was rated as a maximum three star Trust having achieved eight of the nine key indicators (only underachieving on '12 hour waits for emergency admission via A & E') and being rated in the top bands for all three focus areas on the Balanced Scorecard (Healthcare Commission, 2004b)
<table>
<thead>
<tr>
<th><strong>Key Indicator</strong></th>
<th><strong>Explanation</strong></th>
<th><strong>Threshold</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>12 hour waits for admission via A&amp;E post decision to admit</td>
<td>Percentage of patients waiting less than 12 hours for admission via A&amp;E as an emergency following decision to admit. Regarded as a marker of unacceptable patient experience.</td>
<td>Achieved if &gt;99.50%</td>
</tr>
<tr>
<td>All Cancers: 2 week wait</td>
<td>Percentage of patients seen within two weeks of urgent GP referral for suspected cancer to first outpatient appointment with specialist. Part of a staged move towards the NHS Cancer Plan's target that all patients with an urgent GP referral for suspected cancer should wait no more than one month from referral to treatment.</td>
<td>Achieved if &gt;98%</td>
</tr>
<tr>
<td>Financial management</td>
<td>Achievement of the 2003/04 financial position shown in plans submitted to the Department of Health, without the need of unplanned financial support. Financial stability essential to developing patient services in line with NHS Plan</td>
<td>Underachieved if adverse variance from plan of up to 1% of turnover or &lt;£1M without financial support. Significantly underachieved if &gt;1% or &gt;£1M or unplanned financial support</td>
</tr>
<tr>
<td>Hospital Cleanliness</td>
<td>Rating from 1 (Unacceptable) to 5 (Excellent) based on inspection by Patient Environment Action Teams (PEAT)</td>
<td>Achieved if PEAT rating is 3 or more</td>
</tr>
<tr>
<td>Improving working lives</td>
<td>Continued implementation of improving working lives standard Improving staff conditions contributes to better patient care.</td>
<td></td>
</tr>
<tr>
<td>Outpatient and Elective Inpatient and Daycase Booking</td>
<td>The percentage of outpatient appointments and elective admissions that were pre-booked NHS Plan's target of every patient going through a booking system by the end of 2005.</td>
<td>Achieved if Number of outpatients AND Number of elective admissions booked are both equal or greater than 67%</td>
</tr>
<tr>
<td>Outpatients waiting longer than the standard</td>
<td>Number of new outpatients waiting more than 21 weeks April 2003 to February 2004 plus the number waiting more than 17 weeks in March 2003 as a percentage of the total new outpatients during the year (all following a GP referral) Public call for reduced waiting times</td>
<td>Achieved if 0.03% or less</td>
</tr>
<tr>
<td>Patients waiting longer than the standard for elective admission</td>
<td>Number of patients waiting for more than 12 months for elective admission from April 2003 to February 2004 (at the end of each month) plus the number waiting more than 9 months at the end of March 2004 as a percentage of admissions from the waiting list</td>
<td>Achieved if 0.03% or less</td>
</tr>
</tbody>
</table>
A full three star rating meant more independence from central NHS and Whitehall control and the opportunity to become a Foundation Hospital. A zero rating meant more central control and possible sackings for the Trust’s Chief Executive and Board members. Unsurprisingly, a close eye was kept on these indicators. UHL Trust’s Information Management and Technology Directorate (IM&T) produced a monthly ‘Star Ratings’ Management report (University Hospitals of Leicester NHS Trust, 2004b) The first section provided information on the ‘Star’ ratings themselves (Key indicators and Balanced Scorecard) including any local targets which were more ambitious. The second section provided a summary of the Trust’s current performance, by key indicators and scorecard groups, using a ‘traffic light’ system to flag up any underperformances against the final targets. The third section detailed action to be taken to improve areas that are currently underperforming and the final section showed more detailed information on each of the indicators (including past performance, lead executive director and source documents).

National Service Frameworks (NSFs) set out standards for NHS healthcare in certain disease or patient groups. They formed part of the quality framework set out in the report ‘A First Class Service’ (Department of Health, 1998) and shown in Figure 4.8 below.
The NSF for Coronary Heart Disease (NSF for CHD) (Department of Health, 2000a) was published in 2000 and set out a ten year programme to improve the services involved in cardiac care, from prevention, primary and secondary care to rehabilitation services. The NSF was described as

"a practical, evidence-based and flexible approach to tackling CHD which

- Sets National Standards (clinical and organisational) for preventing and treating CHD
- Defines service models for preventing and treating CHD
- Establishes initial milestones, goals and performance indicators against which progress within agreed timescales will be measured
- Identifies practical tools to support implementation"

(Department of Health, 2000a, p 11)

The NSF for CHD published twelve service standards covering seven areas

Standard 10 related to revascularisation:

“NHS Trusts should put in place hospital-wide systems of care so that patients with suspected or confirmed coronary heart disease receive timely and appropriate investigation and treatment to relieve their symptoms and reduce their risk of subsequent coronary events.”
The NSF for CHD stated that the NHS had not invested enough in revascularisation procedures and that rates of revascularisation were low compared to other European countries with long waits for treatment. "This suggests that currently many people who might benefit are not offered revascularisation and those that so have often waited longer than is acceptable" (Department of Health, 2000a, p 40). The NSF set out waiting time targets for access to diagnosis and treatment for revascularisation procedures, two weeks from GP referral to consultant appointment and three months from decision to operate to treatment (Department of Health, 2000a, p 45). These targets fitted in with CHI’s Performance monitoring ratings and the NHS Plan’s targets for shorter waiting times for elective treatment.

In March 2004, the Department of Health published a progress report into the NSF for CHD. Prominently displayed early on (Department of Health, 2004c, p 6) is a “summary of progress” including the fact that the number of patients waiting for heart surgery for more than six, nine and twelve months had dropped to zero by March 2004. Chapter 6 of the report gave more detail on shorter waiting times and related it to several factors including more staff, new facilities, greater efficiency and the patient choice initiative.

UHL Trust’s patient access and data management policy (Prestnall and Barradell, 2004) classified data definitions of hospital activity in order to provide consistency of good practice across the Trust of data entry on to the Hospital Information Support System (HISS – the Hospital’s central administrative database). For example in the section on ‘Adding patients to the Elective Waiting List’ the ‘Original Date of Decision to Admit’ was defined as “ . the date of the first decision that the patient needed to be admitted (regardless of where that took place). This is the date of the first decision to admit a patient to hospital for a given condition which results in the patient being placed on an elective waiting list ” (Prestnall and Barradell, 2004, p 38).

The reason for producing such a document arose, “ . out of the need to maintain consistent and equitable procedures in the administration and management of outpatient and admitted patient activity across the Trust.” (Prestnall and
Barradell, 2004, p 7) There was also a specific objective to produce accurate waiting times for access to services to support the management of waiting lists.

The document was an attempt to integrate its Data Management and Patient Choice & Booking policies (it was written by the managers responsible for data quality and Choose and Book programme respectively) suggesting that Management at the Trust viewed good data management as essential to implement the Government’s booking programme. The document detailed booking policy in association with their recording on HISS, for example, arranging outpatient appointment and inpatient admission dates at the time of referral / addition to list was discussed with the consequent data recording procedures and standards to be followed.

Standards underpin the document and were to be found throughout. National patient access targets for 2005 were to be found in the first section and are shown in Table 4.5 below.

All the standards in the table are national ones but the document does contain local standards, for instance when mentioning responsibilities for the implementation of the good waiting list practice contained in the policy a local standard is stated.

"Within UHL, General Managers (or sufficiently briefed deputies) will attend the weekly Waiting List Meeting, chaired by Directorate of Operations" (Priestnall and Barradell, 2004, p 9)
Table 4.5: Patient access targets mentioned in UHL access document

<table>
<thead>
<tr>
<th>Target</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>By March 2005, there will be a 3 month maximum wait for revascularisation</td>
<td></td>
</tr>
<tr>
<td>By end 2005, every hospital appointment will be booked for the convenience of the patients. Patients will be able to choose from 4-5 providers for planned hospital care.</td>
<td></td>
</tr>
<tr>
<td>By December 2005, there will be a maximum waiting time of 1 month from diagnosis to treatment for all cancers.</td>
<td></td>
</tr>
<tr>
<td>By December 2005, there will be a maximum waiting time of 2 months from urgent referral to treatment for all cancers.</td>
<td></td>
</tr>
<tr>
<td>By December 2005, there will be a maximum waiting time of 3 months (13 weeks) for an outpatient appointment.</td>
<td></td>
</tr>
<tr>
<td>By December 2005, there will be a maximum waiting time of 6 months for inpatients.</td>
<td></td>
</tr>
</tbody>
</table>

This showed the high level attention given to access issues within the Trust which were part of the star ratings UHL Trust had a system of 'Board' reports which gave high level information on the performance of the Trust's directorates in terms of numbers of operations, outpatient appointments, admissions and waiting time performance (University Hospitals of Leicester NHS Trust, 2004a)

One section, early on, was devoted to 'Access and Booking' and showed current progress against the targets mentioned in Table 4.4

4.2.2 Guidance for Waiting List Management

One of the aims of the NHS Plan was to introduce a system where patients can book hospital appointments and admission dates (Department of Health, 2000b, p 104, para 12.16) For this booking system to work without generating multiple appointment and admission cancellations, a hospital must have some idea about how long a patient added to the list today will have to wait in a particular specialty for a particular procedure If patients are treated out of the order in which they are added to the waiting list (out of turn) the variation in waiting time for an elective procedure becomes too great to realistically introduce a booking system.
To try and overcome these problems the NHS Modernisation Agency introduced a guide to effective waiting list management known as CPaT (Clinically Prioritise and Treat), (NHS Modernisation Agency, 2004) It built on two previous initiatives on waiting list management by the Modernisation Agency known as validation of lists and Primary Targeting Lists (PTLs) Validation is defined as a process of checking to see if patients who are due to have outpatient appointments or inpatient admissions still require them (NHS Modernisation Agency, 2003b, p 7) Cleaning up lists in this way should mean that they are not overstated and time is not wasted arranging to see patients who no longer need to be seen Primary Targeting Lists identify long waiting patients who need to be treated within a specified time i.e. those that could break the nine, six and three month maximum waiting time targets (NHS Modernisation Agency, 2003a) The idea of PTLs was to then focus the remaining capacity left before the target date on admitting patients on a PTL (but also bearing in mind that clinically prioritised patients must also be treated) These initiatives were designed to build on one another to support Booking and Choice (See figure 4.9)

Figure 4.9 Relationship between Booking & Choice Programme and Waiting List Management (Source: NHS Modernisation Agency, 2004, p 2)
CPaT is based on two principles

- The proportion of patients seen as a priority has an impact on the waiting times of routine patients. The higher this proportion, the longer routine patients will have to wait.
- The maximum waiting time for routine patients will fall if they are seen in turn i.e. no queue jumping.

(NHS Modernisation Agency, 2004, p 9)

The tools in the CPaT toolkit measured the variation in patient waiting time between the original decision to admit date and the date of admission, and can tell to what extent patients were being seen in chronological order. The CPaT process then encouraged local managers and clinicians to discuss and pinpoint the causes of this variation and make suggestions on how to address these issues.

The CPaT Step Guide (NHS Modernisation Agency, 2004, p 11) was very careful to point out that CPaT does not “challenge the categorisation of individual patients by clinicians.” It also stressed that it is intended to promote “shared understanding among clinicians, managers and administrators to improve the processes that operate the whole waiting list” (p 9). The document tried to defuse any sense of Managers or Government interfering with the way clinicians treated patients.

CPaT was described as being easy to implement, straightforward to use and easily integrated with other waiting list management tools (NHS Modernisation Agency, 2004, p.10). Indeed the defined datasets for the Access database toolkit were small and easily derivable from the National datasets that Trusts have a statutory duty to produce.

UHL’s patient access policy, Prestnall and Barradell (2004), reiterated the good practice disseminated by the NHS Modernisation Agency on waiting list management,
"Key principles of waiting list management are:

- All patients awaiting elective treatment are added to a waiting list,
- Patients added to an elective list are ready to be treated,
- Patients are treated in order of their clinical need;
- Patients with the same clinical need are treated in chronological order (i.e. on a 'first come, first served' basis)"

(Prestnall and Barradell, 2004, p 36)

The access document also set out good practice when deciding who should be added to the list. This included advice that

- Junior staff should only add a patient to the waiting list on consultation with their seniors
- Patients should not be added to a waiting list in case they need treatment in the future. These patients should be reviewed as outpatients
- Patients should not be added to a waiting list if there is no intention of admitting them

(Prestnall and Barradell, 2004, p 38)

It also described procedures to undertake when reviewing the waiting list to ensure it is accurate and valid. These included

- Patient Target Lists, described above
- Writing to patients waiting more than three months asking if they still require the procedure. Patients who inform the Trust that they no longer want the procedure can be removed from the Trust
- Partial booking where patients are asked to contact the hospital to organise an admission date. If they do not do this and there is no response to reminder letters then the patient can be removed from the waiting list and discharged to their GP.

(Prestnall and Barradell, 2004, p 41)

The principles of good waiting list management, list validation and control of list additions that the access document sought to disseminate were intended to make sure that staff at the hospital had policies and strategies in place that
helped them ensure that the Trust met its waiting time targets. However as with the CPaT guidance from the NHS Modernisation Agency, the access document was still careful to state that the responsibility of selecting patients for admission rested with the Consultant (Priestnall and Barradell, 2004, p 42)

CHD Collaboratives were established to help in the achievement of the targets laid out in the NSF for CHD. The idea was to encourage managers, clinicians and others to work together to improve the system of care for patients. It was, in April 2005, replaced by the NHS Heart Improvement Programme (http://www.content.modern.nhs.uk/cmsWISE/Clinical+Themes/CHD/CHD.htm). The CHD Collaborative produced a website (known as 'Rapport Online') to enable the spread of good practice around the management of heart patients (CHD Collaborative, 2004). Patient journeys through the various systems could be viewed, for example, the patient journey for 'Cardiac Surgery' is shown in Figure 4.10. Service improvements, sent in by various staff involved in the CHD Collaborative networks, could be searched and categorised by the stages of the patient journey. One example of this was the Oxford Radcliffe Hospitals NHS Trust reduction of waiting times for elective cardiac surgery by pooling referrals from their cardiology department.

The 'Rapport' website was a powerful source of information on service improvements in Coronary Heart Disease and contained suggestions on all aspects of cardiac treatment, not just elective waiting lists.
Figure 4.10. Patient Journey for Cardiac Surgery (source: Rapport website, CHD Collaborative, 2004)

- **Whole Patient Journey**
  - 27 Improvements

- **Angiography Review**
  - 3 Improvements

- **Cardiologist refers patient for surgery**
  - 20 Improvements

  - **Elective**
    - 6 Improvements

  - **Urgent**
    - 17 Improvements

  - **Outpatient Appointment**
    - 16 Improvements

  - **Cardiac Surgery Waiting List**
    - 26 Improvements

  - **Inpatient Waiting List (White Board)**
    - 18 Improvements

  - **Diagnostic Tests**
    - 6 Improvements

  - **Diagnostic Tests**
    - 2 Improvements

  - **Pre Surgical Intervention (Prehab)**
    - 24 Improvements

  - **Pre Assessment**
    - 16 Improvements

  - **Schedule for Theatre**
    - 12 Improvements

- **Theatre – Procedure Undertaken**
  - 7 Improvements

- **ITU / Recovery Area**
  - 12 Improvements

- **Ward**
  - 21 Improvements

- **Outpatient Review**
  - 11 Improvements

- **Rehabilitation**
  - 11 Improvements
4.2.3 Patient Choice and Booking

The Department of Health published a policy framework for Patient Choice and Booking at the point of referral (Department of Health, 2004a). It was designed to provide guidance to NHS organisations as they prepared to give patients a choice of four to five hospitals and a date and time of their appointment at the time of referral. This was to be achieved by December 2005 though patients requiring heart surgery were given a choice of hospital by April 2005.

Patients were expected to benefit as the greater convenience and certainty were expected to reduce the stress of the referral process. Hospitals were expected to benefit as cancelled and ‘Did Not Attend’ (DNA) appointments reduced in number and the administrative burden of organising appointments also reduced (Department of Health, 2004a, p 4).

The report stressed that more information should be made available for patients to enable them to make an informed choice. Information should include,

- Waiting times
- Location and convenience of the hospital
- Patient experience
- Clinical quality

(Department of Health, 2004a, p 7)

Patients should be offered a choice of hospitals that were able to provide appointments within the thirteen week maximum outpatient waiting time (a new referral must have their first appointment within thirteen weeks, Department of Health, 2004a, p 8). The report went on to say that, “Trusts that prove more popular than anticipated and receive additional referrals through choice may be able to increase activity to enable them to treat the additional patients within the maximum waiting time. PCTs [Primary Care Trusts] should support this”. The report did not consider the effect of an increased number of new outpatient appointments on additions to the elective inpatient waiting list. More inpatients could eventually mean greater waiting times for inpatient surgery. Although the
Government was introducing more capacity and a system of 'Payment by Results' (where Trusts will actually be paid for the number of operations they perform so giving them an incentive to increase throughput), Trusts that perform well at outpatients could end up increasing waits at the inpatient stage.

Choice in the patient pathway through Coronary Heart Disease will only kick in at the treatment stage as speed of diagnosis is considered to be more important than choice at the referral stage. For cardiac surgery choice of hospital and appointment was offered at the point of referral by a cardiologist by December 2005. A preliminary target gave patients a choice of hospital from April 2005 if they require a Coronary Artery Bypass Graft (CABG) or valve repair.

UHL Trust’s ‘Patient Access and Data Management Policy’, Priestnall and Barradell (2004, p 13), noted that patients waiting over six months had, since November 2004, been offered the choice of treatment in a private provider by their PCT. The policy stated a local standard that “Patients transferring between providers under the patient choice initiative will remain on a waiting list until treated. Patients will only be transferred from the waiting list of the original provider when a transfer of responsibility has been confirmed in relation to the patient's ongoing waiting list management.”
4.3 Summary

This chapter has analysed the interview and document data as a first stage in producing a qualitative system dynamics model of the cardiothoracic surgery system at Glenfield Hospital. A summary description of the system will now be attempted.

A patient will be seen in outpatients by a consultant and if further treatment is deemed necessary will be added to the elective waiting list for an operation. Elective patients can have their operations cancelled if there is an emergency admission who needs treatment immediately and who may need the theatre, staff time and/or CICU bed more urgently. Once admitted patients are transferred to CICU or HDU before going on to the general ward and finally discharge.

The consultants have a role in scheduling their own theatre list. This scheduling can be upset by the arrival of an emergency admission which has priority over elective admissions. Emergencies can therefore result in an elective admission and/or operation being cancelled. Associated with this scheduling of elective admissions is a finite capacity for each consultant in the operating theatre that puts a limit on the number of operations he/she can carry out. Consultants manage their own waiting lists independently and do not communicate the complexity of the cases they have scheduled with the other consultants and no analysis is made about the effect of this uncoordinated scheduling on the shared resources (e.g., beds).

Emergency admissions have an effect on "Lengths of Stay" in hospital and "Unoccupied Beds". Emergency patients take up beds that could otherwise be used for elective patients and also tend to stay longer so blocking beds. This in turn will tend to increase the surgical waiting list and so increase the number of emergency patients coming in from the waiting list. Emergencies that occur out of office hours have an effect on staff availability for subsequent elective admissions. 'On call' theatre staff need a certain period of rest, if called out, before they can resume work.
Emergencies can cause an elective admission to be cancelled. There are consequences for elective cancellations. Elective Cancellations can be kept on the ward if they would break the 28 day target if discharged. Hence they cause the number of unoccupied beds to decrease and potentially cause more elective cancellations. Another type of emergency are “Blue Forms”. These are emergency patients who were undergoing a catheter procedure when it becomes clear they need immediate surgery.

After an operation, patients will usually go to the CICU to recover though some may instead go to the High Dependency Unit instead (the Unit offers a level of care somewhere between CICU and an ordinary ward, hence beds here are more efficient to run). Patients on HDU can end up in CICU anyway.

Other departments in the Trust are trying to meet their own targets which can effect the cardiac surgery. In this case admission time targets in Accident & Emergency (A&E). Patients in A&E who are assessed as needing admission must be admitted to a ward within a certain time otherwise the Trust loses a star rating. If a surgical ward bed is all that is available, then it has to be used. Patients admitted in this way are termed ‘bed blockers’ and can block discharges from CICU to the ward and so elective admissions.

Waiting Lists are actively managed as they are the subject of several Standards and Targets, some of which will effect the management of the Hospital if not met. An example is the ‘Star’ ratings. Standards and targets drive the need to monitor and admit long waiting patients before they breach said standards. One way to do this is through the use of waiting list validation and PTLs (Primary Targeted Lists).

Validation is defined as a process of checking to see if patients who are due to have outpatient appointments or inpatient admissions still require them. Cleaning up lists in this way should mean that they are not overstated and time is not wasted arranging to see patients who no longer need to be seen. Primary Targeting Lists identify long waiting patients who need to be treated within a specified time i.e. those that could break the nine, six and three month maximum.
waiting time targets. The idea of PTLs is to then focus the remaining capacity left before the target date on admitting patients on a PTL.

CPaT is based on two principles

- The proportion of patients seen as a priority has an impact on the waiting times of routine patients. The higher this proportion, the longer routine patients will have to wait
- The maximum waiting time for routine patients will fall if they are seen in turn i.e. no queue jumping

CPaT (Clinically Prioritise and Treat) builds on these two other processes to give Managers and Clinicians tools which measure the variation in patient waiting time between the original decision to admit date and the date of admission, and can tell to what extent patients are being seen in chronological order. The CPaT process then encourages local managers and clinicians to discuss and pinpoint the causes of this variation and makes suggestions on how to address these issues.

The Hospital's access policy re-iterates the principles of good waiting list management, list validation and control of list additions that the NHS Modernisation Agency's National focus on waiting list management seeks to impart to Trusts. These principles are intended to make sure that staff at the hospital have policies and strategies in place that will help them ensure that the Trust meets its waiting time targets. However as with the CPaT guidance from the NHS Modernisation Agency, the access policy is still careful to state that the responsibility of selecting patients for admission rests with the Consultant. CPaT is designed to ensure that patients are admitted in as quick a time as possible within the local capacity constraints i.e. they are admitted in as efficient a manner as possible.

The Choose and Book programme is intended to give patients a choice of four to five hospitals and a date and time of their appointment at the time of referral. For the policy to work validation, PTL and CPaT principles need to be implemented.
on waiting lists otherwise Trusts could not possibly give patients a realistic date to come in for treatment. This would result in multiple appointment and admission cancellations rendering the policy pointless.

The qualitative system dynamics model, that is based on this chapter's analysis, is described in the chapter 6. The next chapter describes the development of a spreadsheet model that was intended as a first modelling step to give the stakeholders at Glenfield an initial model they could use immediately.
Chapter 5: The Markov Chain Model

This chapter describes the initial model written to provide a basic prediction of cardiothoracic surgery elective waiting lists and times based on previous activity.

5.1 Introduction

The model was developed for Managers at the Hospital to assess how close they are to meeting the waiting list targets by the set date. As well as predicting the future waiting list, the model can also be used to predict the number of extra operations needed to meet a maximum waiting time. The model runs in Microsoft Excel, a software package which is available throughout the Hospital, and links in to information from the Hospital's Patient Administration System (PAS). Attention was paid to the interface that controls the model to improve its usability.

The model provides an aggregate estimate of factors like operations and additions to the waiting list and does not examine factors effecting these variables.

The Hospital performs about 1,500 heart operations a year (admissions to the cardiothoracic surgery specialty). On average, there will be between 350 and 400 patients on the cardiothoracic surgery waiting lists, at any one time, served by seven cardiothoracic surgeons. Empirical evidence suggests that 31% of admissions for cardiothoracic surgery are classed as emergencies.

The aims of this initial model were to:

- Produce a model to study the dynamics of the Hospital’s cardiothoracic surgery waiting list.
- Use the model to predict the number of extra operations required to meet the Government’s waiting times targets.
- Devise a usable interface to the model for use by the Hospital Management and Clinicians.
The model was developed in association with a consultant. Appendix 4 lists the contributions of the Author.

5.2 Model Structure

The model attempted to describe the cardiac surgery elective waiting list in terms of three queues of differing priority. Information about arrivals on to the waiting list, elective operations and the current state of the queues are taken from the hospital's Patient Administration System (PAS). From these inputs, the model constructs and samples from probability distributions and projects numbers waiting at the end of the month for each month a year ahead. These projections are also split by priority and length of wait.

The waiting list was modelled using a simulation of a Markov chain. The projected waiting list one stage in the future depends on the current state of the waiting list but not on its past states. This implies that the information that guides the future evolution of the waiting list is described in the present state of the waiting list and in the transition probabilities. The waiting list projections do not depend on how it reached that present state. The dependence on the current state is a useful simplifying assumption that enables the possibility of simulation in a spreadsheet. Each month's sampled arrivals and operations effectively modify the transition probabilities between states.

The model attempted to give Managers at the Trust a tool with which to predict the future trend of waiting lists (and maximum waiting time) according to the recent trends of operations, waiting list additions and current waiting list position. Valuable information was gained about what is required by the Trust from the model.

The interface to the model was prototyped with the Users (four in number) at the Hospital. An initial version of the interface was demonstrated to Users at the Hospital who made suggestions as to improvements. Feedback was also collected after they had the opportunity to use the model. Feedback included colour coding the table and graphs so that they could be correlated more easily.
and hiding the priority weightings behind a button to make the screen less 'busy'
Prototyping is a common method of interface development and is detailed in
Nielsen (1993)

Microsoft Excel was used to produce the model as this program is supported
throughout the Hospital, has adequate calculating power and supports a high
level programming language (Microsoft Visual Basic) and also the ability to
produce a high quality, usable interface quickly and easily

Figure 5.1 shows a conceptual model of the overall process for the cardiac
surgery elective waiting list

Figure 5.1 Elective Operations, three streams of priority

Patients arrive on the elective waiting list and are allocated to one of the three
priority streams depending on their need for an operation. If the patient's
condition worsens whilst on the priority or standard queue (also called soon and
routine respectively), they can be given a higher priority or admitted as an
emergency patient. In this latter case they have left the elective waiting list. Other
reasons for leaving the elective waiting list include patient deaths and patients
going to a private provider

Each consultant chooses patients off the waiting list to treat according to their
own criteria or strategy. The model can be adapted to study waiting list dynamics
for an individual surgeon if chosen. It can also be used for an individual type of
procedure or combination of surgeon and procedure. The procedures undertaken
include single and multiple operations. An example of the former is a Coronary

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Artery Bypass Graft (CABG) operation; whereas for multiple procedures, the operation could entail a CABG followed by heart valve replacement.

Some Department of Health funding was provided to allow NHS (National Health Service) patients waiting a certain length of time to be treated in the private sector under the ‘Private Sector Patient Choice’ (PSPC) scheme. Patients had to meet a minimum fitness level. Each consultant was allocated the same number of patient choice places regardless of length of list or maximum waiting time.

A conceptual diagram to illustrate possible state transitions of patients in a waiting list can be seen in Figure 5.2. It shows the possible state transitions for the ‘Standard’ patients waiting under one month, shown in grey in the diagram. If the model operates on one month increments, the patient is either still waiting (one extra month) or has had an operation, or has left the waiting list. Table 5.1 gives an explanation of the States involved.

The data used in the model were obtained from the Hospital’s Patient Administration System (PAS), known as ‘Clinicom’. The Hospital’s IM&T (Information Management and Technology) Department regularly pulled off certain data from the PAS (using a system known as Client Server End User Reporting, CS-EUR) and placed it in data tables held on a SQL-Server database system.

Arrivals on to the Waiting List were obtained from the ‘Waiting List Events’ table. They are known as Waiting List Additions and are split by priority and totalled by month and year of arrival.
Figure 5.2 Patient States and Transitions (NB Not all states and transitions from Waiting List states present are shown so as not to 'clutter' the diagram)

* PSPC = Private Sector Patient Choice
Table 5.1 Explanation of States used in Figure 5.2

<table>
<thead>
<tr>
<th>State</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrivals</td>
<td>Patients added to the waiting list for elective surgery</td>
</tr>
<tr>
<td>Operation</td>
<td>Patients admitted to hospital for elective surgery</td>
</tr>
<tr>
<td>PSPC</td>
<td>Private Sector Patient Choice as described earlier</td>
</tr>
<tr>
<td>Other Leavers</td>
<td>Patients who leave the waiting list for reasons other than operation or PSPC e.g. Patient moves, death etc</td>
</tr>
<tr>
<td>Patients Waiting</td>
<td>Patients who are waiting for elective surgery are classified into three streams of priority, 'Standard', 'Priority' and 'Urgent' and length of wait</td>
</tr>
</tbody>
</table>

Elective Finished Consultant Episodes (FCEs) were used to represent operations. An FCE is an episode of care under one consultant. Elective FCEs can only be the first one in a hospital admission and are responsible for taking a patient off the waiting list. Priority for an FCE was obtained by matching back to the closest Waiting List Addition of the patient. The Hospital involved underwent a merger of three hospitals into one Trust. A merger of their PAS systems meant that FCEs recorded after the merger with an addition before the merger could not always be linked together logically. The problem eventually resolved itself once the merger was far enough in the past. FCEs were totalled by month and year of the start of the episode.

The latest waiting list census is the number of patients currently waiting for admission. The list is updated every day. It acts as a starting point for the model's projections.

Number of leavers from the waiting list were also obtained from the Waiting List Events table and used to estimate the probability of leaving the waiting list altogether.
Transfer Probabilities (between priority streams whilst on the waiting list) were estimated. The PAS did not record a change of priority, and we were unsure if a change would be inputted into the PAS anyway.

Priority weightings (i.e., the likelihood of a patient getting an operation by priority and months waited) were calculated from past data (see Validation section). These priority weightings represent the transition probabilities of the Markov chain. However, the number actually receiving an operation at a particular stage is subject to the availability of the sampled number of operations for that stage.

Data for additions and FCEs were held in an Access database to facilitate the matching process. Additions and elective FCEs were matched on a Hospital ID number to produce all possible matches. The matches were then carefully stripped away to leave the FCE matched to the most recent addition. In this way, priority, waiting list procedure and date of addition can be attached to the FCE. The process was not perfect and about 10% of FCEs were unable to be matched successfully.

Additions, FCEs, and the latest waiting list census figures could also be generated by individual surgeons or procedures or both. Probability distributions for Additions and FCEs were obtained from the Access database whilst figures for the waiting list census were obtained direct from the SQL Server database system. These three sets of figures were updated every time a new consultant or procedure was chosen on the model's 'Front End' (Please see Section 5.5 for a description of the interface to the model).

The model outputs the numbers waiting by priority and length of wait at the end of the month, projected for each month forward for 12 months.

Table 5.2 summarises the data inputs and outputs.
Table 5.2 Data Inputs and Outputs

<table>
<thead>
<tr>
<th>Data Inputs</th>
<th>Data Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current numbers waiting for admission by Priority and Length of Wait (in months)</td>
<td>Predicted numbers waiting by priority and Length of Wait (in months) at the end of each month in the next twelve months</td>
</tr>
<tr>
<td>Elective FCEs (Finished Consultant Episodes)</td>
<td></td>
</tr>
<tr>
<td>Additions to the waiting list.</td>
<td></td>
</tr>
<tr>
<td>Number of PSPC* places per month.</td>
<td></td>
</tr>
</tbody>
</table>

* PSPC = Private Sector Patient Choice

5.3 Operation of Model

The model's output is the number of patients waiting at the end of each month split by priority and months waited. The number waiting for (x) months *this* month depends on the number waiting for (x-1) months *last* month minus the numbers operated on and the number that left the list during the month.

Equation 1 summarises this concept

\[ N_{x,t} = N_{x-1,t-1} - O_t - L_t \]  

(1)

where \(N_{x,t}\) is the number of patients waiting for (x) months *this* month

\(N_{x-1,t-1}\) is the number of patients waiting for (x-1) months *last* month

\(O_t\) is the number of patients operated on during the month and

\(L_t\) is the number of patients who left the list during the month

Figure 5.3 shows this process diagrammatically.
The number of arrivals (additions to list) and operations (FCEs) each month are produced randomly. The model links directly to the Access database to produce a non-uniform probability distribution for operations (FCEs) and additions to list depending on the consultant and procedure chosen. The database pulls off the monthly figures for each variable for the last 36 months. The additions are in three distributions according to the three priorities patients can be assigned. The model samples from these distributions for each month of projection. This means the model is a stochastic one and can be run several times to generate an average performance (e.g., can press 'F9' in Excel to generate a new set of figures).

The model can be run in two modes. It can be run assuming a maximum waiting time has been specified, for example nine or twelve months. Any patients waiting in this band(s) are taken off first. The NHS Trust achieved the nine-month target for maximum wait for elective surgery in March 2003, so it seemed a reasonable model assumption. The remaining operations are divided between the remaining priority/months waited cells according to the priority weightings. Priority Weightings represent the probability a waiting patient will be operated on in the coming month. They are split by operative priority and time band waited.
Priority weightings are calculated from past data. The number of operations for each operative priority and time band waited was calculated for a previous twelve month period for each month. These figures were divided by the number waiting at the start of each month for each priority and time band waited. This results in a set of numerical data between zero and one representing the probability that a patient will be operated on in a certain month by their operative priority and time waited on the waiting list.

For example, if the standard operative priority patients waiting less than a month had a priority weighting of 0.2, this would imply 20% of those patients waiting in that operative priority and time band at the start of the month will have an operation before the end of the month. So, in the first month there are 20 standard patients waiting less than a month. The priority weighting for these patients is 0.2 so four (20%) of them should get an operation. However, the number of operations means that only three are operated on. The higher the weighting the higher the proportion of patients having an operation. The calculation is demonstrated in Figure 5.4.

Net transfers out of each cell are calculated using the number of patients waiting and the transfer probability matrix (see Table 5.3). The transfer probabilities are assumed to be constant however long a patient has been waiting. The 'Exit' probabilities were calculated from the number of leavers, whilst the others were estimated.

Patients are also taken off the list according to the number of places available on the 'Private Sector Patient Choice' scheme. Consultants have an equal number of these places so that their patients can be treated in the private sector. These places are distributed in the same manner as the normal operations but according to a separate 'Private Sector Patient Choice' Priority Weightings for each consultant.
Figure 5.4 Demonstration of Use of Priority Weightings to allocate operations

Numbers on Waiting List by Priority and Months Waited

<table>
<thead>
<tr>
<th>Priority</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urgent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Priority Weightings

<table>
<thead>
<tr>
<th>Priority</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urgent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>0.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Operations that should occur if enough available

<table>
<thead>
<tr>
<th>Priority</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urgent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td>TOTAL</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>=100</td>
</tr>
</tbody>
</table>

SAMPLED OPERATIONS =75

Operations that do occur based on the sampled operations

<table>
<thead>
<tr>
<th>Priority</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urgent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td>(4*75/100)</td>
</tr>
</tbody>
</table>

Table 5.3: Transfer Probability Matrix (probabilities per patient per month)

<table>
<thead>
<tr>
<th></th>
<th>To Priority</th>
<th>To Urgent</th>
<th>To Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Priority</td>
<td>0</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Urgent</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
</tbody>
</table>

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At the time of development (2002/03), Department of Health guidance to NHS Trusts was that no person should be waiting more than six months for an elective heart operation by the end of March 2004. The model was therefore modified so as to estimate the number of extra elective admissions required to meet the target of no patients waiting over six months for an operation. The model would be run the normal way but its operations sample increased by a certain percentage 'x' so more admissions from the waiting list would result.

To optimise the number of operations needed, the model would be re-run with the percentage 'x' being increased by an amount 'y' on each run until no six month waiters would remain by March 2004. This amount 'y' was then halved and the percentage 'x' decreased by 'y'. If there was still no six month waiters, 'y' would be halved and subtracted from 'x' again. This process would be repeated until 'six month waiters' appeared again where upon 'x' would be increased by the amount 'y'. This targeting would continue until 'y' was less than 0.25%.

The purpose of halving 'y' in this way is so that the lowest number of extra operations could be calculated that produced no six month waiters by March 2004. This process is shown in Figure 5.5 below.

Priority Weightings for patients waiting over three months could be adjusted to a User specified figure as this would effect the distribution of those still waiting and the number of operations required to meet the maximum waiting targets.

The targeting was implemented using Visual Basic via Microsoft Excel's Visual Basic editor.
Figure 5.5: Flowchart depicting the targeting process

Run model with increase in operations of ‘x’% →

Any patients waiting six months or more at the end of March 2004?

- Yes: Increase ‘x’% by ‘y’.
- No: Halve ‘y’

Halve ‘y’ →

Is ‘y’ < 0.25%?

- Yes: Stop
- No: Subtract ‘y’ from ‘x’%
5.4 Model Validation

The model was tested to see if it was a realistic predictor of numbers of patients on the waiting list. Figures for the number of patients waiting at the end of April 2002 were entered to see if the general behaviour of the waiting list during that year (April 2002 to March 2003) could be replicated.

To try and get a realistic priority weighting matrix, past data were used to calculate the proportion of patients waiting at the start of each month who were treated in the coming month by priority and length of time on the waiting list. These proportions were calculated for ten of the twelve months in the validation period (waiting list data was unavailable for two of the months). An average of the percentages was taken and this is shown in Table 5.4.

Table 5.4 Average and standard deviation of real data

<table>
<thead>
<tr>
<th>Average Proportion of Patients waiting at start of month treated in month</th>
<th>Months waited</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>4-5</th>
<th>5-6</th>
<th>6-7</th>
<th>7-8</th>
<th>8-9</th>
<th>9-10</th>
<th>10-11</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.06</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urgent</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.06</td>
<td>0.08</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

There was a nine month maximum waiting time target by March 2003 so the priority weightings for patients waiting nine months or more were set to one. This means all patients in these bands are marked for an operation and proportionately more of the sampled operations will be allocated to these waiting bands. Table 5.5 shows the actual priority weightings used.

Table 5.5 Actual Priority Weightings used

<table>
<thead>
<tr>
<th>Actual Priority Weightings Used in Model Validation Run</th>
<th>Months waited</th>
<th>0-1</th>
<th>1-2</th>
<th>2-3</th>
<th>3-4</th>
<th>4-5</th>
<th>5-6</th>
<th>6-7</th>
<th>7-8</th>
<th>8-9</th>
<th>9-10</th>
<th>10-11</th>
<th>11-12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.06</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Priority</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urgent</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The range of data to produce the probability distributions for the operations and waiting list arrivals was restricted to before April 2002. The patient choice places for 2002/03 were also used. These numbered 197.

Figure 5.6 shows the number of patients waiting for cardiothoracic surgery during 2003/2004 as compared to the model's prediction. The bars on the data points show one standard deviation from the average of the twenty runs of the model. Although the model does share the same general trend, it does not drop as quickly as the real data.

Figure 5.7 shows that for numbers waiting over nine months, the model at first predicted a steeper decline though both model and actual ended the year at zero.

Inaccuracies in calculating the priority weightings and using an average priority weighting matrix rather than one that can change over the year contributed to a failure to predict a steeper decline in overall numbers.

Figure 5.6 Actual Waiting List for Cardiothoracic Surgery Apr'02 to Mar'03 compared to Model Prediction.

![Graph showing actual and predicted waiting lists for cardiothoracic surgery with error bars indicating standard deviation.](image-url)
Figure 57. Actual Waiting List for Cardiothoracic Surgery Apr02 to Mar03 compared to Model Prediction: Patients Waiting over Nine Months
5.5 The User Interface

The interface to control the model was developed with managers at the Trust. Their feedback regarding what information they wished to see and what variables they wished to control was gathered from a demonstration of a prototype interface. The present interface is shown in Figure 5.8. Originally it contained the operation priority weightings but these were placed behind one of the buttons shown following feedback from the Users.

Consultants and procedures can be chosen from the drop down menus at the top of the screen. Whenever a new choice is made the model obtains fresh current waiting list information, new probability distributions and information on the trend in waiting lists for that particular combination of consultant and procedure. The model then runs again and generates new output.

Figure 5.8: Top View of model interface
The output is shown in two forms, graphs and a table. The table columns and chart lines are coloured similarly to make matching a particular column of figures to the correct graph easier. Output shows the number waiting over three, six and nine months as these were the planned Government targets for waiting time for heart surgery.

Users of the model can also choose a particular priority to view, can specify the number of private sector patient choice places and also view the actual numbers waiting back to April 2003. The buttons conceal further information and parameters of the model which can only be viewed and/or changed by the entering of a password.

When the model runs, it does so twenty times so that a more accurate ‘average’ is obtained in case one particular run throws up a chance extreme set of figures. The figure of twenty was a trade off between the speed of the model and the production of a more accurate ‘average’. Too high a figure would slow the model down too much, too low and extreme values in a particular run could still persist.

5.6 Further Improvements on the Model

There were two issues that were identified from feedback from Users of the original spreadsheet model. The model was too slow and there was a desire to see Primary Care Trusts (PCTs) added to the model.

The model’s slow response time in predicting the number of extra operations required to meet waiting times targets was raised by Users as a significant limitation. Users could wait up to 15-20 minutes for the model to stop running, a long time to have a working PC slowed down. The model’s slowness was due to the fact that most calculations were being carried out on the spreadsheet itself. The sheer volume of calculations needed to target the activity (which involved running the model several times) meant that the targeting process became very slow (up to thirty minutes).
Several actions were taken to speed up the model (these actions improved the speed of the model by a factor of approximately five, a thirty minute run was cut to 5-6 minutes). Developing the model in Visual Basic code speeded up the model considerably. No longer did the control of the model have to communicate with the spreadsheet many times during the model’s execution. All the data processing was handled within the code leaving the spreadsheet as a data recording device at the end of the run.

The priority weightings were dropped and direct transition probabilities introduced, detailing the exact proportion of patients who were to have operations, leave or still be waiting next month. These probabilities would be adjusted so that the total number of operations did not exceed the sampled figure. Rather than run the model twenty times to achieve an ‘average’ figure, the operations and arrivals distributions were sampled twenty times for each of the twelve month run and averaged. These distributions are the only source of randomness in the model. Rather than calculate the waiting list positions twenty times and average these figures, the model would be run on averaged arrival and operation samples instead so reducing the number of calculations and increasing the speed of the model’s execution. It also meant that the targeting of extra operations could be compared to a baseline run which had the same number of waiting list arrivals in the period.

The targeting method was also changed. The next Government target was the three month maximum wait for elective surgery by March 2005. The target run is based on clearing a set number of waiting patients per month in the higher waiting time bands. This number is calculated according to the number of patients currently waiting more than two months divided by the number of months to achieve the target. Note that this means patients are cleared from the list cumulatively – i.e. if in the first month, twenty are to be cleared then in the second forty will have to be taken out. The number of waiting time bands that figure implies (i.e. that need to be cleared of patients each month) is calculated also based on the number of patients currently waiting. Figure 5.9 clarifies this process.
Figure 5.9. Working out the number of waiting cells to clear each month to reach the three month target

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1 months</td>
<td>72</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-2 months</td>
<td>58</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-3 months</td>
<td>73</td>
<td>48.6%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-4 months</td>
<td>37</td>
<td>95%</td>
<td>100%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>4-5 months</td>
<td>23</td>
<td>89.1%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>5-6 months</td>
<td>17</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Patients to Clear</td>
<td>37.5</td>
<td>75</td>
<td>112.5</td>
<td>150</td>
<td></td>
</tr>
</tbody>
</table>

150 patients waiting more than two months
Four months in which to reach the target
150/4 = 37.5 patients waiting more than two months to be cleared each month (cumulatively)
The cells in the table to the right show the percentage of waiters in each cell that will have to be cleared each month to reach the target

The example in figure 5.9 does not imply that an extra 150 operations will have to be performed. The current waiting list figures are used simply to provide a convenient strategy to gradually reach the waiting times target by March 2005. It does mean concentrating resources towards the longer waiting patients. As the longer waiting patients are cleared, they will not perpetuate in the system so, gradually, the need for more admissions for longer waiting patients diminishes.

To clear the cell entirely, the transition probability to next month’s waiting cell is set to zero and the probability of an operation for that cell is set to

\[ TP_{\text{Operation}} = 1 - TP_{\text{PSPC}} - TP_{\text{Leave List}} \]

where \( TP_{\text{Operation}} \) is the probability of a patient having an operation, \( TP_{\text{PSPC}} \) is the probability that a patient gets a PSPC place (Private Sector Patient Choice) and 200
The number of extra operations required to clear the higher waiting time bands is recorded. The number of extra admissions required is not all that great as the process tends to shift operations away from those waiting under three months to those waiting over three months (i.e. the number waiting under three months rises). A minimum level of operations for those waiting under three months can be set. However, this will increase the number of extra operations needed to achieve the target.

The ability to model by individual Primary Care Trusts (PCTs) was added to the model. PCTs purchase activity from the Trust with different PCTs planning to achieve targets at different rates. The model helped managers estimate the number of extra operations needed to meet waiting time targets for individual PCTs.

The model calculates probability distributions according to data for the individual PCT chosen. The data was obtained through the Hospital’s Patient Administration System. Although this worked reasonably well for the larger PCTs, the validity of the model was questionable when confronted by the small amount of data available for the smaller PCTs. Waiting lists would crash to zero or rise without end because poor data quality or small amounts of unmet demand would have a disproportionate effect on the sampled probability distributions so that waiting list additions and admissions were not matched. This was also a problem for PCT/Consultant combinations.

5.7 Summary

The model can be used to predict the general trend in waiting lists if current trends in additions and operations continue. It can also be used to estimate the number of extra operations required to meet Government waiting times targets. This means the Hospital can plan responses to external shifts in policy. An idea of how many extra operations are required to meet targets and a working model.
to back these estimates up can strengthen the Hospital's hand in negotiations for extra resources to meet those targets.

One of the difficulties with this kind of modelling is the lack of explicitness about the model's structure from the interface. The operation of the model is hidden away amongst the spreadsheet's cells impenetrable to explanation without an expert hand. This can cause problems in communicating the model to managers and clinicians at the Trust. It also means that altering the structure of the model to take account of new ideas is rarely easy, one of the ideas to improve the model is to try and take into account the consultants' sick leave and holiday. However, it proved difficult to disentangle the effects of these on monthly operation rates and incorporate into the model. The model does not take into account seasonal effects.

Feedback played an important role in defining the features of the model, for instance managers asked for the private sector patient choice places to be modelled explicitly so that their effect on the waiting list could be seen more easily.

The model was simplified to improve its speed and transparency. The priority weightings were dropped and transition probabilities to the Operation state calculated from past data.

The aims of this initial model building were met:

- The spreadsheet simulation that was produced uses real data to predict the state of the waiting list of a chosen consultant and/or procedure or the whole cardiothoracic surgery specialty.

- The model can estimate the minimum number of extra operations that will be required to meet waiting time targets.

An interface design was evolved by using feedback from Managers using the model.
The model described in this chapter was used by Hospital Management in the planning of activity for contracts with healthcare commissioners (i.e., Primary Care Trusts) who purchase set number of operations from the trust every year. The level to set this activity very much depended on the desired size of the waiting list and latest maximum waiting time target and output from the model formed a basis for negotiation with the individual Primary Care Trusts. The model's development in Microsoft Excel meant it could easily be integrated with other planning models and documents which were also in spreadsheet form. The model's link to the latest data gave it credibility and a perception developed that it gave 'accurate' predictions.
Chapter 6: The System Dynamics Model

6.1 Introduction

This chapter describes the structure and development of the system dynamics model. It shows the gradual evolution of a quantitative model drawn from a conceptual qualitative model as described in the causal loop diagrams in the following. These qualitative models were produced from the information gathered together in the interview and document analyses described in Chapter 4.

Chapter 5 described the spreadsheet model, developed quickly to give estimates of the extra activity needed to meet waiting time targets and a prediction of future waiting list states if the present elective activity and waiting list addition rates carried on into the future. The spreadsheet model was, however, limited in its scope and did not examine the detail of the patient’s journey of care through the cardiac surgery system.

The next step in the project was to develop a System Dynamics Model that describes the process a patient goes through when undergoing treatment in the cardiac surgery specialty. This model enables users to experiment with more factors affecting the waiting list, for example, bed numbers can be varied, outpatient attendances can be modelled and the effect of catheter rates assessed.

The System Dynamics model describes feedback effects, it describes the effects on one part of the system of events in another e.g. the effect on the outpatient waiting list of the elective operation rate can be seen and experimented with. The System Dynamics model was designed to give information about strategic trends and systemic effects in the care system in response to policy changes or unforeseen events. It was to complement the data model which was to give specific quantitative predictions about waiting lists and times. Waiting lists and times were certainly important performance indicators in the System Dynamics model but were not the only ones.
In Chapter 2, the process for building models was introduced and is shown again here in Figure 6.1 below.

Figure 6.1: Model Building Process (see chapter 2 sect 2.3.3)

- **Problem Perception**
- **Model Formulation**
  - Conceptualise
  - Synthesis
  - Solution
- **Model Identification**
- **Model Validation**
- **Fully Validated Model**

(from Flood and Carson, 1993)

The purpose of this chapter is to describe the model formulation and model identification stages. The next section shows the development of the qualitative model, described by a causal loop diagram, from the sentence description developed at the end of Chapter 4. Section 6.3 shows the mathematical synthesis and solution of this qualitative model and also the identification of the model parameters.

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6.2 The Qualitative model (Causal Loop Diagram)

6.2.1 The Initial Causal Loop Diagram

An initial causal loop diagram was devised to promote discussion with interviewees on their views of the cardiac surgery system. Table 6.1 shows the main resources of the system that were identified at this time and their main states.

Table 6.1 Initial identification of resources and states

<table>
<thead>
<tr>
<th>Resources</th>
<th>Definition of Resource</th>
<th>States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients</td>
<td>People who require medical treatment to maintain their health, in this case an operation</td>
<td>Waiting, Emergency, Elective, Inpatient, Discharge</td>
</tr>
<tr>
<td>Consultant Teams</td>
<td>The group of clinicians required to treat a patient, led by a senior surgeon</td>
<td>Elective Admission Timetabled</td>
</tr>
<tr>
<td>Beds</td>
<td>A place for patients to recover from their treatment.</td>
<td>Occupied, Unoccupied</td>
</tr>
</tbody>
</table>

The aim was to keep the resulting causal loop diagram simple (at least at first) so as not to restrict the interviewee responses. Beds were deliberately not split between Ward beds and Intensive Care beds at this stage.

Figure 6.2 shows the causal loop diagram that resulted.
The diagram indicates that the system's behaviour is influenced by a balancing loop (B) and two reinforcing loops (R). The balancing loop simply means that the number of available beds limits the number of inpatients and the elective admission rate. The two reinforcing loops mean that emergencies occupy beds that otherwise would be taken by elective patients and take up consultant teams' time that would otherwise be spent operating on patients on the waiting list. As a result of this prioritisation of emergencies, patients who are waiting will have to wait longer for an operation, making their condition worse which in turn makes them more likely to become emergency admissions.
6.2.2 Subsequent Causal Loop Diagram

Using the data collected from the interview and document analyses, more resources and states were identified and are listed in Table 6.2

Table 6.2 Subsequent Resources and States Identified

<table>
<thead>
<tr>
<th>Resources</th>
<th>Definition</th>
<th>States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients</td>
<td>People who require medical treatment to maintain their health, in this case an operation</td>
<td>Waiting, Inpatients, New Surgery Outpatients, Emergency Admissions, Elective Cancellations, 28 day Breaches, GP Referrals, Cardiac Catheters, Bed Blockers</td>
</tr>
<tr>
<td>Consultant Teams</td>
<td>The group of clinicians required to treat a patient, led by a senior surgeon</td>
<td>Elective Admission timetabled</td>
</tr>
<tr>
<td>CICU Beds</td>
<td>A Cardiac Intensive Care Unit (CICU) bed is a place for patients to recover from their treatment usually immediately after an operation when they are weakest. There is therefore a high ratio of doctors and specialist nurses for every patient</td>
<td>Unoccupied, Occupied</td>
</tr>
<tr>
<td>Ward Beds</td>
<td>A ward bed is less intensively staffed than a CICU bed. A patient will go to a ward bed when they are stronger, usually after spending some time in a CICU bed</td>
<td>Unoccupied, Occupied</td>
</tr>
<tr>
<td>Theatre Staff</td>
<td>Staff involved in providing care to patients during operations e.g. specialist theatre nurses etc</td>
<td>Unavailable for Elective Admission</td>
</tr>
</tbody>
</table>

The Interview and Document analyses provided more detail on the states of resources and their interaction together, for example, the role 28 day breaches could play in causing further blockages to elective admissions and the way emergency admissions could take up several resources needed to admit an elective patient. These interactions were identified and put together to form a causal loop diagram. Some experimentation was needed to do this as well as
informal feedback from the interviewees. Figure 6.3 shows the resulting causal loop diagram.

Figure 6.3 Causal Loop Diagram version 2

Notice the split of bed types. Patients are transferred to a Cardiac Intensive Care Unit (CICU) bed after being operated on. They will stay usually for a day or two and are then transferred to the ward. Patients who have their elective operations cancelled because of problems with hospital resources (e.g., emergency admissions take up their operating slot and CICU bed) must have their operations re-scheduled within 28 days. If, when these patients are readmitted, their operation is again blocked they are kept on the ward until the next available
slot anses. This occupancy of a ward bed can act as a potential block to other patients being admitted.

The number of beds, staff numbers and emergency admissions puts a limit on the elective operation rate while the waiting list addition rate is limited by the number of new outpatients seen in clinic. The rate at which new outpatients are seen is dependent on information about the outpatient and inpatient waiting lists. A rise in the number waiting for an outpatient appointment will tend to increase the rate at which they are seen, a rise in the number of inpatients waiting will tend to decrease the rate new outpatients are seen.

Figure 6.3 also shows the modelling of other staff types, not just Consultant teams and explicitly models maximum waiting time.

Bed blockers mentioned in figure 6.3 relate to patients stuck on the wards who are medically fit to be discharged but who may need other low level nursing care, e.g. a place in a nursing or residential home, and so cannot be discharged until a place is found.

Figure 6.3 can be used to make some rough predictions of the behaviour of the system to some change or event. For example, an increase in the Cardiac Catheter rate will tend to increase emergency surgery cases and the outpatient waiting list. An increase in emergencies will, in turn, limit resources for elective admissions and could see the waiting list rise. A rise in the outpatient waiting list will eventually see a rise in new outpatient appointments to compensate and so an increase in patients being added to the waiting list.

6.3 The Quantitative Model (Stock & Flow Diagram)

Figures 6.4a and 6.4b shows the stock and flow diagram constructed from the qualitative models above. Figure 6.4a shows the resource structure of the system (the levels, rates and resource flows) while figure 6.4b not only shows the
resource structure of the system but also the information structure superimposed on top (the auxiliary variables and information links)

Figure 6.4b show only Consultant 1’s sessions scheduled. The full model has all seven consultants.

Figure 6.4a shows the main resources of the system. These include Patients, CICU beds, Ward beds and Theatre Staff. The other major resource, Consultants’ Time, is not shown in this diagram as it is modelled using auxiliary variables. It can be found in figure 6.4b. Only one of seven variables representing Consultant Sessions is shown in figure 6.4b, however these variables control the timing of a patient’s move from the waiting list to being an elective admission. Timing is crucial throughout the model, for example, Outpatient clinics occur on certain days or the elective operation rate is only evaluated at certain times of day enabling the cancellation rate to be calculated later on in the day.

Resources are linked by various feedback paths, for instance, the elective operation rate is limited partly by the availability of CICU beds. In turn CICU discharges depends on the Elective Operation Rate (i.e. admissions to CICU), the Length of Stay function (see section 6.3.5 on discharges) as well as available beds on the ward.

There are six areas to the model in figures 6.4a and 6.4b. They are listed in Table 6.3, each will be dealt with in turn.

<table>
<thead>
<tr>
<th>Table 6.3 Areas of the Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Area</td>
</tr>
<tr>
<td>TIME variables</td>
</tr>
<tr>
<td>Consultant Sessions</td>
</tr>
<tr>
<td>Theatre Staff</td>
</tr>
<tr>
<td>CICU Beds</td>
</tr>
<tr>
<td>Ward Beds</td>
</tr>
<tr>
<td>Patients</td>
</tr>
<tr>
<td>Discharges</td>
</tr>
</tbody>
</table>
Figure 6.4a. Stock and Flow Diagram of Cardiothoracic Surgery Department (Resource Structure)

**Theatre Staff**

**TIME Variables**

**Discharges**

**CICU Beds**

**Ward Beds**

**Patients**

**Key**

- Level
- Rate
- Auxiliary Variable
- Resource flow
- Information Link

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Figure 6.4b Stock and Flow Diagram of Cardiothoracic Surgery Department (including Information Structure) NB Only one of the seven "Consultant Sessions" variables is shown to improve clarity of the diagram.
6.3.1 The TIME variables

Figure 6.5 shows the section of the model that defines the time variables used. Consideration has to be given to what time scales to use when simulating the model. Elective operations are scheduled on week days in office hours and consultants are given sessions in an operating theatre (see Table 6.4).
Table 6.4 Consultants’ Scheduled Operating Sessions

<table>
<thead>
<tr>
<th>Consultant Number</th>
<th>Theatre 1</th>
<th>Theatre 2</th>
<th>Theatre 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday AM</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Monday PM</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Tuesday AM</td>
<td>1</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Tuesday PM</td>
<td>1</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Wednesday AM</td>
<td>1</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Wednesday PM</td>
<td>1</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Thursday AM</td>
<td>4</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Thursday PM</td>
<td>4</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Friday AM</td>
<td>4</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Friday PM</td>
<td>7</td>
<td>6</td>
<td>2</td>
</tr>
</tbody>
</table>

Sessions can either be in the morning or afternoon so splitting the day into four parts (“TIME OF DAY”, see Table 6.5) with operations being performed in two of them and scheduled in another seems reasonable. As weekdays have to be modelled, another variable (“REALDAY”, see Table 6.6) is used to represent the day of the week. “NEXTDAY” is simply “REALDAY” + 1 so that operations can be scheduled.

Table 6.5: “TIME OF DAY” Periods

<table>
<thead>
<tr>
<th>Value</th>
<th>Period of Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>8AM – 2PM</td>
</tr>
<tr>
<td>1</td>
<td>2PM – 8PM</td>
</tr>
<tr>
<td>2</td>
<td>8PM – 2AM</td>
</tr>
<tr>
<td>3</td>
<td>2AM – 8AM</td>
</tr>
</tbody>
</table>

Splitting the day into four sessions means that the effects of emergencies (which can happen at any time) and the effect of scheduling elective operations during non-office hours can be modelled.
Table 6.6 "REALDAY"

<table>
<thead>
<tr>
<th>Value</th>
<th>Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Monday</td>
</tr>
<tr>
<td>2</td>
<td>Tuesday</td>
</tr>
<tr>
<td>3</td>
<td>Wednesday</td>
</tr>
<tr>
<td>4</td>
<td>Thursday</td>
</tr>
<tr>
<td>5</td>
<td>Friday</td>
</tr>
<tr>
<td>6</td>
<td>Saturday</td>
</tr>
<tr>
<td>7</td>
<td>Sunday</td>
</tr>
</tbody>
</table>

6.3.2 Consultant Sessions

"Consultant 1 sessions next day" uses the logic of Table 6.4 to work out the number of sessions scheduled for Consultant 1 the following day (i.e., based on the variable "NEXTDAY"). The sessions are scheduled at "TIME OF DAY" = 3 (2AM-8AM) just before the day they take place so as any elective operations do not take place before their apportioned day.

"Consultant 1 sessions next day" works out the number of scheduled operations for this consultant the next day and it is this variable that is sampled by the...
"ScheduleRate" (that takes patients off the waiting list) It is assumed a consultant will do one operation per quarter day session

The full model has seven of these variables, one for each consultant team

6.3.3 Theatre Staff

Figure 6.7: Section of model defining Theatre Staff

If an emergency comes through outside of office hours then a theatre team will have to be brought together to deal with it. If the staff involved are on duty for the following day's elective schedule and do not have enough time to recover then a team will have to be brought together for the elective operations. There is a chance this will not happen and the elective operation may be cancelled.
6.3.4 CICU (Cardiac Intensive Care Unit) and Ward Beds

Figure 6.8. CICU and Ward Beds Section

Figure 6.8 shows the section of the model representing beds. Both CICU beds and ward beds can either be occupied by a patient or empty. The 'CICU Occupation Rate' variable depends on the total number of operations being carried out and the discharge rate from CICU to the wards. The total number of operations, in turn, depends on the number of unoccupied CICU beds that are in existence. This effectively limits the two CICU bed states to be greater than or equal to zero and limits the total of the two states to equal the specified total number of CICU beds.

Discharges from both CICU and the wards are modelled by separate levels and are described in the next section.
The 'Ward Occupation Rate’ depends on the number of discharges from CICU (Effectively the number of occupations of a ward bed) and the number of discharges from the ward. As the number of discharges from CICU depends on the number of Unoccupied Ward beds, this also limits the two Ward bed states to be greater than or equal to zero and limits their sum to equal the specified number of ward beds.

6.3.5 Discharges

It was decided to model discharges from the CICU and the wards as a separate flow so as much control as possible is obtained over the modelling of this critical step in resource use. It can then be made as accurate as possible. Figure 6.9 shows the stock and flow diagram for CICU and ward discharges.

Discharges are modelled as delayed admission signals. To mimic this delay, the elective and emergency operation rates are delayed before being used as an input rate to the ‘Discharges’ level.

The delay times used are different as emergency patients will tend to stay longer in CICU. Once the ‘Discharges’ level is greater than one, the auxiliary variable ‘CICU Discharges Potential’ becomes equal to the integer value of ‘Discharges’. If there are ward beds available, the ‘Actual Number of CICU Discharges’ becomes equal to ‘CICU Discharges Potential’ and the discharge proceeds, causing the ‘CICU Go Rate’ to drain the ‘Discharge’ level.

The delay times are modelled from the observed Length of Stay distributions for Elective patients in CICU (variable “ElectiveLookup”), emergency patients in CICU (variable “EmergencyLookup”) and patients in the wards (variable “WardLookup”). The length of stay is generated using a random variable to ‘look up’ a value in these ‘lookup’ variables. This length of stay becomes the delay in the discharge level.
As can be seen in Figures 6.8 and 6.9, there is a path of auxiliary variables from 'Actual Number CICU Discharges' to 'Ward Setup Rate' that puts a delay into ward admissions so modelling discharges from the ward.
Figure 6.10 Section of model defining Patients in the Cardiothoracic Surgery System (NB TIME variables have been removed to improve visual clarity of diagram)

Figure 6.10 shows the "Resource Flow" of patients in the model. Many patients will be referred to the cardiothoracic surgeons after having a diagnostic catheter under a cardiologist and will enter the Outpatient waiting list. After being seen in outpatients a certain proportion will be referred on to the inpatient waiting list.
Whilst waiting there is a chance a patient's condition will deteriorate and they will be admitted as an emergency sooner than they would have been as an elective patient. Emergency admission also come from 'Blue Form' patients admitted directly from the catheter lab or from an external source like another specialty or hospital.

The "ScheduleRate" variable controls the entry from the waiting list to hospital. The rate simply adds up all the consultants' scheduled operations.

The "Elective Operation Rate" variable takes patients from the scheduled state to the operation state. It takes half of the scheduled elective admissions at "TIME OF DAY" = 0 (the morning session) and the rest of the scheduled admissions at "TIME OF DAY" = 1 (the afternoon session); unless there is an emergency that takes priority, or there are not enough empty CICU beds, or there is no theatre team available because of an emergency occurring outside of the usual working hours. Any scheduled elective admissions left are withdrawn back into the waiting list state by "CancellationRate" at "TIME OF DAY" = 2. Figure 6 11 shows the logic for this process.

Emergency admissions will have priority over elective admissions. The only issue that will prevent an emergency admission is a lack of CICU beds. If this occurs, the emergency admission waits until a bed becomes available.
Figure 6.11: Calculating the Elective Operation Rate (Flowchart)

Key
- EOR = Elective Operation Rate
- CBU = CICU Beds Unoccupied
- TTU = Theatre Teams Unavailable
- Emerg = Emergency Admissions
- EAS = Elective Admissions Scheduled for next day

Notes
- * i.e. Emergency Admissions take up theatre space
- ** check to see if there is enough capacity for scheduled elective admissions
- *** check for emergency admissions as they have priority (and only three theatres)
6.4 Model Identification

This section discusses the process of the identification of the model's parameters, i.e., what external variables in the model control its behaviour and how to evaluate them from information held about the real system. The first step was to go through the model's variables and pull out those that were externally evaluated (not calculated through the model's behaviour). This could prove quite difficult, some constants would be burned inside a formula and a careful process of sifting through each formula ensued.

Table 6.7 below lists the model's parameters identified in this way.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Location *</th>
<th>Section</th>
<th>Current Value</th>
<th>How estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chance Team</td>
<td>Theatre Staff</td>
<td>0.01</td>
<td>Assumed</td>
<td></td>
</tr>
<tr>
<td>Unavailable for next Elective Session</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total CICU Beds</td>
<td>CICU Beds</td>
<td>14</td>
<td>Not estimated Physical number of beds in CICU</td>
<td></td>
</tr>
<tr>
<td>Total Ward Beds</td>
<td>Ward Beds</td>
<td>40</td>
<td>Not estimated Physical number of beds on wards</td>
<td></td>
</tr>
<tr>
<td>Length of Stay in CICU distribution of emergency patients</td>
<td>EmergencyLookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length of Stay in CICU distribution of elective patients</td>
<td>ElectiveLookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length of Stay distribution for Ward patients</td>
<td>WardLookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assumed number of operations a consultant team can perform in one quarter day session</td>
<td>Consultant [1-7] sessions next day</td>
<td>Consultant Sessions</td>
<td>1</td>
<td>Assumed</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scheduled operating sessions for each consultant team in theatre</td>
<td>Consultant [1-7] sessions next day</td>
<td>Consultant Sessions</td>
<td>N/A</td>
<td>From Timetable</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CatheterRate</td>
<td>Patients</td>
<td>See section 6.4.3</td>
<td>Assembled from Catheter dataset</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blue Form Referrals</td>
<td>Blue Form</td>
<td>Patients</td>
<td>See</td>
<td>Assembled from</td>
</tr>
<tr>
<td>Variable</td>
<td>section</td>
<td>Inpatient Episode dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------------------------------------------------</td>
<td>---------</td>
<td>----------------------------------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OPDSurgeryConversionFactor</td>
<td>Patients See section 6 4 4</td>
<td>Assembled from Outpatient Referrals Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other Referrals to Cardiac Surgery outpatients</td>
<td>OtherReferrers Patients See Section 6 4 6</td>
<td>Assembled from Outpatient Referrals Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Outpatient Appointments</td>
<td>NewOPSeenRate Patients See Section 6 4 7</td>
<td>Assembled from New Outpatient Attendances Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DNA Constant</td>
<td>Patients 0 05</td>
<td>Taken from an information report, &quot;Cardio-Respiratory DNA Report 0405&quot;, on DNA rates in the Cardio respiratory directorate during the 2004/05 financial year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConversionFactor (from Outpatients to Waiting List)</td>
<td>Patients See section 6 4 8</td>
<td>Assembled from new Outpatient Attendances Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%LeaveList Per Week</td>
<td>Patients 0 53%</td>
<td>Calculated from Waiting List cancellations Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Probability of External Emergency</td>
<td>Patients Vanous depending on Time of day and RealDay</td>
<td>Assembled from Inpatient Episode dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Threshold for normal distribution for Waiting List Emergency</td>
<td>Waiting List To Emergency Rate Patients 2 4</td>
<td>Calculated from Waiting List cancellations Dataset</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* If blank then Parameter is Rate/Auxiliary in own right

Some parameters have been estimated from data obtained from the real system. In other cases parameters have had to be estimated by the modellers from "best guesses"
6.4.1 "Chance Team Unavailable for next Elective Session"

No data was available to estimate this parameter. Interviewees were also unable to suggest a figure for the number of cancelled operations that occurred due to staff unavailability. It was decided to settle on a figure of one a month for the initial validation, leaving the possibility of further adjustment.

6.4.2 Length of Stay Distributions

Length of stay distributions were generated from the Patient Administration System for the Cardiac Intensive Care Unit (split into elective and emergency) and the Cardiac Surgery wards.

The distributions were generated from a ward stays dataset which included all stays on CICU and the Cardiac Surgery wards between January 2003 and February 2005.

Appendix 5 shows tabulated figures for the length of stay of patients in the CICU and the Cardiac Surgery wards.

Figures 6.12 and 6.13 shows the length of stay distributions for Elective and Emergency patients in CICU. The distributions are both cut off at twenty days. As can be seen from the figures the lengths of stay of emergency patients are further spread out than the elective patients. This is because they tend to be sicker than the elective patients.

Figure 6.14 shows the cumulative probability function used in the model for Elective and Emergency Lengths of Stay on CICU.
Figure 6.12  Elective Patients in CICU Length of Stay Distribution

Figure 6.13: Emergency Patients in CICU Length of Stay Distribution
The Length of Stay distribution on the ward is shown in Figure 6.15 below.

Figure 6.15: Length of Stay Distribution for Cardiac Surgery Wards Jan 2003 to Feb 2005
Figure 6.16 shows the cumulative probability function used in the model of lengths of stay on the cardiac surgery wards.

Figure 6.16 Cumulative Probability Distributions of Length of Stay in Cardiac Surgery Wards Jan 2003 to Feb 2005

6.4.3 "CatheterRate"

The Catheter rate was estimated from a dataset giving daily counts of catheters performed between 1st April 2003 and 31st March 2005. Distributions were estimated for each day of the week as there was considerable daily variability especially between weekdays and weekends.

The Catheter rate distributions were fitted to various Poisson and Normal distributions using the Chi-Squared test. More information on the Chi-Squared
test and the detailed figures of the statistical fitting is given in Appendix 6. Table 6.8 below gives a summary of the results contained in the Appendix.

Table 6.8. Fitted Parameters for Catheter Rate

<table>
<thead>
<tr>
<th>Day Of Week</th>
<th>Distribution</th>
<th>Mean (Variance)</th>
<th>Test Chi Squared Stat</th>
<th>Degrees of Freedom</th>
<th>Tabulated Chi-Squared at 0.05 Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>Normal</td>
<td>12.6 (4.9)</td>
<td>18.02</td>
<td>7</td>
<td>14.07</td>
</tr>
<tr>
<td>Tuesday</td>
<td>Normal</td>
<td>15.8 (5.1)</td>
<td>11.86</td>
<td>7</td>
<td>14.07</td>
</tr>
<tr>
<td>Wednesday</td>
<td>Normal</td>
<td>19.0 (5.6)</td>
<td>8.81</td>
<td>7</td>
<td>14.07</td>
</tr>
<tr>
<td>Thursday</td>
<td>Normal</td>
<td>16.3 (4.3)</td>
<td>13.95</td>
<td>7</td>
<td>14.07</td>
</tr>
<tr>
<td>Friday</td>
<td>Normal</td>
<td>10.4 (3.7)</td>
<td>2.15</td>
<td>7</td>
<td>14.07</td>
</tr>
<tr>
<td>Saturday</td>
<td>Poisson</td>
<td>3.9</td>
<td>6.13</td>
<td>5</td>
<td>11.07</td>
</tr>
<tr>
<td>Sunday</td>
<td>Poisson</td>
<td>2.1</td>
<td>16.74</td>
<td>4</td>
<td>9.49</td>
</tr>
</tbody>
</table>

As Table 6.8 shows, Sunday and Monday could not be fitted to a distribution. The model uses a 'Look up' variable instead containing the observed distribution.

Saturday is fitted to a Poisson distribution as emergencies only are seen on the weekend and so will occur randomly.

Tuesday to Friday are fitted to normal distributions as mostly planned elective work is performed on these days and so there will only be random variation around the scheduled number of catheters for each day. These days tend to have a poorer fit at the smaller end of the distribution. One reason could be the cardiology consultants going on Annual or Sickness Leave so that only Emergencies will be performed meaning a slightly skewed distribution at the lower end.

6.4.4 Blue Form Referrals

The Hospital PAS was queried to find out the dates of admission to the cardiothoracic surgery specialty of patients who have an episode in cardiology before being transferred to cardiothoracic surgery. These, it was assumed, had come through a diagnostic catheter beforehand.
The frequency distribution of the number of daily admissions is shown in figure 6.17.

Figure 6.17 Observed Frequency of Emergency Admissions to Cardiothoracic Surgery from Cardiology April 2003 to March 2005

This matches a Poisson distribution with mean of 1.41 reasonably well, further details can be found in Appendix 7. A Poisson distribution with a mean of 1.41 was used in the model.

6.4.5 "OPDSurgeryConversionFactor" (% Catheter patients go on to Surgery Outpatients)

"OPDSurgeryConversionFactor" represents the percentage of catheter patients who are referred to the Cardiac Surgery outpatients as a result. The parameters in this and the next section were estimated from an Outpatient Referrals dataset consisting of Referral date, patient count and Referral Source. Referral Source was split between "Consultant-this Trust" and "Other". Most of
the former referral source will be from cardiologists referring patients to surgery after a catheter. The dataset was made up of referrals to cardiac surgery outpatients between 7th January 2002 and 23rd September 2004

The catheter dataset was also used to estimate the “OPDSurgeryConversionFactor” parameter. The referral date and date of the catheter procedure were matched and the number of referrals was divided by the number of catheters performed that day to produce a percentage referred to outpatients. These daily percentages were turned into a frequency distribution which was used in the model to produce a daily percentage of catheters referred to the Cardiac surgery outpatients department. This distribution can be seen in figure 6.18 below

Figure 6.18: Frequency Distribution of the Percentage of Daily Catheters referred to the Cardiac Surgery Outpatients
6.4.6 Other Surgery Outpatient Referrals

This parameter was also estimated from the dataset mentioned in the last section. The observed frequency distribution was used in the model and this can be found in Appendix 8.

6.4.7 New Outpatient Appointments ("NewOPSeenRate")

The number of new outpatient appointments is calculated according to the numbers on the outpatient waiting list and the clearance time of the present number on the inpatient waiting list. This is done to control both inpatient and outpatient waiting lists from either crashing to zero or spiralling to infinity.

Figure 6.19 shows the variables that control the new outpatient appointment rate.

Figure 6.19  Network of Auxiliary Variables used to Control New Outpatient Appointments

```
WeeksToClear

WeeksToClear' is the number of weeks to clear the present inpatient waiting list and is calculated once a week by dividing the inpatient waiting list by the number of operations in a week. 'TargetWeeklyClear' is the maximum waiting time target for surgery. 'WaitingListInfluenceOnOPs' then delivers a factor to be used in the calculation of the new outpatient attendances rate based on the difference between the target and the number of weeks to clear the present inpatient list.

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‘WaitingListInfluenceOnOPs’ is finally combined with the outpatient waiting list to generate a final figure for the new outpatient attendances. This is rather a crude way of generating a control in the model and it will be validated in the next chapter through a statistical comparison with observed data.

6.4.8 Conversion Factor (from Outpatients to Waiting List)

The outcome of a new outpatient appointment is recorded and two of those outcomes are “Add to the Inpatient Waiting List” and “Add to the Daycase Waiting List”. The database was queried for these two codes and the number of these as a percentage of the total number of new outpatient appointments generated a monthly conversion to the waiting list rate (for the period January 2002 to September 2004). This was made into a frequency distribution and used to generate a daily conversion rate. This distribution is shown in Figure 6.20 below.

Figure 6.20 Conversion Rate Distribution of New Outpatients to the Inpatient Waiting List
**6.4.9 Percentage Leaving the Inpatient Waiting List Per Week**

The monthly number of waiting list removals (except for removals due to emergency admission) was measured as a percentage of the waiting list at the start of the month. The data ranged from April 2000 to March 2002. The average of these figures was 2.4% i.e. about 2.4% of the list will leave for reasons other than an admission during the month. The model calculates leavers once a week so this parameter is set to 0.53% (2.4/4.5 weeks in a month) of the list leaving per week.

**6.4.10 Probability of External Emergency**

This probability controls the number of non-blue referral emergency surgery patients coming into the system. The number of such ‘external’ emergencies was calculated by Day of Week and Time of Day of admission for the period from 1st January 2001 to 31st July 2004 and is shown in Table 6.9 below.

Table 6.9: External Emergencies Cardiothoracic Surgery 1/1/2001 to 31/7/2004 by Day of Week and Time of Day of Admission

<table>
<thead>
<tr>
<th>Day of Week</th>
<th>Time of Day (see Table 6.5)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sunday (1)</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Monday (2)</td>
<td>13</td>
<td>23</td>
<td>11</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Tuesday (3)</td>
<td>44</td>
<td>42</td>
<td>21</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Wednesday (4)</td>
<td>50</td>
<td>40</td>
<td>36</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Thursday (5)</td>
<td>48</td>
<td>46</td>
<td>37</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Friday (6)</td>
<td>50</td>
<td>62</td>
<td>39</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Saturday (7)</td>
<td>18</td>
<td>21</td>
<td>17</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

The period the dataset was taken across is 186 weeks so the figures above were divided by 186 to get the probability of an emergency occurring during that particular time slice. This delivers the figures in Table 6.10.
Table 6.10 Probability of External Emergencies Cardiothoracic Surgery 1/1/2001 to 31/7/2004 by Day of Week and Time of Day of Admission

<table>
<thead>
<tr>
<th>Day of Week</th>
<th>Time of Day (see Table 6.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Sunday (1)</td>
<td>0.070</td>
</tr>
<tr>
<td>Monday (2)</td>
<td>0.231</td>
</tr>
<tr>
<td>Tuesday (3)</td>
<td>0.237</td>
</tr>
<tr>
<td>Wednesday (4)</td>
<td>0.269</td>
</tr>
<tr>
<td>Thursday (5)</td>
<td>0.258</td>
</tr>
<tr>
<td>Friday (6)</td>
<td>0.269</td>
</tr>
<tr>
<td>Saturday (7)</td>
<td>0.097</td>
</tr>
</tbody>
</table>

These probabilities are roughly constant across weekdays and weekends, the only variability coming through the time of day. The model therefore uses averaged figures across the days as shown in Table 6.11.

Table 6.11 Averaged Probabilities used in Model

<table>
<thead>
<tr>
<th>Day of Week</th>
<th>Time of Day (see Table 6.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Weekends</td>
<td>0.083</td>
</tr>
<tr>
<td>(Days 1 and 7)</td>
<td></td>
</tr>
<tr>
<td>Weekdays</td>
<td>0.253</td>
</tr>
<tr>
<td>(Days 2 to 6)</td>
<td></td>
</tr>
</tbody>
</table>

6.4.11 Elective Patients admitted as Emergencies

Between January 2000 and December 2004, 63 patients were cancelled from the elective waiting list in cardiothoracic surgery because they were admitted as emergencies. This makes an average of about thirteen a year. The model uses random numbers generated with a normal distribution to generate an emergency from the waiting list. If the number is greater than some threshold then an emergency is generated. The threshold was varied and the model run until the number of emergencies averaged about thirteen. This threshold came to be set in this way at 2.4.
6.5 Initial Validation

Some initial validation of the model was undertaken to make sure it made basic, logical sense, i.e. there were no inconsistencies internally in the model, all patients made it through the system, the total number of unoccupied beds never fell below zero etc.

The graph of scheduled elective operations is shown below in Figure 6.21.

Figure 6.21: Scheduled Elective Operations

The elective schedule shows that six operations are being scheduled before each weekday. Three operating theatres are running two sessions a day and, for the moment, it is assumed that one operation can be performed in one session. This makes $3 \times 2 \times 1 = 6$ operations scheduled for each of the five weekdays and this is borne out in the graph of figure 6.20.

Without any emergencies or a limit to CICU or Ward beds, the elective operation rate would be three operations per quarter day (for two quarter days) per weekday. The model was run under the assumption of a limitless supply of beds
and no emergencies. Figure 6.22 shows the resulting elective operations rate confirming the predicted behaviour.

Figure 6.22: Elective Operation Rate with No Emergencies and Unlimited Beds

Limiting the number of beds and introducing emergencies should limit the elective operation rate. The total number of CICU beds and ward beds were reset to fourteen and forty respectively and the model re-run. Figure 6.23 shows the results.

The limit to the number of beds and emergencies are indeed limiting the elective operation rate as expected. Whether the limit is as severe as shown in figure 6.23 depends on the number of discharges from CICU and the wards.
Figure 6.23: Elective Operation Rate with Emergencies and limited Beds

![Elective Operation Rate](image)

Figure 6.24 shows the surgery waiting list under the assumptions of no emergencies and no additions to the list. Unsurprisingly, even with limited beds the size of the list falls quickly.

Figure 6.24: Surgery Waiting List with no emergencies, no additions to list and limited beds

![Surgery Waiting List](image)
Figure 6.24 shows the model has a dominant linear component, pushing the surgery waiting list downwards with a weekly, cyclical component superimposed on top.

Table 6.8 shows the results of an internal check on the model's logic (taken with emergencies and additions to list reinstated to the model). The waiting list at the end of the period should equal the waiting list at the start of the period minus the number of elective operations and patients who leave the list plus the number of patients added to the list during the period. Equation 6.1 shows this logic.

Equation 6.1: End Period Waiting List

Calculated End = Initial - Elective - Leavers + Additions to Waiting List Waiting List Operations from List List

As can be seen in Table 6.12 the model is internally consistent, the calculated waiting list (using equation 6.1) is the same as the model's own calculation.

Table 6.12: Internal Model Logic

<table>
<thead>
<tr>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Waiting List</td>
</tr>
<tr>
<td>Elective Operations</td>
</tr>
<tr>
<td>Leavers from List</td>
</tr>
<tr>
<td>Additions to List</td>
</tr>
<tr>
<td>Calculated End Waiting List</td>
</tr>
<tr>
<td>(from above figures)</td>
</tr>
<tr>
<td>Model End Waiting List</td>
</tr>
</tbody>
</table>
Checking bed occupancy however, a problem is apparent. Figure 6.25 shows Unoccupied CICU Beds during the simulation.

Figure 6.25: Unoccupied CICU Beds

![Unoccupied CICU Beds]

All of the CICU beds are unlikely to be empty at one time. The unoccupied CICU beds also seems to be oscillating. The problem is caused by the method of modelling discharges. The signal reaching the discharge section usually consists of patients grouped into twos and threes. These patients are then being given the same delay time, i.e. the same Length of Stay, unlikely to occur in practice. This means the group is transferring to the ward and eventually being discharged at the same times leading to sudden drops and rises in bed occupancy during weekdays which can be seen in Figure 6.16.

This problem is dealt with in the next chapter.
6.6 Summary

An initial qualitative model was constructed which describes an overview of the system.

Using the interview and document analyses, a second qualitative model was produced and converted into a quantitative system dynamics model.

A process of model identification was undertaken. The model’s parameters were identified and estimated from various sources, though mainly the hospital’s PAS system. It is important to be as accurate as possible when estimating the parameter’s values or probability distributions. Incorrect parameters will lead to incorrect output and predictions from the model and possibly lead to incorrect decisions being taken. This would obviously dent confidence in any model produced and lead to its revision or abandonment. Revising incorrect parameters would lead to issues of validation. Model comparisons with the reference model would have to be re-visited and the validation process done again with stakeholders to renew their confidence in the model. Some stakeholders were disappointed at a lack of a link to live data in the System Dynamics model compared to the data model described in chapter 5, thinking it might lead to less accurate predictions over time. However, since this model is looking at trends and systemic effects rather than exact predictions this should not be a problem if the model is kept reasonably up-to-date on a regular basis.

First steps were taken to validate this model’s behaviour, and a problem with bed occupancy identified. This problem is dealt with in the next chapter on Model Validation.
Chapter 7: Model Validation

7.1 Introduction

This chapter describes validation tests carried out on the system dynamics model. The purpose of these tests was to ensure that the model captures the real world system's structure and behaviour to an accurate degree. This will then give confidence that any output of the model is accurate and can be relied on to make good predictions about the behaviour of the real life system to various different policies that could be applied.

The tests followed those suggested by Wolstenholme (1990) and Sterman (1984) which were referred to in Chapter 2 and are reproduced in Table 7.1 below. As can be seen they are split into three sections: 'Tests of Model Structure' tries to verify that the parts of the real world system needed to provide a solution to the problem perception are accurately recorded and represented in the model. 'Tests of Model behaviour' deal with the model's ability to reproduce the real system's response to certain inputs and try to predict responses not recognised before in the real system. 'Tests of Model Policy' relate to the model's prediction of the results of new policies that may be pursued in the real system.

The tests below involve varying structure or parameters of the model to compare the output of the model to a reference mode. The reference mode is the values of a set of variables that describe a real system's state over a period of time. The model outputs used to compare the tests to the reference mode are the number of elective admissions, the number of emergency admissions, the elective surgical waiting list, CICU and ward bed occupancy and the maximum waiting time of those still on the inpatient waiting list (evaluated weekly).

Figures 7.1 – 7.5, below, show the reference mode for the above outputs.
<table>
<thead>
<tr>
<th><strong>Test of model structure</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure Verification</td>
<td>Is the model structure consistent with knowledge of the system?</td>
</tr>
<tr>
<td>Parameter Verification</td>
<td>Are the parameters consistent with knowledge of the system?</td>
</tr>
<tr>
<td>Extreme Conditions</td>
<td>Does each equation make sense when its inputs take on extreme values?</td>
</tr>
<tr>
<td>Boundary Adequacy (Structure)</td>
<td>Are the important concepts for addressing the problem included within the model?</td>
</tr>
<tr>
<td>Dimensional Consistency</td>
<td>Is each equation dimensionally consistent?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Test of model behaviour</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Behaviour Reproduction</td>
<td>Does the model generate the symptoms and behaviour modes of the real system?</td>
</tr>
<tr>
<td>Behaviour Anomaly</td>
<td>Does anomalous behaviours arise if an assumption of the model is deleted?</td>
</tr>
<tr>
<td>Family Member</td>
<td>Can the model reproduce the behaviour of other examples of systems in the same class as the model?</td>
</tr>
<tr>
<td>Surprise Behaviour</td>
<td>Does the model point to the existence of a previously unrecognised mode of behaviour of the real system?</td>
</tr>
<tr>
<td>Extreme Policy</td>
<td>Does the model behave properly when subjected to extreme policies or test inputs?</td>
</tr>
<tr>
<td>Boundary Adequacy (Behaviour)</td>
<td>Is the behaviour of the model sensitive to the addition or alteration of structure to represent plausible alternatives?</td>
</tr>
<tr>
<td>Behaviour Sensitivity</td>
<td>Is the behaviour of the model sensitive to plausible variations in parameters?</td>
</tr>
<tr>
<td>Statistical Character</td>
<td>Does the output of the model have the same statistical character as the 'output' of the real system?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Test of policy implications</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>System Improvement</td>
<td>Is the performance of the real system improved through use of the model?</td>
</tr>
<tr>
<td>Behaviour Prediction</td>
<td>Does the model correctly describe the results of a new policy?</td>
</tr>
<tr>
<td>Boundary Adequacy (Policy)</td>
<td>Are the policy recommendations sensitive to the addition or alteration of structure to represent plausible alternative theories?</td>
</tr>
<tr>
<td>Policy Sensitivity</td>
<td>Are the policy recommendations sensitive to plausible variations in parameters?</td>
</tr>
</tbody>
</table>
2003 to March 2005

Figure 7: Reference mode data for the number on the elective surgical waiting list from April-

Figure 7: Reference mode data for the number of weekly admissions to the cardiology surgery-

Figure 7: Reference mode data for the number of weekly admissions to the cardiology surgery-
Figure 7.4: Reference mode data for the number of occupied Ward beds in the cardiac surgery.

Figure 7.3: Reference mode data for the number of occupied ICU beds in the cardiac surgery.
Figure 7.5 Reference mode data for the maximum waiting time in weeks of those still on the cardiac surgery waiting list from April 2003 to March 2005.
7.2 Comparison of Model Outputs with Reference Mode

A comparison is made between the output of the model and the reference mode shown in Section 7.1. Figure 7.6 shows the actual elective admissions and the model's elective admission output.

Figure 7.6. Comparison of Model and Reference Mode, Elective Admissions

Figure 7.6 shows that the model underestimates the number of elective admissions.

Figure 7.7 shows the actual emergency admissions and the model's emergency admission output. The chart shows that the model overestimates the number of emergency admissions.

Figures 7.6 and 7.7 show that the present model does not simulate the balance between elective and emergency admissions properly.

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Figure 7.8 compares the surgical inpatient waiting list between the model and the reference mode. As can be seen, the model predicts a rise in the waiting list in opposition to the trend observed in the reference mode. This could be due to the underestimation of elective admissions in the model, which would mean a smaller flow of patients off the waiting list in the model compared to the observed numbers on the actual waiting list.

Figure 7.9 compares the CICU bed occupancy with the model’s output. The model’s prediction is much lower than the reference mode, partly due to the underestimation of elective admissions and the incorrect modelling of length of stays in both CICU and the wards (see Section 7.3.1).

Figure 7.9. Comparison of Model and Reference Mode, CICU Bed Occupancy

Notice also the increase in occupancy past the model’s assumed fourteen beds in March 2004. Clearly, more beds were opened at this time.
7.3 Tests of Model Structure

Reflecting on the model structure, it was felt a number of flows, both information and resource, were either missing or incomplete. The points below give a summary of the alterations made to the model at this stage.

7.3.1 CICU Bed Occupancy Oscillation

The bed oscillation was discussed in the last section of Chapter 6. It was caused by the grouping of admissions so that they were all assigned the same sampled length of stay. To break this oscillation and provide a more realistic simulation of the use of CICU beds, the elective operation rate signal coming into the 'Discharges' section was split up into its component patients and each given a separately sampled length of stay. Figure 7.10 shows the new structure. The signal is split into four parts as there could be, at most, four patients being operated on at the same time.

Figure 7.10: Elective Operation Rate Split into its component patients
In Figure 7.10, the 'ElectiveLookup' holds the CICU length of stay distribution. It is sampled using four random numbers generated with a uniform distribution, 'RandomUni[1-4]', which produce four elective length of stay samples, 'ElectiveLOS[1-4]'. These four length of stay samples are used to delay the split elective operation rate signal. The logic of this splitting is shown in Table 7.2

### Table 7.2 Splitting of the Elective Operation Rate

<table>
<thead>
<tr>
<th>Elective Operation Rate</th>
<th>Elective Operation1</th>
<th>Elective Operation2</th>
<th>Elective Operation3</th>
<th>Elective Operation4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

The delayed variables feed the 'CICU Discharges' level which determines the number and timing of discharges from CICU.

A similar splitting was enacted on the emergency operation rate and the ward admissions signal (from the CICU 'Discharges' section).

7.3.2 Breaking the link between the Surgical inpatient Waiting List and Emergency admissions

This is a very small effect compared to other emergencies and it was felt that the model could be simplified if it was represented by linking the size of the inpatient waiting list (or maximum wait) to the probability of an External Emergency occurring.
7.3.3 Delays between Emergency Admission and Operation

It was found from the interview with Interviewee 4 that some blue form patients (those that arrive from a cardiac catheter procedure needing immediate treatment) can wait on a cardiology ward for their operation. To model these different priority 'streams' within the 'Emergency Admission' patient flows, delay levels were placed in between 'Catheter' and 'Emergency Admission' levels and in between 'External Emergency Rate' and 'Emergency Admission' levels i.e. 'Emergency Admission' becomes emergency patients admitted to the ward or CICU about to have an operation but at the stage before this they can effectively be given differing priorities of admission and can wait for an 'elective slot to appear before their operation is performed. The effect on the model structure is shown in Figure 7.11 below.

Figure 7.11: New model structure of emergency admissions (the information structure has been omitted so as not to clutter the diagram)

The effect on ward beds needs to be considered. There could now be patients waiting for an operation on the ward which will reduce the possibility of a transfer between CICU and the wards. There are also patients waiting on the cardiology wards for an operation, they represent a blocked bed for the cardiology specialty, an important performance indicator.
For external emergency patients, a ward bed will need to be available to admit them, this ward bed then needs to be given up when the emergency patient is operated on. Catheter emergency patients are assumed to remain on a cardiology ward until their operation. This is achieved by including the variable that represents "Other Emergency" admissions in the calculation for the number of ward beds needed to accommodate new admissions (assuming they come to the ward first), which in turn is used to calculate the change of occupancy in ward beds.

Delays between emergency admission and actual operation were investigated and analysis of the data generated a distribution of waits for both 'Blue Form' referrals and 'Other' emergencies. 33% of 'Other' emergencies were performed in three working days, the rest within seven working days. 20% of 'Blue Form' emergencies were performed in three working days, the rest within 21 working days.

7.3.4 The model should show the effect of 'Re-dos'

'Re-dos' are patients who have been operated on and are recuperating on the ward or CICU but who then deteriorate and need to be operated on again. A new patient flow is created linking 'Inpatients' to 'Emergency Admission'. Figure 7.12 illustrates this new link. This needs to be linked to the CICU and Ward discharge rates and occupancy levels as discharges and bed occupancies are occurring that must be accounted for in these parts of the model so as to maintain the model's coherence.

It is assumed 'Re-dos' can be modelled by putting a flow in between 'Inpatients' and 'Emergency Admission.' This way access to an operation can still be controlled through the emergency and elective operation rates.
The model also assumes 'Re-do' patients vacate their bed when they go from 'Inpatients' to 'Emergency Admission' This simplifies the modelling of 'Re-dos' and also avoids resource deadlock e.g. a 'Re-do' patient needing an unoccupied CICU bed to be operated on even though they are occupying one!

### 7.3.5 Variation of Length of Stay in CICU with the size of the inpatient waiting list / maximum waiting time

Patients will tend to be moved from CICU as other patients scheduled for admission are due to come in to the hospital. This ensures the elective operation rate does not suffer because of any unavailability of beds This is modelled by making a CICU discharge more likely to occur if an elective procedure is scheduled to take place in the next time period. Figure 7.13 shows the 'early discharge' model structure and how it feeds into the calculation of the number of CICU discharges
The 'EarlyCICUDischargePotential' variable is calculated as a proportion of the elective patients about to be admitted ('Schedule Rate Shadow' in figure 7.13) and was estimated by adjusting the proportion in association with the 'Probability of a Preadmission Cancellation' variable to obtain the correct overall numbers of Elective Admissions and Operations.

**7.3.6 ‘Elective Admissions’**

Elective patients are admitted for their operation the day before. This means, with the current model structure, that the ‘Eadms scheduled for next day’ level contains patients already admitted. So the ‘Eadms scheduled for next day’ level is replaced with an ‘Elective Admissions’ level, which represents patients admitted to a ward but not yet operated on. The rate from the ‘Surgical Waiting List’ level to the ‘Elective Admission’ level is then the scheduled operations the next day (from the ‘Consultant Sessions’ section) minus the number of cancellations caused by a lack of available hospital resources or because a patient had become too sick for surgery. This is similar to the new structure for emergency patients mentioned in Section 7.3.3 above, and, like emergencies, the effect on ward beds of this change needs to be considered carefully.
Ward bed occupancy is also increased by the number of admissions as they are assumed to be first admitted to a ward. They are assumed to wait three time periods before being either operated on or discharged cancelled. This assumption helps to simplify the model.

7.3.7 The Modelling of Waiting time and Priority

Waiting time is a characteristic of each patient and therefore not easily modelled in System Dynamics which deals with aggregate quantities. Most System Dynamics software packages do have special levels and functions which will track individual discrete entities through them. However these levels are treated as FIFO (First In First Out) queues and this is not adequate to represent a waiting list in which patients can be seen out of order.

Waiting time was therefore modelled by using ordinary levels representing particular time bands. Additions flow into the first level and are taken from the 'Patient' section. The bands are linked together by a rate that represented the aging of the list. Each band represents four weeks (which helped keep the number of levels down) and the assumption is made that a quarter of each age band would move into the next oldest age band level once a week. The waiting list is also split into two different priority streams, 'Urgent' and 'Routine'. Each priority has its own series of time band levels. Figure 7.14 shows the model structure for part of the routine series.
The other outflows from the waiting time levels are the "Routine Admissions" rates. These not only include the routine admissions but also the other leavers from the list. Routine Admissions are taken from the individual "Elective Operation [1-4]" auxiliary variables used in the CICU discharges section. Each variable can take the values of zero or one, if one then this represents an elective operation. An elective operation means one patient has come off the waiting list and this needs to be assigned to one of the waiting time bands. Which band depends on the waiting list strategy adopted. If patients are being seen in turn, then the elective admission must be assigned to the oldest level. If patients are not being seen in turn, then the elective admission is assigned to a random level. Figure 7.15 shows the variables that work out the level for each of the three "Elective Operation" variables i.e. "Routine Bin [1-4]."
In the figure above, if "Routine Bin 1" is equal to one then the value of "Elective Operation 1" is assigned to "Routine Adms 1" which is used in calculating "Routine Admissions 1". If any of the "Routine Admissions" rate variables would make the value of the time band less than zero, then any spare admissions are sent to the next youngest time band through the variables "Spare Admissions". It should also be noted that the "Routine Adms" variables also contain the stream from the "Waiting list leavers" calculated in the "Patient" section of the model. Leavers are assigned randomly to a time band.

Before elective operations and leavers can be assigned to an admissions outflow, they must first be assigned to a priority. This is controlled by two variables "%Routine Admissions" and "%Routine Leavers" which set a level by which each elective admission and leaver is randomly assigned to a priority. The network of variables that achieves this is shown in Figure 7.16.
7.3.8 Elective Operation Rate Calculation

The calculation of the elective operation rate is split into four variables in the new model to make it easier to follow. Figure 7.17 shows the network of variables that are used to calculate the Elective Operation Rate. For clarity some of the structure has been omitted.

Table 7.3 lists the main variables in the network and describes their calculations.
Figure 7.17: Network of Variables to Calculate the Elective Operation Rate

Table 7.3: Main Variables in the Elective Operation Rate Network

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EmergencyOpRateAux</td>
<td>The number of emergency operations possible with the number of Unoccupied CICU Beds available.</td>
</tr>
<tr>
<td>Elective Capacity After Emergns</td>
<td>Works out the elective capacity available (given the number of elective patients waiting) after emergencies and theatre space are taken into account (Emergencies have preference over Elective patients for theatre time)</td>
</tr>
<tr>
<td>Elective Capacity</td>
<td>Works out the elective capacity available after emergencies and Unoccupied CICU Beds are taken into account (Emergencies have preference over Elective patients for CICU Beds).</td>
</tr>
<tr>
<td>ElectiveOpRateAux</td>
<td>Matches up elective capacity to waiting elective patients</td>
</tr>
</tbody>
</table>

The variables take into account the various resource constraints and emergency admissions when calculating the Elective Operation Rate.
7.3.9 Consultant Annual Leave and Sickness

Consultant Annual Leave and Sickness were not modelled in the later versions of the model because of the employment of a locum Consultant. This locum covered the other Consultants during spells of annual leave and sickness. It was felt there was little to be gained by explicitly modelling these effects as they were no longer issues for the Directorate.

7.3.10 New Outpatient Attendances

More detailed information was obtained on new outpatient attendances. The figures were broken down by consultant as well as day of the week. This was done in order to model the effect of individual consultant’s absence. Figure 7.18 shows part of the new model structure. ‘Consultant 1 New Outpatients Lookup’ is the observed cumulative probability distribution of the number of new attendances that occurred in Consultant 1’s weekly clinic between April 2003 and March 2005.

Figure 7.18. New Outpatient Attendances Calculation (Consultant 1)
7.3.11 Revisiting ‘Blue Form’ Levels

The comparison done with the reference mode (see Section 7.2) found that emergencies were too high causing elective admissions to be lower than the reference mode.

The cause was found to be the ‘blue form’ data obtained from the Hospital PAS system. This was found to be estimating too many ‘blue form’ referrals. A more accurate query of the database revealed a better estimate of ‘blue form’ referrals.

7.3.12 Number of Operations per Session

The assumption was made that a Consultant would schedule three patients for one full day of theatre time unless a scheduling problem or patient withdrawal caused a cancellation. This was modelled randomly, with the “Probability of a PreAdmission Cancellation” set quite high (0.7) so as to reproduce roughly the number of patients who come in for admission.

7.3.13 New Model Structure

The Patient section of the system dynamics model after the structural validation are illustrated in figure 7.19a and figure 7.19b. Figure 7.19a shows the resource structure of the ‘Patient’ section of the model with all information structure omitted. Figure 7.19b shows the ‘Patient’ section of the model with the main parts of the information structure included.
Figure 7.19a The 'Patient' section of the model showing only the Resource Structure
Figure 7 19b: The 'Patient' section of the model including major Information Structure
7.3.14 Model Identification

The model's parameters listed in Chapter 6 were reviewed and new parameters in the revised model discovered. The result of this review is shown in Table 7.4.

Table 7.4: The Revised Model's Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Location</th>
<th>Section</th>
<th>Current Value</th>
<th>How estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chance Team Unavailable for next Elective Session</td>
<td>Theatre Staff</td>
<td></td>
<td>0.01</td>
<td>Assumed</td>
</tr>
<tr>
<td>Total CICU Beds</td>
<td>CICU Beds</td>
<td>Varying between 14 and 18</td>
<td>Estimated from CICU Occupation Data</td>
<td></td>
</tr>
<tr>
<td>Total Ward Beds</td>
<td>Ward Beds</td>
<td>50</td>
<td>Estimated from Ward Occupation Data</td>
<td></td>
</tr>
<tr>
<td>Length of Stay in CICU distribution of emergency patients</td>
<td>Emergency Lookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td>Length of Stay in CICU distribution of elective patients</td>
<td>Elective Lookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td>Length of Stay distribution for Ward patients</td>
<td>Ward Lookup</td>
<td>Discharges</td>
<td>See section 6.4.2</td>
<td>Assembled from Ward Stay dataset</td>
</tr>
<tr>
<td>Assumed number of operations a consultant team can perform in one working day session (two quarter days)</td>
<td>Consultant [1-7] Sessions</td>
<td>Consultation Sessions</td>
<td>2 or 3 depending on value of 'ProbOne PreAdm Canc'</td>
<td>Estimated from activity data</td>
</tr>
<tr>
<td>Probability of one pre-admission cancellation</td>
<td>ProbOne PreAdm Canc</td>
<td>Consultation Sessions</td>
<td>0.7</td>
<td>Estimated by varying in association with the variable &quot;EarlyCICUDischargePotential&quot; (see later in table) until the overall number of Elective Admissions and Operations were reproduced</td>
</tr>
<tr>
<td>Scheduled operating sessions for each consultant team in theatre</td>
<td>Consultant [1-7] Sessions</td>
<td>Consultation Sessions</td>
<td>N/A</td>
<td>From Timetable</td>
</tr>
<tr>
<td>CatheterRate</td>
<td>Patients</td>
<td>See section 6.4.3</td>
<td>Assembled from Catheter dataset</td>
<td></td>
</tr>
<tr>
<td>Blue Form Referrals</td>
<td>Blue Form</td>
<td>Patients</td>
<td>See later</td>
<td>Assembled from</td>
</tr>
<tr>
<td>Table Title</td>
<td>Description</td>
<td>Unit</td>
<td>Source</td>
<td></td>
</tr>
<tr>
<td>-------------</td>
<td>-------------</td>
<td>------</td>
<td>--------</td>
<td></td>
</tr>
<tr>
<td>OPDSurgeryConversion Factor</td>
<td></td>
<td>Patients</td>
<td>See section 6.4.5</td>
<td></td>
</tr>
<tr>
<td>Other Referrals to Cardiac Surgery Outpatients</td>
<td></td>
<td>Patients</td>
<td>See Section 6.4.6</td>
<td></td>
</tr>
<tr>
<td>New Outpatient Appointments</td>
<td></td>
<td>Patients</td>
<td>See later</td>
<td></td>
</tr>
<tr>
<td>Conversion Factor (from Outpatients to Waiting List)</td>
<td></td>
<td>Patients</td>
<td>See section 6.4.8</td>
<td></td>
</tr>
<tr>
<td>ProbLeaveList Per Week (formerly %LeaveList Per Week)</td>
<td></td>
<td>Patients</td>
<td>0.053</td>
<td></td>
</tr>
<tr>
<td>Probability of External Emergency</td>
<td></td>
<td>Patients</td>
<td>Various depending on Time of day and RealDay</td>
<td></td>
</tr>
<tr>
<td>Probability of Waiting List Emergency</td>
<td></td>
<td>Patients</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>Delay for 'Blue Form' Emergencies from Admission to Operation</td>
<td></td>
<td>Patient</td>
<td>20% of 'Blue Form' emergencies were performed in three working days, the rest within 21 working days</td>
<td></td>
</tr>
<tr>
<td>Delay for 'Other' Emergencies from Admission to Operation</td>
<td></td>
<td>Patient</td>
<td>33% of 'Other' emergencies were performed in three working days, the rest within seven working days</td>
<td></td>
</tr>
<tr>
<td>Probability of Redo</td>
<td></td>
<td>Patient</td>
<td>0.0168</td>
<td></td>
</tr>
<tr>
<td>Proportion ReDos On</td>
<td></td>
<td>Patient</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>Ward</td>
<td>EarlyCICU Discharge Potential</td>
<td>CICU Discharges / CICU and Ward Beds</td>
<td>0.3</td>
<td>Estimated by varying in association with the variable &quot;ProbOne PreAdm Canc&quot; (see earlier in table) until the overall number of Elective Admissions and Operations were reproduced.</td>
</tr>
<tr>
<td>------</td>
<td>------------------------------</td>
<td>---------------------------------------</td>
<td>------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>&quot;% Routine Admissions&quot;</td>
<td>Waiting Lists and Times</td>
<td>0.54</td>
<td>See Later</td>
<td></td>
</tr>
<tr>
<td>&quot;% Routine Leavers&quot;</td>
<td>Waiting Lists and Times</td>
<td>0.54</td>
<td>See Later</td>
<td></td>
</tr>
<tr>
<td>&quot;% Routine Additions&quot;</td>
<td>Waiting Lists and Times</td>
<td>0.54</td>
<td>See Later</td>
<td></td>
</tr>
<tr>
<td>Routine Strategy</td>
<td>Waiting Lists and Times</td>
<td>0 or 1</td>
<td>Not estimated - set to whether the strategy used in selecting from the waiting list was random (1) or 'in-turn' (0)</td>
<td></td>
</tr>
<tr>
<td>Urgent Strategy</td>
<td>Waiting Lists and Times</td>
<td>0 or 1</td>
<td>See Above</td>
<td></td>
</tr>
<tr>
<td>Number Theatres</td>
<td>Patients</td>
<td>3</td>
<td>Not estimated - physical number of theatres</td>
<td></td>
</tr>
<tr>
<td>Number of Outpatient Referrals Discharged without being seen</td>
<td>DischNotSeenLookup</td>
<td>Patients</td>
<td>See later</td>
<td>Estimated from Outpatient Referrals Dataset</td>
</tr>
</tbody>
</table>

* If blank then Parameter is Rate/Auxiliary in own right

**Blue Form Referrals (Blue Form Lookup)**

The lookup variable describes the probability distribution of the number of blue form referrals that will occur in a day from diagnostic catheter procedures. Figure 7.20 shows this distribution. It was calculated from an inpatient dataset that consists of diagnostic catheters linking to surgery episodes within the same hospital spell.
% Routine Admissions, % Routine Leavers and % Routine Additions

The percentage of admissions that were classed as routine was calculated from the inpatient dataset. This figure was then used for the percentage of leavers (from the waiting list other than by admission) and the percentage of additions to list to ensure a balance was kept between Urgent and Routine lists. This meant that the individual priority lists would not crash or explode during the simulation.

Outpatient Referrals Discharged without being seen

Some outpatient referrals are discharged without being seen for a number of reasons, for example, patients would move area. These need to be taken into account for the outpatient waiting list and so a probability distribution of weekly discharges from outpatients of patients who did not attend any appointment was calculated from the Hospital's information system. This distribution is shown in Figure 7.21 below.
7.3.15 Comparison to Reference Mode

The model was run using the above parameter values and a comparison was made between the model outputs and the actual system state for the period April 2003 and March 2005. The number of CICU beds was estimated from CICU bed activity data and varied through the period. A more detailed statistical comparison is considered in Section 7.4.

Figure 7.22 below shows a comparison between the latest model output (after structural validation) of Occupied CICU Beds and the actual CICU Occupation rate between April 2003 and March 2005. The model data was sampled every fourth time period.
The Model’s predicted occupation is a little higher than the historical data but otherwise a reasonable fit.

Figure 7.23 and Figure 7.24 shows the comparison between the model’s Elective Admissions and Emergency Admissions respectively and the historical data. The plotted data points are admissions that occurred in a time period of a week. Both series show a good fit to the historical data.
Figure 7.25 shows numbers on the Surgery Waiting List comparing the model's prediction to the historical waiting list.

Figure 7.25 Surgery Waiting List, Model versus Actual Apr 2003 to Mar 2005

Again the model data is a reasonable fit to the historical data, underestimating the actual surgery waiting list at first but following the broad trend. However there appears to be a 'phase shift' between the actual figures and the model prediction. The fall in the waiting list of the model prediction starts later than the actual figures. This may be due to inaccuracies in the number of Intensive Care beds that are available. No historic data is recorded on bed numbers and that particular parameter relies on the memories of the managers involved and the occupancy figures which may not be entirely reliable. In reality, it seems that more may have been available before the model assumes they came on line.
7.4 Tests of Model Behaviour

7.4.1 Statistical Character of Reference Mode Comparison

The statistical character of the previous section's reference mode comparison is examined using the Mean Square Error (MSE) and Theil inequality statistics (Sterman, 1984).

The MSE is defined by Equation 7.1.

Equation 7.1 Mean Square Error (MSE) between actual and simulated Datasets (from Sterman, 1984)

$$\frac{1}{n} \sum_{i=1}^{n} (S_i - A_i)^2$$

where $n$ is the number of observations,

$S_i$ is the simulated value at time $t$

$A_i$ is the actual value at time $t$

The MSE sums the squared variations of the simulated data points from their actual counterparts. More weight is given to larger differences and errors of opposite sign do not cancel each other out. The Root Mean Square Percentage Error (RMSPE) can be interpreted as the root of the sum of the squared differences between the actual and simulated as a proportion of the actual values. It is defined in Equation 7.2,

Equation 7.2 Root Mean Square Percentage Error (RMSPE) (from Sterman, 1984)

$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \frac{S_i - A_i}{A_i} \right)^2}$$

where $n$ is the number of observations,

$S_i$ is the simulated value at time $t$

$A_i$ is the actual value at time $t$
The MSE can be broken down using Theil Inequality Statistics into three components. These are $U^M$, the fraction of the MSE that is due to bias, $U^S$, the fraction that is due to unequal variance and $U^C$, the fraction due to unequal covariance (Sterman, 1984).

It should be noted that $U^M + U^S + U^C = 1$

Table 7.5 shows the possible interpretations of the three components.

<table>
<thead>
<tr>
<th>Inequality Statistic</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias $U^M$</td>
<td>Large bias indicates a systematic difference between the model and reality either caused by incorrect specification of parameters or simplifying assumptions which do not compromise the model (which will depend on the purpose of the model)</td>
</tr>
<tr>
<td>Unequal Vanance $U^S$</td>
<td>A large unequal variance and small bias and unequal covariance then the series have similar averages and are highly correlated but the magnitude of the variation about the similar averages differs. This could indicate a systematic error in the same way as a large bias. However if one of the series’ variations is small (thereby suppressing $U^C$) this could just mean the difference between the series is due to random noise or a cycle present in one series but not the other. If the purpose of the model is to investigate the missing cycle then this error could be serious.</td>
</tr>
<tr>
<td>Unequal Covariance $U^C$</td>
<td>A large unequal covariance means the two series’ points do not match though the model mimics the average and dominant trends in the actual values well. This shows that one of the variables has a random component in one of the series, most likely the historical data indicating an unsystematic error.</td>
</tr>
</tbody>
</table>

Of course the comparison between the two series will also depend on the size of the RMSPE. The higher this is the less confidence can be made of an acceptable fit between the model and actual historical data. Table 7.6 gives the summary statistics for the model variables compared in the last section. The table shows that the RMSPE is quite high for Admissions and CICU Bed.
Occupancy, however the Theil statistics show this to be mainly unsystematic, random error

Table 7.6 Summary Statistics for Reference Mode Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Root Mean Square Percentage Error (%)</th>
<th>Mean Square Error (units$^2$)</th>
<th>Un</th>
<th>U^a</th>
<th>U^b</th>
</tr>
</thead>
<tbody>
<tr>
<td>CICU Bed Occupation</td>
<td>47.6</td>
<td>13.3</td>
<td>0.216</td>
<td>0.000</td>
<td>0.784</td>
</tr>
<tr>
<td>Elective Admissions</td>
<td>43.1</td>
<td>47.1</td>
<td>0.008</td>
<td>0.002</td>
<td>0.990</td>
</tr>
<tr>
<td>Emergency Admissions</td>
<td>56.4</td>
<td>20.2</td>
<td>0.001</td>
<td>0.008</td>
<td>0.991</td>
</tr>
<tr>
<td>Surgical Waiting List</td>
<td>13.7</td>
<td>2732.9</td>
<td>0.202</td>
<td>0.000</td>
<td>0.798</td>
</tr>
</tbody>
</table>

7.4.2 Behaviour Reproduction and Sensitivity

The model's behaviour and sensitivity to parameter values is examined in this section. It investigates whether the model responds as the real system would be expected to respond to variations in parameter values and any extreme parameter values.

Varying New Outpatient Attendances

The number of new outpatient attendances is increased by 5%, 10% and decreased by 5% and 10% to see the effect on the Outpatient and Inpatient Waiting Lists compared to the baseline list sizes. The changes to the new attendances are distributed evenly throughout the model simulation period. Extreme changes are also investigated, the new attendances are increased by 100% and decreased by 100%. Again the effect on the Outpatient and Inpatient Waiting Lists is examined.
The decrease in New Outpatient attendances results in a higher Outpatient Waiting List compared to the baseline (a 0% increase in new Outpatient attendances) and lower Inpatient Waiting List as fewer patients are coming off the Outpatient Waiting List (OPWL) leaving fewer to convert to the Inpatient Waiting List (IPWL). A 100% decrease (i.e., no new Outpatient Attendances) will see the OPWL rise rapidly without control and the IPWL dwindle to zero.

Increases in new Outpatient Attendances result in a lower OPWL and a higher IPWL as more patients are being taken off the OPWL and therefore more will convert to the IPWL. A 100% increase (i.e., a doubling of new Outpatient Attendances) sees the OPWL much lower, possibly crashing to zero and the IPWL increasing rapidly.

Figure 7.26 shows the result that the changes to the "New Outpatient Attendances" parameter has on the Outpatient Waiting List. The result is as expected with increases in New Outpatient Attendances causing a decrease in the OPWL compared to the baseline and decreases in New Outpatient Attendances causing the OPWL to increase compared to the baseline.
Figure 7.26 Model Prediction of the Outpatient Waiting List with varying New Outpatient Attendances

![Chart showing the effect of varying New Outpatient Attendances on the Outpatient Waiting List](chart.png)

Figure 7.27 shows the effect that the changes to the "New Outpatient Attendances" parameter has on the Inpatient Waiting List. As expected, increasing New Outpatient Attendances causes an increase in the IPWL compared to the baseline whilst decreasing new attendances also causes the IPWL to decline compared to the baseline.

Decreasing the number of New Outpatient Attendances to zero also causes the OPWL to rise rapidly without control and the IPWL to dwindle to zero as predicted. However, doubling the New Outpatient Attendances, whilst causing the OPWL to fall to zero and the IPWL to initially rise rapidly, causes the IPWL to level off eventually as shown in Figure 7.28 below.
Doubling the New Outpatient Attendances effectively abolishes the Outpatient Waiting List. In fact not all of the extra New Outpatient Attendances can be used. The Outpatient Waiting List sets an upper limit to the number of extra new outpatients that can be seen which, in turn, limits the number of patients who can be added to the Inpatient Waiting List causing it to level off.
Figure 7.28 Model Prediction of Inpatient and Outpatient Waiting Lists after a Doubling of the New Outpatient Attendances

Varying CICU Beds

The number of CICU Beds is varied between 12, 14, 16 and the baseline numbers to see the effect on the Inpatient Waiting List, elective operations and elective cancellations compared to the baseline figures. Extreme changes are also investigated, the effect of running the model with 1400 CICU beds is examined as is the effect of an Admission 'block' on the CICU ward.

An increase in CICU Beds, compared to the baseline run, should increase the Elective Operation Rate which in turn, will cause the Inpatient Waiting List and Inpatient Waiting Times to fall. Decreases in CICU Beds should decrease the Elective Operation Rate which, in turn, will cause the Inpatient Waiting List and Inpatient Waiting Times to rise compared to the baseline. Cancellations should rise with decreasing CICU beds as there will be more chance all will be occupied when an elective admission is scheduled.
A block in CICU (where no admissions into the unit would be possible due to, for example, a hospital acquired infection), would cause a sudden drop in the Elective Operation Rate and a sudden and sustained rise in the Inpatient Waiting List and waiting times.

An extremely large number of CICU Beds will cause a great increase in the Elective Operation Rate and a decrease in the Inpatient Waiting List and waiting times. This will not be sustained as the Inpatient Waiting List will eventually be exhausted of patients and the Elective Operation Rate will be limited to the addition rate. The number of ward beds and theatre time may limit this ‘exhaustion’ effect as they will then become the new bottleneck to the process.

The model responds in the expected manner as shown in Figure 7.29. The number of elective operations increases with increasing CICU beds. The Baseline run starts off with thirteen CICU Beds so, at first, is behind the fourteen CICU bed model run for Elective Operations. However, as the number of CICU Beds increases in the Baseline run, the number of elective operations increases beyond that of the fourteen CICU bed model run.

The model runs also confirm the decreasing Inpatient Waiting List and Waiting Times with increasing CICU Beds as shown in Figure 7.30. The Baseline Run has a higher inpatient waiting list at the start of the model period than the fourteen CICU bed run but as the number of CICU beds increases during the run so the inpatient waiting list decreases below that of the fourteen CICU bed run.
Figure 7.29: Model Prediction of the Cumulative Elective Operations with varying CICU Beds

Figure 7.30: Model Prediction of the Inpatient Waiting List with varying CICU Beds
Figure 7.31 shows the maximum waiting time for those patients on the 'routine' waiting list as predicted by the model with varying numbers of CICU beds ('Routine' is one of two priorities for admission given to patients, the other being 'Urgent'). As expected the maximum waiting time decreases with greater CICU beds.

Figure 7.32 shows the model's prediction of Cancelled Elective Operations with varying numbers of CICU beds. The more CICU Beds, the fewer cancelled elective operations occur, again as would be expected from the real system.

Figure 7.31: Model Prediction of the Routine Maximum Waiting Time (in Months) with varying CICU Beds (NB The model only records waiting time in whole months)
Figure 7.32 Model Prediction of Cancelled Elective Admissions with varying CICU Beds
Figure 7.33: Model Prediction of the Effect of a Month Long Block in CICU (i.e. no admissions or discharges) on the Inpatient Waiting List

![Graph showing the effect of a month long block in CICU on the inpatient waiting list.](image)

Figure 7.33 demonstrates the model's simulation of a month long block of patients coming in or out of CICU. There is a spike in patients on the waiting list which, if compared to the baseline run, is sustained for the rest of the simulation period.

The model was run with the number of CICU beds set to 1,400 and the number of ward beds varied between ten and fifty. The inpatient waiting list crashed to zero in the same time for all the simulation runs whatever the number of ward beds. Figure 7.34 shows the CICU Bed Occupancy for the various numbers of ward beds.

The simulation run with ten ward beds saw the CICU eventually fill up with patients and the waiting list starting to rise again (Figure 7.35). In this case, the ward beds have become the new 'bottleneck' and limit the throughput of patients. Admissions carry on as normal until the CICU is full and then they are limited by the number of ward discharges. The model demonstrates constraints...
limiting patient throughput which have an effect on waiting lists and waiting times

Figure 7 34· Model Prediction of the CICU Bed Occupancy given 1400 available CICU Beds and various numbers of Ward Beds

Varying Theatre Time

As in the case with CICU Beds, more theatre time should enable more patients to come through the system, increasing the Elective Operation Rate, decreasing those on the Surgery Waiting List and reducing waiting times

However the effect may be limited by the number of CICU Beds, increasing the theatre time beyond a certain limit may simply mean more elective cancellations occurring
The model was run using three different theatre time setups. One setup was the normal three theatre setup, another was three theatres for four days of the week and four theatres for the other day in the week and the last was three theatres for three days of the week and four theatres for the other two days. The first extra day was a Thursday and the second extra day was a Friday. The number of patients scheduled by consultants for those days was also increased to take advantage of the extra theatre time when it was available. Table 7.7 shows the number of cumulative elective operations and elective operation cancellations the model predicts over a two year period for the different theatre time setups and various numbers of CICU and Ward Beds.
Table 7.7 Model Prediction of Cumulative Elective Operations and Cancellations over two year period

<table>
<thead>
<tr>
<th></th>
<th>Three Theatres</th>
<th>+ 1 extra day a week in a fourth Theatre</th>
<th>+ 2 extra day a week in a fourth Theatre</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline CICU Beds, 50 Ward Beds</td>
<td>Elective Operations</td>
<td>2,371</td>
<td>2,380</td>
</tr>
<tr>
<td></td>
<td>Elective Cancellations</td>
<td>847</td>
<td>940</td>
</tr>
<tr>
<td>16 CICU Beds, 50 Ward Beds</td>
<td>Elective Operations</td>
<td>2,558</td>
<td>2,570</td>
</tr>
<tr>
<td></td>
<td>Elective Cancellations</td>
<td>788</td>
<td>888</td>
</tr>
<tr>
<td>1400 CICU Beds, 5000 Ward Beds (3820 Initial Waiting List)</td>
<td>Elective Operations</td>
<td>4,173</td>
<td>4,479</td>
</tr>
<tr>
<td></td>
<td>Elective Cancellations</td>
<td>108</td>
<td>42</td>
</tr>
</tbody>
</table>

Table 7.7 shows that extra theatre time at lower bed levels simply leads to more cancellations of elective operations. Theatre time only makes a significant difference to the number of elective operations when there are enough beds and patients on the waiting list to be scheduled for the extra theatre time. Beds and patients are more significant resource constraints. In the case of the 1400 CICU beds, running the model with the usual number of waiting list patients meant the list crashed to zero very quickly, turning waiting patients into a constraint on the system.

7.5 Tests of Policy Implications

The effect of the introduction of some new policies on the system were considered by modelling them in the system dynamics simulation. In particular, one that involved linking inpatient waiting time to new outpatient attendances and another that considered the effect of different levels of cardiac catheters on the system's waiting times.
7.5.1 Linking Inpatient Waiting Time to New Outpatient Attendances

There is a three month waiting time target for Inpatients waiting for heart surgery. One factor that impacts on inpatient waiting times is the number of additions to the list. These additions nearly all come from surgery outpatients where a decision to place a patient on the waiting list is made. More new outpatients means more additions to the list and, eventually, increased maximum waiting times for surgery if more inpatient capacity is not added. How quickly can the maximum waiting time be brought to three months and how many new outpatients can the system see without threatening a three month maximum inpatient waiting time target?

To discover the answers to these questions, the number of new outpatients is linked to the maximum inpatient waiting time. The greater this waiting time is from the three month target then less new outpatient attendances (new outpatient attendances are patients who are seen for the first time in an outpatient clinic) than normal will be allowed to be seen but if the maximum inpatient waiting time is under target then more new outpatient attendances than normal will be allowed to be seen.

This linkage effect is produced by the following equation, Equation 7.3

Equation 7.3. Linking inpatient waiting time to new outpatient attendances

\[ N = N_u (1 + \frac{(W_T - W_P)}{W_P}) \]

where \( N \) is the number of new outpatient attendances

\( N_u \) is the usual number of new outpatients

\( W_T \) is the maximum inpatient waiting time target

\( W_P \) is the present maximum inpatient waiting time

\( N_u \) is the number of average new outpatient attendances generated by taking the average of each consultant's clinic's new outpatient attendance frequency.
distributions. $W_P$ is taken from the maximum inpatient waiting time of Routine Patients on the waiting list as they usually wait the longest. $W_T$ is set to three months.

The model was simulated for a two year period into the future. Patients were chosen from the waiting list 'in turn', i.e. longest waited first. Figure 7.36 shows the maximum inpatient waiting time for various numbers of CICU beds. The chart demonstrates that the more CICU Beds, the quicker the maximum inpatient waiting time takes to reach its target value. Both it and the simulated waiting list (Figure 7.37) show some oscillation around a target value. The oscillation could be do with the evaluation of waiting time by monthly bands. A more detailed breakdown in, for example, weeks, would give the system earlier warning of rising or falling waiting times and make it able to generate a more appropriate response.

Figure 7.36: Maximum Inpatient Waiting Time (Months) predicted by the Model linking Waiting Time to New Outpatient Attendances
The inpatient waiting time target is reached for all numbers of CICU beds considered. Figure 7.38 shows new outpatient attendances for the levels of 12, 14 and 16 CICU Beds. More new outpatients can be seen the more CICU Beds are present. Greater numbers of CICU beds mean a bigger flow of patients leading to lower maximum inpatient waiting times, so more new outpatient attendances can occur and still maintain the same inpatient waiting times.

The next chart (Figure 7.39) shows the outpatient waiting list for various numbers of CICU Beds. The 14 and 16 bed lines show stable, though oscillating outpatient waiting lists. The 12 bed line seems to show an out of control list that is growing. This difference can be attributed to the larger number of new outpatient attendances that the linkage policy causes at higher levels of CICU beds.
Figure 7.38: New Outpatient Attendances predicted by the Model linking Waiting Time to New Outpatient Attendances

Time Period (Quarter Days)

Figure 7.39: Outpatient Waiting List predicted by the Model linking Waiting Time to New Outpatient Attendances

Time Period (Quarter Days)
An outpatient waiting list clearance time was calculated in the model. This is defined as the time it takes to clear the present numbers waiting on the outpatient waiting list for a first outpatient appointment. It is calculated by dividing the number on the outpatient waiting list by the number of new outpatients seen during the last week. Outpatients should not wait longer than 13 weeks to be seen for the first time. Figure 7.40 shows the outpatient waiting list clearance time predicted by the model for various numbers of CICU beds. Only the 16 CICU bed simulation brought the clearance time below 13 weeks.

The policy did not prove to be compatible with a random selection strategy (where patients are chosen at random from the inpatient waiting list). The random selection strategy forces waiting times to stay high depressing new outpatient attendances to a low level causing the inpatient waiting list (and inpatient waiting times) to crash to zero and the outpatient waiting list to rise to a high level. The crash in inpatient waiting times causes the new outpatient attendances to rise making the outpatient waiting list drop and the inpatient waiting list (and waiting times) increase. The cycle repeats and the inpatient and outpatient waiting lists start to oscillate substantially producing instability in the system.
7.5.2 Varying the level of cardiac catheters

Cardiac catheters have an influence on surgical waiting times and waiting lists. Patients having a catheter will, if appropriate, be referred to the cardiac surgery specialty as either an outpatient or an emergency inpatient (a so-called 'Blue Form'). An outpatient referral will spend time waiting on the cardiac surgery outpatient waiting list. An emergency inpatient will possibly block an elective operation by being allocated the bed or theatre time that the elective patient would otherwise occupy. The model was simulated to assess the effect of different levels of cardiac catheters on the cardiac surgery waiting times. Waiting time targets for cardiac catheters also exist so an increase in their level is a possibility. The model was simulated over a two year period and with the waiting patients being seen 'in turn'. The mechanism of linking maximum inpatient waiting time to the level of new outpatients was in place in the model. The number of CICU Beds was simulated as sixteen and ward beds was set at fifty.
Table 7.8 below demonstrates the different levels of cardiac catheters the model was subjected to and the effect the levels had on the ‘Blue Form’ referrals.

Table 7.8: Cardiac catheter levels and associated ‘Blue Form referrals over which the model was simulated.

<table>
<thead>
<tr>
<th>Catheter Level Increase from Baseline</th>
<th>-10%</th>
<th>-5%</th>
<th>0</th>
<th>5%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Catheters</td>
<td>7,474</td>
<td>7,888</td>
<td>8,302</td>
<td>8,716</td>
<td>9,130</td>
</tr>
<tr>
<td>‘Blue Form’ Emergencies</td>
<td>453</td>
<td>483</td>
<td>525</td>
<td>535</td>
<td>573</td>
</tr>
<tr>
<td>Number of Elective Operations</td>
<td>2,586</td>
<td>2,595</td>
<td>2,537</td>
<td>2,581</td>
<td>2,520</td>
</tr>
</tbody>
</table>

Inpatient waiting lists and waiting times were largely unaffected by the differing levels of cardiac catheters. As Table 7.8 shows the number of elective operations changed little with ‘Blue Form’ Emergencies. Most of the increase in ‘Blue Form’ Emergencies could be absorbed by the system without blocking elective operations. Also the mechanism of linking maximum inpatient waiting time to the level of new outpatients meant that any increase in outpatient referrals from higher numbers of cardiac catheters would be reflected as higher waiting times and lists in outpatients. Figure 7.41 shows the simulated outpatient waiting list for various levels of cardiac catheters and Figure 7.42 demonstrates the effect on the outpatient waiting list clearance time.
Figure 7.41: Effect of different levels of cardiac catheters on the outpatient waiting list

Figure 7.42: Effect of different levels of cardiac catheters on the outpatient waiting list clearance time
A 13 week waiting time target for outpatients at 16 CICU beds is only a
problem if catheters increased by 10%. This, of course, assumes that patients
on the inpatient waiting list are seen 'in turn'. In practice it can be difficult to
choose patient 'in turn'. There will be some variation caused by patients
themselves, some will be unavailable on the appropriate date or they will want
another day for the operation. Staffing 17 or 18 CICU beds would be a
precaution against high outpatient waiting times and give some insurance
against a rise in cardiac catheter numbers.

7.6 High Frequency Fluctuations

The preceding sections saw validation tests of the model where one parameter
(for example, numbers of CICU beds, new outpatient attendances) was
changed to see the effect on key performance measures of the system (for
example, the inpatient waiting list). Whilst these changes showed noticeable
differences in the long term 'low frequency' trends, 'high frequency' fluctuations
were also observed in the different parameter value graphs. These 'high
frequency' fluctuations are identical in each line, for example, figure 7 27 is
reproduced below clearly showing identical fluctuations for each level of new
outpatient attendances

The effect is caused by random number generation in the Vensim system
dynamics software. The inpatient waiting list shown above depends on a
number of factors (these include emergencies, non-cardiology referrals to
surgery outpatients and the proportion of new outpatient attendances
converting to the inpatient waiting list) that are generated using streams of
random numbers produced by the software. These random number streams
are dependent on a 'seed' value. In the simulation runs that produced the data
in the figure above, these 'seed' values were always the same, hence the level
and timing of emergencies etc. were also the same across the simulation runs.
These factors influence the inpatient waiting list day to day and so cause the
'high frequency' fluctuations seen in the graph. The inpatient waiting list's long
term development is thus only effected by the level of new outpatient attendances

Figure 7.43 Reproduction of Figure 7.27, Model Prediction of the Inpatient Waiting List with varying New Outpatient Attendances

To see the effect of using random number seeds, the simulation runs were repeated but each time different 'seeds' were used for the factors mentioned above (with the exception of new outpatient attendances as their level was the only factor that needed to be varied regularly to validate the behaviour of the model) The result is shown in figure 7.44 below

As can be seen, the low 'frequency' long term trends are roughly the same as those shown in figure 7.27. However the high 'frequency' fluctuations differ each time

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7.7 Summary

This chapter has seen the process of validation of the model described. The model went through tests of structure, behaviour and policy and was amended as a result. The next chapter discusses the policy implications of the model for the cardio-respiratory directorate, the added value of the model and the original contribution of the study.

The model was used by some stakeholders in the directorate. Some felt, however, that it was too complex. There was certainly a great number of levels and information structure though the model was divided into more understandable functional areas corresponding to the main resource flows (for example patients, beds etc.). Another factor in its lack of take up was the use of the NHS Modernisation Agency’s ‘Plan-Do-Study-Act’ (PDSA) cycle to meet waiting time targets (whereby long waiters are tracked and management action taken before they breach the target). For some stakeholders the achievement of the targets meant management attention drifted away from modelling.
despite the aim of producing a strategic model that was not just for measuring the performance of waiting lists and times
Chapter 8: Discussion

8.1 Introduction

In Chapter 7, the validation of the model was described and some potential policy implications investigated. Tests of model structure and behaviour were carried out and changes made to the model to make it a more 'realistic' fit of the real system.

Chapter 8 discusses the policy implications in relation to the cardio-respiratory directorate and the model's potential for use outside of the directorate. This chapter also discusses the added value of the model and brings out the study's original contribution.

8.2 Impact of the Model and the Study

The model gives insights into how to meet maximum Waiting Times targets for inpatient cardiac surgery. It can estimate the maximum number of new outpatient attendances the system can support whilst keeping inpatient waiting times below three months for various configurations of theatre time and Cardiac Intensive Care Unit (CICU) beds. Figure 8.1 summarises the maximum attendances. As the figure shows, the greater the number of CICU beds, the greater the number of new outpatient attendances that can be accommodated without jeopardising the maximum waiting time target. Choosing patients 'in-turn' from the waiting list means more new outpatient attendances can occur and keep within the maximum waiting time target than if patients were chosen out of turn or randomly.

Controlling new outpatient attendances in this way means, in turn, less variation in additions to the inpatient waiting list, and less variation in inpatient waiting times provided patients are seen 'in-turn'. This leads to the system controlling its patient flow and being able to use its resources to their maximum potential to meet the waiting time target.
CICU beds and theatre time can then be set at a level needed to make the system cope with demand within the target maximum wait times set. These ideas are based on the theory of constraints as developed by Goldratt (Goldratt and Cox, 1993) and applied in the health service by Silvester, et al. (2004) and disseminated through the management guides (NHS Modernisation Agency, 2005).

The guides set out guidelines for working that can maximise the performance of a healthcare system and improve patient flows. Although they state that models are not strictly necessary to apply this approach, the model developed in this study adds the ability to see the effect of several policy changes on the system without the dangers inherent in changing a real system of care. A ‘modelling’ approach could also speed up the time it takes to find an optimal policy, though this would be dependent on an adequate validation of the model. The model can thus be used to demonstrate that a maximum waiting time can be achieved within current resources or an argument for more resources can be made by demonstrating that current resources cannot reach the required level of performance.
Figure 8.2 shows the maximum inpatient waiting time as a function of new outpatient attendances. It should be noted that the maximum waiting time is measured in whole months so any variations in waiting time in the Figure 8.2 are smoothed out and the relationship between the two is not quite as linear. It should also be noted that the version of the model used to generate these figures does not have a direct link between maximum inpatient waiting time and numbers of new outpatient attendances targeting a certain waiting time. The chart shows that the more new outpatient attendances allowed over a period of time then the greater the maximum inpatient waiting time at the end of that period.

Figure 8.2: Maximum Inpatient Waiting Time (at end of Period) as a function of New Outpatient Attendances (Model Projections over One Year, 3 Theatres, 16 CICU Beds, 'in-turn' selection strategy)

The model shows that CICU beds form a constraint or a bottleneck on the directorate's ability to move patients through the system. Patient flow is most sensitive to the number of CICU beds rather than extra theatre time. In these circumstances extra theatre time merely acts to increase admissions but not necessarily operations. If the system is like a funnel, increasing theatre time widens the funnel mouth but not the flow through the other end. Indeed
increasing theatre time without sufficient CICU beds simply leads to more elective cancellations as Table 8.1 below shows

Table 8.1: Elective Operations and Cancellations as a function of Theatre Time for 16 CICU beds (Model Projections over One Year)

<table>
<thead>
<tr>
<th>Three Theatres</th>
<th>Three Theatres + One Day per Week in Fourth</th>
<th>Three Theatres + Two Days per Week in Fourth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elective Operations</td>
<td>Cancellations</td>
<td>Elective Operations</td>
</tr>
<tr>
<td>1254</td>
<td>391</td>
<td>1279</td>
</tr>
</tbody>
</table>

It should be noted that the model makes certain assumptions on outliers and length of stay in CICU; it may be possible for staff to 'juggle' beds and get patients through the system without cancellation of their operations so Table 8.1 may be overstating the effect.

Scheduling of admissions is crucial. Less variability in admissions means the optimal number of CICU beds can be planned more easily i.e. less variability in admissions means less variability in free CICU beds.

A major cause of variability in elective admissions are emergency admissions. They have priority over elective admissions and will block an elective if not enough CICU beds are available to go round. The model assumes that one emergency admission can be accommodated in one theatre without disrupting the elective schedule but more than one will block an equivalent elective admission on theatre time.

Table 8.2 shows the number of electives at different levels of emergencies and number of CICU beds. Table 8.2 demonstrates the blocking effect of emergency admissions. Electives and emergencies have an inverse relationship to each other.
Using the model in conjunction with the Theory of Constraints, measures that improves patient flow could be established and an estimate of the maximum possible new outpatient attendances (and hence additions to the waiting list) that does not threaten the maximum waiting time of three months could be made. This is useful for Payment by Results (PbR) to estimate the extra number of operations that could be done without threatening inpatient waiting times. PbR is the reform to healthcare finance whereby hospitals will be funded for the number of operations they actually perform instead of receiving a 'block' payment with little reference to their activity.

The data model described in Chapter 5 has proved more popular with managers than the more strategic system dynamics model. A number of reasons could account for this. The data model was a spreadsheet model written in the Microsoft Excel software package (a program which the managers would have been familiar with already) and this integrated better with the hospital’s commissioning process (the process of negotiating with primary care trusts to see how much of the hospital’s activity or operations they wish to purchase) than the system dynamics model. The model complexity of the data model is less than the system dynamics model despite the graphical nature of the latter modelling method. This would ensure the data model is easier to understand.
The data model had a direct link to data from the hospital’s Patient Administration System and so was perceived by managers to be more up to date and accurate. Management were more focused on meeting waiting time targets and so were more interested in the model that met those objectives despite the fact that the two models were meant to complement each other.

Harper and Pitt (2004) considered the issues and challenges that face projects in healthcare modelling. This was based on their experiences working with various organisations in the National Health Service (NHS) including hospital trusts and health authorities.

The five they discussed in their paper include:

1. Scale, complexity and change

The Authors point out the scale of the NHS, the fact that it employs one million people and is Europe’s biggest organisation. The healthcare system is very complex with various factors contributing to this complexity including demographics, social and behavioural factors, clinical and technological factors, and the variation present in treating individual patients. Strategic changes in one part of the organisation cannot be considered in isolation to the other parts.

2. Diversity

Healthcare providers have their own operations and ways of doing things which make them very diverse organisations. Neighbouring Trusts could have very different ways of collecting and analysing data, for example. One approach to modelling could be to limit the scope of models to individual institutions though this would lead to a lot of time and effort producing models that are not applicable to the wider healthcare context.
3. Buy-in and Credibility

Modelling is often unfamiliar to healthcare staff and they will regard it cautiously. Models must therefore be developed with potential Users in order to gain credibility. Validation of the model is fundamental to this process. Buy-in may also be gained by ensuring that the project shows obvious and quick benefits to the organisation.

4. Conflicting Objectives

The healthcare organisation will have conflicting political agendas. Management will want to use any models to effect organisational change, sometimes to staff working practices. This can lead to clashes between staff groups. It is essential that the modeller protects against distortion and misuse of their models. Models should be used to help quantify the impact of change and assist in objective decision making.

5. Data Issues

There are vast amounts of data in healthcare organisations, in paper and electronic form. However, hospitals will collect vast amounts of detailed records on patients but then make little use of it. Data quality also varies widely between healthcare organisations. Some hospitals will have dedicated data quality teams to address this issue though this is not universal.

In the present study the initial data model described in Chapter 5 was developed quickly with the Users involved and gave quick results that were integrated into the directorate's planning process. This gained it credibility among the stakeholders. The system dynamics model was also developed with the Users which helped gain it credibility amongst some of the stakeholders. However the decision not to link it to the hospital Patient Administration System data damaged that credibility and led to the system dynamics model not being taken up as successfully as the data model. The system dynamics model was also regarded as too complicated by Users.
Users felt there were a large number of levels and adjustable parameters and the model was not easily navigated in the Vensim software interface.

The Plan-Study-Act-Do (PDSA) cycle of the 'Model for Improvement' mentioned in Chapter one has to some extent overtaken both models as the method to achieve waiting times targets. Modelling could be incorporated into the PDSA cycle to improve prediction of any proposed changes otherwise such changes could be regarded as merely 'trial and error' experimentation on the real system.

8.3 Potential for Model Use in Policy Studies

The model has potential for assessing the impact of any service changes on inpatient waiting times, for example Table 8.3 shows the effect on waiting times of increasing cardiac catheters. Please note these figures are produced without a link allowing maximum inpatient waiting time to influence the number of new outpatient attendances. As we saw in Chapter 7 such a link would effectively insulate inpatient waiting times and lead to catheter numbers influencing outpatient waiting times instead.

Table 8.3 The Effect of increasing Cardiac Catheters on Surgery Waiting Time (Model Projections over One Year, 14 CIU Beds, 3 theatres, 'in-turn' selection from waiting list)

<table>
<thead>
<tr>
<th>Catheters</th>
<th>Average Waiting Time (at end of period)</th>
<th>Maximum Waiting Time (at end of period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3,500</td>
<td>8-11 weeks</td>
<td>12-15 weeks</td>
</tr>
<tr>
<td>4,168</td>
<td>8-11 weeks</td>
<td>16-19 weeks</td>
</tr>
<tr>
<td>4,500</td>
<td>12-15 weeks</td>
<td>16-19 weeks</td>
</tr>
</tbody>
</table>

As Table 8.3 shows the increase in catheters increases both the average waiting time and the maximum waiting time for elective admission.

The model could be extended to assess measures for achieving the 18 week target between GP referral and the start of treatment. As most GP referrals into the cardio-respiratory directorate come into the cardiology specialty rather than
the cardiac surgery specialty, the model would have to be extended into cardiology and outpatient waiting times in cardiology modelled

The model also has potential to be used in other surgical specialties and could be extended and/or modified to include medical specialties. One mechanism to achieve this would be to involve the central Information department where analysts assist the directorates with their information needs.

8.4 Added Value of the Study

The study has introduced management in the directorate to a wider range of modelling methods (other than simple spreadsheet models). The directorate has seen how modelling can be used as a tool to assess and quantify the impact of service changes before they are introduced. Thus modelling can complement the cautious, gradual process of change suggested by the 'Plan Do Study Act' (PDSA) cycle promoted by the NHS Modernisation Agency. Although only system dynamics and Markov chains were used in the models produced during the study, other techniques were introduced to managers like Discrete Event Simulation.

The study has also given the directorate a systems view of their cardiac surgery specialty. Cardiac surgery can be viewed as a series of interconnected stages each influencing the flow of patients through the system. Figure 8.3 shows a schematic of the stages of care a patient goes through in the cardiac surgery system. Maintaining waiting time targets in one part of the system has consequences for another, for example maintaining inpatient waiting times could impact on outpatient waiting times as the inpatient waiting time would limit the number of new outpatients that could be seen.

8.5 Original Contribution

The study has produced a model that simulates waiting lists and times for treatment in a cardiac surgery specialty using the system dynamics modelling
method. System Dynamics has been used to model inpatient waiting lists before, Garcia and Busto (1998) carried out a study into a waiting list in a Spanish hospital. That model was a more strategic study than the present one, its aim was to demonstrate the futility of the waiting list initiatives being used by the Spanish health service to reduce the number of patients waiting. In contrast, the model produced in the present study simulates the main factors responsible for affecting elective admissions and waiting lists like intensive care beds and theatre time. The range of factors modelled gives the present study's model a flexibility in the possible policy studies that could be carried out.

Figure 8.3 Schematic of Patient Flow through the Cardiac Surgery System

The study has produced a model using the system dynamics method that demonstrates how the theory of constraints can be used to explain and predict inpatient waiting times. The model has demonstrated where the main 'bottleneck' in the cardiac surgery system resides and has suggested strategies for managing that 'bottleneck'. Another study has also used the theory of constraints and system dynamics in this way though in a different setting. Quinn, et. al (2005) describe a study to improve the performance of a
hospital’s pathology laboratory in the time it takes to draw and analyse blood samples (Hospital pathology laboratories analyse tissue and other material taken from patients to help doctors diagnose symptoms). The various stakeholder groups were blaming the laboratory for a perceived lateness in laboratory results. Late results meant delayed clinical decisions resulting in delayed discharges which impacted on the hospital’s finances. This, in turn, meant the hiring of new phlebotomists (staff that take blood samples) was curtailed so further exacerbating the laboratory’s poor performance. The authors argued that to break out of this vicious cycle, the hospital groups would have to think systematically.

Using the Theory of Constraints in conjunction with a system dynamics simulation model, Quinn et al (2005) showed that solving the bottleneck in the laboratory would simply make the ‘Time to make clinical decisions’ the new bottleneck in the system. Hospital performance would only improve if factors affecting this variable, like the timing of ward rounds, were improved as well.

The Theory of Constraints suggests in the present study that, to maintain a certain maximum inpatient waiting time, the numbers of patients coming onto the inpatient waiting list need to be controlled. The inpatient waiting list is, effectively, the queue that sits before the main bottleneck in the system, the cardiac intensive care unit (CICU). Numbers of elective operations (i.e., the flow of patients from the waiting list and through the cardiac surgery system) are limited by the number of beds in the CICU. Patients come on to the inpatient waiting list from outpatients therefore for various numbers of CICU beds a maximum number of new outpatient attendances can be quantified that will not threaten the maintenance of a certain maximum waiting time (depending on selection strategy from the waiting list). The model has quantified this effect for the three-month waiting time target (see Figure 8.1).

The model itself has shown that CICU beds are a bigger constraint on inpatient waiting times in the cardiac surgery specialty at the hospital than theatre time. Expanding theatre time will only improve performance if the number of CICU beds is increased as well.
The model has also shown how the system will cope with transients when a temporary month long block in CICU was simulated (i.e., where no patients were allowed in or out of the Unit). This showed a spike in the inpatient waiting list (as reproduced in figure 8.4 below) compared to the baseline run (the simulation run without a block) that was sustained for the rest of the simulation period.

Figure 8.4: The Effect of a Month Long Block in CICU on the Inpatient Waiting List

In practice, the inpatient waiting list would probably come down gradually over time as service commissioners redirected referrals elsewhere and the Hospital Management would endeavour to perform more operations than usual possibly with extra resources.
Chapter 9: Conclusions

9.1 Aims and Objectives

Chapter 1 set out a number of Aims and Objectives for this Study. In this concluding Chapter these Aims and Objectives will be reviewed in light of the work performed. It will also make a number of recommendations and indicate areas of future possible work.

The first aim of the study is stated below along with its objectives.

Aim 1
To describe, explain and predict patient waiting times for cardiac surgery procedures in Glenfield Hospital, Leicester.

Objective 1.1
Discover the information that managers and clinicians at the Hospital use to control the cardiac surgery system.

This objective has been achieved through the use of qualitative analysis of the Interview carried out and the Document analysis. The System is controlled by the scheduling of patients, beds and theatre staff. Measures such as inpatient waiting time and the size of the inpatient list are used to review performance. Clinical audits ensure the quality of the work carried out.

Objective 1.2
Identify and compare models and modelling methods used in healthcare settings.

The literature search identified and compared various healthcare models that used a variety of methods. These included analytical methods like queuing models and ‘black box’ models, Markov chains, Discrete Event Simulation, Petri Nets and System Dynamics.
various methods were compared and System Dynamics was felt to be the best method to model the cardiac surgery system.

**Objective 1.3**

*Identify and assess the range of variables, including funding and management issues which impact on patient waiting times for cardiac surgery procedures.*

Inpatient Waiting Times are impacted by resources like CICU beds, staff, theatre time but also emergencies blocking elective operations and the number of additions to the list (mostly caused by new outpatient appointments).

The second aim is set out below,

**Aim 2**

To develop a waiting list model/tool for the use of the stakeholders at the Hospital

**Objective 2.1**

*Design and develop a linking mechanism for information to be accessed directly from the Hospital’s Patient Administration System so that it is conveniently displayed/monitored for managers and clinicians and other stakeholders.*

The link was put in place for the data model described in Chapter 5, however it was not pursued in the System Dynamics model as it was felt to be unnecessary and got in the way of using the model. However the repercussions of this were that the System Dynamics model did not always have up-to-date data which damaged stakeholders’ confidence in it for making accurate predictions.

**Objective 2.2**

*Develop a model interface allowing information produced by the model to be displayed optimally*
A model interface has been developed for the data model described in Chapter 5. The system dynamics model uses the graphical interface (with its ‘stock and flow’ diagram conventions) of the Vensim software in which it was developed.

Objective 2.3

*Evaluate the final model with stakeholders and suggest recommendations for further work.*

The validation tests described in Chapter 7 built confidence in the system dynamics model, however there was a feeling amongst stakeholders that it was too complicated and did not integrate well with the manner in which the waiting list was managed. The data model described in Chapter 5 was used to make predictions of waiting lists and waiting times that was integrated into the management of waiting lists and activity commissioning (in which the level of operations to be performed in the coming financial year are negotiated with purchasers of healthcare in the Primary Care Trusts). Recommendations are made in the next section.

9.2 Recommendations

Recommendations include

Develop the system dynamics model without the political constraints of waiting time targets. The model could be developed with management focus on making a tool for them to experiment on their system of care without changing the real system. This could then be incorporated into the Plan-Do-Study-Act (PDSA) planning cycle. Waiting times and lists would still form key performance indicators in the model but would not be the main focus.

Improve the Integration of the system dynamics model with the recommended waiting list management techniques. Waiting list management relies on tracking patients who are close to breaching a waiting time target. This can...
have implications for the mix of patients surgeons would have to operate on in the near future. A mix of more complicated procedures could mean less patients being operated on and longer lengths of stay in the hospital which would have implications for meeting waiting time targets. The model could be adjusted to take account of this mix of patients and examine whether there is an 'optimum' mix that would not threaten waiting times. In this way modelling can be incorporated into the planning process.

Adapt and spread the model outside of the cardiac surgery specialty. Other specialties would be interested in a systems model of their processes. The system dynamics model might be examined for certain 'molecules' (Hines, 2005), small genetic structures that describe similar processes common to waiting lists across specialties. These could be adapted for use in other specialties' models. Other specialties' systems will differ of course. Some won't have dedicated intensive care facilities and most or all patients may not require a spell in intensive care. For cardiac surgery the main diagnostic test that cause delays are cardiac catheters which are actually managed by another specialty, cardiology. A wider range of diagnostic tests may cause more delays in other specialties and may mean more levels modelling patients' time in outpatient. There are however many similarities between specialties' processes of care. Patients are referred by General Practitioners (GPs) or other specialties on to an outpatient waiting list and from there will be seen, diagnosed and either treated or placed on the inpatient waiting list. Stakeholders from each specialty would have to validate their individual specialty's model.

Establish modelling tools for use by staff. Some basic modelling packages are available at low cost (Vensim for example). A variety of tools covering various modelling techniques would give managers maximum flexibility. 'Simul8' is a popular package for Discrete Event Simulation, the original software was produced to solve a hospital resource allocation problem.
9.3 Suggestions for Further Work

Further work developing a multi-methodological intervention is suggested by a paper by Mabin, et al. (2006). They set out the complementary nature of system dynamics and certain ‘thinking processes’ tools involved in applying the Theory of Constraints (ToC), by way of a classification of operational research (OR) methods developed by Mingers (2003). Mingers’ classification describes OR methods by the appropriateness of their use according to the nature of the problem domain (social, personal and material) and the phase of intervention. While system dynamics is felt to capture the social and material problem domains adequately, it is not classified as representing individual viewpoints of the problem domain well. Mabin, et al. (2006) suggest use of the ‘evaporating clouds’ and ‘current reality branch’ (CRB) thinking processes in conjunction with system dynamics to give a fuller picture of a problem domain which would lead to more acceptable solutions to the issue at hand.

‘Evaporating clouds’ is a thinking process within ToC that tries to find a solution to a conflict between two opposing viewpoints. Mabin, et al. (2006) gave an example of someone trying to give up smoking. This is shown in Figure 9.1 below.

Once the dilemma is visualised in this way, ways may be sought to resolve it. To start this process the assumptions underpinning the processes involved in Figure 9.1 are listed and thought through. Some of these assumptions are shown in Figure 9.1 as thought bubbles or clouds. Sometimes when articulated some assumptions can be seen as false and the conflict evaporates.

Surviving assumptions are listed and challenges to them (or ‘injections’) generated and also listed. Whether these injections are good or flawed solutions to the conflict needs to be clarified with another of ToC’s thinking processes. In this example, Mabin, et al. (2006) used the ‘current reality branch’ (CRB) process. This process starts with action D (from Figure 9.1) and goes through the positive and negative effects of action D to achieve the
requirement B and how it will also lead to not achieving the requirement C. These steps are also repeated for D' to achieve C and not achieving B (again letters refer to Figure 9.1).

Figure 9.1: Theory of Constraints (ToC) 'evaporating cloud' (from Mabn, et al. (2006))

When these links are laid out, a solution to the conflict or dilemma becomes clearer. Injections from the evaporating cloud are tried our and adapted until a working solution appears. A minimal set of injections that achieve the objective are then chosen.

Mabn, et al. went on to construct a Causal Loop Diagram (CLD) from the development of the evaporating cloud and 'current reality branch'. This is shown in Figure 9.2. The CLD helps to build a picture of the system under study and its possible future development.

Mabn, et al. have shown how to use the thinking processes of ToC to come up with solutions to conflict situations and then use System Dynamics to describe the possible solutions in a systemic way. This could be taken further and a Stock and Flow simulation drawn from the CLD and the consequences of the
possible solutions evaluated. In healthcare, the multi-methodological intervention described could be used to come up with possible solutions to the conflict between achieving targets and maintaining standards of care.

Figure 9.2: Causal Loop Diagram of Smoking Conflict (from Mabin et al., 2006)

- Negative Influence

+ Positive Influence

Delay
Appendix 1: Topic Guide

The purpose of the research is to model the cardiothoracic surgery system at Glenfield to produce a tool to predict the waiting list for elective surgery and see the effects of different management strategies to deal with waiting lists on the system and the list.

This includes finding hidden barriers and thresholds in the management system behind the surgical waiting list and behaviours that affect the functioning of that system.

Permission to tape record interview

Right not to answer any interview and to terminate the interview at any time

Answers will remain anonymous

1. Introduction

Aim To get knowledge of interviewee's experience of managing waiting lists and modelling.

Experience of managing waiting lists, what strategies used to keep on top of numbers/time waited
Assessment of models used previously
Assessment of COWL model if used
What information would interviewee wish to get from a waiting list model.

2. The current system

Introduce with System Dynamics model in Vensim (may need introduction)
2.1 Patient Referrals

**Aim** To find out where waiting list patients are referred from. To discover any hidden waits patients may experience before they get to the waiting list.

2.2 Criteria for Entry on to the Waiting List

**Aim.** To discover if patients are delayed in being placed on the waiting list.

Who makes decisions on entry to the waiting list (who are the gatekeepers).

Are there any conditions where patients would not be treated.

2.3 Criteria for Leaving the Waiting List

**Aim.** To find out the reasons patients leave the list. To find out who gets priority and does it match to recorded priority.

Other reasons patients are prioritised e.g. complaining.

Are there patients on the list who should not be there?

Who makes decisions to take patients off the list?

2.4 Use of Resources

**Aim.** To find out how resources like ITU beds, ward beds, theatres and staff are scheduled to meet demand.

Staff shortages

ITU bed closures

Bed turn-around times

Emergency patients delaying/postponing elective admissions (elective patients ability to opt for another slot/surgeon).

How is length of time in theatre estimated?

Operations per slot
How far can resources be 'stretched' (e.g. getting patients into outlying beds if no specialty beds)?

Other resources not mentioned here delaying admissions
Staff 'gaming' the system for their patients' advantage

3. Other Issues

Aim To discover if the interviewee has any ideas or suggestions about the research

Are there any other issues missed or would like to raise?
Are there any other staff that could be interviewed with regard to this research?
Appendix 2: Interview Notes

A2.1 Interview 1 3rd August 2004 10:30am

1. Introduction

Aim: To get knowledge of interviewee's experience of managing waiting lists and modelling

Experience of managing waiting lists, what strategies used to keep on top of numbers/time waited.
Assessment of models used previously.
Assessment of COWL model if used.
What information would interviewee wish to get from a waiting list model.

Interviewee 1 has not used models before. She had dabbled in management of waiting lists for the last ten years but as monitoring and reporting on waiting lists rather than actual management. Interviewee 1 reported on numbers, how long patients had waited, where they came from, whether they were contracted or non-contracted patients and kept an eye on inappropriate referring behaviour by referring consultants (external consultants?) This mostly done by another manager now.

COWL model – Main problem was its speed, the model is too slow. It takes 20 minutes to work out numbers to be brought in from the waiting list. Interviewee 1 would print off numbers from COWL model but no action would be taken by those this information was disseminated to. Managers now take reports off the Intranet (patient lists). COWL output is a good summary but is not used by Managers who prefer to go through lists (printed off at least once a week). Managers say they want to change but then do not have time to enact change. COWL model needed updating, good to find out numbers to bring in but unacceptably slow.
Management did want QSCAN (Q – something?, another model) but no one has been identified to run/manage it. Has broad range of output that reports the same thing. However some clinicians against it.

No value in any models if no one uses the information they provide to take action. Struggle between Clinicians and Managers. Perception of usefulness. If not perceived as useful then what is point.

2. The current system

*Introduce with System Dynamics model in Vensim (may need introduction)*

Question on Rising numbers on the waiting list causing more emergencies or rising waiting time.

If numbers on the waiting list are rising, this will generally mean they are waiting longer so both rising numbers and times cause more patients to become emergencies. These patients will generally come in as Urgents from Cardiology (blue forms). They also stay longer so Unoccupied beds will fall causing the Waiting List and elective cancellations to rise. Cardiology Urgents will sit on Cardiology ward for surgery.

Bottlenecks include the wards, CICU.

If emergencies are admitted at night, then theatre staff on call will come in but if these staff are needed the next day, they may not be able to work as need a certain time off. Generally will cobble a team together but may not be able to, so may lose half a day's work. Then this will lead to a cancelled elective operation which may be difficult as will end up with a patient who needs to be done within 28 days.

2.1 Patient Referrals
Aim: To find out where waiting list patients are referred from  To discover any hidden waits patients may experience before they get to the waiting list.

2.2 Criteria for Entry on to the Waiting List

Aim: To discover if patients are delayed in being placed on the waiting list

Who makes decisions on entry to the waiting list (who are the gatekeepers). Are there any conditions where patients would not be treated.

Consultants see new outpatients, see their diagnostic tests, may send back to Cardiology if not felt to be in need of surgery  Others added to waiting list based on consultants' knowledge and clinical experience

2.3 Criteria for Leaving the Waiting List

Aim: To find out the reasons patients leave the list. To find out who gets priority and does it match to recorded priority

Other reasons patients are prioritised e.g. complaining. Are there patients on the list who should not be there WHO makes decisions to take patients off the list.

Management have to bring in long waiting patients to meet standards but clinicians want to bring in sicker patients  Clinicians know about priority and urgency of their patients  Leads to conflict

Clinical Urgency versus NHS targets

One of the Performance Indicators is the Number of deaths after CABG  So if admit a patient whose waited longer rather than one waiting for a CABG who then dies then problems
Management and Consultants working to different targets.

2.4 Use of Resources

**Aim:** To find out how resources like ITU beds, ward beds, theatres and staff are scheduled to meet demand.

*How is length of time in theatre estimated? (Is it?)*

- **Operations per slot**
- **Emergency patients delaying/postponing elective admissions (elective patients ability to opt for another slot/surgeon).**
- **How far can resources be 'stretched' (e.g. getting patients into outlying beds if no specialty beds)?**
- **Staff shortages.**
- **ITU bed closures.**
- **Bed turn-around times**
- **Other resources not mentioned here delaying admissions**
- **Staff 'gaming' the system for their patients' advantage.**

Long waiting elective patient on ward if blocked by emergency will be sent home unless that will breach the 28 day standard so they will stay on the ward. They stay there until their operation can be done ASAP. Another elective patient will be cancelled if that is the only way.

Consultants make their own list for each day, compiled the afternoon before.

ICU staff tell Theatre staff on the day how many beds are/will be available. If not enough beds then there is a discussion as to who to cancel, final decision resting with the Head of Service. No standard way of resolving cancellations. No analysis of who is being cancelled (by Urgency, length of wait etc) (gaming - Consultant may say "Patient will die", to get bed, who to say is wrong).
Patients rarely go straight to ward – Progressive Care, Patients with low Parsonnet score are intubated in surgery and go to High Dependency Unit rather than CICU and then back to the ward after 4 hrs but most end up back in CICU

Patients outlie on other specialty's wards occasionally, but not fair on other staff not trained in looking after surgery patients

3. Other Issues

Aim: To discover if the interviewee has any ideas or suggestions about the research

Are there any other issues missed or would like to raise.
Are there any other staff that could be interviewed with regard to this research

DC - Master Scheduler.

A2.2 Interview 2 30th September 2004 2pm

1. Introduction

Aim: To get knowledge of interviewee's experience of managing waiting lists and modelling

Experience of managing waiting lists, what strategies used to keep on top of numbers/time waited.
Assessment of models used previously
Assessment of COWL model if used
What information would interviewee wish to get from a waiting list model.

{NB Asked Interviewee to describe job role}
Role involves

- Ensuring there are no long waiters, TCI dates are scheduled in a timely manner according to what theatres and catheter labs available
- Training and managing Waiting List clerks
- Data accuracy of HISS Waiting List

- Make sure standards are met and flag to top if they not able to

(Standards include

- Patients are on the Inpatient Waiting List within 48 hours of being informed of their entry
- 3 month wait by end March 05 (trying for Dec 04)
- 28 day cancellations

Uses reports on the Intranet System from the Data Management System to list Waiting patients. Tries to get TCI dates from Consultants across the directorate

Monitors suspensions and D06/D07 patients (Outpatients who are added to the Inpatient/Daycase Waiting List) so no one 'pops out' of the woodwork.

Used a waiting list model when worked in Orthopaedic Surgery. Did not use COWL model much as role is more data quality/timely information rather than strategic, forecasting however role is moving that way.

Would want from a model

To see the effect of the complexity of casemix of those scheduled to come in would have on the system i.e. more complex cases would occupy beds for longer. Would there be an optimum casemix

Annual Leave, Sickness of consultants, also effect of bank holidays (one surgeon only operates on Mondays)
More flexible capacity for consultants (Look back at utilisation of sessions last year).

Problems from lack of other staff e.g. perfusionists

2. **The current system**

*Introduce with System Dynamics model in Vensim (may need introduction).*

2.1 **Patient Referrals**

**Aim** To find out where waiting list patients are referred from. To discover any hidden waits patients may experience before they get to the waiting list

Cardiac Surgery is open to emergencies from any specialty and hospital. Surgeons have set days for emergency ‘on-call’.

‘Blue form’ catheter patients are diagnostic catheter patients who need surgery immediately and are too sick to be sent home. Consultants do not allocate theatre time to emergencies specifically, just schedule elective patients hence the need to cancel admissions. ‘Blue form’ patients currently at 15/16 a month.

Elective/Transfers/Emergencies (go direct to CICU)

2.2 **Criteria for Entry on to the Waiting List**

**Aim** To discover if patients are delayed in being placed on the waiting list

*Who makes decisions on entry to the waiting list (who are the gatekeepers)*

*Are there any conditions where patients would not be treated.*
Adding an outpatient to the Inpatient Waiting List, a consultant fills in an Outcome form in clinic which is entered by the clerk into HISS as “Added to IPWL” (Outpatient Appt Outcome). But later on if the consultant changes his mind or a mistake is made his secretary won’t write the letter and the patient is not added to the list. So discrepancies build up. The system has a lot of hand-offs of paper based data so potential for errors is large. Another example the secretaries do not know how to enter data on to HISS so have to send paper data to clerks.

Visiting Consultants in Cardiology – waiting lists are managed by other hospitals but are counted as Glenfields.

2.3 Criteria for Leaving the Waiting List

Aim: To find out the reasons patients leave the list. To find out who gets priority and does it match to recorded priority.

Other reasons patients are prioritised e.g. complaining
Are there patients on the list who should not be there.
Who makes decisions to take patients off the list.

Interviewee 2 gives list of patients to Consultants’ secretaries who schedule theatre lists.

Coded theatre list so know who is long waiter so can make sure they are less likely to be cancelled.

Patients on the list are sometimes unfit medically or no longer want procedure and so the consultant decides to remove them.

2.4 Use of Resources
Aim: To find out how resources like ITU beds, ward beds, theatres and staff are scheduled to meet demand.

How is length of time in theatre estimated? (Is it?)
Operations per slot
Emergency patients delaying/postponing elective admissions (elective patients ability to opt for another slot/surgeon).
How far can resources be ‘stretched’ (e.g. getting patients into outlying beds if no specialty beds)?
Staff shortages.
ITU bed closures.
Bed turn-around times.
Other resources not mentioned here delaying admissions
Staff ‘gaming’ the system for their patients’ advantage.

{Question about elective patients ability to opt for another slot/surgeon asked}

Pointed out that Patient Choice scheme was being introduced where patients could opt for another hospital for their operation when added to the list
Whether this was coming in for cancelled elective patients on the ward to get their ops quicker wasn’t sure Suggested talking to Alison Godfrey-Vallence, ITU Sister.

3. Other Issues

Aim: To discover if the interviewee has any ideas or suggestions about the research.

Are there any other issues missed or would like to raise.
Are there any other staff that could be interviewed with regard to this research.

Bed Blockers from A&E. Trolley wait standards threaten Star Status. Patients have to be admitted into the hospital within a certain time period so if
cardiorespiratory bed is the only one available, then has to be used. But this knocks on, potentially blocking the CICU discharging patients and blocking elective admissions. CDU Unit – Stroke patients going directly there instead of the A&E at the Royal.

Consultants manage their lists independently and don’t communicate about them so is not known until the day of operation how complex the cases are so do not know what effect this will have on the later operation of the system.

List patients chronologically in the month rather than just Urgency.

A2.3 Interview 3 22nd March 2005 4pm

Interviewee’s reaction to a brief presentation of the system dynamics model

Possible scenarios

Consultant Sessions – suggestion of spreading out consultant sessions might improve the throughput of patients was thought to be difficult to implement in practice because of staff and possible increase in costs.

Modelling of holidays and annual leave now not crucial as these times are being covered by an Associate Specialist, though there is a question of whether there are differences in cases he takes up in terms of risk/complexity and what effect that could have. Also consultants starting to work in teams to cover each other e.g. Paediatrics, Valves.

Length of stay increased recently in ITU. Cardiology are taking simpler patients leaving more complex cases with surgery.

Staffing levels, for example 13 whole time equivalents on the wards are currently on maternity leave.
What is the maximum new outpatient slots possible without breaking the 3 month inpatient waiting target for each surgeon? i.e. Relate elective admission rate to waiting list addition rate (approx 95% conversion rate from new outpatients). How will this then effect outpatient waits? Also surgeons have certain slots for paediatrics, urgents etc

Interviewee hoped to use evidence from model to go back to commissioners to see if they'll buy more activity and then could get an extra surgeon for the extra capacity

A2.4 Interview 4 15th July 2005 10:30am

1. Are there any delays for patients caused by diagnostic tests?
   a. in elective admission for surgery?
   b. in other parts of the cardio-respiratory directorate?

2. Emergency admissions: the model currently assumes they will be taken into theatre immediately whatever the time of day, are there any occasions when the emergency would wait for the next elective scheduled slot?

3. Elective admissions: The model currently cannot model potential 28 day breaches as it cannot model cancellations on the day of surgery. To do this it would have to model the booking process. How far ahead are patients on the waiting list booked / scheduled for surgery? Is booking leading to an increase in cancellations?

4. Structure Verification: Apart from the above is there anything about the model's structure that seems incorrect?

5. Boundary Adequacy (Structure) Apart from the above are there concepts that the model does not include e.g. would it be useful to examine cardiology in more breadth?
6 Is there anything else you would like to comment on about the model or the research?
Appendix 3: Numbered Quotations from Qualitative Analysis

A3.1 ‘Consultants’ Code Network View

2.93
“Consultants see new outpatients, see their diagnostic tests, may send back to Cardiology if not felt to be in need of surgery.”

2.94
“Others added to waiting list based on consultants' knowledge and clinical experience.”

2.139
“Consultants make their own list for each day, compiled the afternoon before.”

3.120
“Patients on the list are sometimes unfit medically or no longer want procedure and so the consultant decides to remove them.”

3.158
“Consultants do not allocate theatre time to emergencies specifically, just schedule elective patients hence the need to cancel admissions.”

3.159
“Consultants manage their lists independently and don’t communicate about them so is not until the day of operation how complex the cases are so do not know what effect this will have on the later operation of the system.”

A3.2 ‘Emergencies’ and ‘Elective Cancellations’ Codes Network View

2.1
“Long waiting elective patient on ward if blocked by emergency will be sent home unless that will breach the 28 day standard so they will stay on the ward.”
They stay there until their operation can be done asap. Another elective patient will be cancelled if that is the only way.

2 2
"If emergencies are admitted at night, then theatre staff on call will come in but if these staff are needed the next day, they may not be able to work as need a certain time off. Generally will cobble a team together but may not be able to, so may lose half a days work."

2 66
"If numbers on the waiting list are rising, this will generally mean they are waiting longer so both rising numbers and times cause more patients to become emergencies. These patients will generally come in as Urgents from Cardiology (blue forms). They also stay longer so unoccupied beds will fall causing the Waiting List and elective cancellations to rise. Cardiology Urgents will sit on Cardiology ward for surgery."

2 88
"Then this will lead to a cancelled elective operation which may be difficult as will end up with a patient who needs to be done within 28 days."

3 160
"'Blue form' catheter patients are diagnostic catheter patients who need surgery immediately and are too sick to be sent home."

A3.3 ‘CICU’ Code Network View

2 146
"Patients rarely go straight to ward – Progressive Care, Patients with low Parsonnet score are intubated in surgery and go to High Dependency Unit rather than CICU and then back to the ward after 4 hrs but most end up back in CICU. (N B. Parsonnet score rates the clinical risk of a patient’s outcome, the higher the score the higher the risk of a poor outcome)"
3.142
"Bed Blockers from A&E. Trolley wait standards threaten Star Status. Patients have to be admitted into the hospital within a certain time period so if cardiorespiratory bed is the only one available, then has to be used."

3 143
"But this knocks on, potentially blocking the CICU discharging patients and blocking elective admissions."

A3.4 ‘Managing Waiting Lists’ network view

2 26
"how long patients had waited"

2 36
"to work out numbers to be brought in from the waiting list."

2 37
"Managers now take reports off the Intranet (patient lists)"

2 38
"Managers who prefer to go through lists"

2 42
"find out numbers to bring in."

2.106
"Management have to bring in long waiting patients to meet standards."

3 30
"reports on the Intranet System from the Data Management System."

3 32
"Tries to get TCI dates from Consultants across the directorate."
“Monitors suspensions and D06/D07 patients”

“Interviewee 2 gives list of patients to Consultants' secretaries who schedule theatre lists”

“Coded theatre list so know who is long waiter so can make they are less likely to be cancelled”

A3.5 ‘Conflict’ Network View

“Management have to bring in long waiting patients to meet standards but clinicians want to bring in sicker patients. Clinicians know about priority and urgency of their patients. Leads to conflict.”

“A3.6 ‘Knock on Effects’ Network View

“Clinical Urgency versus NHS targets.”

“One of the Performance Indicators is the Number of deaths after CABG. So if admit a patient whose waited longer rather than one waiting for a CABG who then dies then problems.”

“Management and Consultants working to different targets.”
"Another elective patient will be cancelled if that is the only way."

3 142
"Bed Blockers from A&E. Trolley wait standards threaten Star Status. Patients have to be admitted into the hospital within a certain time period so if cardiorespiratory bed is the only one available, then has to be used"

3 157
"know what effect this will have on the later operation of the system "

339
Appendix 4: Collaboration with Consultant

The model was developed in collaboration with a consultant, Fred Charlwood. Basic construction of the spreadsheet was carried out by Fred Charlwood including how the model samples random variables for Operations and Additions and uses these values to project ahead for the next 12 months for ALL consultants and ALL procedures.

The following elements were created and developed by myself:

- Development of the interface,
  More details are given on the model interface are given in section 5.5
- The 'Private Sector Patient Choice' option,
  Over the last few years extra operations have been funded by the Department of Health in the private sector. These allowed patients on the waiting list who were fit enough and who wanted to, to be treated by their consultant in the private sector. These were to alleviate waiting list pressures and allow the Trust to meet its waiting list targets. Modelling these extra operations involved putting in an extra priority weighting section as the patients who were treated tended to be those who had not waited that long and were routine (because of the fitness criteria). These were then added in to the 'net transfers out' part of the main modelling spreadsheet. NB This extra funding PSPC programme should not be confused with the National 'Patient Choice' programme.
- Splitting the model by consultant and procedures,
  There was a requirement by the management at the cardio-respiratory directorate to split the model's output down by consultant and procedure. This satisfied the planning objectives as to where to allocate resources like operating time. New Code had to be written to make sure the data appropriate for the chosen consultant and procedure was drawn into Excel.
- Obtaining data direct from the PAS system,
An Access database was used to take data from the main hospital PAS system. This involved writing accurate queries and matching operations to waiting list additions:

- Storing data in the Access database,
- Producing the probability distribution from the data stored in the Access database;

Accurate queries had to be written that produced a probability distribution from the raw datasets and also had the correct filters to take out the chosen consultant and procedure.

- drawing that data into Excel.
- The addition of PCTs into the model
- The estimation of the minimum number of extra operations that will be required to meet waiting time targets.
Appendix 5: Tabulated Figures for Length of Stay in CICU And Wards

Length of stay has been cut off at 20-25 days in Table A5.1 below for ease of presentation.

Table A5.1 Numbers of Patients in CICU and Cardiac Surgery Wards by Length of Stay (Quarter Days) Jan 2003 to Feb 2005

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</tr>
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343
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<th>2</th>
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<td>66-67</td>
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<td>0</td>
<td>3</td>
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<td>2</td>
<td></td>
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<td>7</td>
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<td>2</td>
<td>9</td>
<td></td>
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<tr>
<td>77-78</td>
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<td>0</td>
<td>4</td>
<td></td>
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<tr>
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<td></td>
</tr>
<tr>
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<tr>
<td>80-81</td>
<td>1</td>
<td>0</td>
<td>7</td>
<td></td>
</tr>
</tbody>
</table>
Appendix 6: Chi Squared Goodness of Fit Tests on the Daily Catheter Rate Distributions

This appendix describes the procedure that was undertaken to fit the daily cardiac catheter numbers to Poisson or Normal distributions using the Chi Squared distribution. These procedures are drawn from Anderson et al (2002, p.460). The appendix goes on to reproduce the calculation of the Chi-squared test statistic for each of the daily distributions of the catheter rate.

The Catheter rate was estimated from a dataset giving daily counts of catheters performed between 1st April 2003 and 31st March 2005. Distributions were estimated for each day of the week as there was considerable daily variability especially between weekdays and weekends.

Tables A6.1 and A6.2 below set out the procedures for the goodness of fit tests for Poisson and Normal distributions. Tables A6.3 to A6.9 show the results of the goodness of fit tests for the seven days of the week, Monday to Sunday. The weekdays are fitted to normal distributions whilst the weekend days are fitted to Poisson distributions as only emergencies will be seen at the weekend so the distributions for these days should be random.
Table A6.1: Procedure for a Goodness of fit Test to a Poisson Distribution (from Anderson et al (2002), p 463)

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>State the Null Hypothesis: ( H_0 ): The population has a Poisson probability distribution</td>
</tr>
</tbody>
</table>
| 2.   | Select a random sample and  
|      | a. Record the observed frequency \( f_i \) for each value of the Poisson random variable  
|      | b. Compute the mean number of occurrences, \( \mu \) |
| 3.   | Calculate the expected frequency \( e_i \) for each value of the Poisson random variable. Multiply the sample size by the Poisson probability of occurrence for each value of the Poisson random variable. If there are fewer than five expected occurrences for a category then combine adjacent values and reduce the number of categories accordingly. |
| 4.   | Calculate the chi squared test statistic: \[
\chi^2 = \sum_{i=1}^{k} \frac{(f_i - e_i)^2}{e_i}
\]
|      | where \( k \) is the number of categories. |
| 5.   | Reject \( H_0 \) if \( \chi^2 > \chi^2_\alpha \) where \( \alpha \) is the level of significance and there are \( k-2 \) degrees of freedom |

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
</table>
| **1** | **State the Null Hypothesis:**  
\( H_0: \) The population has a Normal probability distribution |
| **2** | **Select a random sample and**  
   a. Compute the mean number of occurrences, \( \mu \), and the standard deviation, \( \sigma \)  
   b. Define equal probability intervals such that the expected frequency is at least five for each interval  
   c. Record the observed frequency \( f_i \) of data in each interval |
| **3.** | **Calculate the expected frequency \( e_i \) for each interval. Multiply the sample size by the probability of a Normal random variable being in the interval.** |
| **4** | **Calculate the chi squared test statistic.**  
\[ \chi^2 = \sum_{i=1}^{k} \frac{(f_i - e_i)^2}{e_i} \]  
where \( k \) is the number of categories. |
| **5** | **Reject \( H_0 \) if \( \chi^2 > \chi^2_\alpha \) where \( \alpha \) is the level of significance and there are \( k-3 \) degrees of freedom.** |
Table A6.3: Goodness of Fit Test to a Normal Distribution (Mean 12.6, Variance 4.9) for the catheter rate on Mondays

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected (104 observations)</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 6.34</td>
<td>14</td>
<td>10.4</td>
<td>3.6</td>
<td>12.96</td>
<td>1.25</td>
</tr>
<tr>
<td>6.34 - 8.51</td>
<td>4</td>
<td>10.4</td>
<td>-6.4</td>
<td>40.96</td>
<td>3.94</td>
</tr>
<tr>
<td>8.51 - 10.08</td>
<td>8</td>
<td>10.4</td>
<td>-2.4</td>
<td>5.76</td>
<td>0.55</td>
</tr>
<tr>
<td>10.08 - 11.41</td>
<td>7</td>
<td>10.4</td>
<td>-3.4</td>
<td>11.56</td>
<td>1.11</td>
</tr>
<tr>
<td>11.41 - 12.63</td>
<td>11</td>
<td>10.4</td>
<td>0.6</td>
<td>0.36</td>
<td>0.03</td>
</tr>
<tr>
<td>12.63 - 13.86</td>
<td>9</td>
<td>10.4</td>
<td>-1.4</td>
<td>1.96</td>
<td>0.19</td>
</tr>
<tr>
<td>13.86 - 15.19</td>
<td>21</td>
<td>10.4</td>
<td>10.6</td>
<td>112.36</td>
<td>10.80</td>
</tr>
<tr>
<td>15.19 - 16.76</td>
<td>10</td>
<td>10.4</td>
<td>-0.4</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>16.76 - 18.93</td>
<td>9</td>
<td>10.4</td>
<td>-1.4</td>
<td>1.96</td>
<td>0.19</td>
</tr>
<tr>
<td>More than 18.93</td>
<td>11</td>
<td>10.4</td>
<td>0.6</td>
<td>0.36</td>
<td>0.03</td>
</tr>
<tr>
<td><strong>Sum:</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>18.12</strong></td>
<td></td>
</tr>
<tr>
<td>Degrees of Freedom: 7</td>
<td></td>
<td></td>
<td></td>
<td>$\chi^2_{0.05} = 14.07$</td>
<td></td>
</tr>
</tbody>
</table>

Therefore reject the null hypothesis, the population does not have a normal distribution.

Table A6.4: Goodness of Fit Test to a Normal Distribution (Mean 15.8, Variance 5.1) for the catheter rate on Tuesdays

<table>
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<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected (105 observations)</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 9.11</td>
<td>12</td>
<td>10.5</td>
<td>1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>9.11 - 11.37</td>
<td>9</td>
<td>10.5</td>
<td>-1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>11.37 - 13.02</td>
<td>12</td>
<td>10.5</td>
<td>1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>13.02 - 14.4</td>
<td>6</td>
<td>10.5</td>
<td>-4.5</td>
<td>20.25</td>
<td>1.93</td>
</tr>
<tr>
<td>14.4 - 15.69</td>
<td>12</td>
<td>10.5</td>
<td>1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>15.69 - 16.97</td>
<td>9</td>
<td>10.5</td>
<td>-1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>16.97 - 18.36</td>
<td>15</td>
<td>10.5</td>
<td>4.5</td>
<td>20.25</td>
<td>1.93</td>
</tr>
<tr>
<td>18.36 - 20</td>
<td>4</td>
<td>10.5</td>
<td>-6.5</td>
<td>42.25</td>
<td>4.02</td>
</tr>
<tr>
<td>20 - 22.26</td>
<td>16</td>
<td>10.5</td>
<td>5.5</td>
<td>30.25</td>
<td>2.88</td>
</tr>
<tr>
<td>More than 22.26</td>
<td>10</td>
<td>10.5</td>
<td>-0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Sum:</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>11.86</strong></td>
<td></td>
</tr>
<tr>
<td>Degrees of Freedom: 7</td>
<td></td>
<td></td>
<td></td>
<td>$\chi^2_{0.05} = 14.07$</td>
<td></td>
</tr>
</tbody>
</table>

Therefore cannot reject the null hypothesis, the population has a normal distribution.
Table A6.5 Goodness of Fit Test to a Normal Distribution (Mean 19.0, Variance 5.6) for the catheter rate on Wednesday

<table>
<thead>
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<th>Interval</th>
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<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
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<td>10.5</td>
<td>-1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
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<td>11.64 - 14.12</td>
<td>14</td>
<td>10.5</td>
<td>3.5</td>
<td>12.25</td>
<td>1.17</td>
</tr>
<tr>
<td>14.12 - 15.93</td>
<td>4</td>
<td>10.5</td>
<td>-6.5</td>
<td>42.25</td>
<td>4.02</td>
</tr>
<tr>
<td>15.93 - 17.45</td>
<td>14</td>
<td>10.5</td>
<td>3.5</td>
<td>12.25</td>
<td>1.17</td>
</tr>
<tr>
<td>17.45 - 18.86</td>
<td>10</td>
<td>10.5</td>
<td>0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td>18.86 - 20.27</td>
<td>13</td>
<td>10.5</td>
<td>2.5</td>
<td>6.25</td>
<td>0.60</td>
</tr>
<tr>
<td>20.27 - 21.79</td>
<td>7</td>
<td>10.5</td>
<td>-3.5</td>
<td>12.25</td>
<td>1.17</td>
</tr>
<tr>
<td>21.79 - 23.59</td>
<td>12</td>
<td>10.5</td>
<td>1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>23.59 - 26.07</td>
<td>12</td>
<td>10.5</td>
<td>1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
<tr>
<td>More than 26.07</td>
<td>10</td>
<td>10.5</td>
<td>-0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Sum: 8.81</td>
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</tr>
</tbody>
</table>

Therefore cannot reject the null hypothesis, the population has a normal distribution

$\chi^2_{0.05} = 14.07$

Table A6.6 Goodness of Fit Test to a Normal Distribution (Mean 16.3, Variance 4.3) for the catheter rate on Thursdays

<table>
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<th>Interval</th>
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<th>Difference</th>
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<th>Squared Difference / Expected Frequency</th>
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<td>Less than 10.58</td>
<td>9</td>
<td>10.5</td>
<td>-1.5</td>
<td>2.25</td>
<td>0.21</td>
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<td>10.58 - 12.48</td>
<td>8</td>
<td>10.5</td>
<td>-2.5</td>
<td>6.25</td>
<td>0.60</td>
</tr>
<tr>
<td>12.48 - 13.86</td>
<td>11</td>
<td>10.5</td>
<td>0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td>13.86 - 15.03</td>
<td>20</td>
<td>10.5</td>
<td>9.5</td>
<td>90.25</td>
<td>8.60</td>
</tr>
<tr>
<td>15.03 - 16.1</td>
<td>6</td>
<td>10.5</td>
<td>-4.5</td>
<td>20.25</td>
<td>1.93</td>
</tr>
<tr>
<td>16.1 - 17.18</td>
<td>7</td>
<td>10.5</td>
<td>-3.5</td>
<td>12.25</td>
<td>1.17</td>
</tr>
<tr>
<td>17.18 - 18.35</td>
<td>14</td>
<td>10.5</td>
<td>3.5</td>
<td>12.25</td>
<td>1.17</td>
</tr>
<tr>
<td>18.35 - 19.73</td>
<td>10</td>
<td>10.5</td>
<td>-0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td>19.73 - 21.63</td>
<td>11</td>
<td>10.5</td>
<td>0.5</td>
<td>0.25</td>
<td>0.02</td>
</tr>
<tr>
<td>More than 21.63</td>
<td>9</td>
<td>10.5</td>
<td>-1.5</td>
<td>2.25</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Sum: 13.35

$\chi^2_{0.05} = 14.07$

Therefore cannot reject the null hypothesis, the population has a normal distribution
Table A6.7. Goodness of Fit Test to a Normal Distribution (Mean 10.4, Variance 3.7) for the catheter rate on Fridays

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected (104 observations)</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 5.67</td>
<td>10</td>
<td>10.4</td>
<td>-0.4</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>5.67 - 7.29</td>
<td>11</td>
<td>10.4</td>
<td>0.6</td>
<td>0.36</td>
<td>0.03</td>
</tr>
<tr>
<td>7.29 - 8.46</td>
<td>10</td>
<td>10.4</td>
<td>-0.4</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>8.46 - 9.48</td>
<td>10</td>
<td>10.4</td>
<td>-0.4</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>9.46 - 10.38</td>
<td>12</td>
<td>10.4</td>
<td>1.6</td>
<td>2.56</td>
<td>0.25</td>
</tr>
<tr>
<td>10.38 - 11.29</td>
<td>9</td>
<td>10.4</td>
<td>-1.4</td>
<td>1.96</td>
<td>0.19</td>
</tr>
<tr>
<td>11.29 - 12.29</td>
<td>14</td>
<td>10.4</td>
<td>3.6</td>
<td>12.96</td>
<td>1.25</td>
</tr>
<tr>
<td>12.29 - 13.46</td>
<td>9</td>
<td>10.4</td>
<td>-1.4</td>
<td>1.96</td>
<td>0.19</td>
</tr>
<tr>
<td>13.46 - 15.08</td>
<td>10</td>
<td>10.4</td>
<td>-0.4</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>More than 15.08</td>
<td>9</td>
<td>10.4</td>
<td>-1.4</td>
<td>1.96</td>
<td>0.19</td>
</tr>
<tr>
<td>Sum:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.15</td>
</tr>
</tbody>
</table>

Degrees of Freedom=7 \( \chi^2_{0.05} = 14.07 \)

Therefore cannot reject the null hypothesis, the population has a normal distribution.

Table A6.8: Goodness of Fit Test to a Poisson Distribution (Mean 3.9) for the catheter rate on Saturdays

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>9</td>
<td>10.13</td>
<td>-1.13</td>
<td>1.27</td>
<td>0.62</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>15.83</td>
<td>-0.83</td>
<td>0.69</td>
<td>0.04</td>
</tr>
<tr>
<td>3</td>
<td>22</td>
<td>20.70</td>
<td>1.30</td>
<td>1.69</td>
<td>0.08</td>
</tr>
<tr>
<td>4</td>
<td>24</td>
<td>20.30</td>
<td>3.70</td>
<td>13.67</td>
<td>0.67</td>
</tr>
<tr>
<td>5</td>
<td>11</td>
<td>15.93</td>
<td>-4.93</td>
<td>24.30</td>
<td>1.53</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>10.42</td>
<td>-0.42</td>
<td>0.17</td>
<td>0.02</td>
</tr>
<tr>
<td>7-8</td>
<td>13</td>
<td>8.70</td>
<td>4.30</td>
<td>18.49</td>
<td>3.17</td>
</tr>
<tr>
<td>Sum:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.13</td>
</tr>
</tbody>
</table>

Degrees of Freedom=5 \( \chi^2_{0.05} = 11.07 \)

Therefore cannot reject the null hypothesis, the population has a Poisson distribution.
Table A6.9: Goodness of Fit Test to a Poisson Distribution (Mean 2.1) for the catheter rate on Sundays

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>18</td>
<td>12.42</td>
<td>5.58</td>
<td>31.12</td>
<td>2.51</td>
</tr>
<tr>
<td>1</td>
<td>28</td>
<td>26.39</td>
<td>1.61</td>
<td>2.58</td>
<td>0.10</td>
</tr>
<tr>
<td>2</td>
<td>23</td>
<td>28.04</td>
<td>-5.04</td>
<td>25.45</td>
<td>0.91</td>
</tr>
<tr>
<td>3</td>
<td>11</td>
<td>19.86</td>
<td>-8.86</td>
<td>78.58</td>
<td>3.96</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>10.55</td>
<td>0.45</td>
<td>0.20</td>
<td>0.02</td>
</tr>
<tr>
<td>5-7</td>
<td>13</td>
<td>6.56</td>
<td>6.44</td>
<td>41.53</td>
<td>9.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Sum:</td>
<td>16.74</td>
</tr>
</tbody>
</table>

Degrees of Freedom=4, $\chi^2_{0.05} = 9.49$

Therefore reject the null hypothesis, the population does not have a Poisson distribution.
Appendix 7: Goodness of fit test to Poisson Distribution of Daily Blue Form Referrals

The table below sets out the Chi squared 'goodness of fit' test for fitting the 'Blue Form' referral rate to a Poisson distribution.

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>128</td>
<td>127.25</td>
<td>0.75</td>
<td>0.57</td>
<td>0.004</td>
</tr>
<tr>
<td>1</td>
<td>190</td>
<td>179.13</td>
<td>10.87</td>
<td>118.25</td>
<td>0.660</td>
</tr>
<tr>
<td>2</td>
<td>121</td>
<td>126.08</td>
<td>-5.08</td>
<td>25.78</td>
<td>0.204</td>
</tr>
<tr>
<td>3</td>
<td>46</td>
<td>59.16</td>
<td>-13.16</td>
<td>173.16</td>
<td>2.927</td>
</tr>
<tr>
<td>4</td>
<td>19</td>
<td>20.82</td>
<td>-1.82</td>
<td>3.31</td>
<td>0.159</td>
</tr>
<tr>
<td>5-9</td>
<td>16</td>
<td>7.57</td>
<td>8.43</td>
<td>71.07</td>
<td>9.389</td>
</tr>
<tr>
<td>Sum:</td>
<td></td>
<td></td>
<td></td>
<td>13.345</td>
<td></td>
</tr>
</tbody>
</table>

Therefore cannot reject the null hypothesis, the population has a Poisson distribution.

\[ \chi^2_{001} = 15.09 \]
Appendix 8: Goodness of fit test to Poisson Distribution of Other Referrals to Surgery Outpatients

The table below sets out the Chi squared 'goodness of fit' test for fitting the 'Other Referrals' referral rate to a Poisson distribution.

Table A8.1. Goodness of Fit Test to a Poisson Distribution (Mean 1.70) for the daily 'Other' referrals to Surgery Outpatients

<table>
<thead>
<tr>
<th>Interval</th>
<th>Observed</th>
<th>Expected</th>
<th>Difference</th>
<th>Squared Difference</th>
<th>Squared Difference / Expected Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>218</td>
<td>129.14</td>
<td>88.86</td>
<td>7896.28</td>
<td>61.15</td>
</tr>
<tr>
<td>1</td>
<td>190</td>
<td>219.55</td>
<td>-29.56</td>
<td>873.47</td>
<td>3.98</td>
</tr>
<tr>
<td>2</td>
<td>133</td>
<td>186.64</td>
<td>-53.64</td>
<td>2876.92</td>
<td>15.41</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>105.77</td>
<td>-55.77</td>
<td>3110.26</td>
<td>29.41</td>
</tr>
<tr>
<td>4</td>
<td>56</td>
<td>44.96</td>
<td>11.04</td>
<td>121.97</td>
<td>2.71</td>
</tr>
<tr>
<td>5</td>
<td>26</td>
<td>15.29</td>
<td>10.71</td>
<td>114.78</td>
<td>7.51</td>
</tr>
<tr>
<td>6-8</td>
<td>34</td>
<td>5.66</td>
<td>28.34</td>
<td>803.29</td>
<td>141.99</td>
</tr>
<tr>
<td>Sum:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>262.15</td>
</tr>
</tbody>
</table>

Therefore reject the null hypothesis, the population does not have a Poisson distribution

The model therefore used the observed frequency distribution as shown in figure 8A 1.
Figure 8A.1: Observed Frequency Distribution of daily 'Other' referrals to Surgery Outpatients.
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