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Novel approaches to radiotherapy planning and scheduling in the NHS

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Novel approaches to radiotherapy planning and scheduling in the NHS

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Summary

The main subject matter of this thesis concerns radiotherapy patient scheduling subproblems formulated as four separate shop scheduling problem models (i.e. hybrid flowshop, flowshop, mixed shop and multiple identical parallel machine scheduling problems) based on the characteristics of the intricate real-life treatment processes observed at the Arden Cancer Centre in Coventry, UK. Insight into these processes was gained by developing and using a novel discrete-event simulation (DES) model of the four units of the radiotherapy department. By typifying the subproblems as well-known scheduling problem models, it was intended that methods amenable to them such as heuristics be used in the study.

Four novel constructive heuristics based on priority dispatching rules and strategies adapted from some established algorithms have been developed and implemented using the C++ programming language. Further, these heuristics were incorporated into the DES model to create schedules of appointments for the patients generated daily. The effectiveness and efficiency of the constructive heuristics have been tested using the following performance criteria: minimising i) average waiting time to the start of treatment, and ii) average percentage of patients late for their treatment, and iii) the amount of overtime slots used for the patients received in a given period of time. The coordinated constructive heuristics and the DES model have also been tested using possible alternative pathways patients can follow in the treatment unit. The aim of these tests was to compare the efficiency of the radiotherapy department's current pathway to other possible pathways. Further, strategies for using maximum allowed breaches of targeted due dates, reserved slots for critical treatments and overtime slots was also included in the heuristics.

The results of several tests showed that the heuristics created schedules of appointments whose average waiting times for emergency, palliative and radical treatments improved by about 50%, 34% and 41%, respectively, compared to the historical data. However, their major slack was evidenced by the fact that about 13% of the patients needing palliative treatment were expected to be late for treatment compared to about 1% of those requiring radical treatment.

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Declaration

I declare that the work described in this Ph.D. thesis, unless otherwise acknowledged in the text, is my own and has not been previously submitted for any academic degree.

Signed: ____________________

Truword Kapamara

"*The key is not to prioritize what's on your schedule, but to schedule your priorities.*"

(Stephen R. Covey)

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Chapter 1

Introduction

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Cancer is a class of chronic diseases characterised by uncontrolled growth and metastasis of invasive and malignant abnormal cells to different parts of the human body (Altman and Sarg 2000:56). By about 2000, many people in the UK were diagnosed with this pernicious disease and about 120,000 died from it each year (Department of Health 2000). Since the early 1900s, several cancer treatments have been developed and used effectively. One of these is radiotherapy, an essential mode of treatment involving the use of ionising radiation to treat cancers. Most importantly, the total therapeutic radiation dose is usually divided into small portions (called *fractions*) that are delivered daily over a period of time to maximise the destruction of the injurious cells while minimising damage to healthy tissue. In addition, 40% of those cured of cancers in UK were treated by radiotherapy (Royal College of Radiologists 2003).

This chapter introduces the prolonged waiting times issues in radiotherapy departments in the UK and other countries, the elaborate treatment processes conducted in the radiotherapy department at the Arden Cancer Centre at the University Hospitals Coventry and Warwickshire National Health Service (NHS) Trust which was the main collaborator in this study, complexities of scheduling radiotherapy patients and the methods that can be used to tackle healthcare related problems such as minimising radiotherapy patient waiting times are also emphasised. The objectives of this study and the outline of this thesis are also stated at the end of this chapter.

1.1 Patient waiting time issues

In the UK, radiotherapy patient waiting time (or delay) is defined as the difference between the date when the decision to treat by radiotherapy is made and the date of delivering the first fraction of the entire radiotherapy course for the patient (Department of Health 2000). More crucially, radiotherapy waiting times are measured in consecutive days including bank holidays and weekends.

Lately, the demand for radiotherapy has risen with the growth of the incidences of cancer. Disparities between the demand for radiotherapy and the capacity of the available limited equipment and human resources affect the patient waiting times. Most studies on retrospective data on the treatment of cancers reported the following conclusions that the delays: i) allow cancerous cells to proliferate (Mackillop 2007), ii) increase local recurrence of the diseases (Huang *et al.* 2003), iii) increase tumour volume (Jensen *et al.* 2007), and iv) lower survival rates of the patients (Richards *et al.* 1999, Do *et al.* 2000, O'Rourke and Edwards 2000, Seel and Foroudi 2002). Hence, cancer centres worldwide endeavour to obtain as short as reasonably achievable delays.

In 1993, the Joint Council for Clinical Oncologists (JCCO) proposed waiting time targets for the most common treatments (i.e. emergency, palliative, and radical treatments) delivered in radiotherapy departments in the UK. Emergency treatments are critical treatments for relieving intense pain. Palliative treatment concerns alleviating pain or symptoms without necessarily curing the disease. Emergency treatments are palliative treatments that are more critical. Radical treatments are meant to cure the cancers. Most studies and audits have revealed that radiotherapy waiting times have recently worsened in several countries (Mackillop *et al.* 1996, Royal College of Radiologists 1998, Spurgeon *et al.* 2000, Ash *et al.* 2004, Lim *et al.* 2005, Summers and Williams 2005, Mackillop 2007, Drinkwater and Williams 2008). The UK fares badly in the comparison of radiotherapy waiting times and survival rates in the developed countries (Spurgeon *et al.* 2000).

In recent years, there has been a marked increase in efforts to tackle the issue of prolonged patient waiting times in radiotherapy departments in the UK. Radiotherapy departments wish to deliver fast and high quality service to cancer patients using their limited resources. However, like many other healthcare systems, they are characterised by disparities between capacity and fluctuating demand, elaborate patient flow processes and scarce resources. Furthermore, various ways of booking radiotherapy patients are being used in various radiotherapy departments. At the Arden Cancer Centre, the current booking system involves senior radiographers manually creating and amending various appointments for the patients until they obtain the most suitable schedule of the appointments. Thus, the senior radiographers that could be helping with the treatment procedures and enhancing patient care, spend time some of their time booking appointments for patients. In addition, in this manner of booking patients, mistakes are committed and it can be difficult to compensate for the 'unused slots' on the machines to be used by the patients as reported in (Haylock *et al.* 2005).

1.2 Treatment processes

The treatment processes normally conducted in most radiotherapy departments in the UK can be described as three-step processes. Figure 1.1 illustrates the three major steps followed by patients during their treatment. The first step involves procedures for staging the patient's cancer after referral to a cancer centre by their General Practitioner (GP). In this step, the advancement of the cancer is determined using imaging equipment. The second step involves creating treatment plans of the radiation to be received by the patient. The images obtained in the first step are used to create these treatment plans which are either complex or simple depending on the calculations of the intensity of the radiation beams prescribed by the doctor. Further accuracy verification of each treatment plan is also conducted in this second step before the treatment plans are forwarded to the next division of the radiotherapy department for the procedures of the third step to be performed. These procedures involve the delivery of the prescribed fractions to the patient on treatment machines such as the linear accelerators (linacs) over several consecutive days.

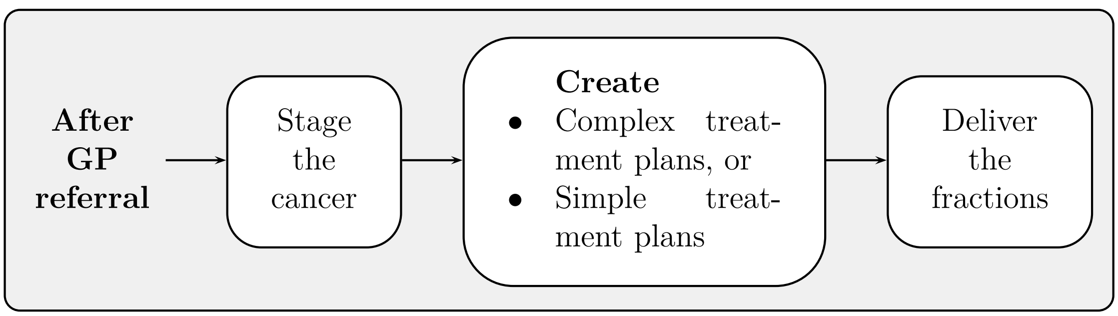

Figure 1.1: A high level flowchart illustrating major steps of radiotherapy followed in the UK

1.3 Complexities of booking patients

There are aspects of the steps of the treatment process in Figure 1.1 which complicate the manner in which radiotherapy patients can be booked or scheduled on available times or dates. These complexities are due to the intricacy of the procedures in the steps shown in Figure 1.1 such as uncertainty of patient arrival, constraints enforced by the Arden Cancer Centre's work practices, scarcity of human resources as doctors, radiographers and technicians, and lack of diagnostic (i.e. imaging equipment) and treatment equipment such as linacs.

The foremost aspect of radiotherapy that complicates the booking of patients in departments in the UK is the waiting time targets proposed by the JCCO. Booking appointments taking into consideration the deadlines suggested by the JCCO can be worsened by any delays in the submission of patient information to the senior radiographers that book the appointments. Furthermore, in the first step of staging cancers, the availability of the patient's doctor is a major constraint that impacts patient waiting times. According to the work practices of the Arden Cancer Centre, if the doctor is not immediately available, then the patient's staging procedures can be delayed by a number of days.

The arrival of patients after referral to the centre by their GP is uncertain. Different numbers of patients requiring the three treatments (i.e. emergency, palliative and radical) can arrive at the centre in different proportions on a given date. For example, at the Arden Cancer Centre, the arrival of patients requiring emergency treatments was infrequent. There are multiple identical machines of certain treatment machine types (i.e. high and low energy linacs), while there are also single machines of some treatment machine types. This contributes to the complexity of the scheduling of patients depending on which type of the treatment machine was prescribed by the doctor (i.e. the one with multiple identical machines available or on the single machine).

The scarcity of human resources also contributes to the complexity of the booking of patients. Each machine in the department has to be driven by a specified compliment of staff. Thus, the shortage of staff can lead to circumstances whereby some machines that are not fully booked are shutdown to avail their staff on the fully booked machines. In addition, the aforementioned impact of unavailability of doctors further complicates the booking of appointments and thus, impact the resulting waiting times obtained.

1.4 Solving healthcare problems

Many researchers have used various methods to solve different healthcare problems. Computer simulation and modelling has been one of the most common operational research (OR) techniques applied to healthcare problems as shown by the taxonomy of these problems in (Jun *et al.* 1999). Other OR methods from the theory of scheduling have been used to tackle healthcare problems. An example of healthcare problems solved by such methods include the notorious nurse rostering problem (Cheang *et al.* 2003).

1.4.1 Simulation and modelling

Computer simulation and modelling is a problem solving methodology that involves mimicking a real-life system over a period of time. There are many computer simulation software for solving healthcare problems and one of them is

Simul8 (Simul8 Corporation 2009). These techniques have been used to solve a wide variety of healthcare problems in various departments at hospitals as shown by the studies reviewed in (Jun *et al.* 1999). Some of the benefits of using simulation and modelling on healthcare problems include the ability to assess the impact of changes in the flow of patients, examine resources requirements, investigate complex relationships among the different model variables, identify bottlenecks in complex models and most importantly, to understand a given system.

Although notable research on healthcare problems has been carried out using simulation and modelling techniques, the paucity of papers on problems impacting radiotherapy departments is noticeable. Some of the simulation and modelling studies that have been conducted on all the processes in radiotherapy issues are in (Proctor 2003, Proctor *et al.* 2007, Hoogeland 2008). In this thesis, simulation and modelling techniques were employed to help in understanding every part of the treatment process through collecting data, building a model and experimenting with different scenarios considered as cost effective options for the Arden Cancer Centre.

1.4.2 Scheduling

There are many OR optimisation methods for solving intrinsically complex problems. These include exact enumerative, heuristic or approximation and metaheuristic methods. Exact enumerative methods such as dynamic programming and branch-and-bound algorithms create solutions by listing schedules and eliminate the non-optimal schedules. Heuristics can produce good solutions using minimal computational effort although they cannot guarantee near-optimal schedules. Metaheuristics are optimisation algorithms that use frameworks inspired by science and nature.

In the literature, some studies focused on solving the scheduling of patients in the last step (i.e. delivery of fractions) shown in Figure 1.1 using heuristics, metaheuristics and other methods (Petrovic *et al.* 2006, Petrovic and Leite-Rocha 2008, Petrovic *et al.* 2009). The use of scheduling techniques on radiotherapy scheduling problem has not been as intense as the studies on other healthcare problems such as the aforementioned nurse rostering problem.

Much research has been conducted in the area of scheduling and, in this context, it provides a motivation to use some of these scheduling techniques as starting points for the development of the radiotherapy scheduling methods. Baldwin (2006) suggested that cancer clinics can be likened to manufacturing industries so that production scheduling techniques that solved some of the scheduling problems can be applied to some of the cancer clinic's problems. In this thesis, new constructive heuristics based approach to scheduling patients in the steps that they follow in their treatment process of an archetypical radiotherapy department in the UK such as the Arden Cancer Centre were introduced. The heuristics are intended to reduce the waiting times, percentage of late patients and the amount of overtime accumulated by department. By providing each patient's schedule of appointments on the machines and facilities in his or her treatment regime, the heuristics are intended to enable radiotherapy departments to provide to patients more information about their treatment upon the receipt of the referral forms. This may help to improve the management of patients flow in the radiotherapy process and minimise the cancelations or patients not attending treatment procedures for their regime.

1.5 Objectives of the research

This research is focused on examining the elaborate treatment processes used in radiotherapy (especially at the Arden Cancer Centre) and the scheduling of radiotherapy patients. The main objectives of this study are as follows:

1. to examine, understand and document the treatment processes followed in the radiotherapy department,

2. to develop a discrete-event simulation (DES) model of the radiotherapy department at the Arden Cancer Centre to be used to analyse the existing treatment system using various 'what-if' scenarios which do not involve the need for huge capital outlays, such as: analysing the existing system when the number of staff is reduced, staff can work for extended working hours, and the patients can be attended to even when their doctor is not available in the radiotherapy department,

3. to gather essential information which characterises the treatment processes and can be used to formulate radiotherapy patient scheduling problems that can be identified in the different parts of the entire treatment process,

4. to develop novel constructive heuristics that solve the radiotherapy patient scheduling problem formulated using waiting times as one of the key performance measures of the schedules of patient appointments generated,

5. to develop a new software tool that can be deployed in the radiotherapy department at the Arden Cancer Centre for scheduling the radiotherapy patients

1.6 Thesis outline

This thesis comprises ten chapters. Chapter 2 covers an overview of cancers and their treatments while also emphasising the issues exacerbating the waiting times problem in the UK which include i) staff and equipment provision, and ii) the clinical effects of prolonged waiting times.

Chapter 3 provides an in-depth description of the treatment processes conducted in the radiotherapy department at the Arden Cancer Centre, a cancer centre at the University Hospitals Coventry and Warwickshire NHS Trust, during the period between September 2006 and December 2008. It comprises separate flowcharts of the processes followed in the planning, physics, pretreatment and treatment units. A flowchart which is a combination of all the other four flowcharts is used to 'walk-through' the paths followed by patients of certain pathological conditions from the time of submission of a radiotherapy request form to the delivery of their last fraction.

Research studies on radiotherapy, cancer-related and other healthcare problems, conducted using simulation and modelling, and the theory of scheduling techniques are reviewed in Chapter 4. For the simulation and modelling approaches, most papers focused on DES techniques compared to other techniques such as agent-based simulation and others, while for the scheduling theory, the methods considered ranged from exact enumerative methods to meta-heuristics.

Chapter 5 discusses DES models developed in this study to understand the radiotherapy treatment processes at the Arden Cancer Centre using the seven steps of model building suggested in the literature.

In Chapter 6, four radiotherapy patient scheduling problems are formulated for the four units involved in the treatment of cancer patients in the department. These problems are i) hybrid two stage flowshop, ii) two machine flowshop, iii) mixed shop scheduling, and iv) parallel identical machine scheduling problems for the planning, physics, pretreatment and treatment units respectively.

Chapter 7 discusses the novel constructive heuristics proposed to solve the aforementioned four subproblems using a basic framework that involves reordering an input sequence of patients using priority dispatching rules and then scheduling each patient's appointments using various strategies.

In Chapter 8, the results of the computational tests conducted using the simulation model of the department with the heuristics integrated to it are analysed. Four different alternative pathways that can be adapted by the radiotherapy department for patients in the treatment unit are compared based on their performances and the quality of schedules of appointments generated for patients in a given period.

Finally, concluding remarks for the thesis are given in Chapter 9 together with directions of future research work on radiotherapy patient scheduling problems. The thesis comprises an extensive list of refereneces, which covers many relevant books, internet websites and papers. Glossaries of key terms and mathematical symbols appear after the concluding remarks to provide the meaning of common words, abbreviations, and acronyms used in the text.

Chapter 2

Cancer and its treatments

Contents

2.1 Introduction

In the early 1900s, surgery was the only way of treating cancers. Later on, radiotherapy evolved to become an effective treatment mode in the late 1930s, on the back of Wilhelm Conrad Röntgen's discovery of x-rays in 1895. Similarly, another treatment mode termed chemotherapy was developed and used to cure cancers since the mid-1900s.

This chapter discusses cancers, their treatments and other issues about radiotherapy using examples from the radiotherapy department at Arden Cancer Centre at the University Hospitals Coventry and Warwickshire National Health Service (NHS) Trust in Coventry, UK. The problems prevalent in radiotherapy departments in general in the UK are also introduced.

The next Section introduces the cancers treated at the Arden Cancer Centre. Section 2.3 discusses cancer treatments including radiotherapy. In Section 2.4, the radiotherapy problems (i.e. particularly in the UK) are also discussed. Lastly, Section 2.5 gives the concluding remarks.

2.2 Cancers

Cancers are generally classified into five groups, namely: i) carcinoma, ii) sarcoma, iii) myeloma, iv) lymphoma, and v) leukemia, depending on the presumed origin of the abnormal cells. Carcinomas originate from tissues of organs and make up between 80–90% of the cancers while sarcomas are from bone or connective tissues. Myeloma are cancers from the bone marrow while lymphomas are from the lymphatic system. Leukemia are cancers from blood cells. However, cancer centres in the UK normally further classify these cancers into various cancer categories. In Table 2.1, the 15 cancers that are diagnosed and treated at the Arden Cancer Centre are defined.

2.3 Treatments

In the UK, about 49% of all the cancers cured are treated by surgery, 40% are treated by radiotherapy while the rest are treated by chemotherapy (Royal College of Radiologists 2003, National Radiotherapy Advisory Group 2007*a*). Surgery involves the removal of the tumour by a surgeon using cutting instruments while radiotherapy involves using measured doses of ionising radiation to treat cancers (The Christie 2008). The doses of ionising radiation are usually administered in small doses (i.e. *fractions*) over a specified period of consecutive days to minimise damage to healthy tissue and organs. Chemotherapy involves the treatment of cancer with cytotoxic drugs that target and destroy fast reproducing cells.

In the recent years, these modes of treatment have been used independently or in combination to maximise eradication of the cancerous cells. Normally, radiotherapy or chemotherapy can be administered before or after surgery. When given before surgery (i.e. pre-operative treatment), the main aim is to reduce the tumour size so that surgery is more effective. Similarly, when given after surgery (i.e. post-operative treatment), the aim is to ensure that residual tumour from the targeted tumour volume is completely destroyed and lessen possibilities of recurrence.

When radiotherapy or chemotherapy is delivered with a curative intent (i.e. to cure the cancer), the treatment strategy or scheme used is termed *radical* treatment. Radical radiotherapy or chemotherapy is intended to destroy the abnormal cells. It can be pre-operative (i.e. *neoadjuvant*), post-operative (i.e. *adjuvant*) or just an independent treatment. Treatment which is non-radical and is delivered to alleviate pain and increase life expectancy is called *palliative* treatment. At the Arden Cancer Centre, these treatments (see Table 2.2) are used to describe and triage patients treated by either radiotherapy or chemotherapy. The treatments described in Table 2.2 were extended by the Joint Council of Clinical Oncology (1993) to include *emergency* treatments. Emergency treatments intend to quickly relieve a patient of pain, bleeding, or other conditions normally prevalent in can-

Table 2.1: Cancers treated at the Arden Cancer Centre and their descriptions

Cancer category	**Description**
Benign	mild and non-progressive tumours (Wikipedia 2009*a*)
Gynaecological	malignant growth from the female reproductive system (Cancer Research UK 2008*f*)
Skin	tumour growths on the skin
Breast	uncontrolled growth of breast cells (BreastCancer.Org 2008)
Head and neck	tumours affecting the head and neck region
Soft tissue and bone	tumours affecting bone and soft connective tissue
Central nervous system (CNS)	malignant growths in the central nervous system
Lympho-reticular	tumours of the lymphatic and reticular systems
Unknown primary	cancers whose origin cannot be located (Cancer Research UK 2008*e*)
Digestive system	tumours in the gastrointestinal system (e.g. stomach cancer)
Male genital	tumours affecting male reproductive system (e.g. prostate cancer)
Unspecified	unspecified tumours in organs
Endocrine gland	tumours in the endocrine system (e.g. thyroid gland)
Respiratory	tumours in the respiratory system (e.g. lung cancers)
Urinary	tumours of the urinary system (e.g. kidney cancers)

cer patients: a) spinal cord compression, b) vena caval obstruction, and c) airway obstruction. Hence, as defined in Table 2.2, emergency treatments are palliative.

Table 2.2: Treatments delivered in radiotherapy and chemotherapy

Treatment scheme	**Description**
Adjuvant	An additive treatment given after surgery to remove all detectable tumour growths, although there are chances of tumour recurrence (Wikipedia 2008)
Palliative	Treatment given to control or prevent symptoms of a disease
Radical	Treatment given to eradicate tumours and prolong survival

Work practices at cancer centres in the UK differ. At the Arden Cancer Centre, patients are classified using categories shown in Table 2.3. Patients requiring the most immediate (i.e. within 24 hours) palliative treatment are classified as *Urgent*, while those requiring palliative treatment within 48 hours are *Emergency* patients. Some pre-operative radical treatments, are given high precedence for the patients to meet their already booked surgery dates. These patients are categorised as *Priority* patients. Historical data obtained from the Arden Cancer Centre shows that most (i.e. about 88%) of the patients treated were categorised as *Standard* patients as shown in Table 2.4. These patients required either palliative or radical treatment. Finally, the patients that normally require radical treatment and are allowed to choose dates they preferred to visit the department to be treated are *Elective* patients.

Table 2.3: Patient categories used at the Arden Cancer Centre

Category	**Brief description**
Urgent	require palliative treatment within 24 hours
Emergency	require palliative treatment within 48 hours
Priority	for radical radiotherapy before a specific surgery date
Standard	either palliative, radical or adjuvant radiotherapy required
Elective	mostly radical or adjuvant radiotherapy required

Table 2.4: A break down of the proportions of the Arden Cancer Centre patient categories

Category	**Percentage of patients (%)**
Urgent	1.3
Emergency	0.7
Priority	0.3
Standard	88.3
Elective	9.4

2.4 Radiotherapy

The use of radiotherapy has grown worldwide as reported in (Delaney *et al.* 2005). In the UK, by circa 2015, a rise in demand for radiotherapy of about 20% is expected due to the changes in the demographics, ageing population susceptible to cancers and the growth of cancer incidences which results in the delivery of more fractions (see Table 2.5) (Royal College of Radiologists 2000, Royal College of Radiologists 2003, Ash *et al.* 2004, Dodwell and Crellin 2006, National Radiotherapy Advisory Group 2006*a*, National Radiotherapy Advisory Group 2007*a*, National Radiotherapy Advisory Group 2007*b*). Hence, it is imperative that radiotherapy departments such as the Arden Cancer Centre be able to predict their future waiting times performances using their current resources and make necessary contingency plans for their radiotherapy capacity to meet the expected rise in demand.

Table 2.5: Expected growth of total cancer incidences between 2005 and 2016 adapted from (National Radiotherapy Advisory Group 2007*b*:2)

	2010/11	**2015/16**
Total population	3%	5%
Total incidence of cancer	8%	16%
Total fractions to be delivered	8%	17%

Radiotherapy capacity is the amount of time that a machine is available to treat patients. It can be affected by staff shortages and lack of equipment. Demand for radiotherapy is measured using the total number of fractions delivered in a given period of time (Royal College of Radiologists 2000). The National Radiotherapy Advisory Group (2007*a*) predicted that demand for radiotherapy will be greater than the current capacity and encouraged all radiotherapy departments in the UK to maximally use existing equipment. The direct relationship between equipment provision (i.e. capacity) and the number of cancer patients treated within a specified time, reported in (Royal College of Radiologists 2000, Royal

College of Radiologists 2003) means that when capacity is less than the growing demand, patient waiting times are protracted (Dodwell and Crellin 2006:107).

2.4.1 Waiting times in radiotherapy

There are different definitions of waiting times in radiotherapy worldwide as discussed in (León *et al.* 2003, Lim *et al.* 2005). In the UK, waiting time is defined as difference between the date of cancer diagnosis and the date when the first treatment fraction is delivered (Department of Health 2000, Department of Health 2001). It is measured in consecutive days including weekends and bank holidays. In this study, radiotherapy waiting time has been defined as the time difference between the date when the decision to treat by radiotherapy is made and the date when the first fraction is delivered.

For the past two decades, waiting time has been adopted as a yardstick for the quality of service cancer centres provide in the UK. Hence, the JCCO proposed waiting time targets for emergency, palliative and radical treatments shown in Table 2.6 in its efforts to reduce the waiting times to be as short as reasonably possible. However, despite the efforts by the JCCO, an audit on waiting times conducted 12 years ago revealed that waiting times were much worse than the JCCO targets (Royal College of Radiologists 1998:7).

Radiotherapy waiting times have been shown to be worsening in other countries including Canada, Australia and New Zealand (Mackillop *et al.* 1996, Spurgeon *et al.* 2000, Mackillop 2007). However, according to Spurgeon *et al.* (2000), the UK fares badly in the comparison of waiting times and survival rates in the developed countries. Ash *et al.* (2004) re-audited the waiting times based on the JCCO targets. They showed that waiting times had degenerated between 1998 and 2003 for each treatment as summarised in Table 2.7.

More patients waited longer than the recommended JCCO targets maximum allowed waiting times for radical, palliative, and post-operative treatments between 1998 and 2005. However, Table 2.7 shows improvements between 2005 and 2007. Even in the recent years, reducing the waiting times to the proposed targets has proved to be difficult to achieve as manifested by the results of re-audits in (Summers and Williams 2005, Drinkwater and Williams 2008). According to Drinkwater and Williams (2008), the percentage of patients who failed to meet the JCCO targets for radical and palliative treatments were generally the same as those for 1998 (see Table 2.8). For emergency treatments, more patients did not meet the JCCO target in 2007. Such improvements (i.e. for palliative and radical treatments) have been was attributed to the availability of more equipment and expertise in the radiotherapy departments.

Table 2.6: JCCO waiting time targets adapted from (Joint Council of Clinical Oncology 1993:6)

Standard	**JCCO targets (in days)**		
	Emergency	**Palliative**	**Radical**
Good practice	1	2	14
Maximum acceptable	2	14	28

Table 2.7: Comparison of the results of waiting times audits conducted in 1998, 2003 and 2005 using percentages of patients waiting longer than the JCCO targets; adapted from (Summers and Williams 2005)

Treatments	**1998** (%)	**2003** (%)	**2005** (%)
Radical	32	72	53
Palliative	25	60	33
Post-operative	39	62	57

2.4.2 Effects of long waiting times

It is important to discuss the impact of protracted waiting times on the survival rate, tumour recurrence rate, cure of cancer or any psychological distress to patients. Delays in commencing radiotherapy can permit the proliferation of the abnormal cells and affect outcomes of radical or adjuvant treatment (Mackillop 2007). For example, a review of treatment delays for head and neck cancers showed that for patients being treated with postoperative treatments, a delay of 6 weeks in starting treatment led to an increase in local recurrence by about 2.6 times (Huang *et al.* 2003). They affirmed the associations between delay and the risk of recurrence in carcinomas of the head and neck and breast cancers. Additionally, longer waiting times were also associated with an increase in the tumour volume doubling in (Jensen *et al.* 2007) and by examining the correlation between long waiting times and survival rates worldwide, it was found that long waiting times lowered the survival rates (Richards *et al.* 1999, Do *et al.* 2000).

Table 2.8: Comparison of the 1998 and 2007 audit results using percentages of patients that did not meet the JCCO targets; adapted from (Drinkwater and Williams 2008)

Treatments	**1998** (%)	**2007** (%)
Emergency	8	86
Radical	32	32
Palliative	25	22

Do *et al.* (2000) showed that the likelihood of death increased by 2% per day and that 3 additional days wait resulted in 6% decrease in survival rate. Seel and Foroudi (2002) reviewed research on direct and indirect effects of prolonged waiting times in radiotherapy. For breast cancers, the studies showed that delays of more than 6 months had significant impact on local control and the overall survival. For gliomas showed a reduction in survival with each increase in waiting times in radiotherapy. For oesophageal cancers, Seel and Foroudi (2002) showed that waiting times more than 40 days between surgery and post-operative radiotherapy were related to poor survival. It was found that 21% of some lung cancer tumour growths became incurable due to the long waiting times for radiotherapy (O'Rourke and Edwards 2000).

On the contrary, some researchers did not find correlations between long waiting times and tumour control or survival (León *et al.* 2003). For laryngeal tumour growths, studies on retrospective data did not reveal any effect of treatment delays for waiting times between 9 and 180 days with a median of 43 days examined. Therefore, although fewer studies such as in (León *et al.* 2003)did not demonstrate significant associations between long waiting times and tumour control, survival rates, recurrence or tumour proliferation, most of the papers on the effects of protracted waiting times asserted that indirectly, long delays caused increased psychological distress to patients and their families (Dische 2000, León *et al.* 2003).

2.4.3 Staff and equipment issues

Radiotherapy staff includes doctors, radiographers, specialist nurses, physics technicians and physicists. Doctors decide the mode of treatment, prescribe the treatment regime and also examine the patients. Radiographers work on machines such as the computed axial tomography (CT) scanners and linear accelerators (linacs) to treat cancers. Specialist nurses provide essential nursing care to patients before and during treatment while physics technicians provide technical support services such as commissioning, decommissioning, calibration, repair and maintenance of machines. Physicists are responsible for optimising and checking complex treatment plans.

Equipment

At the Arden Cancer Centre, the radiotherapy department has a complement of machines shown in Table 2.9. The simulator, integrated brachytherapy unit (IBU) and CT scanner are for staging cancers by taking images used to create treatment plans. Machines such as the deep X-ray (DXR), betatron, high dose rate (HDR) and linacs are for delivering the ionising radiation. The high energy (HE) and low energy (LE) linacs produce 25 MeV and 6 MeV beams, respectively.

LE linacs are preferred for superficial tumours while the HE linacs are for the more profound cases.

Table 2.9: Machines and facilities used in the department at the Arden Cancer Centre

Machine or facility	Quantity	Description
Linacs	5	Machines for the acceleration of electron beams normally between 4 and 25 MeV (Wikipedia 2009*b*)
CT Scanner	1	Produces 3D images of cancers by taking images from several different angles
Simulator	1	Used to take radiographs of the lesion and verify that the treatment plan is correct prior to administering the ionising radiation (National Radiotherapy Advisory Group 2007*a*)
DXR	1	X-ray machine specifically designed to produce more penetrating X-rays compared to diagnostic machines like the simulator (Pervan *et al.* 1995:264)
Betatron	1	Treatment machine that produces high energy X-ray beams for treating special cancers
IBU	1	Integrated brachytherapy unit for imaging tumour volumes
HDR	1	High dose rate for brachytherapy
Mould room	1	A room where masks and shields used in treatment are made
Planning computers	3	Computers for the virtual outlining and planning required for complex treatment plans by doctors

Staff

In the UK, the achievement of the waiting time targets has reportedly been affected by the shortage of staff in radiotherapy departments (Moore 2004). Most radiotherapy departments in England have showed high staff vacancy rates (National Radiotherapy Advisory Group 2006*b*:12). In particular, the radiotherapy department at Arden Cancer Centre typically has doctors whose availability is very limited; a doctor works up to about 4 hours a week as shown in Table 2.10. For example, doctor numbered 7 can only examine patients on a Thursday between 1.00pm and 5.00pm in the week. The entire staff complement in the department is illustrated in Table 2.11. Treatment unit radiographers are shared amongst the seven machines. Due to the shortage of physics technicians, work in the mould room and complex treatment plan calculations had to be alternated judiciously.

Table 2.10: A roster of the doctors, represented using numbers 1–12 as anonyms

Day	**Morning** (9.00am–1.00pm)	**Afternoon** (1.00pm–5.00pm)
Monday	5	1
Tuesday	10	8
Wednesday	3 (9.00am–11.00am) 4 (11.00am–1.30pm)	6
Thursday	12 (9.00am–10.00am) 2 (10.00am–12.30pm)	7
Friday	9	11

Table 2.11: Staff complements for the radiotherapy department

Staff	**Quantity**
Doctors	12
CT scanner and simulator radiographers	5
Treatment unit radiographers	25
Pretreatment radiographers	3
Physicists	11
Dosimetry technicians	7
Engineering technicians	6
Special nurses	3

2.5 Concluding remarks

This chapter has given an overview of cancer and its treatment in the UK. The 3 principal modes of cancer treatment have been briefly discussed as well as the types of treatments. The problem of long waiting times and their effects were also discussed. Radiotherapy waiting time was defined as the difference between the date when the decision to treat by radiotherapy is made and the date when the first fraction is delivered. Performance of radiotherapy departments in the UK was analysed using the percentages of patients who waited longer than targeted waiting times for each treatment (i.e. emergency, palliative and radical treatments).

The current booking systems of the departments may be inadequate as demonstrated by the results of the waiting time audits conducted within the last decade. Due to the low staffing and equipment provision issues in radiotherapy departments, it is imperative that existing capacity be fully utilised. Therefore, the rest of this thesis focuses on gaining insight into radiotherapy treatment processes using discrete-event simulation models and developing algorithms that can be used to book appointments for all procedures in order to meet the targets for radiotherapy departments in the UK.

Chapter 3

Radiotherapy processes

Contents

3.1 Introduction

In this chapter, the treatment processes conducted in the radiotherapy department at the Arden Cancer Centre are discussed. When the ionising radiation is delivered from a source at a distance from the patient's body, the process is called *teletherapy*. At times, radioactive seeds are inserted next to the tumour to destroy it, a method called *brachytherapy* (BT). The other method called *unsealed sources therapy* (UST) involves administering the ionising radiation by ingestion or injection in the form of soluble radioisotopes.

After a patient is referred to the department by a GP, the treatment process is commenced by a multi-disciplinary meeting of doctors who recommend the most appropriate treatment mode. If radiotherapy is recommended, the patient's doctor completes a request form which can either be a radiotherapy booking form, radionuclide therapy request form, or radiotherapy physics form for teletherapy, UST or BT, respectively. The completed form is then forwarded to a booking desk for further action.

The next Sections discuss the three treatment processes conducted in the department. Teletherapy processes are described in Section 3.2. A discussion of the BT processes follows in Section 3.3. Section 3.4 discusses the UST processes. In each Section, a formal model of the corresponding process using flowcharts is given. Finally, concluding remarks on the treatment processes are given in Section 3.5.

3.2 Teletherapy

Teletherapy, also called external beam therapy (EBT), comprises intricate procedures conducted in four units of the radiotherapy department. These four units include: i) planning, ii) physics, iii) pretreatment, and iv) treatment units. In the planning unit, the tumour volume (i.e. tumour growth to be targeted by radiation) is imaged using various machines. The images acquired from the machines are then used in the physics and/or pretreatment units for dosimetry calculations, and accuracy checks and verifications. Finally, the verified dose calculations are delivered in the treatment unit through a scheme called *fractionation*, which aims for maximum tumour eradication while minimising negative side effects of the radiation. Fractionation can be defined as the division of the total therapeutic dose of radiation into small doses (i.e. fractions) to be administered over a period of days or weeks (The Free Dictionary 2009).

In the planning unit, there is a desk, manned by a radiographer, where the booking of appointments for the planning and treatment procedures based on the submitted forms is done. A completed form has details about the patient's treatment which include: i) planning unit machine or facility, ii) treatment machine, and iii) treatment plan complexity, to be used. The radiographer uses the details on the form to manually create and amend schedules of appointments for the procedures to be conducted on the machines and/or facility in the planning and treatment units.

3.2.1 Planning unit

The process of imaging the tumour volume, also called staging, provides indications of the advancement of the cancer. In radiotherapy, accurate staging is critical because treatment is directly related to tumour stage. The tumour volume is imaged using a simulator or computed axial tomography (CT) scanner in the planning unit. The simulator, such as the one shown in Figure 3.1, takes radiographs used to line-up a patient for treatment. The CT scanner (i.e. shown in

Figure 3.2) takes images from different angles and builds a 3-dimensional image of the tumour volume.

Figure 3.1: A patient on a simulator. Taken from CancerHelp UK, the patient information website of Cancer Research UK: www.cancerhelp.org.uk (Cancer Research UK 2008*c*)

Figure 3.2: A patient on a CT scanner. Taken from CancerHelp UK, the patient information website of Cancer Research UK: www.cancerhelp.org.uk (Cancer Research UK 2008*b*)

Some patients may require a mask for immobilisation during the planning and treatment procedures. These patients can be the infirm or those with cancers close to delicate organs who need a mask or shield to immobilise them so that staging/treatment can be done with precision. Masks and shields are made in the mould room. At the Arden Cancer Centre, this room has a single couch where patients were supported and materials such as wax or gypsum used to create an impression of their head, chest, or limbs. Figures 3.3 (a) and (b) show a perspex shield, and mask being moulded using gypsum.

(a) **(b)**

Figure 3.3: Shield and mask made in the mould room; (a) adapted from (North of England Cancer Network 2008); and, (b) Taken from CancerHelp UK, the patient information website of Cancer Research UK: www.cancerhelp.org.uk (Cancer Research UK 2008*a*)

Normally, when a patient visited the radiotherapy department for the planning unit appointments, if they required a shield or mask, they visited the mould room first where their shields or masks were made. The patient would have been booked for that procedure at a time when their doctor was available in the department. Upon completing the mould room procedure, the patient visited either the CT scanner or simulator (i.e. depending on the planning unit machine recommended by the doctor for the imaging procedure). For example, head and neck cancer patients usually require masks and they follow the route $1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 6$ in Figure 3.4, since they usually visit the CT scanner. For other cancers, the patients may not require masks and they take the route $1 \rightarrow 4 \rightarrow 7 \rightarrow 8$ if the imaging procedure has to be conducted on the simulator. Generally, Figure 3.4 shows that the machines or facilities visited by the patient in the planning unit depend on whether a mask is required and the type of machine to be used to stage the cancer.

When a patient was shown to the simulator or CT scanner room, radiographers normally waited for the doctor to see the patient. The doctor explained the impending planning and treatment procedures to the patient. The patient had to accede to radiotherapy otherwise the process would be terminated. If the patient

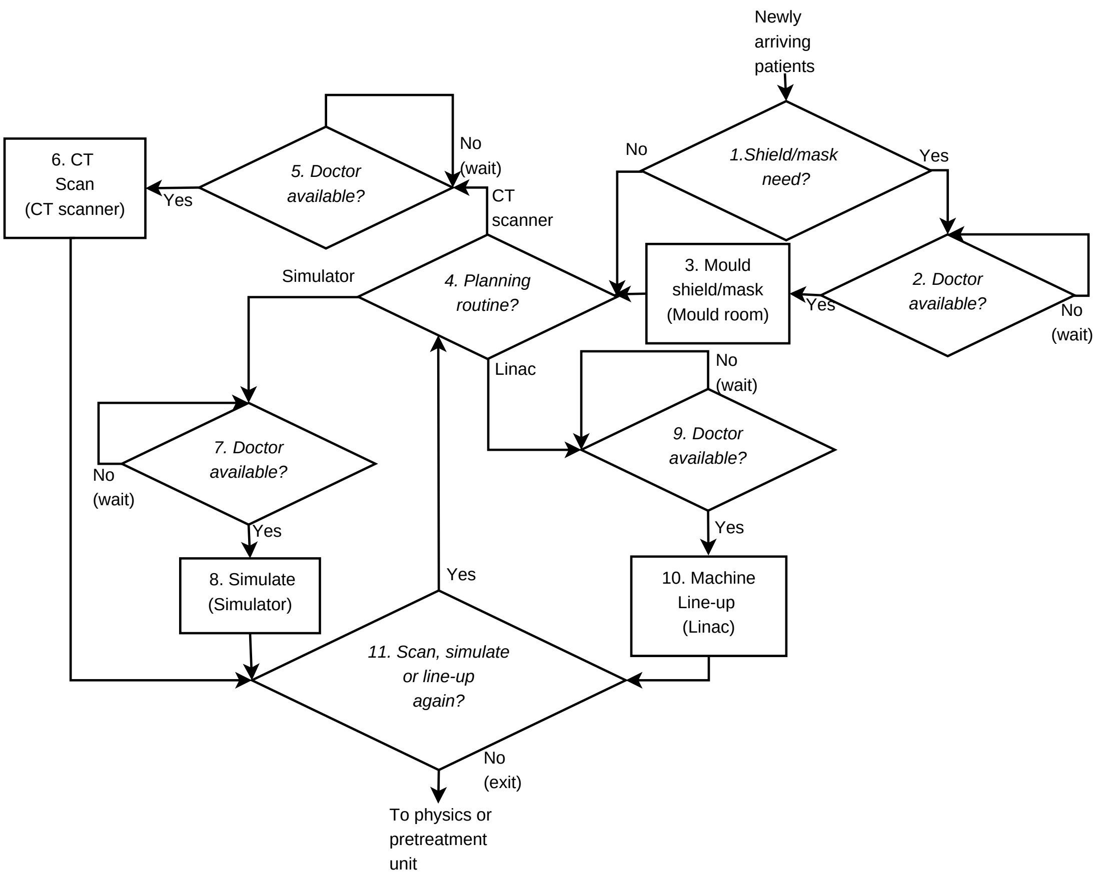

Figure 3.4: A flowchart of the procedures conducted in the planning unit

assented to continue with the procedures, radiographers prepared the patient on the machine and conducted the scan (i.e. on a CT scanner) or simulation (i.e. on a simulator). Some cancers required extra involvement of doctors, especially when radiographers needed to tattoo the lesion or other parts like the head, neck, limbs, or torso. A good example of such planning procedures were for most breast cancers.

For some patients, after the doctor had consulted them, some simulator procedures took considerable processing time when radiographers intermittently stopped the machine to reposition the patient on the machine until the process was completed satisfactorily. The machine line-up procedures (see procedure 10 in Figure 3.4) were usually included on the simulator schedule of appointments, although they were conducted on the linacs. These procedures were for patients who were deemed too large for the simulator or CT scanner. For such patients, the radiographers usually identified a free linac for the procedure or wait until 4.30pm when treatment procedures were over.

As shown in Figure 3.4, the routines in the planning unit involved doctor consultations. It was mandatory that the doctor had to be available for each procedure in the planning unit. The amount of time the doctor spent with a patient on a given procedure was uncertain. Most doctors examined their patients before the commencement of the planning procedure and instructed the radiographers on how they had to image the lesion. The output of the planning unit operations were digital images, required for treatment plan outlining and planning, and/or dosimetry calculations. At times, some patients visited the machines and/or facility when their doctor was absent. Such practices were recommended by the Joint Council of Clinical Oncology (1993) to fast-track the treatment of the most critical patients (i.e. patients requiring treatment of conditions like spinal cord compression, vena caval and airway obstruction, normally prevalent in radiotherapy departments).

For some patients, the treatment plans calculated and verified in the physics and or pretreatment units had to be 'checked' in the planning unit before the patient commenced (and/or even during) their treatment. These procedures were normally conducted on the simulator in the absence of the patient's doctor and termed 'treatment plan verification checks'. Such procedures were meant to improve the accuracy of the treatment plans. Some patients had to visit the simulator for the plan verification several times. These subsequent visits helped in verifying if the moulded mask still fitted properly (i.e. if the patient required a mask and it had been made before), tattoos of the lesion had not been washed off, or simply preparing the patient for further treatment. Historical records from the department showed that some patients revisited the planning unit for the 'treatment plan verification checks' more than twice or thrice in their treatment regime.

3.2.2 Physics unit

The digital images obtained from the planning unit were used in the physics unit to generate treatment plans normally through two operations: i) outlining and planning, and ii) dosimetry calculations and accuracy checks. Outlining and planning involved determining the most appropriate angle and intensity of radiation beams to treat the cancer. Only treatment plans requiring complex calculations were handled in the physics unit. For example, most breast and/or CNS cancers required complex outlining and planning procedures, calculations and accuracy checks.

Firstly, the physics unit technicians performed the outlining and planning operation using the digital images obtained from the planning unit. This operation involved finding perfect radiation beam angles illustrated in Figure 3.5. Upon completion, the patient's doctor checked their outlining and planning output (i.e. Figure 3.5), approved and signed it, if it was satisfactory. The technicians then proceeded to do the dosimetry calculations. When the doctor was unavailable, the outlining and planning plans were shelved until the doctor was available to approve and sign them.

Figure 3.5: Image of the configuration of radiation beams. Taken from CancerHelp UK, the patient information website of Cancer Research UK: www.cancerhelp.org.uk (Cancer Research UK 2008*d*)

Recently, the department's planning unit has been equipped with a computer system that enables doctors to create the outlining and planning plans themselves as soon as the digital images have been obtained from the simulator or CT scanner. This has been termed 'virtual outlining and planning'. In this case, after the doctor has created the 'virtual outlining and planning', he or she forwarded the output to the physics unit for the dosimetry calculations and accuracy checks only. However, some doctors had busy schedules for their days in the department and did not find time to do the 'virtual outlining and planning'. Thus, they normally recommended the digital images to be sent straight to the physics unit. The procedures performed in the physics unit are illustrated by the flowchart in Figure 3.6.

When the technicians completed the second operation (numbered 4 in Figure 3.6), physicists or radiotherapy scientists checked for errors in the treatment plans. This was done twice by different physicists sequentially (see procedures 5 and 6 in Figure 3.6). Upon completing the accuracy checks, the physicists forwarded the treatment plans to the pretreatment unit. There were four workstations used by four technicians in the physics unit office. All four technicians were involved in each of the procedures (i.e. 2 and 4 in Figure 3.6). Notably at the centre, the four technicians involved in generating the treatment plans were also involved in the moulding of shields and masks in the mould room. Hence, the technicians could only do one of the three procedures: 1 moulding masks and shields in the mould room, 2 creating outlining and planning plans, or 3 dosimetry calculations, at a time. Mould room procedures had higher precedence than the other procedures since they physically involved the patient. Therefore, outlining and planning, and dosimetry calculations had to be performed when the mould room was vacant.

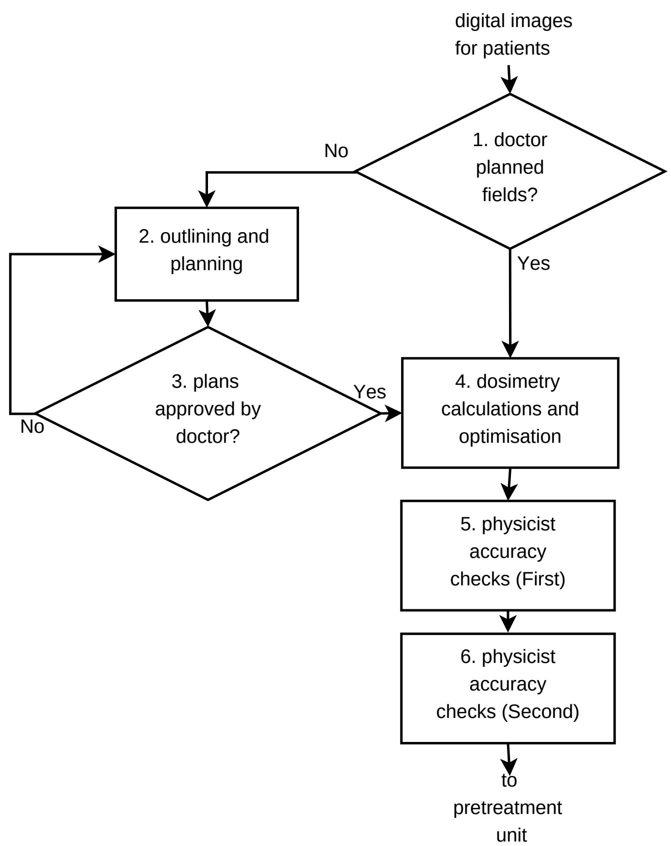

Figure 3.6: A flowchart of the procedures performed in the physics unit

3.2.3 Pretreatment unit

The pretreatment unit can be described as an interface between the preparation for treatment and the actual treatment. Digital images for the patients that do not require complex calculations are forwarded straight from the planning unit. Simple dosimetry calculations and accuracy checks are performed in the pretreatment unit. Only one calculation and check is performed on treatment plans created in the physics unit. This calculation ensures that the treatment plans are precise so that positive effects of the radiation are realised on the patient.

At the Arden Cancer Centre, the pretreatment unit comprises an office with 3 desks for 3 radiographers that work on the simple dosimetry calculations and accuracy checks of treatment plans. The images forwarded from the planning unit normally require simple calculations and accuracy checks to create treatment plans. For example, patients requiring critical treatments such as emergency treatment, have their treatment plans created in the pretreatment unit after the planning unit procedures.

Radiographers performed the calculations on the three desks in the pretreatment unit. Figure 3.7 shows the flowchart of the procedures performed in the

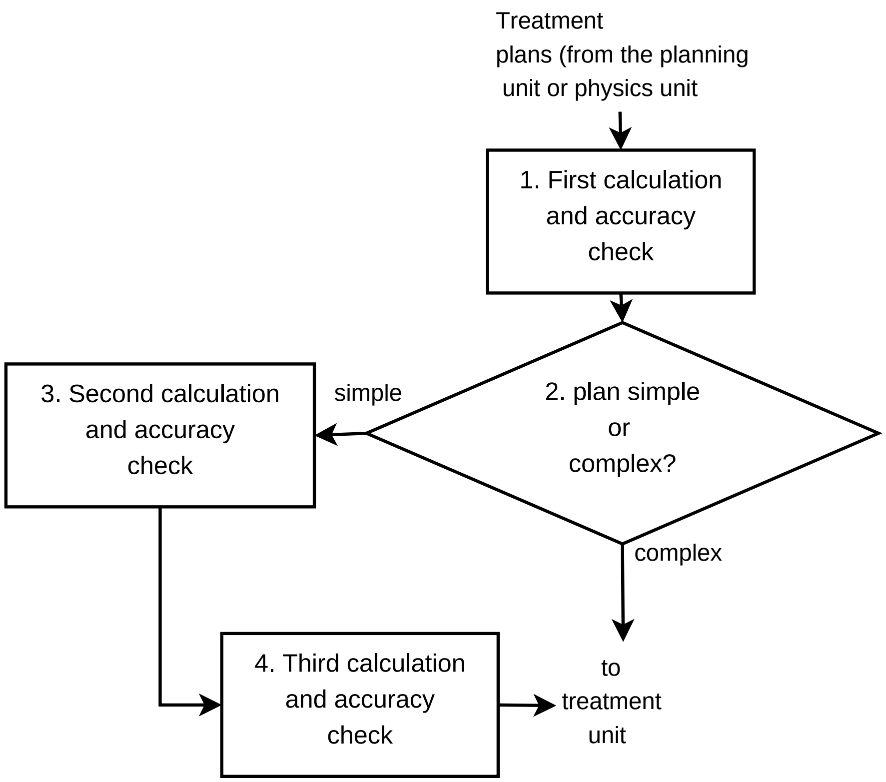

Figure 3.7: A flowchart of the pretreatment unit procedures

pretreatment unit. Each procedure was performed by a different radiographer (i.e. procedures 1, 3 and 4 in Figure 3.7). For the treatment plans requiring simple calculations and accuracy checks, each procedure had to be performed by a different radiographer to enhance the likelihood of error detection. Treatment plans created in the physics unit were considered complex and had only one calculation and accuracy check procedure performed on them (i.e. procedure 1) before they were forwarded to the treatment unit.

3.2.4 Treatment unit

The ultimate procedures of the EBT processes are conducted in the treatment unit. These include: a final accuracy check on all the treatment plans and the actual delivery of the fractions. The final accuracy check is performed prior to the delivery of the fractions by a radiographer in the treatment unit. As discussed in Chapter 2, the machine complement in the department at the Arden Cancer Centre comprised HE and LE linacs, DXR and a betatron.

A flowchart of the procedures conducted by radiographers in the treatment unit is shown in Figure 3.8. When patients attended their treatment unit appointment for the first time, radiographers explained the treatment unit routines in what is termed the radiographer session (i.e. procedure 5 in Figure 3.8). This was a short session meant to familiarise the patient with the staff and the treatment unit procedures to be performed during the course of their treatment.

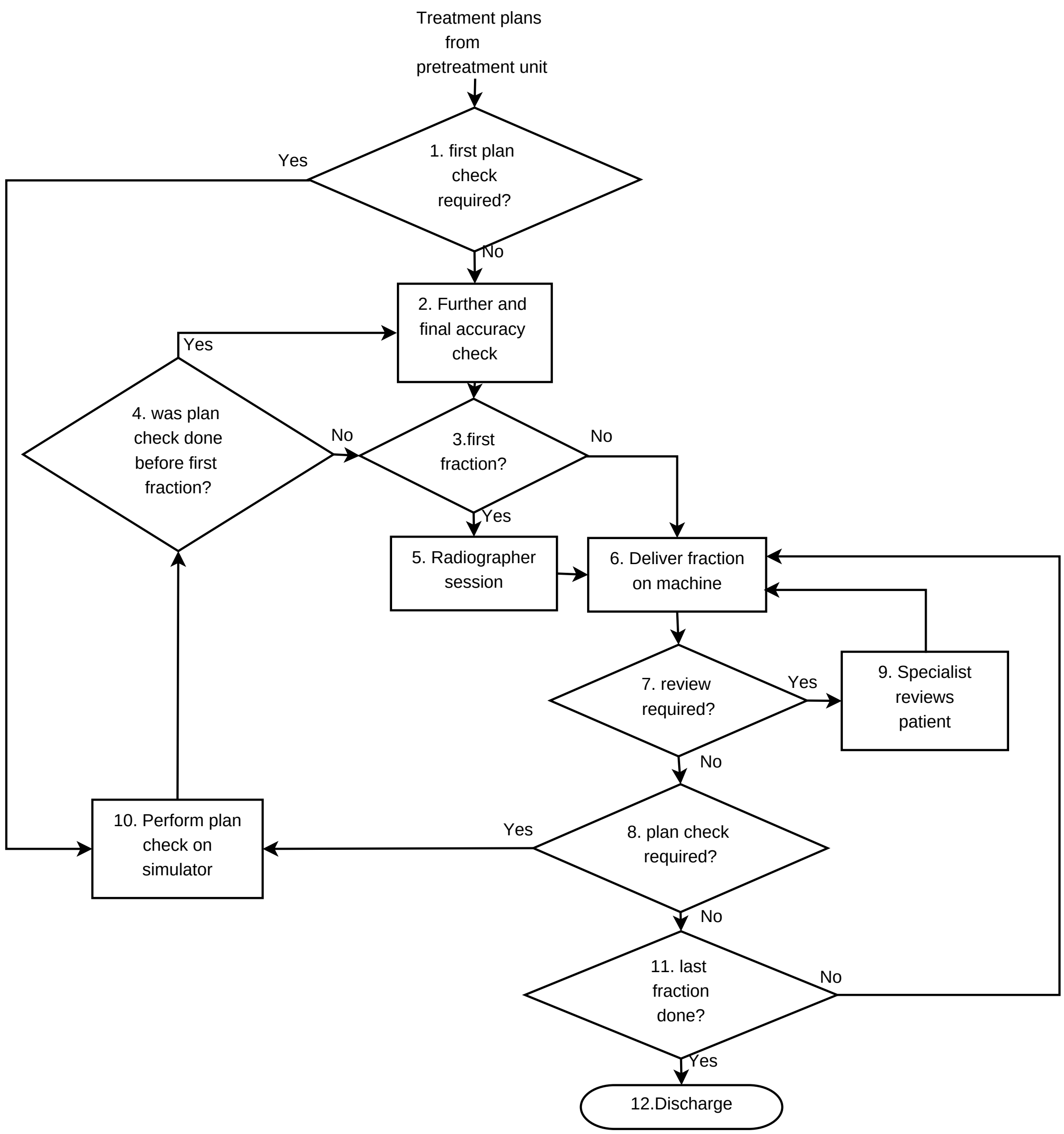

Figure 3.8: A flowchart of the treatment unit procedures

Fractions are delivered daily except for weekends and bank holidays when the radiotherapy department is closed. Figure 3.9 shows a patient in a position for receiving treatment on a linac. After receiving several such fractions, some patients require on-treatment review (OTR) sessions (see procedure 9 in Figure 3.8). These OTRs were conducted by specialists on the patients to monitor treatment effectiveness. In addition, some patients required treatment plan verification checks to verify their treatment plans on the simulator before the commencement of, or during, their treatments. Such patients, also termed 'phased treatment patients', normally had their total dose divided into multiple phases. Each phase comprised several fractions prescribed by their doctor. Before completing a phase, the patient had to undergo a plan verification check on the simulator in preparation for the next phase. Historical data obtained from the radiotherapy department between 2005 and 2007 showed that some patients had up to 3 phases in their treatment courses.

Figure 3.9: A patient on an Elekta Synergy(R) linac. Image taken from Elekta website `www.elekta.com` (Elekta AB 2009)

The OTRs can best be described as processes parallel to the radiotherapy treatment. The appointments for these procedures depended on the appointments booked for treatment created in the planning unit. Depending on the cancer, the OTRs were conducted by specialists mostly working part-time in the department. For example, head and neck cancers were reviewed before the last fraction by a dietician on Wednesdays (between 9.00am and 5.00pm). Other OTRs were conducted by the patient's doctor or volunteer radiographers (i.e. staff from the MacMillan Cancer Support). These were booked for Mondays, Thursdays, and Fridays although at least one MacMillan radiographer was available everyday. A specialist nurse reviewed patients diagnosed with CNS cancers weekly on Tuesdays before their fractionation scheme is over. Similarly, breast cancer patients also meet a breast care nurse weekly on Tuesdays.

3.2.5 Appointment scheduling practices

The radiographer manning the EBT booking desk in the planning unit, considered several factors when manually creating the schedules of appointments for the planning and treatment unit procedures for the patients. In most cases, the doctors brought the completed request forms for their patients on the day of week they were working in the department. Using the details in the forms, the radiographer created appointment slots for the planning unit procedures first before contacting the patient to inform him or her the appointments. *Elective* patients were allowed to suggest alternative dates of appointments if they did not concur with those created by the radiographer.

The treatment procedures were booked on the day the patient attended and completed the planning unit procedures. Hence, patients did not know their treatment dates until they attended the planning procedures. The manner in which the treatment unit procedures were booked was similar to the planning unit procedures. Notably, the booking desk is manned mostly by senior radiographers, when the information on the forms was vague, they used their expertise to determine the patient's pathways. The following is a list of some of the factors radiographers considered:

1. Whether or not the patient was to have first definitive treatment, the first clinical intervention intended to palliate or cure a patient's disease (NHS 2008).

2. Category 1 cancers. These included conditions such as: i) spinal cord compression (emergency treatment) ii) vena caval obstruction (emergency treatment) iii) airway obstruction (emergency treatment) iv) head and neck cancers v) cervix cancers vi) lung cancers, and vii) bladder cancers.

3. Category 2 cancers. In the radiotherapy department, the cancers included were all the cancers in Table 2.1 except the Category 1 cancers.

4. Doctor availability which included the day of the week and times when the doctor was in the radiotherapy department.

5. Date of referral by the GP to the radiotherapy department.

6. Decision to treat date, the date when radiotherapy was recommended to palliate or cure the patient.

7. Treatment type (either emergency, palliative, radical or adjuvant).

3.2.6 Limitations caused by the work practices

The following list gives some of the practices and restrictions considered when booking patients for the planning and treatment procedures.

- The department is open 5 days (Monday through Friday) although the historical data showed a few emergency treatments done on Saturdays and Sundays. The department restricts its activities to a 5 day working week due to the difficulties in securing manpower and other resources beforehand for the weekend shifts

- Category 1 cancer patients commence their treatment on Mondays while Category 2 cancer patients can start treatment on any other day of the week (i.e. Monday to Friday).

- Doctors availability in the department is very limited as discussed in the previous chapter (see Table 2.10).

- The department infrequently required services of specialists such as language interpreters for interpretation to non-English speaking patients. The appointments for a patient could be affected if one such specialist could not be secured.

- The department uses JCCO targets discussed in the previous chapters (see Table 2.6).

- Planning or treatment appointment interruptions were normally a result of machine breakdowns, ambulance failure to collect patients, patients not attending (for example, due to bad weather or holidays), or treatment plans not ready. Formally, the radiotherapy department had no maximum allowable interruptions restriction, but booking staff allowed a maximum of two interruptions for radical treatments and none for palliative or adjuvant. Normally, when a machine broke down during working hours, the patients in the queue are asked to wait and be treated on other machines or are re-booked on another appointment dates

- Machine availability was affected by service and maintenance dates. The DXR was normally taken out of service for maintenance on Tuesdays, the second week of each month. Similarly, the simulator was serviced and maintained on Thursdays, the third week of each month. There were normally three service and maintenance dates for the contractors, on Thursdays in the third week of June, September and November. The CT scanner was taken out of service for maintenance on the last week of each month on Wednesdays. The contractor's service and maintenance dates for the CT scanner were in June, September and November. The HDR was taken out of service for maintenance in the first or second week after every three months beginning in January. Table 3.1 depicts a sample of the machines schedule for weekly and monthly service and maintenance obtained in 2007. The column, representing Fridays, was shaded to denote the day on which the linac had its monthly service and maintenance. All the unshaded cells with the machine names were weekly service and maintenance dates. The low energy (LE) and high energy (HE) linacs were shutdown after 2.00pm for weekly services and for the whole day for the monthly services.

- The department is also closed on bank holidays.

Table 3.1: A sample of the maintenance and service dates for the linacs used in 2007

	Date	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
January	1	-	HE1	HE2	LE1	HE3	-	-
	8	-	LE2	HE1	HE2	LE1	-	-
	15	HE3	-	LE2	HE1	HE2	-	-
	22	LE1	HE3	-	LE2	HE1	-	-
	29	HE2	LE1	HE3	-	LE2	-	-
February	5	HE1	HE2	LE1	HE3	-	-	-
	12	-	HE1	HE2	LE1	HE3	-	-
	19	-	LE2	HE1	HE2	LE1	-	-
	26	HE3	-	LE2	HE1	HE2	-	-

- Number of radiographers made available on the machines is limited according to the minimum (min.) and maximum (max.) staff requirements shown in Table 3.2. When there is shortage of staff in the department, some machines such as the DXR are at times closed for some time

Table 3.2: Staff requirements by the machines/facilites in the department.

Machine or facility	**Staffing levels**	
	Min.	**Max.**
CT scanner	2	3
Simulator		
Mould room		
Pretreatment	3	≥ 3
Physics planning	4	≥ 4
Linac	3	4
Betatron		
DXR	2	3

Staff requirements

Each machine or facility has a range of the number of staff that can drive it (see Table 3.2). The CT scanner, simulator and mould room require at least two radiographers. Similarly, at least three radiographers are required to care for the patients and operate the linacs.

A normal working day for the planning unit machines and facility (i.e. the mould room) commences at 9.00am and ends at 5.00pm. All the radiographers work from 9.00am to 5:00pm every working day. However, due to late patient arrivals, longer processing times and/or unavailability of doctors, the daily schedule may require staff to work overtime to finish patients queued for the day. Normally, the overtime period is between 5.00pm and 8.00pm. However, the department does not work during the early hours of the morning like some radiotherapy departments reported in (White *et al.* 2007, Calman *et al.* 2008).

Work in the physics unit commences at 9.00am and terminates at 5.00pm. The technicians and physicists also work from 9.00am to 5.00pm. In the pretreatment unit, radiographers work on the treatment plans from 9.00am to 5.00pm. In the treatment unit, although radiographers start work at 9.00 and finish at 5.00pm, the delivery of fractions actually commences at 9.20am and terminates at 4.20pm from Monday to Friday. The first 20 minutes are for preparing the machines for the day. The final 40 minutes are for shutting down and preparing the treatment plans for the patients to be treated the following day.

3.3 Brachytherapy

Placing sealed radioactive seeds into, or next to the tumour volume to maximise its destruction is a process called brachytherapy (Royal College of Radiologists 2007). It is normally used as an additive to either chemotherapy or EBT. Unlike EBT, the radiation is delivered once (i.e. not in fractions). However, the method is uncommon at the Arden Cancer Centre, with less than 100 patients treated annually, according to the historical data. In most cases, the patients that undergo BT have gynaecological cancers (i.e. an estimated 80–90% of the BT patients) and the rest comprise of cancers such as respiratory and oesophageal cancers.

The entire process flowchart for BT procedures is shown in Figure 3.10. For example, respiratory and gynaecological cancer patients usually have the applicator inserted in the HDR room (i.e. procedure 4 in Figure 3.10) and endoscopy department (i.e. procedure 3 in Figure 3.10), respectively. Some cervical cancer patients are admitted into the hospital and an applicator inserted next to the lesion in the operating theatre (i.e. procedure 2 in Figure 3.10).

Once the applicator is inserted, the tumour volume is imaged (i.e. in a similar way imaging is done in EBT) on an integrated brachytherapy unit (IBU) to obtain digital images that are then used to create treatment plans (i.e. procedure 5 in Figure 3.10). Normally, a physicist and technician work on the treatment plans which can either be generic or specific depending on the complexity of the cancer. If generic treatment plans are required, procedures 6 and 8 are performed. Otherwise, procedure 9 is performed before the doctor approves and signs them. Generic treatment plans are normally created for gynaecological cancers which are prevalently treated in the department.

When the treatment plan has been checked for errors, the doctor approves it and the patient then receives treatment on the HDR machine as illustrated in

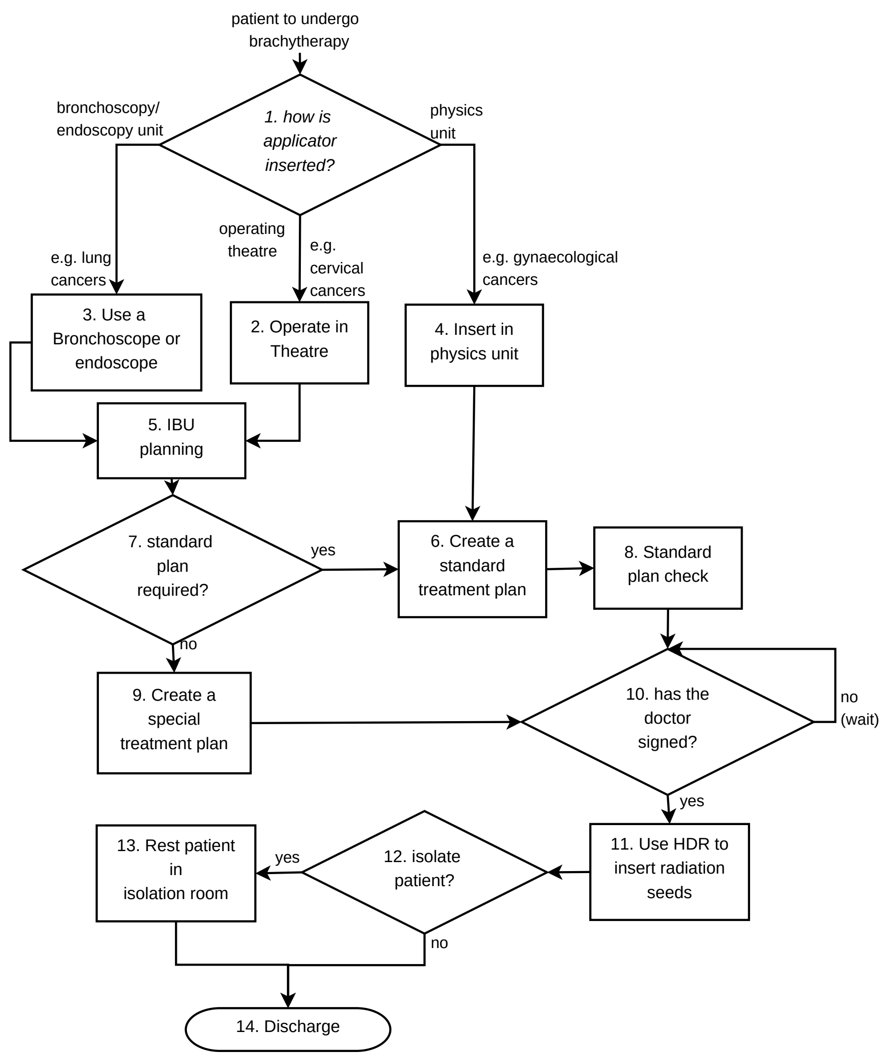

Figure 3.10: A flowchart of the brachytherapy procedures

Figures 3.11 (a) and (b). Some patients whose treatment involves iodine radioactive seeds are decontaminated before being discharged by admitting them into a decontamination ward for approximately 2 hours (i.e. procedure 13 in Figure 3.10). Most gynaecological cancer patients (i.e. who had not gone through the theatre) are treated on Tuesdays and Thursdays while patients who had the applicator inserted in the theatre are treated on Tuesdays only. Respiratory cancers are treated on Fridays because of staff shortages while oesophageal cancers are treated on Thursdays when the doctor of the patients is available to oversee the procedures.

(a) **(b)**

Figure 3.11: A patient on the HDR machine; Images (a) and (b) taken from the WellSpring Oncology website `www.wellspringoncology.org` (WellSpring Oncology 2009)

3.4 Unsealed sources therapy

When ionising radiation is ingested or injected in the form of soluble radioisotopes such as iodine (^{131}I), phosphorus (^{32}P), strontium (^{89}Sr), samarium (^{153}Sm), and yttrium (^{90}Y), the process is called UST. It is used to deliver the first definitive treatment for the conditions in Table 3.3. However, unlike BT and EBT, UST does not involve intricate routines. Figure 3.12 shows the flowchart of the procedures for dispensing the UST radioisotopes normally performed by a physicist and/or technician. Upon receipt of the booking request form, staff order radioisotopes to be used (i.e. procedure 1 in Figure 3.12). UST is bespoke and hence, quantities of the radioisotopes are ordered per patient. The treatment dates must coincide with doctor availability times because the doctor must monitor the treatment. However, if the patient is urgent and the doctor cannot be available, treatment can be expedited by bypassing the doctor.

To treat the cancers in Table 3.3, the following had to be considered. The ^{131}I liquid is delivered on two week standing orders every Wednesday for thyrotoxicosis or thyroid cancers. At most, 6 thyrotoxicosis (7 if there is an urgent case) patients are treated the following day, Thursday. Thyroid cancers are treated on Fridays because they are admitted into a decontamination ward (i.e. procedure 7 in Figure 3.12) for at most two hours. Thereafter, they are admitted into other wards and eventually discharged on Monday. The department has 2 decontamination wards and thus, up to 2 thyroid cancer patients can be treated each week.

The ^{153}Sm and ^{89}Sr radioisotopes were given as intravenous injections to soothe pain in the bones for prostate cancers. The doctor performed the injection procedure. Similarly, polycythemic cancer patients are also given an injection of the ^{32}P radioisotope by the doctor. These radioisotopes are ordered five days in advance of the treatment date. In addition, due to the unavailability of the doctors, the doctor must be booked ten days in advance of the treatment date. It

Table 3.3: Cancers and the radioisotopes used to treat them by UST in the department

Cancer	Radioisotope	Description
Thyrotoxicosis	^{131}I	the thyroid gland producing excess hormones which affect the body (MedInfo 2004)
Thyroid	^{131}I	cancer of the thyroid gland
Prostate	^{89}Sr or ^{153}Sm	cancer of the prostate gland
Thrombocytosis	^{32}P	excess platelets in the blood caused by disease (Wikipedia 2009*d*)
Thrombocythemia	^{32}P	excess platelets are produced causing blood clotting (Merck c. 2009)
Polycythemia	^{32}P	increase of red blood cells in the body (Wikipedia 2009*c*)

takes about 30 minutes to prepare and dispense the soluble radioisotope for each patient (i.e. for procedure 3 in Figure 3.12). Historical data showed that the ^{131}I radioisotope was the most commonly used radioisotope while ^{153}Sm was barely used by the department.

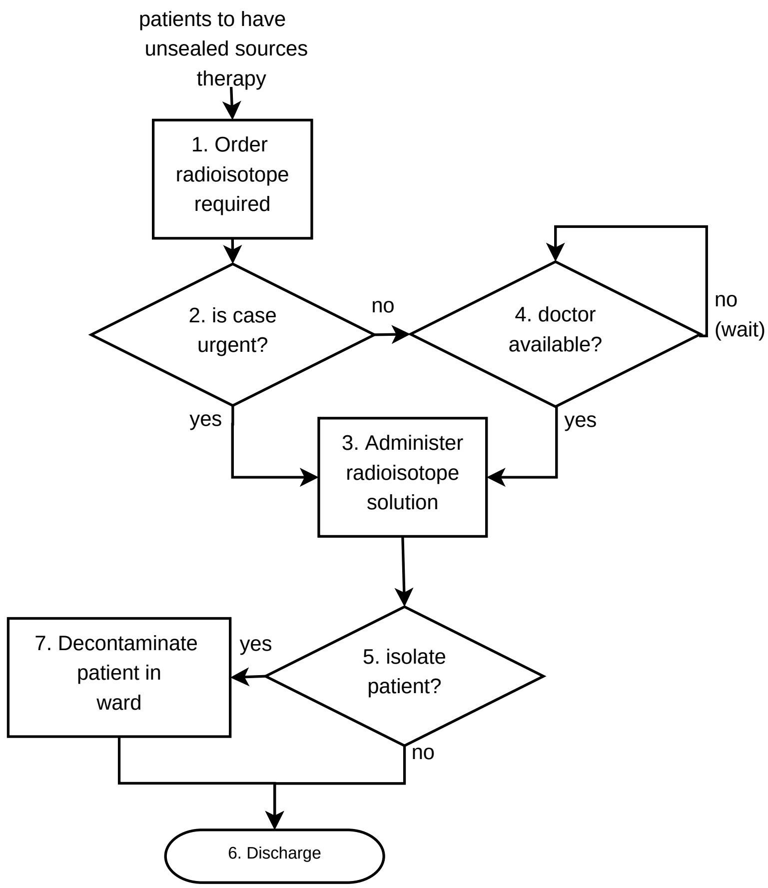

Figure 3.12: A flowchart of the UST procedures

3.5 Tracing the patient pathways

Since patients take different treatment pathways in the radiotherapy department, the procedures for EBT discussed in this chapter can all be incorporated into in a single flowchart shown in Figure 3.13. The following are examples of pathways that can be taken by patients requiring emergency and radical treatments.

3.5.1 *Emergency treatment: spinal cord compression*

Most patients needing emergency treatment (e.g. spinal cord compression) are forwarded to the planning unit for imaging of the cancers on the CT scanner. Assuming that no mask or shield was needed and using Figure 3.13, the pathway for such patients is as follows. After decision points 1, 5 and 6, procedure 7 is performed. Most patients do not need multiple visits to the CT scanner and thus after decision point 11 and 13, the digital images obtained from procedure 7 are forwarded to the pretreatment unit for procedure 14, 22 and 23 (i.e. for simple treatment plans).

Patients requiring emergency treatment usually do not need plan verification checks. Therefore, procedures 25, 28 and 29 are performed because the patients would be receiving the first and only fraction (because emergency treatments normally require a single fraction). In this case, no OTRs and plan checks (i.e. decision points 31 and 32 respectively) are needed. The patient is then discharged (i.e. terminal step 34) after receiving his or her only fraction. This pathway can be denoted using the numbered steps in Figure 3.13 as: $1 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 11 \rightarrow 13 \rightarrow 14 \rightarrow 21 \rightarrow 22 \rightarrow 23 \rightarrow 24 \rightarrow 25 \rightarrow 26 \rightarrow 28 \rightarrow 29 \rightarrow 31 \rightarrow 32 \rightarrow 33 \rightarrow 34$

3.5.2 *Radical treatment: head and neck cancers*

Head and neck cancer patients require a mask for immobilisation during the planning and treatment procedures. Hence, they must visit the mould room first before visiting the other machines in the planning unit (i.e. steps 1, 2, 3 and 5 in Figure 3.13). Images of tumour growth are taken on the CT scanner when their doctor is available. Therefore, according to Figure 3.13, from decision point 5, the path comprises steps 6 and 7 for the CT scan to be performed. In most cases, patients do not require multiple scans or simulations (i.e. procedures 7 or 9), so the digital images obtained after procedure 7 are forwarded to the physics unit for complex dosimetry calculations.

Assuming the doctor did not do virtual outlining and planning using the images from the CT scanner, procedures 16, 18, 19 and 20 are performed to ensure that the complex treatment plans are created. After the accuracy checks performed by the physicist in procedure 20, the complex treatment plans are then forwarded to the pretreatment unit for a single calculation and accuracy check. In this case, only procedure 14 is performed. Normally, before these patients undergo treatment in the treatment unit, the treatment plans are verified on the simulator. Therefore, the steps followed after procedure 14 include: 21, 24, 9, 12 and 27.

After decision point 27, the further accuracy checks of the treatment plans (i.e. procedure 25) are performed because the plan verification checks performed on the simulator had been performed before the first fraction was delivered. Upon completion of procedure 25, the ultimate procedures of delivering the fractions sequentially over the prescribed period of time are then performed. For example, if 10 fractions had been prescribed for a head and neck patient, the subsequent pathway can be traced as follows. Procedures 26, 28, 29, 31, 32 and 33 are performed for the first of the ten fractions. Thereafter, the steps $26 \rightarrow 29 \rightarrow 31 \rightarrow 32 \rightarrow 33$ are repeated 7 times (i.e. up to the 8^{th} fraction) and finally, the steps $26 \rightarrow 29 \rightarrow 31 \rightarrow 30 \rightarrow 26 \rightarrow 28 \rightarrow 29 \rightarrow 31 \rightarrow 32 \rightarrow 33 \rightarrow 34$ are performed for the OTR performed before the completion of the prescribed fractions.

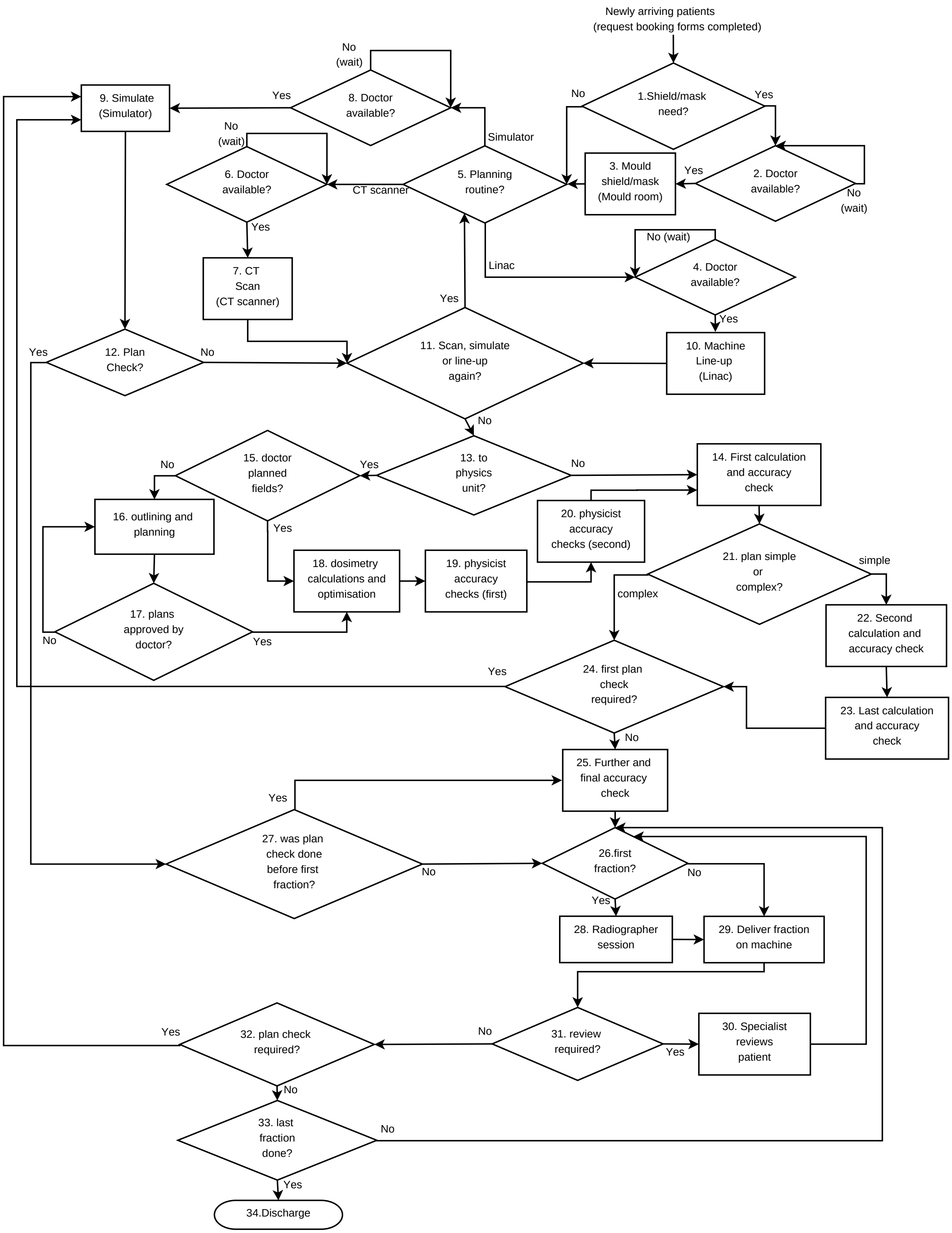

Figure 3.13: A flowchart of all EBT procedures (i.e. combination of Figures 3.4, 3.6–3.8)

3.6 Concluding remarks

In this chapter, the intricacy of the 3 treatment processes: external beam therapy (EBT), brachytherapy (BT) and unsealed sources therapy (UST), has been shown using process flowcharts. The EBT process comprises procedures performed in four units (i.e. planning, physics, pretreatment and treatment units) of the radiotherapy department at the Arden Cancer Centre while those for the BT and UST processes are conducted in the physics unit only. The most crucial resource whose availability in the departments is limited is the doctor. Their limited availability in the department (i.e. as discussed in Chapter 2) can be considered a major constraint to the booking of appointments for the patients.

The problem in the radiotherapy departments can be subdivided into four separate subproblems representing the four units (i.e. planning, physics, pretreatment and treatment units). Although the EBT is the most commonly used treatment process, the scope of any study of the radiotherapy issues should include the BT and UST processes as well since they all share the same resources (i.e. doctors and physicists). To gain insight into the flow of patients, the development of discrete-event simulation models can be considered crucial. Developing the models helps in determining patient arrival patterns, processing times on machines, cancer diagnoses, treatment type distributions and many other attributes of patient flow in the department. The next chapters should dwell on the development such models in order to understand the processes better.

Chapter 4

Operational research and healthcare problems

Contents

4.1 Introduction

Most healthcare problems involve many constraints due to the complex and elaborate processes that patients undergo, as explained in Chapter 3. Most of these problems concern the delivery high quality service using limited resources in the shortest time reasonably achievable. Many researchers have applied various approaches to different healthcare problems. Amongst these approaches, are various operational research techniques that have been used to solve healthcare problems for the past 50 years.

Some of the healthcare problems considered in the literature include staff scheduling, outpatient and inpatient appointment scheduling, distribution of medical supplies within wards and/or departments, allocation of beds, scheduling of operating room theatres for surgical procedures, designing medical facilities, determining the extent of the spread of infectious diseases and many others.

There is a noticeable paucity of papers on tackling the radiotherapy patient flow management problems using operational research techniques. Most of the literature on radiotherapy related problems has been on the actual planning and treatment of patients such as in (Haas 1999). Literature on the radiotherapy patient flow problems focused on: a) audits of waiting times, b) effects of delays to cancer control and survival rates, and c) equipment provision. Managing patient flow in radiotherapy can be difficult due the constraints and elaborate treatment processes presented in Chapter 3. However, researchers have also adapted some operational research techniques which have been used to solve other hard problems to tackle healthcare problems. In this chapter, literature on some of the techniques that have been used and/or can potentially be used to solve radiotherapy and other healthcare problems are reviewed.

This chapter is organised as follows. Section 4.2 reviews literature on the application of simulation and modelling techniques to tackle healthcare problems. This is followed by Section 4.3 which reviews studies which applied the theory of scheduling techniques such as exact methods, heuristics and optimisation algorithms on healthcare problems. Lastly, Section 4.4 gives the concluding remarks.

4.2 Simulation and modelling

Computer simulation and modelling is one of the most commonly used operational research technique applied to healthcare problems. It can be defined as a problem solving methodology that involves mimicking a real-life system over a period of time (Pidd 2004). Simulation models can be continuous, discrete-event, or combined (i.e. both discrete and continuous). The distinction between these models as well as the advantages and disadvantages of using them are explained in (Banks *et al.* 1996, Banks 1998, Law and Kelton 2000, Fishman 2001, Pidd 2004). A continuous simulation has been defined as the modelling of systems in which the state variables change continuously over time (Banks *et al.* 1996, Law and Kelton 2000, Pidd 2004).

In combined models, state variables may change discretely, continuously, or continuously with discrete events superimposed (Alan and Pritsker 1998). Compared to discrete or continuous simulations, there are not many studies that used combined simulations. An example of such simulations is the model to project the supply and demand for primary healthcare in Indiana, United States from 1970 through to 2000 in (Standridge *et al.* 1977). However, the most commonly used simulation and modelling technique in studies of healthcare systems is discrete-event simulation (DES). It is the modelling of systems in which the state variable changes only at a discrete set of points in time (Banks *et al.* 1996).

In recent years, DES has been applied widely to healthcare problems. There are many benefits of using DES in studying healthcare systems. DES allows the end user to assess the efficiency of existing healthcare systems and designing new systems. In addition, DES can be used to forecast the impact of changes in the flow of patients, examine resources requirements, investigate complex relationships among the different model variables, identify bottlenecks in complex models and, most importantly, to understand a given system. Some of these healthcare problems were based on outpatient clinics, emergency departments, surgical centres, pharmacies, orthopedics departments, radiology units, radiotherapy and chemotherapy departments. Although there are challenges associated with simulation modelling in healthcare systems discussed by Lowery (1996*b*), DES has been described as an effective tool in the search for more efficient health care systems (Proctor 1996).

Even though most papers on simulation and modelling in healthcare may involve the use of DES, it does have its demerits. As a result, other simulation approaches are growing in popularity for healthcare modelling. Jun *et al.* (1999) presented a review of the future directions of DES in healthcare that involve use of soft systems methodologies (SSM) (Avison and Fitzgerald 2003:469). Several papers have reported the combination of DES and SSM or data mining to improve the acceptance of the outcomes, understanding, full engagement and ownership of simulation models in healthcare (Lehaney 1996*b*, Lehaney 1996*a*, Lehaney *et al.* 1999, Lehaney and Paul 1999, Brailsford *et al.* 2006, Sachdeva *et al.* 2007, Ceglowski *et al.* 2007, Eldabi *et al.* 2007). Another approach that has recently gained popularity in healthcare modelling is system dynamics (SD) modelling. Brailsford (2008) gave a succinct introduction of SD modelling based on the comparison of DES and SD in (Lane 2000, Morecroft and Robinson 2005, Morecroft and Robinson 2006). Further, when implementation problems were encountered using DES to study outpatient phlebotomy and specimen collection centres, Rohleder *et al.* (2007) used additional SD modelling. One key demerit of DES reported in these papers is that its data requirements are higher than for approaches such as SD.

4.2.1 Developing simulation models

The development and evaluation of a simulation model involves some key steps that have been discussed in (Lowery 1996*b*, Banks *et al.* 1996, Lowery 1998, Fishman 2001, Law and McComas 2001). These include: 1) problem formulation, 2) conceptual model building, 3) data collection, 4) model building, 5) verification and validation, 6) experimental design, and 7) documentation and reporting. For decades, these steps have been used to develop simulation models to understand and solve various healthcare problems.

Although all these seven steps are important in the development of simulation models, step *5)* is crucial because it involves ensuring that the model is an accurate representation of the real system. Verification entails debugging the computer program used to develop the simulation model while validation involves calibrating the model through an iterative process of comparing the behaviour of the model to the real world system and improvements being made for any discrepancies (Banks *et al.* 1996:399).

There is an extensive literature on validation of simulation models which includes (Kleijnen 1999, Cheng 2006, Martis 2006). Law and Kelton (2000) argued that the method of verifying and validating a model depends on the aims of modelling the system. For example, understanding the behaviour of a system is one valuable outcome of simulation modelling even if the model built is not accurate (Robinson 2001). Therefore, in this case, the model developed may not be as accurate as when a DES is being developed for some other purposes.

Some of the methods of verifying and validating simulation models suggested include: a) animation, b) historical data validation, c) face validity tests, d) comparison to other models, e) internal validity, f) extreme conditions tests, g) Turing tests, h) traces, and i) statistical techniques (Sargent 1999, Sargent 2000, Sargent 2004). Balci *et al.* (2000) provided a guidance to developing and executing a plan to verification, validation and accreditation of simulation models. Statistical techniques are normally used to demonstrate the validity of simulation models. However, some researchers argue that even if these formal statistical techniques lead to the conclusion that a model is not accurate, the model may still be valid for the purposes for which it was developed (Lowery 1996*b*). For example, in the studies by Werker *et al.* (2009) model validation was performed by modelling processing times with real data, and by checking that the model outputs reasonably match actual system outputs in consultation with hospital system experts.

In the experimental design step, alternative scenarios (i.e. 'what-if' analysis) to be simulated and the 'warm-up' and result collection periods of the models are determined. A warm-up (i.e. transient) period is the time taken to remove the initialisation bias from the simulation models while results collection period is the time interval during which output data from the simulation model is obtained. Estimates of the transient and results collection periods for simulation model are important for assuring the accuracy of the performance of the simulation model.

There have been several studies on determining these key issues for a simulation model. Hoad *et al.* (2008) reviewed literature on the research conducted to date on determining the warm-up period of a simulation model. In their discussion of procedures for estimating the transient period, the simple graphical method (Robinson 2004) was one of the simplest methods which involved visual inspection and human judgement of the time-series output collected after running the simulation model. Other studies on determining initial transient period include (Robinson 2007). In a similar study, Hoad *et al.* (2007) described methods of estimating how many replications should be run to achieve required accuracy for a DES model output. They developed an algorithm that was demonstrably efficient for automating the selection of replication runs. However, most studies reported in literature have used simple methods such as the rule of thumb (Law and McComas 1991) or simple graphical method.

4.2.2 Cancer-related problems

There have been very few papers on DES studies on patient flow management in a radiotherapy or chemotherapy departments. A key paper on a DES study of the Arden Cancer Centre radiotherapy department reported in (Proctor 2003, Proctor *et al.* 2007) used Simul8 (Simul8 Corporation 2009) models to evaluate the effects of the factors identified as the bottlenecks for the EBT process. These papers compared performances of the department on 'what-if' scenarios such as additional treatment machines and/or doctors. Offord (2002) also developed a DES model of a radiotherapy department in Plymouth, UK using Simul8 and presented results of several such scenario tests. The models developed in these studies did not include the BT and UST processes discussed in Chapter 3.

The results of these studies showed that changes to working hours of the machines enabled more patients to be treated but had implications to staffing requirements as emphasized in the study on work patterns viable for radiotherapy departments in (Routsis *et al.* 2006). A model of the radiotherapy department of a hospital in Eindhoven, Netherlands developed using software called Enterprise Dynamics (Incontrol Simulation Solutions 2009) was used to find the impact of various ways of allocating patients to the linacs in (Hoogeland 2008). The notable difference in the studies by (Proctor 2003, Proctor *et al.* 2007) and (Hoogeland 2008) is the number of doctors involved and their availability in the departments. The doctors in (Hoogeland 2008) were available from 8.00am to 8.00pm compared to the staffing levels at the Arden Cancer Centre discussed in Chapter 2. Further, Hoogeland (2008) focused on the allocation of patients to linacs using the department's existing human and machine resources. Scenarios that explore the use of existing resources only can be considered cost-effective. It is imperative that studies on radiotherapy issues consider such scenarios.

To illustrate how models can represent the elaborate processes of treatment planning, Werker *et al.* (2009) recently developed a DES model for procedures in the planning, physics and pretreatment units for the EBT process using simulation software called Arena (Kelton *et al.* 2007). One of their findings was that reducing the variability and length of doctor-related delays contributed most to improving the planning times (i.e. amount of time taken to prepare a treatment plan). They considered 3 of the 4 units of a typical radiotherapy department in the UK (i.e. as discussed in Chapter 3) and left out one crucial unit of the EBT process where patient flow can be impeded. Therefore, although they demonstrably reduced the overall waiting times, further improvements on waiting times can be achieved when the treatment unit is also considered.

It is noticeable that the DES studies on radiotherapy patient flow problems discussed did not include other treatment processes such as the BT and UST. This can be attributed to the fact that not many patients are treated by these processes. However, a DES study which includes all these processes can show a closer reflection of how the availability of the resources affects the waiting times. DES studies on the radiotherapy patient flow management issues can take inspiration from other DES studies on other departments such as the chemotherapy department.

DES has been used meritedly to study problems in chemotherapy departments and other cancer related issues. For example, a study in (Baesler and Sepúlveda 2001, Baesler and Sepúlveda 2006) combined a DES model and a multi-objective metaheuristic algorithm called the genetic algorithm (GA) to find the best resource combinations for the chemotherapy department of a cancer treatment centre. When compared to the existing scenario, the DES and GA used by Baesler and Sepúlveda (2001) improved the objective functions by 18–25%. Instead of using DES for 'what-if' analysis, the GA was used to find the best allocation of the existing resources.

(Sepúlveda *et al.* 1999) examined the use of DES to improve the processes of a cancer centre to analyse the patient flow and the impact of alternative floor layouts of a new building using various scheduling approaches. They concluded that the DES model developed justified relocation to other facilities and also identified scheduling methods which increased patient throughput by 30%. One demerit of such an approach is the huge computational effort needed by the scheduling method incorporated into the DES model. Baesler and Sepúlveda (2001) did not report the amount of time the DES model with the GA ran before results were obtained.

Some DES studies were performed to help analysts understand treatment processes. These include: the comparison of three colorectal cancer screening strategies in (Tafazzoli *et al.* 2005) and decision making in healthcare management in (Baldwin *et al.* 1999). They affirmed that DES can be useful for understanding healthcare problems and the collection of data for the problem being studied.

4.2.3 Other healthcare problems

Since the 1950s, DES has been used to investigate the challenges of scheduling appointments in healthcare departments. Healthcare providers endeavour to ensure that the patients flow is unimpeded in their systems. Most healthcare providers tend to solve their problems by using additional resources (Haraden and Resar 2004). This can imply more costs that some departments cannot afford. Therefore, simple and easily implementable endeavours should be considered by healthcare departments (Proudlove *et al.* 2007).

The earliest studies on appointment scheduling aimed at reducing patient waiting times are in (Bailey 1952, Bailey and Welch 1952). They developed a scheduling rule which produced encouraging patient flow and admission results for an outpatient clinic. Scheduling of appointments involves assigning slots on the schedules to incoming requests (Guo *et al.* 2004). It is integral to the overall management of patient flow. Guo *et al.* (2004) used DES models developed using the software called Arena (Kelton *et al.* 2007) and tested the impact of several scheduling rules on patient flow and utilisation of resources. More studies on DES and appointment scheduling rules are in (Ho and Lau 1992, Ho and Lau 1999, Wijewickrama and Takakuwa 2005, Wijewickrama and Takakuwa 2008).

Ho and Lau (1992) evaluated nine scheduling rules that reduced client waiting time and server idle time. They extended their work to evaluate 50 scheduling rules via simulation. Similarly, Wijewickrama and Takakuwa (2005) aimed at reducing patient waiting time and evaluated the performance of the appointment scheduling rules under different environmental conditions. Further, they studied appointment systems used in out-patient departments by incorporating appointment rules and patient characteristics in a multi-facility system (Wijewickrama and Takakuwa 2008). The appointment scheduling rules examined in these studies were simple compared to the optimisation algorithm used in (Baesler and Sepúlveda 2001). Kopach *et al.* (2007) published an appointment scheduling approach using DES models. They investigated the effects of patient throughput, no-shows, and continuity care using open access appointment scheduling. They defined open access as an approach that involves patients seeing their doctors a day or two after making an appointment in order to limit long-term patient bookings.

The following survey demonstrates the application of DES to many healthcare problems. DES models were used in making substantive decisions on clinic sizes and staffing in (Isken *et al.* 1999). Studies that aimed at increasing efficiency to maximise the utilisation of staff include (Centeno *et al.* 2000). A major impeded reported was the lack of data from the hospitals. DES studies have also mostly included ancillary units such as the radiology departments and other imaging units. Examples of such studies on the diagnostic units include (Ramakrishnan *et al.* 2004, Patrick and Puterman 2007, Ramis *et al.* 2008). In these papers, the use of scheduling rules to better the booking of appointments for the patients in the diagnostic units was not included. One of their aims was to develop models that were helpful in understanding the scope of the problem in the imaging units.

The management of the capacities of bed provisions, emergency rooms, surgical theatre rooms and other resources is another challenging healthcare problem whose popularity has grown recently. Lowery (1996*a*) used a DES model to design an appointment scheduling system to control hospital bed occupancy. Baesler *et al.* (2003) used DES model to estimate the maximum possible demand increment in an emergency room of a private hospital and determined the number of resources (e.g. number of doctors) required by the hospital. Ballard and Kuhl (2006) used a DES model to introduce a methodology for determining the maximum capacity of a surgical suite. The DES model calculated hospital efficiency and showed that the surgical suite's utilisation was better than when traditional utilisation measures were used.

Ramis *et al.* (2001) also developed a DES model of a surgical unit to evaluate different alternatives of its operations to maximise patient throughput. For accident and emergency (A&E) departments, Gunal and Pidd (2006) developed a DES model to investigate the impact of various 'what-if' scenarios of the amount of time patients wait for treatment. Further, Gunal and Pidd (2007) also used models of the A&E, out-patient and in-patient departments of a hospital to reduce patient waiting times. The studies in (Gunal and Pidd 2006, Gunal and Pidd 2007) did not include appointment scheduling rules to prioritise the patients. Prioritisation of patients can be useful in dealing with cases where the arrival of patients requiring critical treatments is uncertain as substantiated in (Lim *et al.* 2005).

Studies related to controlling bed occupancy involved the studies on length of stay in hospitals. A DES model was developed to examine and evaluate the alternative configurations to reduce the length of stay in an A&E department (Samaha and Armel 2003). Changes to the way of allocating beds to patients were recommended. Scheduling methods can be used before exploring alternatives such as purchasing more beds or building additional facilities. For a surgical department, a DES model was used to aid capacity planning decisions (VanBerkel and Blake 2007). Analysis of the DES model results showed the impact of redistributing beds between sites and length of stay. A DES study of a renal unit was conducted to estimate the demand for renal replacement therapy in England by 2010 (Roderick *et al.* 2004). It was found that demand for renal replacement by elderly patients can increase to about 1,000 per million population.

Davies (2007) reported the use of lean methodologies (Womack and Jones 2003, Drew *et al.* 2004) and a DES model to compare the performance of two proposed lean methodologies using patient throughput and cost-effectiveness achieved. Medeiros *et al.* (2008) developed and implemented an approach to patient flow in an emergency department. They used a DES model to evaluate the performance of the emergency department. The DES model provided a detailed view of the system under different conditions.

DES has been successfully used to determine the best policies and strategies for a healthcare department. Using a DES model developed using Simul8 (Simul8 Corporation 2009), Katsaliaki and Brailsford (2007) determined the ordering policies which reduced wastes and shortages, increased service levels, improved safety procedures and reduced costs in blood inventory system management for a typical UK hospital. To investigate policies that can effectively reduce appointment delays and patient no-shows, Giachetti (2008) used a DES model. The most effective policy involved segregating habitual no-show patients and double-booking them when they made appointments. In a system where new patients continually arrive, identifying and segregating no-show patients can be difficult.

DES models have also been applied to infectious disease epidemiology studies.

For example, Hughes *et al.* (2006) described a DES model of tuberculosis (TB) and the human immunodeficiency virus (HIV) disease parameterised to show the epidemics in Zimbabwe. In a further study, Mellor *et al.* (2007) used the DES model in (Hughes *et al.* 2006) to evaluate new strategies for improved detection of TB cases in high HIV prevalence scenarios.

This survey on DES studies has shown that many healthcare problems studied had different objectives. DES can be used to gain insight into aspects of the problem being studied. Its merits include the ability to conduct 'what-if' analyses. For patient flow management issues, it is important to find different configurations of resources (e.g. machines or human) that improve waiting times. However, an appointment scheduling approach can help address cases such as when to treat patients requiring critical treatments, a key issue yet to be address by studies on patient flow management as suggested by (Jun *et al.* 1999).

4.2.4 Other simulation approaches

Healthcare problems have been studied using other simulation approaches such as queuing theory and Monte Carlo simulations. Another key study paper on radiotherapy patient flow using analytical queuing models derived from queuing theory (Dickof *et al.* 1999, Thomas 2003) predicted the effects of the changes on capacity and demand, and patient waiting times. After testing the queuing models, Dickof *et al.* (1999) concluded that: 1) extended hours can be expensive for a radiotherapy department, 2) management for the departments must use flexible treatment systems to accommodate fluctuations in patients, 3) decentralisation of the booking of patient appointments was essential, and 4) bottlenecks should be avoided to optimise patient throughput.

They affirmed that such models can provide insight into the operations of a radiotherapy department. It can be inferred that fluctuations of patient arrivals certainly affect the booking of appointments. In addition, the decentralised booking of appointments means that not many people can tamper with the created schedules of appointments. This is akin to the practices at the Arden Cancer Centre where the booking of appointments is handled in the planning unit only.

Doswell and Pegler (1990) proposed a mathematical model for examining patient flows to plan for expansions of a radiotherapy department. Similarly, Thomsen and Nørrevang (2009) reported a model for managing effectively the capacity of a radiotherapy department with differentiated waiting times. These models improved the booking process and derived prospective waiting times on a daily basis. Such prospective waiting times can be useful in developing strategies for booking patients requiring different treatments. Further, some radiotherapy departments use the Basic Treatment Equivalent (BTE) model to predict the amount of time a patient can spend on linacs and also estimate the workload (Burnet *et al.* 2001, Griffiths *et al.* 2002). Models such as the BTE are for the treatment unit only and do not address the issues in other units such as the planning, physics and pretreatment unit described in Chapter 3.

(Ekaette *et al.* 2007) studied the uncertainties in cancer staging and radiation treatment decisions in the radiotherapy process for postoperative breast cancer patients using a Monte Carlo simulation approach. The probability of errors in staging and treatment for post-surgery breast cancer patients was small, but not trivial. Therefore, accurate staging of cancers is essential. A simulation and modelling study of the length of stay in hospitals for heart failure patients using a Markov model is in (Shaw and Marshall 2007). They showed that Markov models can accurately model the flow of heart failure patients. Such use of Markov models to solve healthcare problems has been discussed in (McClean and Millard 2007). Sherlaw-Johnson *et al.* (2007) developed analytical tools for monitoring occurrence infections acquired by patients during hospital stays. They monitored the infected wounds against the length of stay.

Simulation techniques on infectious diseases epidemiology problems are also in (Barth-Jones *et al.* 2000, Shechter *et al.* 2004). Barth-Jones *et al.* (2000) used Monte Carlo simulation tests to analyse the HIV vaccine effects and trial designs. Similarly, Shechter *et al.* (2004) used Monte Carlo simulation of a cohort of HIV positive patients to explicitly model two components of HIV progression: adherence and the acquisition of resistance. These models provided an insight into several therapeutic decisions regarding HIV care.

Cayirli and Veral (2003) comprehensively reviewed the appointment scheduling techniques for outpatient departments. In further work, Cayirli *et al.* (2006) used simulation models to assess ambulatory healthcare performance and the interactions between appointment scheduling and patient characteristics. Essentially, they concluded that patient sequencing has a greater effect on ambulatory healthcare than the choice of an appointment rule. The sequence of patients should be reordered so that those needing critical treatments are always at the head of the sequence.

Patient classification in appointment scheduling systems was assessed in (Cayirli *et al.* 2008) as further work to the study in (Cayirli *et al.* 2006). They investigated ways of improving appointment systems by incorporating approaches to patient classification and compared them to the commonly used first-come, first-serve (FCFS) appointment method. The FCFS can be considered a benchmark rule for comparing different rules that ensure patients requiring critical treatments are treated first. A model developed for an Ear, Nose and Throat outpatient department was used to examine various appointment schedules and evaluate their effects on the department (Harper and Gamlin 2003). This model identified critical factors that influenced patient waiting times and queues in the department.

4.2.5 Simulation software

The market has myriad of simulation software. Some of the software used in the studies discussed were Arena (Kelton *et al.* 2007) and Simul8 (Simul8 Corporation 2009). An extensive survey of DES software and the problem areas can be used, as well as the benefits and drawbacks of the software is in (Swain 2005). The frontiers of simulation software and how they can help several industries are discussed in (Swain 2007). Most DES software provide visual simulations, by allowing the user to create iconic representations of the real system under investigation by drawing objects on the screen, that are very beneficial especially in healthcare (Swisher *et al.* 2001). DES software such as Arena and Simul8, are easy to use and support the simulation of stochastic processes (Pidd 2004).

4.3 Scheduling

The theory of scheduling has been used to solve a class of problems that are combinatorial in nature and prevalent in production or manufacturing systems. The study of scheduling in production systems led to the conception of different models of the production scheduling problems and various methods to solve them. These problems include: i) job shop problems (JSP) and flow shop problems (FSP) discussed in (Baker 1974, French 1982, Morton and Pentico 1993, Sule 1997, Pinedo 2002) and other studies, ii) open shop problems (OSP) derived from the FSP as discussed in (Gonzalez and Sahni 1976, Chen and Strusevich 1993, Strusevich 1998, Błażewicz *et al.* 2001, Prins 2008), iii) group shop problems (GSP) derived from the JSP and FSP as discussed in (Blum 2002, Sampels *et al.* 2002, Liu *et al.* 2005), iv) single machine problems, v) parallel machine problems, and vi) mixed shop scheduling problems, whose investigation was initiated by Masuda *et al.* (1985). Many production scheduling problems have been solved by first likening them to these shop scheduling problems. Scheduling was defined in (Lopez and Roubellat 2008) as follows:

> “Scheduling is the organisation over time of the execution of a set of tasks, taking into account time constraints (deadlines, precedence constraints, etc) and capability and capacity constraints on resources required for the tasks”

These shop scheduling problem models can be defined as follows. A JSP involves a finite set of jobs (n) that undergo operations on a finite set of machines (m) but all jobs not necessarily following the same route. Conversely, in FSP all jobs follow the same route while in an OSP, jobs do not have a defined point of entry into the system. Among the variants of FSPs investigated in the literature, there are hybrid flow shop (HFS) problems which consist of a series of production stages, each of which has several parallel machines (Chen 1995, Linn and Zhang 1999, Low *et al.* 2008). In this case, some of the production stages may have one machine but at least one stage should have multiple machines (Linn and Zhang 1999). Furthermore, a job can go through one or more of the production stages. In the radiotherapy departments, the patients can be considered as the jobs and the movement of patients in the units typified as these shop scheduling problems.

Among the variants of HFSs investigated for the past two decades, is the two-stage HFS discussed in (Gupta and Tunc 1991, Oğuz *et al.* 1997, Oğuz *et al.* 2003). A GSP is a generalisation of the JSP and OSP (Sampels *et al.* 2002). It has been shown in (Gonzalez and Sahni 1976, Lenstra *et al.* 1977) that these problems belong to a class of problems that are considered to be intrinsically difficult to solve. A single machine problem is the simplest form of a JSP. Most complicated JSPs are often decomposed into single machine problems (Pinedo and Chao 1999, Pinedo 2005). Parallel machine problems involve a number of machines that can be identical and can process arriving jobs. If the machines are identical, an arriving job can be processed on any one of the available machines. There are various algorithms developed to solve these problems as discussed in (French 1982, Pinedo and Chao 1999, Pinedo 2002, Pinedo 2005, Kravchenko and Werner 2007, Kravchenko and Werner 2009).

Mixed shop scheduling problems involves different subsets of the arriving jobs being processed as in a FSP or JSP and the other can be processed as in an OSP (Masuda *et al.* 1985, Ishii *et al.* 1987, Shakhlevich *et al.* 2000). Another shop scheduling problem that has been studied over the past decade is multi-resource shop scheduling problems. Multi-resource shop scheduling problems involve situations in which an operation may need several resources (that are usually chosen from a given set) to be processed (Dauzère-Pérès *et al.* 1998). Some scheduling problems have been inspired by parallel processing in computing systems whereby tasks can be processed on multiple processors at the same time (Drozdowski 1996). This has been termed multiprocessor task scheduling (Oğuz *et al.* 2003, Oğuz *et al.* 2004).

The study of problems from manufacturing and other industrial sectors resulted in the conception of other shop scheduling problem models from the ones listed earlier. A good example is the multi-processor scheduling problems that were derived from computing systems. Therefore, a healthcare problem which involves the movement of patients among several human and/or machine resources can be used to derive more such problem models if patients can be likened to jobs.

The shop scheduling problems have been shown to be non-deterministic polynomial time (NP) hard problems. In computational complexity theory, NP-hard is a class of problems that do not have a polynomial time algorithm (Papadimitriou and Steiglitz 1982, Pinedo 2002, Pinedo 2005). Many methods in the literature have been applied to these NP-hard problems and their time complexity reported in (Brucker and Knust 2009). Some well-known NP-hard problems such as the traveling salesman problem (Lawler *et al.* 1985) and others in (Papadimitriou and

Steiglitz 1982) have been solved using several approaches that can be classified as: a) exact enumerative methods, b) heuristics or approximation methods, and c) metaheuristics.

Typifying healthcare scheduling problems

In recent years, researchers have attempted to solve healthcare scheduling problems by representing or typifying them by using shop scheduling models in order to apply methods that have previously been successfully used in the manufacturing sector. It was suggested that For example, one of the first papers to propose the modelling of cancer clinic problems as the shop scheduling models was by (Baldwin 2006). In his analysis of the problems of minimising waiting lists, patient lateness for treatment and maximising the utilisation of therapy machines, Baldwin (2006) suggested that cancer clinics can be likened to manufacturing industries so that some of the techniques used successfully to solve the aforementioned problems can be employed on them.

This suggestion was also accentuated by a study in (Bertrand and de Vries 2005) which compared production control in manufacturing industries to healthcare and concluded that production concepts were applicable to healthcare. It is worth noting that in the literature, some well-known healthcare problems such as nurse rostering (Burke *et al.* 1998, Cheang *et al.* 2003) have been investigated using production scheduling techniques. Therefore, patient flow management in radiotherapy departments can be solved using methods amenable to the shop scheduling problem models.

Papers that suggested likening radiotherapy patient flow management problems to the shop scheduling models of the manufacturing sector were published in the mid-2000s. It is important to survey some of the approaches used to solve such problems prior to this period. In the 1970s and 1980s when radiotherapy was gaining popularity as one of the most effective ways of treating cancers, there was more emphasis on automating radiotherapy departments as evidenced by the study reported in (Ragan 1989) to balancing the workload of radiotherapists. Ragan (1989) also emphasised the need to automate the scheduling of physicians, pretreatment and treatment appointments for radiotherapy facilities to achieve efficiencies similar to manufacturing industries.

The work by Ragan (1989) was later affirmed in the early 1990s in (Junor 1993, Larsson 1993). Junor (1993) described the main objectives of each radiotherapy department and succinctly stated that the radiotherapy patient scheduling problems in the UK must aim to improve: i) treatment service quality, ii) patient satisfaction, and iii) staff morale. Like Ragan (1989), Larsson (1993) also reported an initiative to automate the scheduling of patients in a radiotherapy facility using spreadsheets on a personal computer in order to maximise the efficient use of equipment and staff.

The initiative by Larsson (1993) was about a scheduling system endeavoured to meet the following key criteria: a) cost-effectiveness, b) implementable in a reasonable time frame, c) robust and self maintaining, d) user friendly, e) patient throughput, and f) adaptive. Larsson (1993) also acknowledged the need to allow plans for contingencies such as changes in fluctuating staffing levels, patient numbers, fractionation patterns, and unplanned machine down times for the scheduling system to be more robust. These key factors can be useful in developing automated scheduling systems for radiotherapy departments or clinics.

The papers by (Ragan 1989, Junor 1993, Larsson 1993) can be considered as key publications on the scheduling of radiotherapy patients. They identified main objectives of the problem although some of them cannot be quantified. Further, Larsson (1993) even asserted the need to plan for contingencies such as change of fractionation patterns and patient numbers which were discussed in Chapter 2. However, to be able to develop an approach amenable to the radiotherapy patient scheduling problem, the intricate treatment processes discussed in Chapter 3 should be understood in order to successfully characterise the movement of patients as jobs in a typical manufacturing problems. Besides understanding the treatment processes, the methods that have been used in studies on scheduling problems should also be identified and examined.

4.3.1 Methods for solving scheduling problems

Optimisation methods classified as either exact enumerative, heuristic or approximation, or metaheuristic have been investigated and applied to several scheduling problems. Exact enumerative methods list possible schedules and then eliminate non-optimal schedules from the list to leave the optimal ones only (French 1982:87). Examples of these methods include dynamic programming and branch and bound (BB) algorithms. Dynamic programming was proposed by Bellman in the 1950s to solve mathematical allocation problems and it involves solving a complex problem by breaking it down into smaller simpler decision steps.

The BB algorithm was proposed by Land and Doig in the 1960s and like dynamic programming, it involves listing candidate solutions (i.e. those that satisfy the constraints in the model under investigation) and then eliminating the non-optimal ones using upper and lower bounds of the objective function. A BB algorithm uses a tree search approach that works by searching through all the candidate solutions, eliminates the non-optimal solutions and outputs the optimal solution that provides the best objective function value. When the problem being analysed is not NP-hard in the strong sense (Papadimitriou and Steiglitz 1982), it is possible to solve it exactly (Błażewicz *et al.* 2001:64). It has been shown that these exact enumerative methods cannot be applied to large instances of NP-hard problems (Morton and Pentico 1993). Large instances of JSPs can involve more jobs or machines. If the radiotherapy scheduling problem is typified as a JSP, the more patients received and machines visited as discussed in Chapter 3, the larger the size of the scheduling problem. Hence, exact methods cannot be amenable to such large problems as discussed in the literature.

Heuristic or approximation methods are normally applied to difficult scheduling problems. They can find good solutions or near optimal solutions but they are not guaranteed to succeed all the time. Furthermore, these methods are used on large NP-hard problems that normally cannot be solved using exact enumerative methods. A formal definition of these methods was given as follows:

> "A heuristic is a technique which seeks good (i.e. near-optimal) solutions at a reasonable computational cost without being able to guarantee either feasible or optimality, or even in many cases to state how close to optimality a particular feasible solution is." (Reeves and Beasley 1995)

Metaheuristics are optimisation algorithms that combine heuristic methods in a higher level framework aimed at efficiently and effectively exploring a solution space by taking inspiration from science and nature. These metaheuristics include: a) simulated annealing (SA) (Kirkpatrick *et al.* 1983), b) tabu search (TS) (Glover 1986), c) genetic algorithms, and d) ant colony optimization (ACO) (Dorigo and Stützle 2004).

> "A metaheuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions " (Osman and Laporte 1996)

4.3.2 Application of exact enumerative methods

There are some key papers that demonstrate the growing application of methods to solve patient flow management in radiotherapy departments worldwide. Mixed integer programming (MIP) optimisation models have recently been used to solve a radiotherapy patient scheduling problem in the treatment unit at the General Hospital of Cosenza in Italy (Conforti *et al.* 2008). The MIP models were aimed at reducing the waiting times of patients and produced results which were better than what radiographers achieved. When compared to the EBT process described in Chapter 3, the scope of the problem studied in (Conforti *et al.* 2008) included fewer constraints for a treatment unit in the department at the Arden Cancer Centre. Further, the MIP models considered only the first fraction without including the rest of the fraction prescribed for the patient. In this case, the size of the problem was reduced so that the use of the MIP models was possible. The fewer constraints considered imply that the problem investigated was not closer to the real-life problem in radiotherapy departments.

Further work on the study in (Conforti *et al.* 2008) which involved the use of a block scheduling strategy was reported in (Conforti, Guerriero and Guido

2009). An integer linear optimization model and a non-block scheduling strategy was used. A block scheduling strategy was defined as splitting the workday into a fixed number of time blocks/slots, which usually have the same duration. Hence, the non-block scheduling strategy involved using uncertain processing times for each patient. Patients were not assumed to have the same processing times on the linacs. The non-block scheduling strategy was more efficient than block scheduling because the use of uniform appointment blocks/slots in block scheduling poorly represented the real-life workload at radiotherapy department because treatments can take either more or less time than the assigned block/slot time (Conforti, Guerriero and Guido 2009, Conforti, Guerriero, Guido and Veltri 2009). Non-block scheduling strategy can make the schedule of appointments as compact as possible. Although these MIP models produced encouraging results, the constraints considered were too few for a typical UK radiotherapy department.

The 3 treatment processes have presented different challenging problems for researchers. The problem of determining where to place radionuclide seeds in order to deliver sufficient radiation that maximises the destruction of the tumour while minimising damage to the surrounding normal tissue for BT patients was also investigated using MIP models (Lee and Zaider 2004). They outlined approaches to ensure that the problem was solvable using the BB algorithms used to solve similar problems. This involved ensuring that the size of the problem had to be small as suggested in (Morton and Pentico 1993).

4.3.3 Application of heuristics

Heuristics can be used to produce good solutions for several scheduling problems in the literature. Although heuristics do not guarantee near-optimal solutions, the computational effort required to produce the good solutions is minimal compared to metaheuristics and exact enumerative algorithms. More about the different heuristics in the literature are, for example given in (Baker 1974, French 1982, Sule 1997, Morton and Pentico 1993, Pinedo and Chao 1999, Pinedo 2002, Pinedo 2005).

Haylock *et al.* (2005) reported the evaluation of a custom-built electronic scheduling system developed by IMS (IMS 2009) to improve the efficient use of radiotherapy machines. The scheduling system reduced the mean waiting time from 45 days down to 18 days and hence, the number of cancellations of appointments by the patients was reduced. However, they did not describe in detail the methods used to compensate for the 'unused slots' in the treatment appointment schedules of the scheduling system. Therefore, it can be surmised that the study by Haylock *et al.* (2005) involved the automation of a radiotherapy department's system and did not include scheduling strategies to create or amend appointments.

Another scheduling system was developed and connected to the central information management system for patient treatment by heavy ion radiotherapy in

Japan (Toyama *et al.* 2002). Like Haylock *et al.* (2005), Toyama *et al.* (2002) did not give details of how the schedule for each patient was generated. However, the latter reported that after the implementation, the system was simultaneously useful in saving time to generate treatment schedules and informing staff about the most up-to-date treatment schedules. It was understood by staff at the Arden Cancer Centre that an automated system can be as good as manual systems. Hence, radiotherapy departments need intelligent systems that involve strategies inspired by the scheduling theory in the booking/scheduling patient appointments.

Another study which focused on the treatment unit of a radiotherapy department but using a different scheduling method was reported in (Petrovic *et al.* 2006). It concerned two algorithms for generating schedules of appointments for linacs for a real-life problem. The first algorithm generated schedules of patients forward from the earliest feasible start date while the other booked the patient appointments backward from the latest feasible start date (i.e. the due date determined using the JCCO waiting time targets). The results of tests reported in (Petrovic *et al.* 2006) conducted using real-life data showed improved performance for the patients requiring either palliative (by the first algorithm) or radical (by the second algorithm) treatments. The algorithms included a step that reordered a sequence of patients received on a given day using priority dispatching rules. This study did not include procedures done in the planning, physics and pretreatment units which also affect the overall waiting times for patients.

The two algorithms developed in (Petrovic *et al.* 2006) can be used to inspire more research on the problem using heuristics or approximation methods. More crucially, it compared the performances of the algorithms on palliative and radical treatments. Most radiotherapy departments in the UK report their performance based on the average waiting times for each treatment (i.e. emergency, palliative and radical) obtained over a given period of time (i.e. annually). In (Conforti *et al.* 2008), no such comparisons were made based on the treatments needed by radiotherapy patients. Each algorithm involved two stages; the first concerned the prioritisation of patients and the other applied the aforementioned strategies to schedule the patients. Petrovic *et al.* (2006) characterised the problem as a parallel machine scheduling problem but did not a problem classification suggested in (Graham *et al.* 1979) to state the characteristics of the problem. Using this classification, the number of HE and/or LE linacs in the machine environment would have been stated.

The following is a survey of studies involving the use of heuristics on some of the scheduling problems. A binary integer programming (BIP) model of a health examination centre was developed and solved using a heuristic algorithm in (Chern *et al.* 2008). A BIP model has variables that are either 0 or 1. An increase in the number of resources considered (i.e. doctors and examinees) resulted in more constraints being formulated. The BIP models became difficult to solve exactly and hence, a heuristic algorithm was proposed to minimise patient (i.e. examinee) waiting time, and doctor idle time. Constructive greedy heuristics and a tabu search algorithm were developed and used in a decision support system to allocate resources in (Oddi and Cesta 2000). Heuristics can be used to create initial solutions for optimisation algorithms such as the tabu search. These heuristics can be based on established algorithms applied to scheduling problems in (Johnson 1954, Moore 1968, Baker 1974, Lawler 1977, French 1982, Nawaz *et al.* 1983, Kanet and Zhou 1993, Morton and Pentico 1993, Sule 1997, Alvarez-Valdes *et al.* 2004). For example, the Moore's algorithm (Moore 1968, French 1982) was proposed to minimise the number of tardy jobs for single machine scheduling problems.

Liu and MacCarthy (1991) proposed several heuristics to solve the single machine sequencing problem with ready times in order to minimise the mean completion time or the sum of the completion times. Johnson (1954) investigated the 2-machine FSP to minimise the maximum flow time (stated as $n/2/\mathrm{F}/F_{max}$) and developed the Johnson's algorithm for solving the problem. Nawaz *et al.* (1983) proposed a heuristic that produced near-optimal solutions for a 3-machine FSP (stated as $n/3/\mathrm{F}/F_{max}$) aimed at minimising makespan. This heuristics (i.e. Johnson's algorithm) was reportedly used by Oğuz *et al.* (1997) in their Heuristic H1 for the two-stage flowshop problem. Framinan *et al.* (2004) reviewed some heuristics that have been applied to a permutation FSPs. Several effective and efficient heuristics were proposed and applied to variants of the OSPs. Some of the studies on the application of heuristics to OSPs include (Chen and Strusevich 1993, Strusevich 1998, Mosheiov and Oron 2008, Prins 2008).

The discussion on heuristics should begin with their simplest form, priority dispatching rules (PDR), which involve jobs being assigned priority and the one with the highest priority scheduled first. Examples of PDRs are the Earliest Due Date (EDD), Shortest Processing Time (SPT), and several others, extensively discussed in (Baker 1974, French 1982, Morton and Pentico 1993, Pinedo 2002). In a study on methods amenable to JSPs, Jain and Meeran (1999) concluded that most PDRs produced reasonably good solutions more suitable to be used as initial solutions for other algorithms. A combination of these PDRs produces what have been termed composite PDRs. Researchers have conducted several tests on the applications of PDRs to JSP, FSP and OSP to find the quality of solutions obtained using various objectives in (Baker and Kanet 1983, Baker 1984, Vepsalainen and Morton 1987, Raghu and Rajendran 1993, Holthaus 1997, Holthaus and Rajendran 1997*b*, Holthaus and Rajendran 1997*a*, Holthaus and Ziegler 1997).

Holthaus and Rajendran (1997*b*) proposed a PDR termed the work-in-next-queue (WINQ) rule, for allocating jobs to the machine with least number of jobs in its queue and found that it reduced the waiting time of jobs by using shop floor information about the machine for subsequent operations of jobs. Composite PDRs which include the WINQ rule were efficient for performance criteria such as minimising mean flowtime and tardiness (Holthaus 1997). Therefore, Mohanasundaram *et al.* (2002) proposed and compared several composite PDRs to solve a dynamic JSP and other such studies include (Raghu and Rajendran 1993, Holthaus and Rajendran 1997*b*, Dominic *et al.* 2004). The PDRs such as EDD, SPT and WINQ can be used in constructive algorithms to prioritise jobs in the same way as Petrovic *et al.* (2006) used the EDD and other ways of prioritising patients. Further, the WINQ can be applied on a parallel machine environment to determine the machine with the least number of jobs awaiting processing. Using the definitions of the shop scheduling problem models, such parallel machine environments can be found in the pretreatment unit, where 3 similar desks are available for calculations and accuracy checks, and the treatment unit as discussed in Chapter 3 and (Petrovic *et al.* 2006).

The first-come-first-serve (FCFS) rule is a simple scheduling rule that has been used in various manufacturing, healthcare or other systems as a useful benchmark. Vermeulen *et al.* (2009) studied the problem of scheduling patients in a diagnostic unit using a parameterised algorithm and compared it to the FCFS rule. Another example involves the use of local search and constructive heuristics to solve a surgery loading problem (Hans *et al.* 2008) and comparing the results to those obtained using the FCFS rule.

4.3.4 Application of metaheuristics

There has been an increased application of optimisation algorithms on healthcare problems. Algorithms such as those in (Petrovic *et al.* 2006) can be useful in providing initial solutions for adapting metaheuristics to the radiotherapy scheduling problem. Adapting metaheuristics to schedule radiotherapy patients can be one of the frontiers of solving this scheduling problem. Many healthcare problems including the nurse rostering problem have been studied using these optimisation methods.

The greedy randomised adaptive search procedure (GRASP) was developed by Feo and Resende (Feo and Resende 1995, Resende 1999, Pitsoulis and Resende 2002, Resende and Ribeiro 2003) and has been successfully applied to several production scheduling problems. In (Petrovic and Leite-Rocha 2008), GRASP was used to further improve the schedules of appointments generated by constructive heuristic algorithms. GRASP improved some of the schedules generated but for about 40% and 20% of the schedules, GRASP failed to improve and worsened the considered objective function respectively. This can be attributed to the lack of a better prioritisation method for sorting patients in the GRASP. In (Petrovic *et al.* 2006), the EDD rule was used to prioritise patients which did not require emergency treatment. However, the GRASP in (Petrovic and Leite-Rocha 2008) can pave the way for research on other metaheuristics for the radiotherapy patient scheduling problem although only the treatment unit was considered.

In radiotherapy, the GA proposed by Holland in 1975 (Goldberg 1989) and inspired by the theory of evolution (Holland 1994), has been mostly used to optimise the treatment planning as investigated in (Haas 1999). An automated scheduling system based on GAs for scheduling of patients with different therapy needs to a limited number of treatment machines was proposed in (Podgorelec and Kokol 1997). The GA produced performed better than benchmark methods and it was suggested it can be adjusted for use on similar complex problems. Similarly, an optimisation framework called the diagnostic process optimisation (DIAPRO) based on evolutionary algorithms was proposed to optimise diagnostic unit processes (Podgorelec and Kokol 2001). The DIAPRO improved each of the considered objectives. For the nurse rostering problem, GAs combined with heuristics were used and the nurse schedules obtained were of good quality compared to those produced by human experts (Moz and Pato 2007).

Petrovic *et al.* (2009) presented a multi-objective GA for scheduling radiotherapy patients in the four units of the radiotherapy department at the Arden Cancer Centre using objectives: 1) minimisation of the average waiting times, and 2) minimisation of the average tardiness of the patients that needed emergency, palliative and radical treatments. The GA reduced the average waiting times and tardiness by 35% and 20%, respectively using two scenarios of expediting the approval of treatment plans in the physics unit by doctors. The computational efficiency of the GA was not reported. Most of the patients requiring emergency treatments did not meet their waiting time targets because the GA did not include prioritisation of patients received. It can be concluded that the use of optimisation algorithms like GA or GRASP in (Petrovic and Leite-Rocha 2008) does not guarantee improved results in all cases.

Some metaheuristics such as simulated annealing (SA) and tabu search (TS) have been applied to some healthcare problems but not the radiotherapy scheduling problem. Seminal ideas of the TS algorithm were proposed by Hansen (1986) and further developed into a framework by Glover (1986). The structure and technical aspects of the TS algorithm are in (Glover 1989, Glover *et al.* 1993, Dammeyer and Voß 1993, Glover and Laguna 1995, Glover and Laguna 1997). A hybrid TS algorithms was proposed for the nurse rostering system for a Belgian hospital (Burke *et al.* 1998) and produced high quality schedules of nurses compared to manually created ones. Another application of the TS algorithm to a nurse rostering problem is in (Beddoe and Petrovic 2003). In some hospitals the TS algorithm has been used to solve problems of distributing supplies using minimal human (i.e. porters) and equipment (i.e. carriers or trolleys) resources (Michelon *et al.* 1994). Further, the TS algorithm has been shown to be efficient on dynamic scheduling problems compared to the SA and GA (Liu *et al.* 2005).

The SA algorithm was proposed in the 1980s using ideas used in the 1950s to simulate the cooling of material in a heat bath (i.e. annealing). Kirkpatrick *et al.* (1983) refined these ideas and developed the SA algorithm for solving optimisation problems by searching a large solution space. Some of the technical aspects of SA are in (Kirkpatrick *et al.* 1983, Dowsland 1995). Examples of its adaptation to healthcare problems include the scheduling of physicians or patients in (Winands *et al.* 2005, Vermeulen *et al.* 2006). In (Vermeulen *et al.* 2006), the SA aimed to create the schedules of appointments in response to the changes in the uncertain arrival of patients at the hospital.

4.4 Concluding remarks

This chapter has reviewed studies based on discrete-event simulation (DES) and production scheduling methods. The dearth of papers on studies on radiotherapy-related problems is noticeable. DES has been shown to help in understanding the problem being studied only. For the radiotherapy problems, the DES studies focused on the EBT process only. The other treatment processes, UST and BT, which require crucial resources (i.e. doctors) were not included. These papers focused on 'what-if' analysis of several scenarios which can be deemed not cost-effective. Such scenarios include testing the DES models with additional equipment or other key resources such as doctors. This thesis has been founded on the fact that most of the resources used in the radiotherapy department at the Arden Cancer Centre are expensive. Hence, In this context, the scenarios tested had to involve the use of current machine and/or human resources only.

Some of the few papers that reported the application of scheduling methods focused on the treatment unit of a typical UK radiotherapy department only. MIP models were formulated for a problem which did not consider most of the constraints found in a real-life radiotherapy department discussed in Chapter 3. Hence, the problem solved can be considered not close to a typical real-life UK radiotherapy scheduling problem. Two-stage constructive heuristics developed for a problem identified in the treatment unit had strategies that minimised the objective function for each type of treatment (i.e. palliative and radical). The use of a genetic algorithms on a problem which considered all the four units of the department resulted in improvements of the performance criteria although their computational efficiency was worse than expected. It is essential that the four units of the department be considered when formulating the radiotherapy scheduling problem to be solved using methods that require less computational effort. Further, more constraints have to be considered for the problem to closely represent real-life radiotherapy scheduling problems.

It can be argued that by focussing solely on the EBT process, the problem is less closer to a real-world radiotherapy department problem. However, it is crucial that the DES study of the department be used to reveal to what extent the BT and UST processes affect the interaction of the entities in the radiotherapy department. Since not many patients are treated by the BT and UST processes, it can be fairly concluded that such studies of scheduling patients focus on the EBT process.

Chapter 5

Simulation models

Contents

5.1 Introduction

This chapter discusses the development of DES models of the department based on the processes in Chapter 3. The aims of the DES study include: to assess the efficiency of the existing systems and conduct tests on several 'what-if' scenarios, understand the treatment processes and identify where the flow of patients is impeded. The flowcharts in Figures 3.4, 3.6–3.8, 3.10 and 3.12 in Chapter 3 were used as conceptual models of the existing system in the department. Data were collected from the department through interviews, observations and analysis of several retrospective records of patients. The models were developed using Simul8 (Simul8 Corporation 2009), an easy to use computer simulation software that can visually represent the real-life treatment processes.

The rest of this chapter is organised as follows. Section 5.2 discusses the scope of the problem in the department. In this discussion, the objectives of the development of the department's simulation models and its assumptions are stated. Section 5.3 describes the data collected from the department. The models built based on the procedures for the four units of the department are in Section 5.4. Section 5.5 discusses the verification and validation of the model for all the 3 treatment processes. This is followed by a discussion of the tests and analysis of the 'what-if' scenarios conducted using the developed models in Section 5.6. Lastly, Section 5.7 gives the concluding remarks.

5.2 Problem statement

The department's waiting times for palliative and radical treatments were worse than the JCCO recommended targets according to data collected between 2005 and 2007 as shown in Figure 5.1 which compares the average waiting times for EBT to the JCCO targets in (Joint Council of Clinical Oncology 1993). The average waiting times for palliative and radical treatments were worse than the JCCO targets by about 2 and 15 days respectively. For the UST processes, it took an average of 61.5 days for patients to be treated after diagnosis as shown in Figure 5.2. For the EBT process, Figures 5.3 and 5.4 show waiting times for patients that needed radical and palliative treatments, respectively.

The average waiting time for patients that required palliative treatment was 15.5 days and for those that needed radical treatment was 42.4 days. There were some patients whose treatment was prolonged by more than 100 days as shown in

Figure 5.4. For patients that required radical treatment, the mode of their waiting times was 28 days. Some of these patients had to wait for up to 200 days according to the data collected between 2005 and 2007. The department endeavours to manage the movement of patients through its four units to improve objectives stated in (Junor 1993). Objectives like improving staff morale or patient goodwill cannot be quantified. Improvement of cost-efficiency has to involve more data gathering to determine the financial implications of using some of the resources in the model. Waiting times for each of the treatment can be considered a yardstick for the quality of service. The shorter the average waiting times, the better the quality of service. Therefore, the problem at the department is about reducing the average waiting times to the levels targeted by the JCCO.

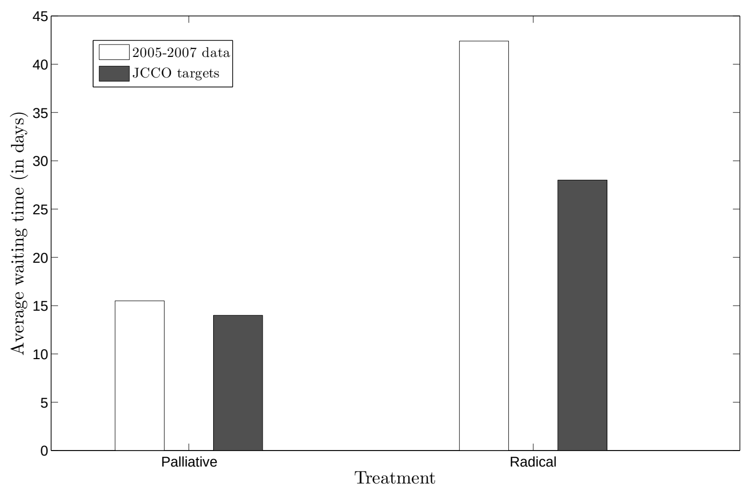

Figure 5.1: Average waiting times obtained from data collected between 2005 and 2007

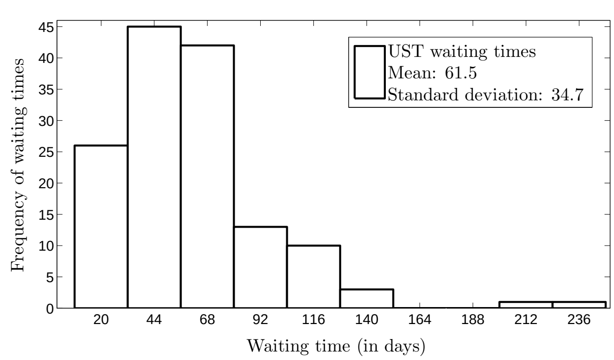

Figure 5.2: A plot of the waiting times obtained from retrospective UST data

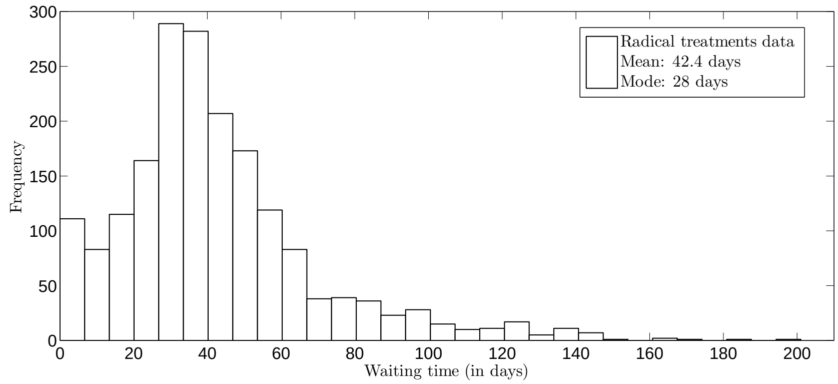

Figure 5.3: A plot of the waiting times for patients that needed radical treatment collected between 2005 and 2007

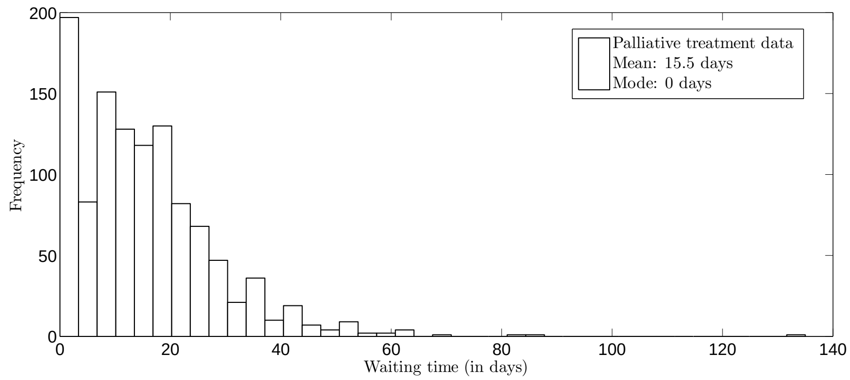

Figure 5.4: A plot of the waiting times for patients that needed palliative treatment collected between 2005 and 2007

5.2.1 Objectives of the models

The objectives of the DES study of the department are as follows.

a) To gain insight into the inherent complexities of the interactions of resources (i.e. machines, doctors, physicists, patients, and dosimetry technicians) in the treatment processes.

b) To analyse the performance of the existing treatment system under several scenarios like reduced staff, extended working hours, and no permitted doctor bypasses in the planning and physics units. Doctor bypasses can be considered as fast-tracks for patients to be simulated, scanned or have their plans approved even when the doctor is absent.

c) To determine the scope of the radiotherapy scheduling problem to be formulated in this study by gathering essential information about the treatment processes given percentages of the total number of patients treated through the 3 processes (i.e. BT, UST and EBT). 2%, 8% and 90% of the patients were treated through the BT, UST and EBT respectively.

d) To develop DES models for generating patient details to be used in the scheduling method proposed.

5.2.2 Assumptions of the models

Some assumptions were made about some of the work practices of the department due to the paucity of data on some procedures. Some of the critical assumptions made are as follows.

a) It was assumed booking request forms arrive at 9.00am on the day when the doctor was available in the department. In the real-world, these forms arrive at anytime of the day. Historical data collected did not include arrival times of the forms in the planning unit for each doctor.

b) It was assumed that there were no delays between the time when the decision to treat by radiotherapy was made and submission of booking request forms to the planning unit.

c) It was assumed that the department was closed at weekends although historical data had some patients treated on Saturdays and Sundays.

d) It was assumed that patients visited the simulator only for plan verification checks at the end of each treatment phase. Some patients revisited either the simulator or CT scan during treatment.

e) Historical data collected between September 2005 and January 2007, used to develop the model had no clearly classified records for patients requiring emergency treatment. Therefore, it was assumed that no patients needing emergency treatment were received.

f) It was assumed that patients undergoing treatment were punctual for their visits. It was deemed not essential to model the early and late arrival for appointments pattern shown in Figures 5.5 and 5.6. About 85% arrived early while 15% were late for treatment visits. About 70% and 30% were early and late respectively, for the planning unit procedures.

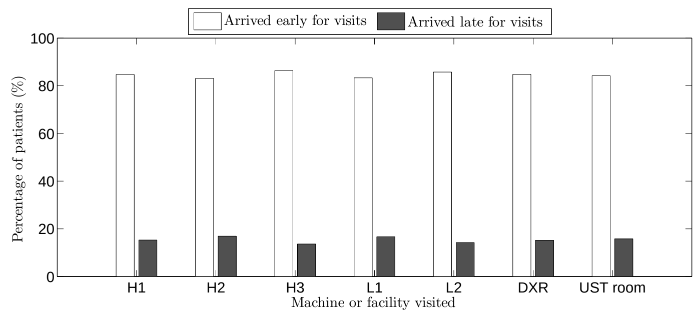

Figure 5.5: Percentage of patients in time or late for their treatment appointments

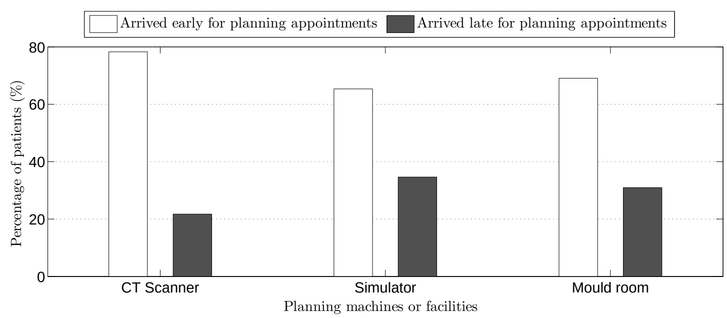

Figure 5.6: Percentage of patients in time or late for their planning appointments

5.3 Data collection

In this study, data were collected from the department's computer database system, by observing and interviewing radiographers, physicists, technicians, and other personnel in the planning, physics, pretreatment and treatment units. Data taken from the computer database system was for patient records from September 2005 to January 2007 and February 2008 to May 2008.

5.3.1 Data on doctors

Observations revealed that doctors are crucial for procedures performed in the planning and physics units (as illustrated in Figures 3.4 and 3.6). Doctors were sometimes bypassed in the treatment processes. About 75% of the patients were seen by their own doctor before the planning procedures while 25% had their procedures performed in the absence of their doctors (see Table 5.1). Notably, those examined in the absence of their doctor were possibly seen after normal working hours or by a locum doctor.

The time taken by the doctor seeing a patient ranged from less than a minute

Table 5.1: Doctors' presence or absence for the planning procedures

Cancer	Doctor present (%)	Doctor absent (%)
Benign	100.0	0.0
Breast	98.0	2.0
CNS	75.9	24.1
Digestive system	72.0	28.0
Endocrine gland	89.5	10.5
Gynaecological	60.9	39.1
Head and neck	53.1	46.9
Lympho-reticular	60.6	39.4
Male genital	34.8	65.2
Respiratory	70.4	29.6
Skin	100.0	0.0
Soft tissue and bone	66.7	33.3
Unknown primary	93.3	6.7
Unspecified or other	92.3	7.7
Urinary	43.3	56.7
Overall	74.6	25.4

to about eleven minutes as shown in Figure 5.7. The mean and mode of these times are 2.9 and 2.0 minutes respectively. It can be concluded that most of the doctor-patient consultations prior to procedures in the planning unit were less than 5 minutes long. Table 5.2 lists the percentages of the patients allocated to each of the 12 doctors by cancer diagnosis. Each cancer diagnosis has a doctor or doctors that was allocated most patients. For example, for head and neck cancers, doctors represented by anonyms 1 and 5 were responsible for most of these patients, 32 and 60%, respectively.

5.3.2 Data on processing times for treatment machines

HE and LE linacs have lower processing times. They normally have more patients to treat in a day compared to the other machines and/or facilities. The DXR and betatron are less busy than the linacs as discussed in Chapter 3. The best fitting probability distributions chosen from up to 32 distributions (i.e. including continuous and discrete probability distributions), not selected a priori, were used to model the processing times obtained from the data collected from each machine. These distributions were obtained using Stat::Fit (Geer Mountain Software Corporation 2009), a statistical toolbox which tests for goodness of fit by comparing input data to fitted distributions. These tests make the hypothesis that the fit is good and ranks all distributions based on Chi Squared, Kolmogorov-Smirnov and Anderson Darling tests and gives an indication of their acceptance

Table 5.2: A distribution of the percentage of patients seen by each doctor 1–12 classified using cancer diagnosis

Cancer	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Benign	0.0	0.0	3.1	17.7	2.4	40.2	0.0	6.1	0.0	17.9	12.2	0.0
Breast	12.6	0.2	0.0	20.6	17.7	0.2	0.0	8.8	3.1	0.0	36.6	0.2
CNS	0.0	0.0	0.8	7.0	0.0	86.7	0.8	0.0	0.0	3.9	0.8	0.0
Digestive system	1.0	1.0	0.0	0.6	14.5	4.5	0.7	14.2	0.0	1.0	27.9	35.0
Endocrine gland	0.0	0.0	3.3	6.7	35.0	51.7	0.0	0.0	1.7	0.0	1.7	0.0
Gynaecological	0.0	0.0	0.0	36.2	0.0	7.9	0.0	0.0	0.0	55.9	0.0	0.0
Head and neck	31.8	0.0	0.0	0.4	59.5	0.0	0.0	0.0	7.1	1.2	0.0	0.0
Lympho-reticular	0.5	0.0	28.2	41.2	0.5	4.8	1.0	0.5	0.0	3.4	19.6	0.5
Male genital	21.0	11.6	19.3	11.8	0.2	0.0	4.6	28.5	0.0	0.2	3.1	0.0
Respiratory	0.6	15.4	25.4	0.0	0.0	0.2	3.2	0.0	0.0	49.2	0.2	5.8
Skin	13.0	0.0	0.0	3.2	1.6	56.1	13.4	5.7	0.0	3.0	4.1	0.0
Soft tissue and bone	0.0	3.6	0.0	0.0	3.6	7.1	0.0	0.0	0.0	10.7	75.0	0.0
Unknown primary	4.7	14.8	7.0	7.8	11.7	13.3	6.3	3.9	0.8	13.3	11.7	4.7
Unspecified or other	2.9	14.7	8.8	2.9	0.0	23.5	5.9	2.9	0.0	32.4	2.9	2.9
Urinary	26.1	11.3	11.3	16.2	0.0	0.0	0.7	31.7	0.0	2.8	0.0	0.0

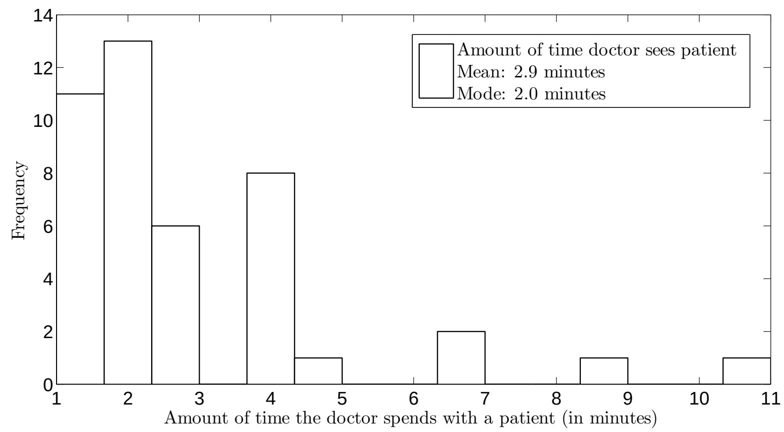

Figure 5.7: A plot of the amount of time the doctors consulted their patients (in minutes)

as a good representation of the input data. An example of fitted distributions for the processing times of HE linacs is illustrated in Figure 5.8. Weibull distribution was ranked highest and selected as the best fitting distribution. Figures 5.9–5.13 show these probability distributions selected to estimate the processing times of the machines and facility.

Auto::Fit of Distributions

distribution	rank	acceptance
Weibull(8., 1.29, 6.32)	100	do not reject
Beta(8., 146, 1.44, 32.5)	76.1	do not reject
Gamma(8., 1.49, 3.93)	64.2	do not reject
Pearson 6(8., 1.31e+005, 1.48, 3.3e+004)	62.8	do not reject
Erlang(8., 2., 2.93)	22.6	do not reject
Lognormal(8., 1.39, 1.)	1.21	do not reject
Exponential(8., 5.85)	0.859	do not reject
Chi Squared(8., 4.99)	4.64e-002	do not reject
Uniform(8., 33.4)	0.	reject
Pearson 5(8., 0.839, 1.67)	0.	reject
Rayleigh(8., 5.25)	0.	reject
Triangular(8., 33.8, 8.26)	0.	reject
Power Function(8., 36.1, 0.515)	0.	reject

Figure 5.8: A screenshot of the list of automatically fitted probability distributions from Stat::Fit

The use of fitted probability distributions to estimate the processing times for the machines can help in quickly building DES models. However, using raw empirical data instead of distributions ensures that the DES model uses processing times that are much closer to real-life. This can be substantiated by the fact that some of the plots shown in Figures 5.9–5.13 do not cover the frequencies of some of the processing times from the historical data.

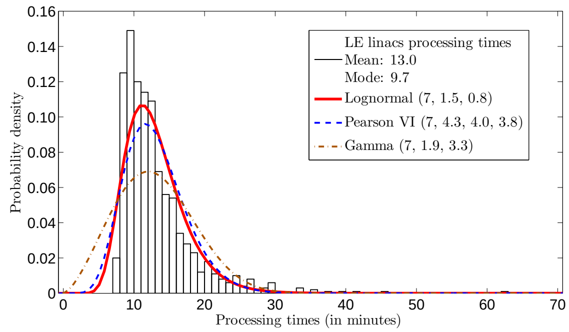

Figure 5.9: A Lognormal distribution plot of the processing times for LE linacs

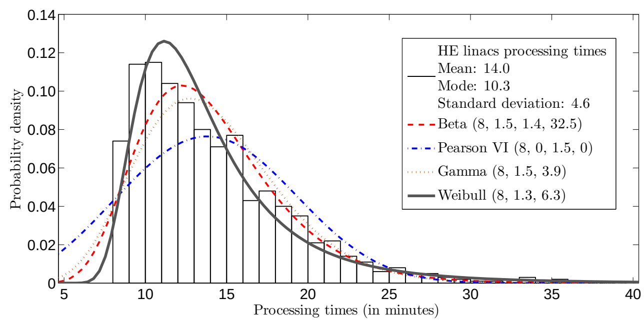

Figure 5.10: A Weibull distribution plot of the processing times for HE linacs

5.3.3 Data on processing times for other resources

The time taken to perform some of the procedures was estimated based on data obtain through interviewing staff. For example, the time spent by technicians on the first procedure done in the physics unit (i.e. outlining and planning) was estimated this way. Table 5.3 shows a list of the probability distributions (all parameters are given in minutes) used to estimate the amount of time patients spent on some of the machines and facilities for these procedures. Parameters of the uniform distributions listed in Table 5.3 are the lower and upper bounds of the time spent performing the procedure.

5.3.4 Data on time between treatment procedures

Doctors delayed submitting booking request forms of about 70% of the patients by about a day after the decision to treat was made as shown in Figure 5.14.

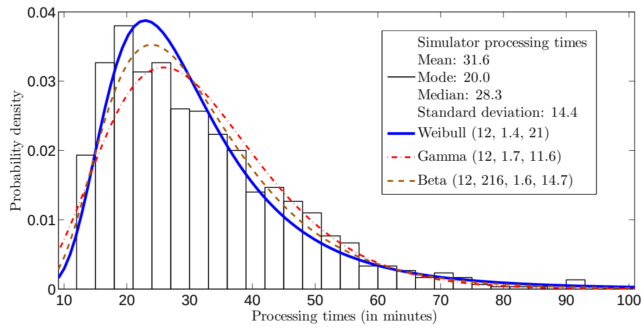

Figure 5.11: A Weibull distribution plot of the processing times for the simulator

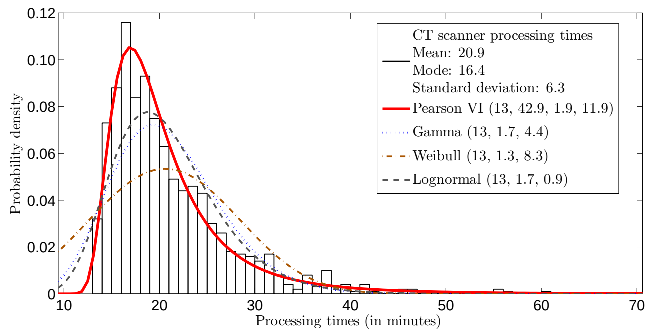

Figure 5.12: A Pearson VI distribution plot of the processing times for the CT scanner

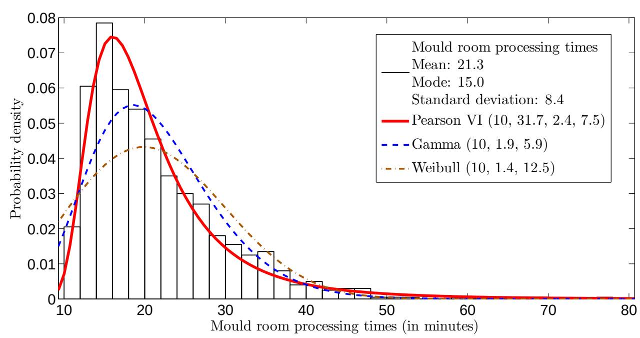

Figure 5.13: A Pearson VI distribution plot of the processing times for the mould room

Some patients experienced delays of up to 22 days before their appointments were booked. Hence, for a patient requiring palliative treatment whose request form was delayed by 10 days, there was only 4 days left before the JCCO targeted due date for treatment. Radiographers had to book appointments for all the procedures within the 4 days for the patient to meet the JCCO targeted waiting time for palliative treatments.

Table 5.3: Probability distributions for the amount of time patients spent on machines and facilities

Procedure	**Probability distribution**
Outlining and planning (physics unit)	Uniform (25, 30) minutes
Complex dosimetry calculations and checks (physics unit)	Uniform (45, 60) minutes
Pretreatment dose calculations and checks	Uniform (25, 30) minutes
Final dose calculations and checks (treatment unit)	Uniform (25, 30) minutes
Initial radiographer session	Average (5) minutes
Isotope delivery (UST)	Uniform (12, 15) minutes
Decontamination	Fixed (120) minutes
Applicator insertion in the operating theatre (BT)	Normal (45, 15) minutes
Applicator insertion in the physics unit (BT)	Uniform (5, 7) minutes
Bronchoscopy (BT)	Uniform (25, 30) minutes
Endoscopy (BT)	Uniform (25, 30) minutes
Imaging tumour on IBU (BT)	Uniform (25, 30) minutes
BT treatment planning	Uniform (25, 30) minutes
BT plan checks	Uniform (30, 45) minutes
Treating on HDR (BT)	Uniform (15, 20) minutes

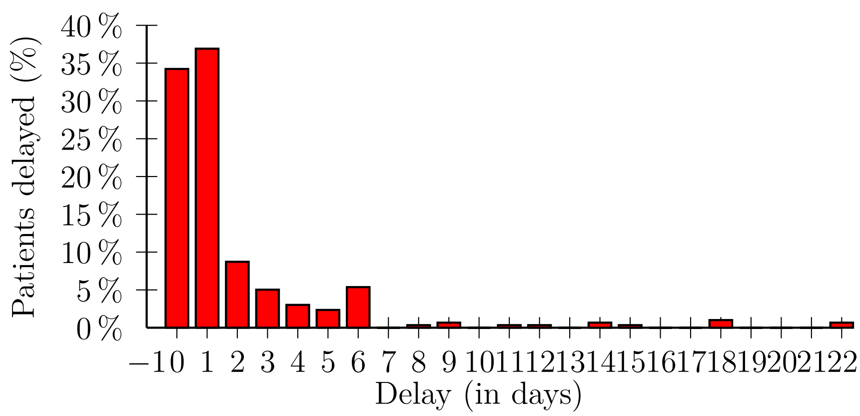

Figure 5.14: A plot of the delays in submission of request forms to the planning unit by the doctors

The processing times estimated using probability distributions as discussed in Section 5.3.2 can be considered as some of the crucial parameters for the model. Parameters considered the most sensitive included the amount of time that elapsed between consecutive procedures between booking of appointments and planning unit procedures (i.e. simulation, scanning or mask moulding), procedures in the planning and physics units, and those performed in the physics and pretreatment units. Using some of the data collected, several probability distributions were tested to determine the ones that would achieve the desired results (i.e. waiting times closer to the historical data). The probability distributions shown in Tables 5.4 and 5.5 were obtained in this process. Some of these probability distributions were used to estimate the amount of time that elapsed between procedures performed in different units. For example, the Triangular distribution (see Table 5.4) was used to estimate the amount of time some patients that required radical treatment had to wait between submission of a booking request form and staging of their cancers on the simulator.

Table 5.4: Time that elapsed between appointment booking to the completion of the planning unit procedures

Treatment	Urgency	Machine or facility	Distribution
Palliative	Urgent	CT scanner	Fixed (10) minutes
		Simulator	
		Mould room	
	Non-urgent	CT scanner	Exponential (8.4) days
		Simulator	Exponential (8.6) days
		Mould room	Fixed (10) minutes
Radical	Urgent	CT scanner	Pearson V (1.1, 9.7) days
		Simulator	Triangular (0, 0, 31) days
		Mould room	Fixed (10) minutes
	Non-urgent	CT scanner	Exponential (21.8) days
		Simulator	Uniform (0, 37) days
		Mould room	Exponential (21.8) days

Table 5.5: Time that elapsed between planning and physics or pretreatment units procedures

Treatment	Urgency	Distribution
Palliative	Urgent	Fixed (10) minutes
	Non-urgent	Exponential (8.3) days
Radical	Urgent	Beta (1.3, 2.7, 0, 46) days
	Non-urgent	Exponential (11.7) days

5.3.5 Data on cancer diagnosis and patient categories

Breast cancers are the most commonly treated cancers in the department while about 1% of the total number of patients that come through the department are treated for soft tissue and bone, and unspecified or other cancers. Figure

5.15 illustrates the distribution of all the 15 cancers treated in the department. Over 10% of the patients are treated for male genital, respiratory or skin related cancers.

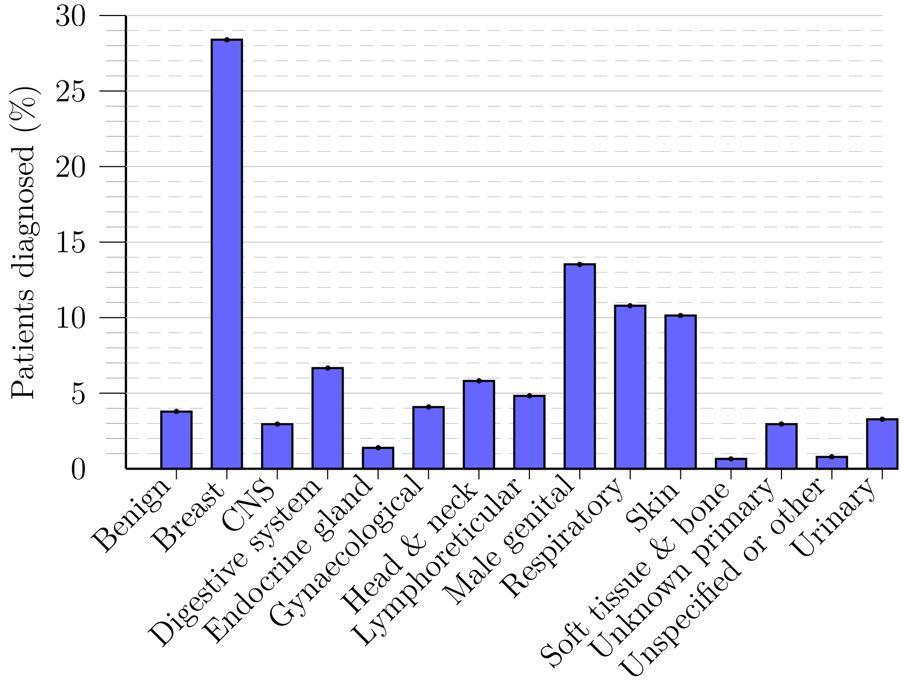

Figure 5.15: A plot of the distribution of cancers treated

For patients treated through the UST process, the most prevalent diagnosis were thrombotoxicosis, thyroid and prostate cancers. More than 60% of the patients that were treated by the UST processes were diagnosed of thrombotoxicosis. The rest comprised patients diagnosed with thyroid, thrombocytosis, thrombocythaemia, polycythaemia and the prostate cancers. Similarly, for patients treated through the BT treatment system, about 60% had gynaecological cancers while about 25% and 7% had been diagnosed with cervix and oesophageal cancers respectively.

In Table 5.6, the proportions of the patients who required treatments such as adjuvant, palliative, radical are shown. Cancers classified as digestive system, respiratory, unknown primary, unspecified or other and urinary had the more percentages of patients that needed palliative treatment compared to the rest that had more patients requiring radical treatment. More crucially, the percentages of the patients who received each of the JCCO treatments are shown in Table 5.7. About 67% and 31% of the patients received radical and palliative treatment respectively. New data (i.e. collected in 2008) showed that about 2% of the total patients required emergency treatment. Hence, it can be surmised that the request forms submitted on most days comprised mostly patients requiring radical treatment. Prioritisation of the list of received patients was imperative as discussed in (Lim *et al.* 2005).

Table 5.6: Percentages of the total patients by cancer diagnosis and treatment

Diagnosis	Adjuvant	None	Palliative	Radical
Benign	0.0	0.0	33.3	66.7
Breast	0.1	0.4	23.2	76.3
CNS	0.0	0.0	19.2	80.8
Digestive system	0.0	0.0	53.0	47.0
Endocrine gland	0.0	5.0	25.0	70.0
Gynaecological	0.0	0.0	24.1	75.9
Head and neck	0.0	1.6	3.6	94.7
Lympho-reticular	0.0	1.0	34.0	65.1
Male genital	0.0	1.6	42.7	55.7
Respiratory	1.7	0.7	73.7	24.0
Skin	0.0	0.7	5.7	93.6
Soft tissue and bone	0.0	3.6	35.7	60.7
Unknown primary	0.0	0.0	83.6	16.4
Unspecified or other	0.0	0.0	87.9	12.1
Urinary	0.0	1.4	57.5	41.1

Table 5.7: Percentages of patients treated per treatment

Treatment	Percentage of patients (%)
Emergency	2.0
Palliative	31.0
Radical	67.0

Patients data from 2005–2007 were classified as urgent or non-urgent. In this case, the urgency was different from the *Urgent* treatments that have to be delivered within 24 hours as explained earlier. The department determined the urgency of each cancer case even though the patient required radical treatment within 28 days as recommended by the JCCO. Table 5.8 shows the percentages of urgent versus non-urgent patients for each cancer diagnosis. Besides determining the percentage of urgent or non-urgent patients, it was important to extrapolate the percentages of patients treated as in or out-patients. Table 5.9 gives a breakdown of the percentage of in and out-patients for each cancer diagnosis. Generally, about 11% of the patients treated in the department were in-patients while the rest were out-patients.

Table 5.8: Percentages of the patients by cancer diagnosis and categorisation of whether their treatments were urgent or not

Cancer diagnosis	**Urgent** (%)	**Non-urgent** (%)
Benign	0.0	100.0
Breast	2.0	98.0
CNS	8.2	91.8
Digestive system	4.7	95.3
Endocrine gland	25.0	75.0
Gynaecological	3.5	96.5
Head and neck	2.9	97.1
Lympho-reticular	8.5	91.5
Male genital	5.9	94.1
Respiratory	5.9	94.1
Skin	1.9	98.1
Soft tissue and bone	3.6	96.4
Unknown primary	22.2	77.8
Unspecified or other	15.2	84.8
Urinary	10.0	90.0

Table 5.9: Percentage of patients treated as in or out-patients per cancer diagnosis

Cancer diagnosis	**In-patients** (%)	**Out-patients** (%)
Benign	3.7	96.3
Breast	3.8	96.2
CNS	22.0	78.0
Digestive system	16.3	83.7
Endocrine gland	73.7	26.3
Gynaecological	10.0	90.0
Head and neck	5.7	94.3
Lympho-reticular	27.7	72.3
Male genital	9.6	90.4
Respiratory	14.0	86.0
Skin	1.8	98.2
Soft tissue and bone	28.6	71.4
Unknown primary	39.8	60.2
Unspecified or other	17.7	82.3
Urinary	15.6	84.4
Overall	11.0	89.0

Auto::Fit of Distributions

distribution	rank	acceptance
Negative Binomial(4., 0.285)	100	do not reject
Discrete Uniform(0., 29.)	0.	reject
Geometric(9.06e-002)	0.	reject
Poisson(10.)	0.	reject

Figure 5.16: Fitted distributions for the arrival of request forms in the planning unit

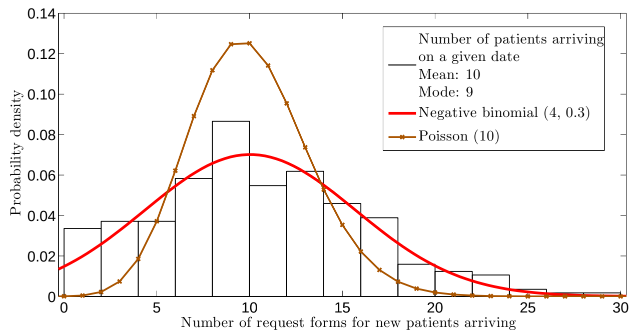

Figure 5.17: Negative binomial distribution used to estimate patient arrivals

5.3.6 Data on patient arrival patterns

The pattern of arrival of request forms in the planning unit was estimated using fitted probability distributions obtained using Stat::Fit as described earlier. A Negative Binomial distribution was considered the best fitting distribution as shown in Figure 5.16. A plot of the distribution used for the model is illustrated in Figure 5.17. The minimum and maximum number of request forms received in the planning unit in a given day was 0 and 29, respectively.

5.3.7 Data on machines and facilities usage

Doctors and/or radiographers in the planning unit determined the machines to be visited by each patient. The percentage of patients with different cancer diagnosis that used either the mould room, CT scanner and/or simulator are listed in Table 5.10. Most of the patients diagnosed with head and neck, male genital and urinary cancers visited the CT scanner. The rest visited the simulator. Therefore, the simulator was generally busy compared to the CT scanner.

In Table 5.11, the HDR was commonly used to treat gynaecological cancers while most patients diagnosed with the other cancers were treated on one of the 3 HE linacs referred to as HE3. The DXR machine was generally used to treat skin

Table 5.10: Percentage of patients per cancer diagnosis that visited the planning unit resources. All the values are in (%)

Cancer diagnosis	Mould room	CT scanner	Simulator
Benign	33.3	0.0	66.7
Breast	3.3	10.5	86.2
CNS	52.2	1.2	46.6
Digestive system	8.2	30.7	61.1
Endocrine gland	44.1	14.7	41.2
Gynaecological	4.5	35.6	59.9
Head and neck	38.6	45.2	16.2
Lympho-reticular	22.6	9.7	67.7
Male genital	2.8	53.1	44.2
Respiratory	8.7	22.9	68.4
Skin	19.2	0.4	80.4
Soft tissue and bone	16.1	25.8	58.1
Unknown primary	20.5	8.3	71.2
Unspecified or other	10.8	5.4	83.8
Urinary	3.5	51.0	45.5

and benign cancers. The distribution of patients on the 8 machines shows that some machines were used to treat more patients than others. It can be concluded that most doctors prescribed certain types of machines than others.

5.3.8 Data on treatment plan complexity

Treatment plan complexity can be used to determine the pathway followed by a patient in the physics and pretreatment units. Data collected was classified using four levels of complexity of the treatment plans generated for the patients. For some cancer diagnoses including soft tissue and bone, and unspecified or other cancers, the data had no treatment plan complexity levels marked as shown in Table 5.12. About 75% of the treatment plans created in the department were simple. This implies most of these plans were created in the pretreatment unit. Less than 1% had complex treatment plans created for their treatment while the other 24% had intermediate or 'none' treatment plans created by the radiographers. It was assumed that patients whose treatment plan complexity was complex or intermediate visited the physics unit. This implies that less than 15% of the total patients were expected to have their treatment plans created in the physics unit.

Table 5.11: Percentage of patients per cancer diagnosis treated on the treatment machines. LE1 and LE2 represent the 2 LE linacs while HE1, HE2, HE3 represent the 3 HE linacs. All the values are in (%)

Diagnosis	Betatron	DXR	LE1	LE2	HE1	HE2	HE3	HDR
Benign	0.0	16.6	0.0	0.0	66.7	0.0	16.7	0.0
Breast	0.0	0.3	14.1	42.0	7.4	5.0	31.2	0.0
CNS	0.0	1.3	9.2	27.6	10.5	17.2	34.2	0.0
Digestive system	0.0	0.0	25.4	11.2	8.2	16.4	34.9	3.9
Endocrine gland	0.0	0.0	0.0	28.6	21.4	7.1	42.9	0.0
Gynaecological	0.0	0.0	19.8	1.1	6.1	11.4	13.7	47.9
Head and neck	0.0	3.2	8.7	38.9	6.4	22.2	20.6	0.0
Lympho-reticular	2.9	2.9	15.3	22.6	10.3	12.4	33.6	0.0
Male genital	0.0	0.0	37.1	9.7	5.2	8.5	39.5	0.0
Respiratory	0.0	2.5	17.6	32.0	4.9	13.3	29.1	0.6
Skin	0.0	85.8	6.7	1.4	1.9	1.1	3.1	0.0
Soft tissue and bone	0.0	0.0	12.5	25.0	0.0	6.2	56.3	0.0
Unknown primary	0.0	0.0	16.3	17.4	9.3	7.0	50.0	0.0
Unspecified or other	0.0	11.1	33.3	22.2	3.7	7.4	14.8	7.5
Urinary	0.0	0.0	39.3	8.9	1.8	11.6	36.6	1.8

Table 5.12: Percentage of patients per cancer diagnosis and treatment plan complexity levels. All the values are in (%)

Cancer diagnosis	Complex	Intermediate	None	Simple
Benign	0.0	0.0	100.0	0.0
Breast	0.2	3.5	0.7	95.6
CNS	1.7	63.8	1.7	32.8
Digestive system	2.1	46.9	2.0	49.0
Endocrine gland	0.0	33.3	33.3	33.4
Gynaecological	4.6	38.6	0.0	56.8
Head and neck	0.0	29.2	12.5	58.3
Lympho-reticular	3.3	6.7	83.3	6.7
Male genital	0.0	33.3	66.7	0.0
Respiratory	3.3	6.7	83.3	6.7
Skin	0.0	0.0	100.0	0.0
Soft tissue and bone	–	–	–	–
Unknown primary	0.0	33.3	0.0	66.7
Unspecified or other	–	–	–	–
Urinary	0.0	33.3	0.0	66.7
Overall	0.7	13.1	11.8	74.4

5.3.9 Data on prescribed fractions

Data showed that some patients went through up to 3 treatment cycles (i.e. treatment phases) as shown in Table 5.13. About 93% of the patients had no prescribed treatment phases. Once their prescribed fractions were completed, they were then discharged. For the rest, about 3%, 4% and 1% had 1, 2 and 3 additional treatment phases respectively, recommended by the doctor in their treatment regime. Modelling the prescription of fractions to patients for each patient suffering from any of the 15 cancers diagnosis involved using distributions shown in Figures A.1–A.15 in Appendix A. Some patients were prescribed up to 30 fractions for their treatment regime.

5.3.10 Data on treatment processes used

The EBT process was the most commonly used method of treating patients as shown in Table 5.14. About 4 and 6% of the patients needed treatment through BT and UST. Some cancer diagnosis like head and neck, lympho-reticular, skin, soft tissue and bone, and unknown primary cancers, were never treated using UST or BT as shown in Table 5.14. This data was essential in generating patients who follow 3 different pathways which correspond to the 3 treatment processes in the DES model.

Table 5.13: Percentage of patients (%) for different prescribed treatment phases per cancer diagnosis

Cancer diagnosis	**0**	**1**	**2**	**3**
Benign	100.0	0.0	0.0	0.0
Breast	99.7	0.0	0.3	0.0
CNS	85.0	8.7	6.3	0.0
Digestive system	94.7	1.8	3.5	0.0
Endocrine gland	65.0	10.0	20.0	5.0
Gynaecological	82.9	4.7	12.4	0.0
Head and neck	41.1	25.4	26.6	6.9
Lympho-reticular	95.2	1.9	2.9	0.0
Male genital	95.8	1.4	2.8	0.0
Respiratory	98.7	0.9	0.4	0.0
Skin	99.1	0.0	0.2	0.7
Soft tissue and bone	82.1	3.6	14.3	0.0
Unknown primary	95.3	0.0	3.1	1.6
Unspecified or other	97.0	3.0	0.0	0.0
Urinary	91.5	2.1	5.7	0.7
Overall	93.0	2.7	3.7	0.6

Table 5.14: A distribution of patients treated by the 3 treatment processes

Cancer diagnosis	**EBT** (%)	**UST** (%)	**BT** (%)
Benign	4.4	95.6	0.0
Breast	99.8	0.2	0.0
CNS	98.8	1.2	0.0
Digestive system	97.2	0.4	2.4
Endocrine gland	28.3	71.7	0.0
Gynaecological	52.3	0.4	47.4
Head and neck	100.0	0.0	0.0
Lympho-reticular	100.0	0.0	0.0
Male genital	98.0	2.0	0.0
Respiratory	99.5	0.0	0.5
Skin	100.0	0.0	0.0
Soft tissue and bone	100.0	0.0	0.0
Unknown primary	100.0	0.0	0.0
Unspecified or other	89.3	3.6	7.1
Urinary	98.3	0.0	1.7
Overall	90.6	5.6	3.8

5.3.11 Data on radioisotopes

Since treatment by UST involved administering soluble radioisotopes (i.e. ^{131}I, ^{32}P, ^{89}Sr and ^{153}Sm), the data showed the distribution of the patients treated by them as illustrated in Table 5.15. Radioisotope ^{131}I was prevalently used to treat most of the cancers while the other 3 were used rarely. ^{32}P was only used on patients that had benign and unspecified cancers while ^{89}Sr and ^{153}Sm were used to treat male genital related cancers.

Table 5.15: Percentage of patients treated by the four UST isotopes. All values are in (%)

Cancer diagnosis	^{131}I	^{32}P	^{89}Sr	^{153}Sm
Benign	96.0	4.0	0.0	0.0
Breast	100.0	0.0	0.0	0.0
CNS	100.0	0.0	0.0	0.0
Digestive system	100.0	0.0	0.0	0.0
Endocrine gland	100.0	0.0	0.0	0.0
Gynaecological	100.0	0.0	0.0	0.0
Head and neck	0.0	0.0	0.0	0.0
Lympho-reticular	0.0	0.0	0.0	0.0
Male genital	0.0	0.0	72.7	27.3
Respiratory	0.0	0.0	0.0	0.0
Skin	0.0	0.0	0.0	0.0
Soft tissue and bone	0.0	0.0	0.0	0.0
Unknown primary	0.0	0.0	0.0	0.0
Unspecified or other	0.0	100.0	0.0	0.0
Urinary	0.0	0.0	0.0	0.0

5.4 Building the models

The process flowcharts discussed in Chapter 3 were considered as the conceptual models of the units. The four units were first separately modelled using Figures 3.4 and 3.6–3.8 for the EBT process. The flowcharts in Figures 3.10 and 3.12 were used to developed separate models for the UST and BT processes. All the separate models were incorporated into the final simulation model of the department. The simulation software chosen for building the models was Simul8 (Simul8 Corporation 2009).

5.4.1 Using Simul8

Simul8 allows the user to create a visual representation of the real-life system being modelled using the following objects: a) work item, b) entry point, c) work centre, d) resources, e) storage bin, and f) exit point. Work items represent entities to be processed (e.g. patients). An entry point is defined as the point where work items are created and 'pushed' into the model. Work centres are the entities, like machines, which process work items. Resources are entities needed to operate work centres (e.g. radiographers for driving a simulator). Storage bins represent the points work items queue until a work centre is ready to process them. Finally, an exit point is the point where work items that no longer required to be processed are deemed complete and leave the model. These objects were fundamental to the creation of the separate DES models using Simul8.

5.4.2 Planning unit model

The DES model of the planning unit comprised five key entities: doctors (i.e. 13 doctor entities), booking desk, mould room, simulator and CT scanner as shown in Figure 5.18. These were connected in such a way that the patients would first visit doctor entities before proceeding to the machines. For 12 of the 13 work centres representing the doctors, the shift patterns of each doctor were defined so that patients would be examined during the doctor's shift only. The 13^{th} work centre (i.e. with 0 minutes processing time) represented a bypass entity used by patients that had their procedures performed in the absence of their doctors.

The receipt of request forms generated at the entry point was modelled on the EBT booking desk. The bookings were estimated using the probability distributions listed in Table 5.4. After the completion of the simulator or CT scanner procedures, patients exit the planning unit model. As a separate model, the planning unit DES model can mimic the pathways taken in the planning unit. However, the use of resources (especially radiographers) was not accurately represented. In the real-life department, radiographers are versatile; they can work in any of the 3 units: planning unit, pretreatment and treatment unit. Hence, it was essential to incorporate all the separate models into one.

5.4.3 Physics unit model

The main entities included in the DES model in Figure 5.19 were the mould room, technicians workstations, physicists and doctors. Like the planning unit model, 13 doctor work centres were also included. The 13^{th} doctor work centre was for treatment plans approved in the absence of the doctor. As shown in the physics unit DES model, after dosimetry calculations, two physicists checked the calculations for accuracy sequentially. After 'Physicist 3' completes the last verification checks, the treatment plan exits the physics unit.

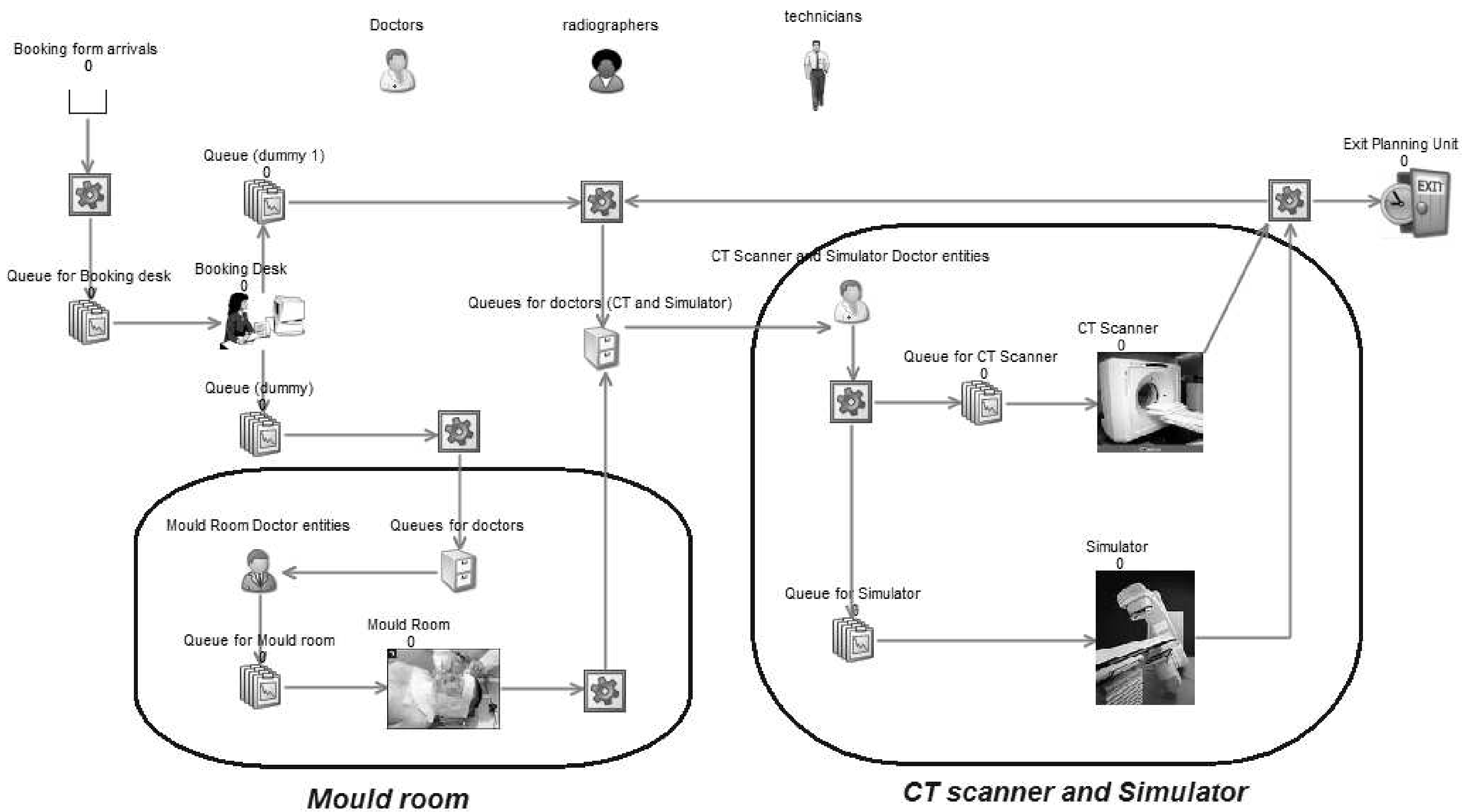

Figure 5.18: A screenshot of the simulation model of the planning unit

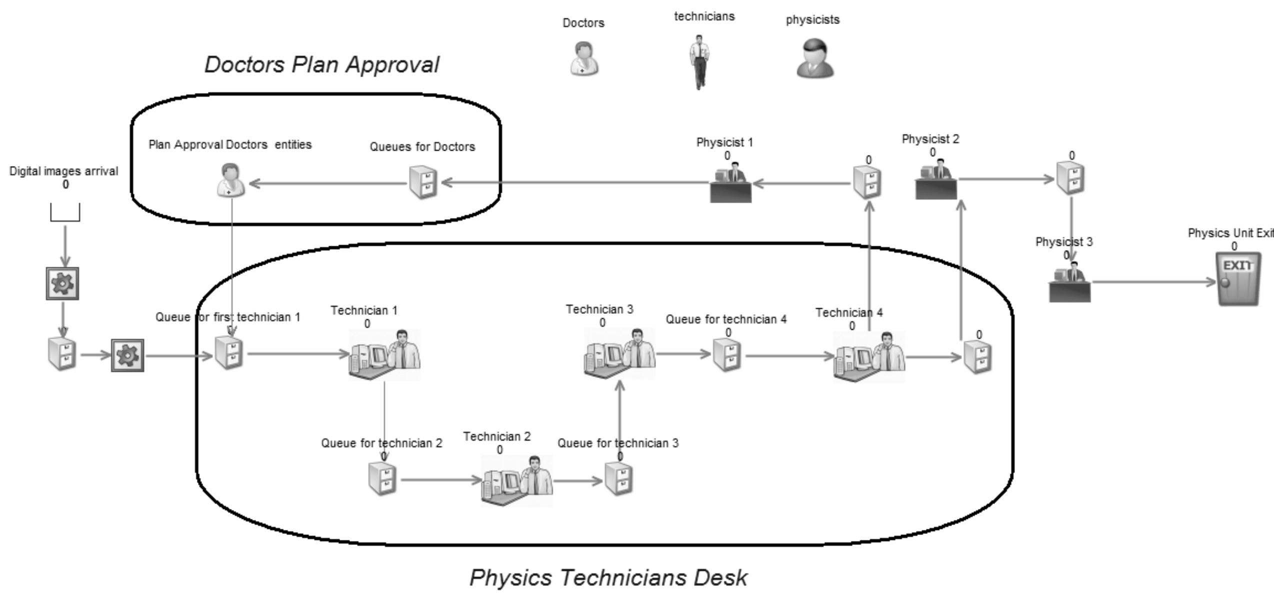

Figure 5.19: A screenshot of the simulation model of the physics unit procedures for EBT

UST and BT procedures were modelled as shown in Figures 5.20 and 5.21 respectively. Four key entities were included in the DES model for the UST process: doctors, ^{131}I, ^{32}P, and ^{89}Sr and ^{153}Sm radioisotopes. As explained in the previous chapter, the 'Iodine 131' work centre was connected to the two decontamination wards (i.e. 'Decontamination Ward 1' and 'Decontamination Ward 2'). In Figure 5.21, the main entities included the IBU, HDR, applicator insertion methods (i.e. theatre, bronchoscopy, endoscopy and the BT room), treatment plan creation, verification and checking of treatment plans, doctors and the two decontamination wards. The decontamination wards shown in Figures 5.20 and 5.21 were shared between patients treated by UST using the iodine radioisotope, ^{131}I and those treated by BT.

5.4.4 Pretreatment unit model

Since each radiographer performed one calculation and checks to verify the accuracy of a treatment plan, the entities representing the desks were interconnected as shown in Figure 5.22. These entities represented the 3 different radiographers (i.e. staff resources) that worked on the treatment plans: 'Radiographer 1', 'Radiographer 2' and 'Radiographer 3'. Each desk entity is connected to the other two desk entities and the exit point to represent all the possible routes that a treatment plan can follow after a procedures on the desk was completed. Such a configuration of the desk entities shows that a treatment plan had no definite starting and ending point for its procedures. Further, the configuration of desks conforms to the definition of the open shop environment discussed in Chapter 4.

5.4.5 Treatment unit model

The DES model of the treatment unit in Figure 5.23 shows entities for the machines and workstations where further verifications of the dosimetry calculations were performed. These workstations were connected to each treatment machine so that upon completion of these further calculation checks, the patient proceeded with the actual fraction delivery. The interconnections of the machines modelled cases where patients can be swapped from one machine to the other during their treatment (i.e. for the HE and LE linacs).

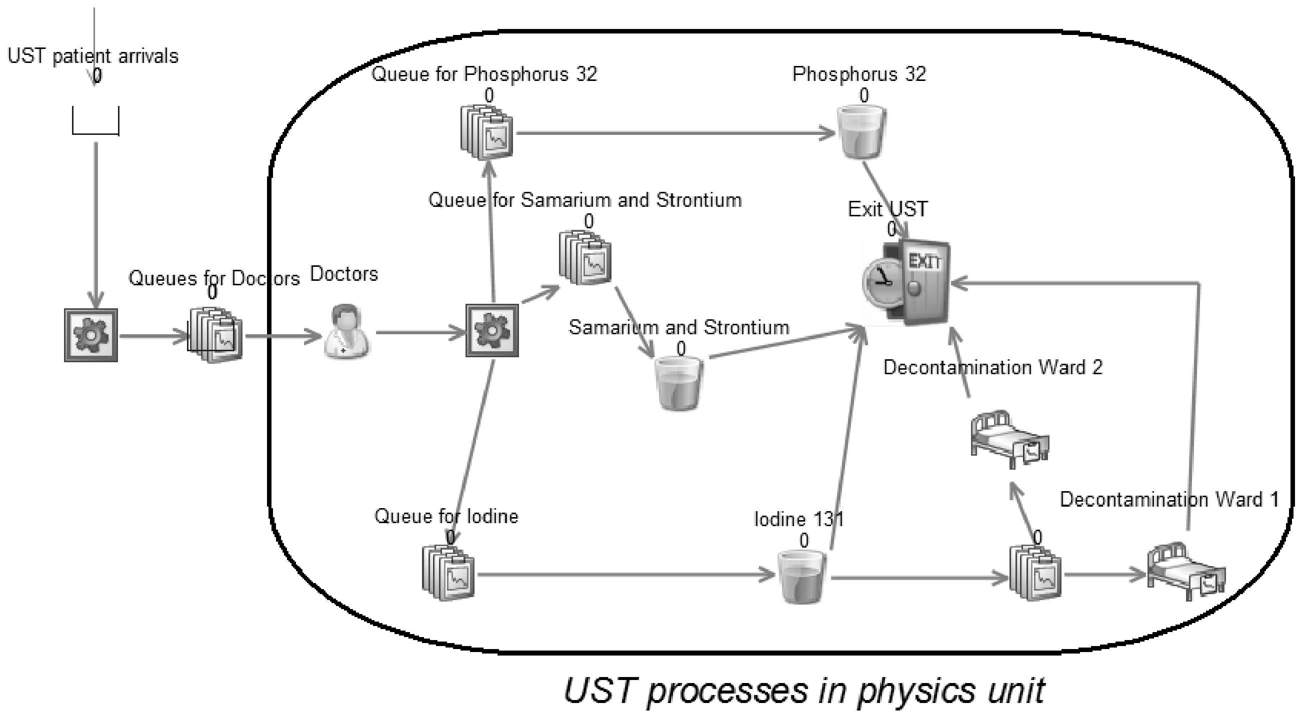

Figure 5.20: A screenshot of the simulation model of the UST procedures

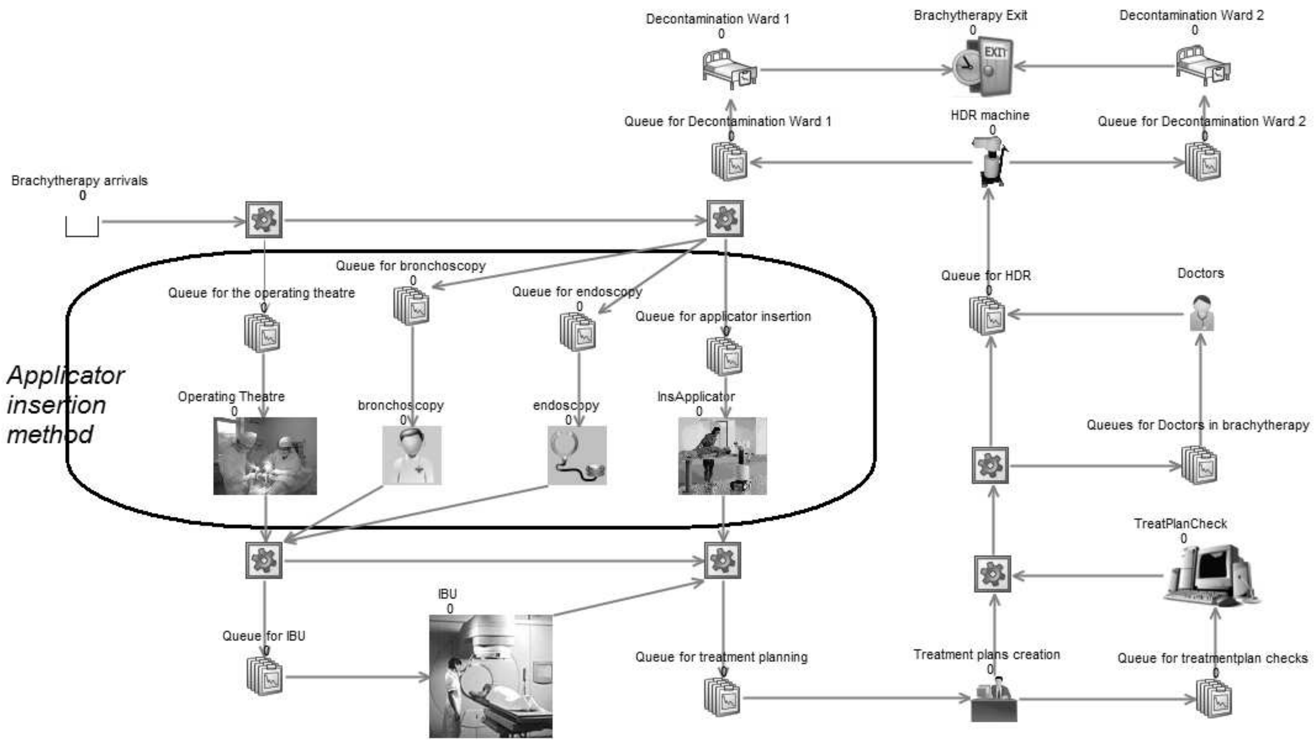

Figure 5.21: A screenshot of the simulation model of BT procedures

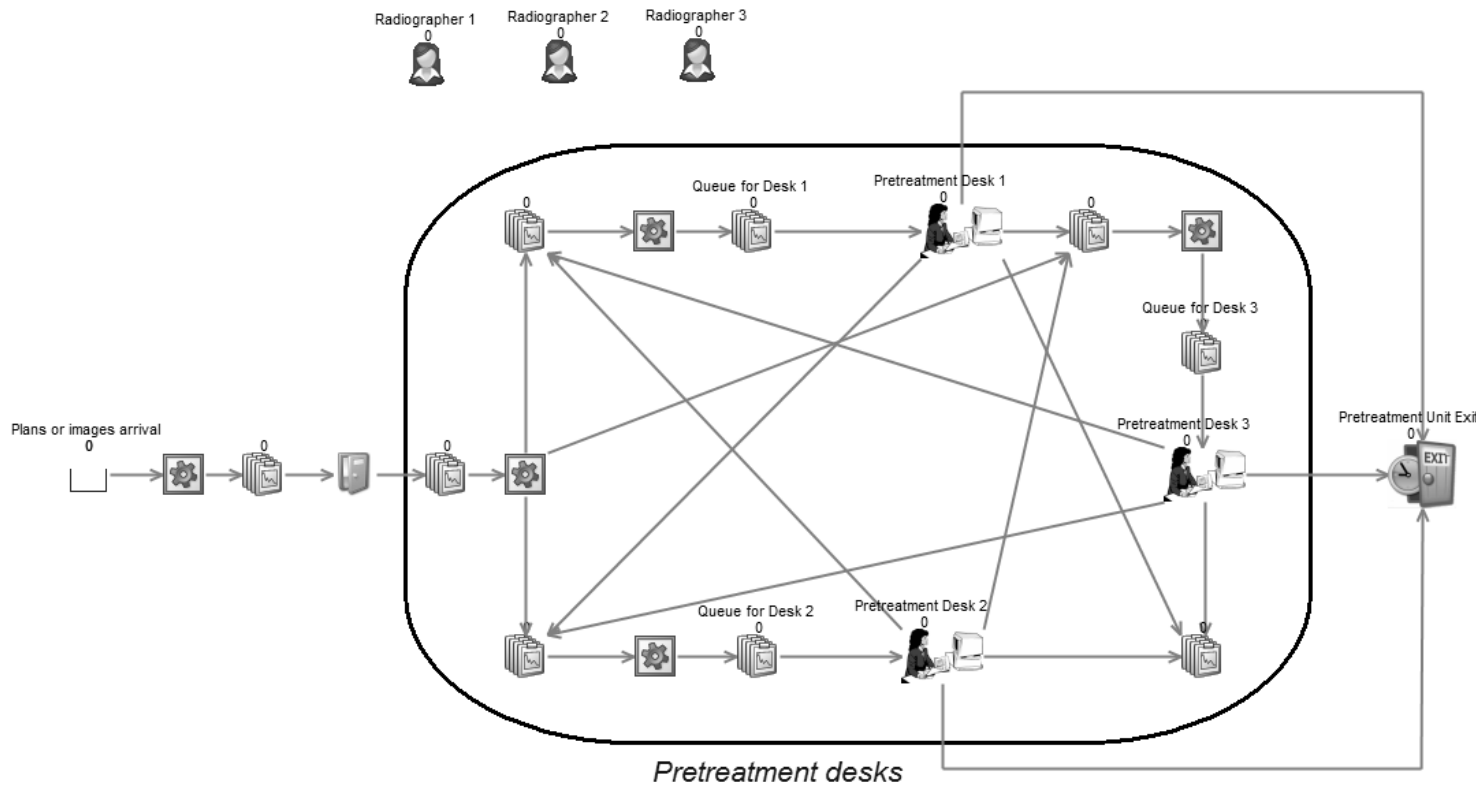

Figure 5.22: A screenshot of the simulation model of the pretreatment unit

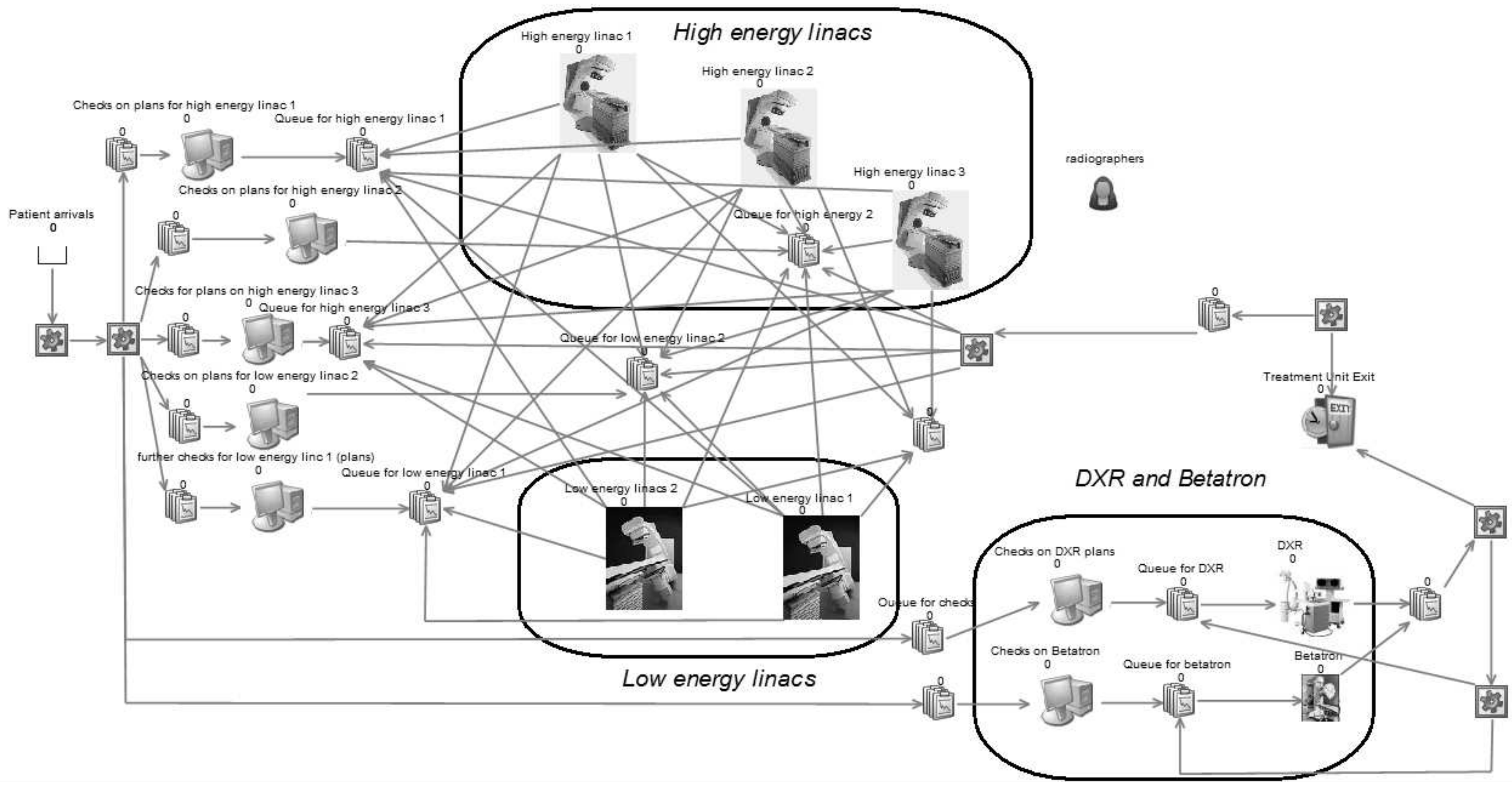

Figure 5.23: A model of the treatment unit procedures showing entities representing low energy linacs, DXR and the betatron

5.5 Model verification and validation

Verification can be described as the process of checking that the model is behaving as it is supposed to do. Validation involves checking that the model is behaving as the real system behaves. Some of the methods of verifying and validating simulation models suggested in the literature include animations, historical validation, face validity and statistical tests. In simulation, the main aim is to to construct a model that appears reasonable on its 'face' to users and others who are knowledgeable about the real-world system being investigated (Banks 2005). If these users or experts feel that the DES model is adequate, then it has face validity. In this study, the DES models in Figures 5.18–5.23 were incorporated into one simulation model representing the processes conducted in the radiotherapy department at the Arden Cancer Centre. This simulation model was run using different scenarios described later in this chapter.

Transient and results collection periods

When the simulation model for the department was run, it was imperative to determine the appropriate transient and results collection periods. The transient period is the amount of time the model runs before the system reaches steady state. The results collection period is the amount of time the simulation model was run after the transient period where the results are being collected. A simple graphical method of examining the trend of the utilisations of some of the machines over a period of time was used to determine the transient and results collection period (i.e. in months).

There are more efficient methods of determining the transient and results collection periods for a simulation model discussed in (Robinson 2004, Robinson 2007). The model was run several times using different number of months for the transient and results collection periods as shown in Figure 5.24. Since the trend of the utilisations of the CT scanner, simulator and HE1 generally tended to be steady after about 12 months, the results collection period was determined to be 12 months. In Figure 5.25, after about 12 months, the utilisations of some the machines tended to be stationary although for the LE1 linac, the utilisations did not seem to stabilise after 12 months. This can be attributed to the difference in the amount of patients that visited the two LE linacs. LE1 was visited generally used to treat less patients than LE2. The transient period for the DES models of the department was also set to 12 months.

Statistical tests for validation

Statistical tests such as the two-sample Kolmogorov-Smirnov test, Ansari-Bradley test, and Wilcoxon ranksum test were used to validate the DES model. The null hypothesis of the two-sample Kolmogorov-Smirnov test is that two data

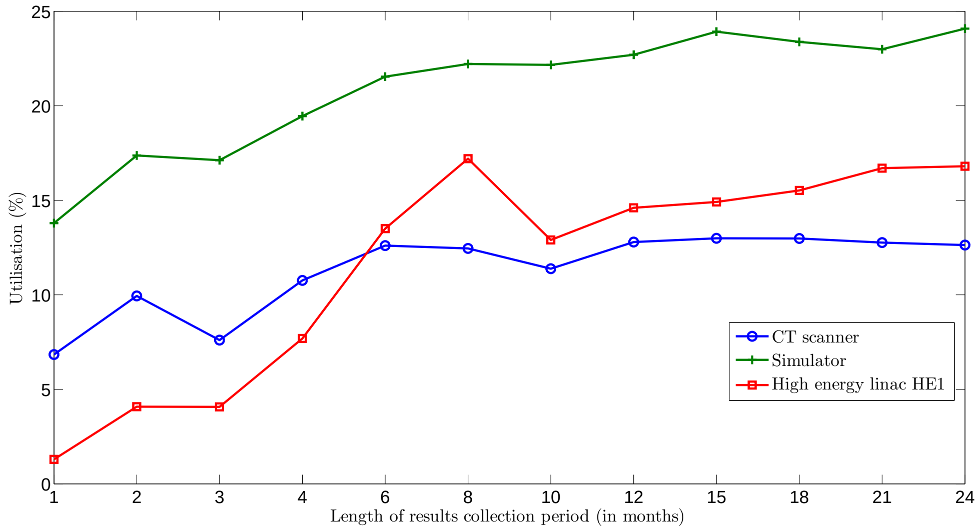

Figure 5.24: Utilisation of the CT scanner, simulator and linac HE1

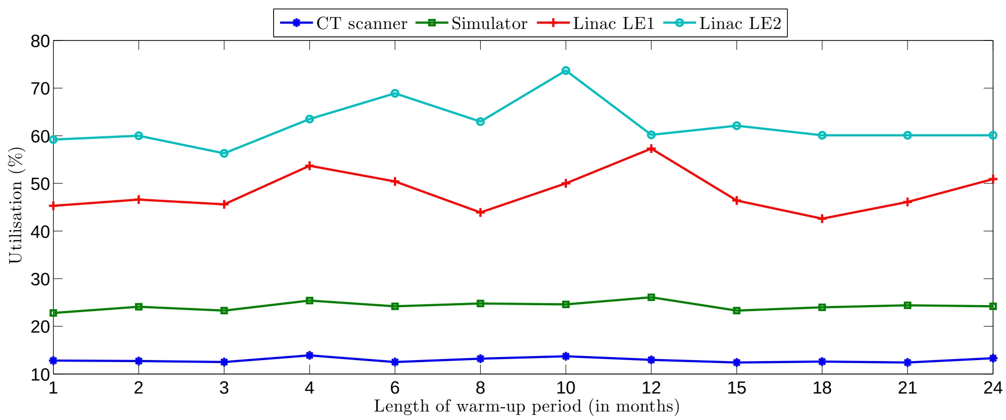

Figure 5.25: Utilisation of some of the machines using different transient periods

samples are from the same continuous distribution while the Ansari-Bradley test has the null hypothesis that two samples come from the same distribution against the alternative hypothesis that they come from different distributions that have the same median and shape. Wilcoxon ranksum tests the null hypothesis that two samples are from the same distributions with equal medians, against the alternative that they do not have equal medians. These statistical tests were chosen to determine how reasonably close the results of the model can be to the historical data.

Some of the results of the tests on the waiting times obtained from the model (i.e. 10 runs) and historical data are shown in Table 5.16. The two-sample

Kolmogorov-Smirnov test rejected the null hypothesis for all the 10 runs. Eight of the 10 Ansari-Bradley tests rejected the null hypothesis. This implies that for eight times, the test accepted the alternative that each of the two samples were from distributions with the same median and shape. Similarly, eight out of 10 times, the Wilcoxon ranksum test did not reject the null hypothesis that the two samples were from the same distribution with equal median. Therefore, two of the statistical tests (i.e. Ansari-Bradley and Wilcoxon ranksum tests) showed that the two samples (i.e. waiting times from the model and the historical data) were reasonably close with respect to their equal medians and shape of the distributions although the Kolmogorov-Smirnov test rejected that they can be from the same continuous distribution.

Table 5.16: Results of 3 statistical tests between real-life data and the model for 10 different runs

Run	Ansari-Bradley	Wilcoxon rank sum	Kolmogorov-Smirnov
1	rejected	not rejected ($p = 0.16$)	rejected
2	rejected	not rejected ($p = 0.12$)	rejected
3	rejected	not rejected ($p = 0.16$)	rejected
4	rejected	rejected	rejected
5	rejected	not rejected ($p = 0.13$)	rejected
6	rejected	not rejected ($p = 0.26$)	rejected
7	not rejected ($p = 0.06$)	not rejected ($p = 0.05$)	rejected
8	rejected	rejected	rejected
9	rejected	not rejected ($p = 0.23$)	rejected
10	not rejected ($p = 0.07$)	not rejected ($p = 0.20$)	rejected

Other verification and validation tests

In some cases, statistical tests can be inconclusive (Pidd 2004, Banks 2005) and thus, other methods of validating models can be used. Observing the DES model animations affirmed that the work items (i.e. patients) followed the correct pathways. For example, patients requiring the treatments (i.e. palliative and radical) were traced to verify their pathways after each procedure.To further ascertain how reasonably close the model was to the real-life system, the distributions discussed in Sections 5.3.1–5.3.10 were obtained from the model and compared to other data obtained in 2003 used in (Proctor 2003) and 2008.

The flowcharts discussed in Chapter 3 were used to trace and verify the movement of patients from the entry point to the exit points. A face validity test was performed by a senior radiographer. The radiographer was asked to inspect the model inputs and outputs (i.e. waiting time results obtained by the model versus those from historical data) and observe the animated patient flows. The DES model was confirmed to be reasonably close to the real-life treatment processes based on the closeness of the waiting times obtained by the model and the queues for machines observed. The waiting times results of the DES model used in these tests were for the EBT processes only. These are plotted in Figures 5.26, 5.27 and 5.28. In Figure 5.26, waiting times for all the treatments (i.e. palliative and radical) are compared while Figure 5.27 shows the comparison of waiting times for palliative treatments only. Figure 5.28 shows the comparison of the waiting times for radical treatments for historical data and those obtained after running the DES model.

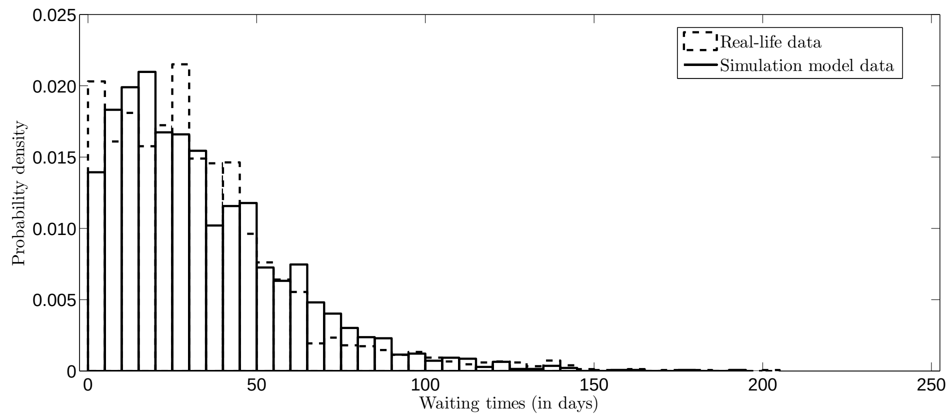

Figure 5.26: Comparison of the historical data and waiting times obtained from run 7 (in Table 5.16) of the model

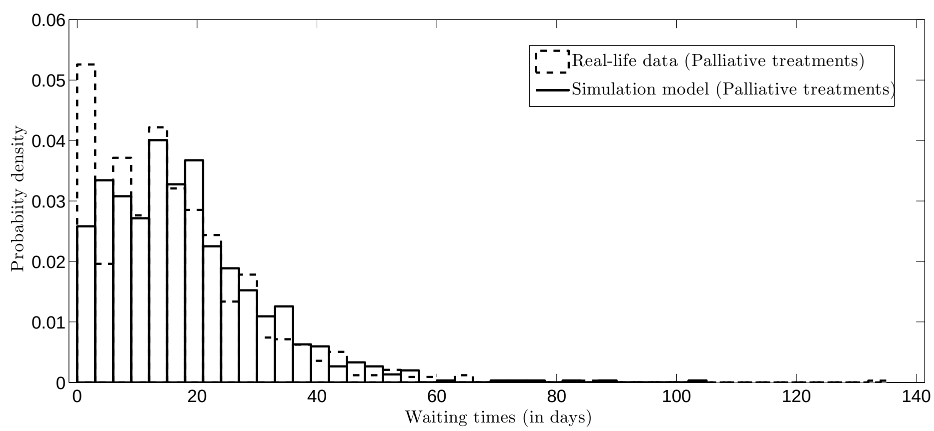

Figure 5.27: Comparison of the waiting times for palliative treatments from the historical data and run 7 (in Table 5.16) of the model

The historical data had no records of the dates when patients for BT had their procedures performed. An average of 7.3 days waiting time for these patients was obtained from the model. Results for the UST waiting times were not close to the historical data as shown in Figure 5.29. The average waiting time for UST patients was about 44 days compared to 61.4 days from the historical data. The historical data obtained in 2007 and 2008 as well as that used for the study in (Proctor 2003) was used in the validation of the DES models.

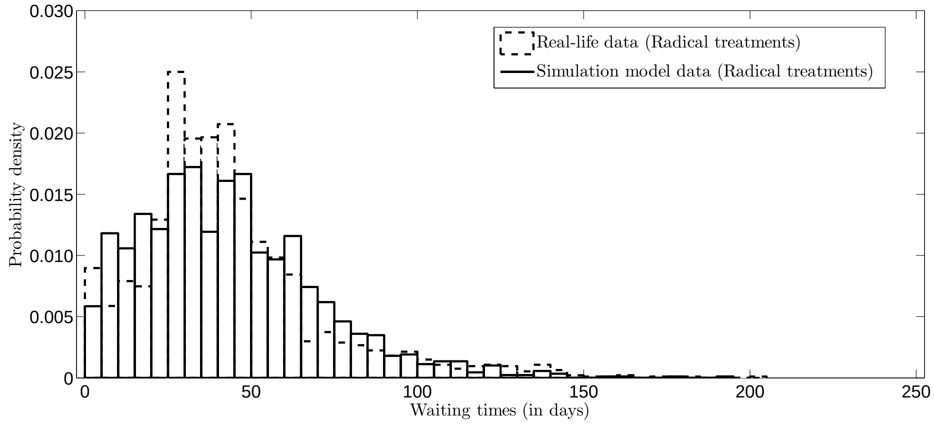

Figure 5.28: Comparison of the waiting times for radical treatments from the historical data and run 7 (in Table 5.16) of the model

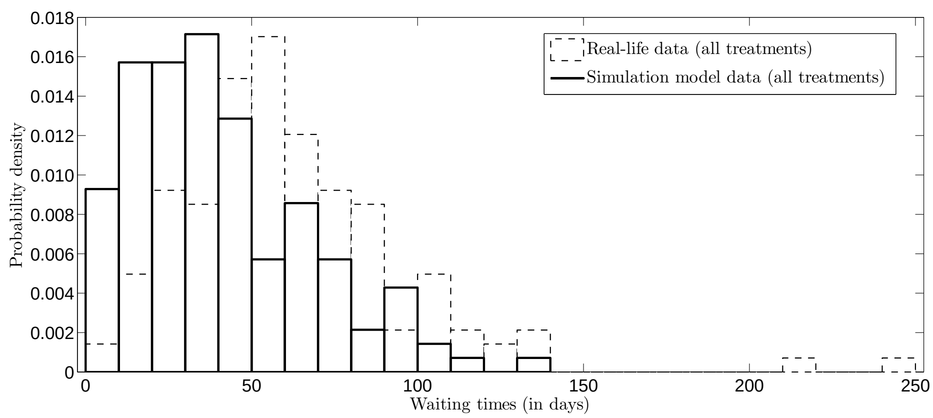

Figure 5.29: Comparison of the waiting times for the UST process obtained from the historical data and model

5.6 Scenario tests

A simulation model is a tool that decision makers use to assess the impact of various changes in the system. The following 'what-if' scenarios were designed to confirm the impact of various changes to the DES model of the department. Such scenarios included: 1) extended working hours for the machines and facilities, 2) enforcing doctor presence for the planning and physics unit procedures,

3) reduced and increased staffing levels of radiographers, and 4) machine breakdowns. One of the aims of the DES study was to focus on the 'what-if' scenarios that can be considered cost-effective (i.e. implementable without the need for capital outlays). Therefore, determining the performance of the model when additional machines were made available was not included in the scenario tests.

A single run of the simulation model showed excessive patient queuing on the treatment machines (especially the HE and LE linacs). This can be attributed to the proportions of the patients that visited linacs HE3 and LE2 as shown in Table 5.11. Queues also intermittently formed on the work centres representing the 12 doctors in the planning and physics units (i.e. on the simulator, CT scanner and physics outline and planning). Such queues were unavoidable due to the limited availability of the doctors in the department (see Table 2.10).

Table 5.17: Average waiting time results from the historical data and the model (for 10 runs)

Data	**Palliative**	**Radical**	**All**
Developed model	17.3	42.7	33.1
Historical	15.5	42.4	32.3

The DES model was run 10 times in order to improve the accuracy of the results collected. Each run used different random number seeds automatically generated by the Simul8 software in order to increase variability and haphazardness of events in the model. The results of the average waiting times at 95% confidence intervals produced after each run were compared to those obtained from the historical data as shown in Table 5.17. Average waiting times for radical treatments were worse from the historical data by about 0.7%. Considering all the patients treated, the average waiting times from the model were worse by less than a day to the historical data. For palliative treatments, the average waiting times from the model were worse from historical data by about 10%. More patients requiring radical treatments were generated and they occupied the treatment capacity. When patients requiring palliative treatment were generated, there was insufficient capacity to fast-track their treatment although they had the highest priority in the queues.

5.6.1 Scenario 1: Extended working hours

Working hours were extended for the resources (i.e. both human and machines excluding the doctors) in the department to 8.00pm excluding weekends. The model with these extended working hours (i.e. scenario 1 model) was also run 10 times with different random number seeds for the same transient and results collection periods. A comparison of the average waiting time results obtained from the scenario 1 model are shown in Figure 5.30. A noticeable reduction in the average waiting time for patients who had radical treatment by up to 3 days was evident. For all patients treated, the average waiting times marginally improved but for palliative treatments, the results were generally the same.

Since about 67% of the patients treated needed radical treatment, the model had more patients requiring radical treatment at any time during the runs. Hence, more working hours for the machines and radiographers implied that more of these patients (i.e. needing radical treatment) were treated. Most patients that required palliative treatments had to wait longer before commencing treatment. It can be concluded that patients that need radical treatment are most likely to benefit from extension of working hours than patients requiring palliative treatment. Results in Figure 5.30 affirm the need to develop appointment scheduling rules that prioritise as well as reduce the patients requiring radical treatment from occupying most of the immediate appointments.

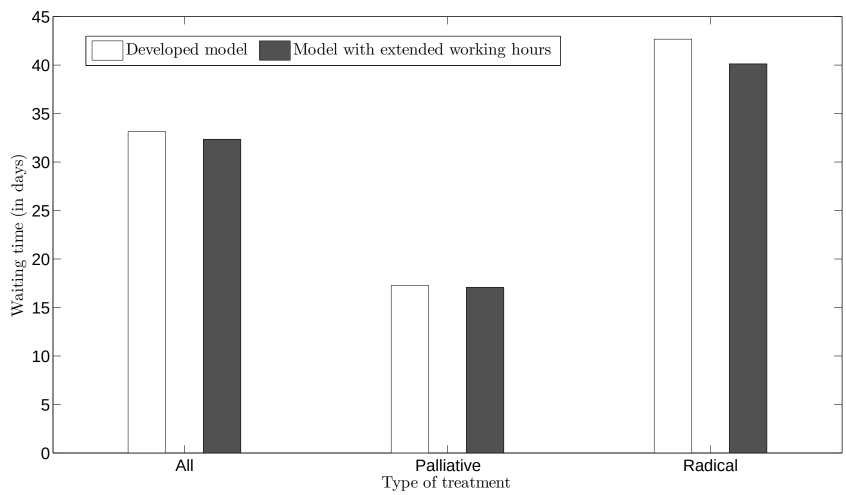

Figure 5.30: A comparison of the average waiting times from the developed model and scenario 1 model

5.6.2 Scenario 2: Enforcing doctor presence

The doctor availability times in the department (see Table 2.10) were discussed in Chapter 2. These doctors are only available once a week and if a patient was not examined on the day the doctor was available, then he or she had to wait for at least 7 days to be seen by the doctor. About 25% of the patients had their planning unit procedures completed in the absence of their doctors (see Table 5.1). The presence of doctors for the planning unit procedures is crucial in the treatment process. It was understood by the staff at the Arden Cancer Centre that the presence of the doctor during planning enhances the quality of the service of the department. Therefore, the developed model was tested after enforcing the doctor's presence requirement.

Enforcing doctor presence for the procedures resulted in queues of patients forming on the machines and mould room. Skipping the doctor requirement resulted in less queuing of patients. Most importantly, as shown in Figure 5.31, the average waiting times of the patients requiring palliative treatment worsened by about 12% while those for patients requiring radical treatment also worsened by about 6%. For all patients, the average waiting time worsened by 7%. It can be concluded that if the department wishes to ensure that the planning unit procedures were performed in the presence of the doctor only, then the work centres representing doctors can be considered bottlenecks of the treatment processes. Since the department endeavours to deliver improved service quality, enforced doctor presence for the planning unit procedures and reduced waiting times can be considered as the key requirements in future studies of the EBT processes. Such key requirements ensure that the department addresses the waiting times issues using its existing resources (i.e. complement of doctors).

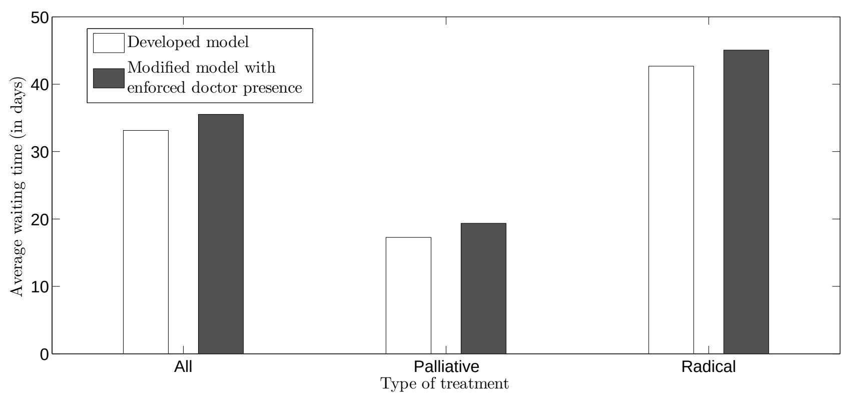

Figure 5.31: A comparison of the average waiting times from the developed model and scenario 2 model

5.6.3 Reduced and increased staff (Scenarios 3 and 4)

As discussed earlier, the staffing levels of all the human resources involved in the treatment processes are essential. In particular, radiographers are involved in 3 of the four units where the various planning or treatment procedures are conducted. Hence, it was crucial to find the performance of the department if the number of radiographers available in each of the units was reduced or increased. Tests with reduced staffing levels (i.e. Scenario 3) involved a scenario whereby radiographer staffing levels in the planning, pretreatment, and treatment units were all reduced by one from the existing staffing levels. For increased staffing levels (i.e. Scenario 4), the tests involved adding two or three extra radiographers to each pool of radiographers available for each unit. The modified simulation model was again run 10 times using the same transient and results collection periods.

Extra radiographers in the system marginally improved some of the results obtained as shown in Table 5.18. The most noticeable improvement was for the average waiting times of patients that needed radical treatment. An increase of radiographers improved the results by about 2 days. Furthermore, the average waiting times of all patients that visited the department improved by about 1 day while the results of patients that required palliative treatment was generally the same as the developed model. Reducing existing staffing levels of radiographers marginally worsened the average waiting times of all treatments. Some entities which needed radiographers to operate them (i.e. CT scanner, simulator, linacs, DXR and others) stopped working until the minimum number of radiographers required to operate them were available.

The 'what-if' scenarios such as adding extra radiographers can help when making decisions on the number of additional staff (i.e. radiographers) required by the department. Tests on such scenarios have to demonstrate the minimum number of additional radiographers that improves the performance of the department. In this case, adding extra radiographers was conducted to show the sensitivity of adding extra radiographers to a department that has low staffing levels.

Table 5.18: Comparison of the average waiting times from the developed model, and Scenario 3 and 4 models

Treatment	Developed model	Scenario 3	Scenario 4
All	33.1	33.5	32.5
Palliative	17.3	17.4	17.3
Radical	42.7	43.0	40.4

5.6.4 Scenario 5: Machine breakdowns

Each machine in the department had to be serviced and maintained according to a schedule created by the planning unit. However, there can be cases when machines breakdown while patients were waiting to be treated. Such machine breakdowns can impede patient flow mostly in the treatment unit. To test the performance of the developed model under such disturbances, the Simul8 software was set to mimic the machine breakdowns for linacs only (i.e. HE and LE linacs). The times between the machine breakdowns for the 5 linacs were set as follows: 1) HE1 was set to a fixed distribution of 10.3 days, 2) HE2 was 22.4 days, 3) HE3 was 4.4 days, 4) LE1 was 5.2 days, and 5) LE2 was 4.7 days. The time to repair the machines was estimated to be a fixed 2 hours.

The average waiting times obtained for patients requiring radical treatment were worse by about a day compared to the developed model as shown in Table

5.19 while the result for patients requiring palliative treatment was generally the same. Generally, the results for scenario 5 marginally worsened from those obtained from the developed model. Scenario 5 tested machine breakdowns which affect the linacs for about 2 hours of the day only. Machine breakdowns that affect the machines over several days can adversely impact the waiting times of patients to be treated. The developed model did not consider the planned machine service and maintenance dates from the schedule. These can impact the waiting times because some of the machines can be out of service for an entire day or weekend as discussed in Chapter 3.

Table 5.19: Comparison of the average waiting times obtained from the developed model and Scenario 5 models

Treatment	Developed model	Scenario 5
All	33.1	34.3
Palliative	17.3	17.4
Radical	42.7	43.8

5.7 Concluding remarks

A DES model of the department was built based on 6 separate models of the EBT, UST and BT processes using Simul8. Waiting time was the performance criterion considered in the analysis of results from 5 different scenarios. Stringently enforcing doctor presence for some procedures showed noticeable worsening of the performance measure while the other scenarios tested showed marginal changes. It was understood that staff at the Arden Cancer Centre staff consider doctor presence as essential for good service quality delivery. Enforcing their presence for the procedures can be considered as a key constraint. Results for palliative treatments showed that prioritising patients where queues were formed was an inadequate way of improving the results. More strategies which make more capacity available when patients needing critical treatments arrive are essential.

This DES study focused on 'what-if' scenario tests on the EBT processes. Sharing crucial resources such as doctors withn the BT and UST models did not inhibit the interactions of the entities in the EBT model. However, insight into the treatment processes gained from developing the models can be used to formulate radiotherapy scheduling problems (i.e. for each of the four units) and propose methods of solving them. These methods should include strategies of making radiotherapy capacity available for the uncertain arrival of patients needing critical treatments.

Chapter 6

Radiotherapy scheduling problem

Contents

6.1 Introduction

In this chapter, the radiotherapy scheduling problem is formulated based on the characteristics of the treatment processes explained in Chapters 3 and 5. It was shown that the performance of the department (i.e. EBT process only) can be affected by the limited doctor availability, staff shortages and extended working hours. Historical data shows that the BT and UST processes have waiting time issues which the department has to address. However, the department is mainly interested in improving the waiting times of the EBT process whose common waiting times problem was investigated in (Petrovic *et al.* 2006, Conforti *et al.* 2008, Conforti, Guerriero and Guido 2009, Conforti, Guerriero, Guido and Veltri 2009, Petrovic and Leite-Rocha 2008, Petrovic *et al.* 2009).

This chapter is organised as follows: in Section 6.2, the notation used in the formulation of the problem is listed followed by Section 6.3 which states the assumptions, constraints and objectives of the problem. Section 6.4 defines the radiotherapy scheduling problem experienced in the radiotherapy department at the Arden Cancer Centre. Lastly, Section 6.5 gives the concluding remarks.

6.2 Notation

Data

H : scheduling horizon given in days

n_d : total number of new patients arriving on day d, $d = 1, 2, \ldots, H$

N : total number of patients for a given horizon H, where

$$N = \sum_{d=1}^{H} n_d \tag{6.1}$$

δ_j : number of days patient j's request form was delayed before it was submitted to the planning unit, $j = 1, 2, \ldots, N$

a_j : date when decision to treat patient j is made, $j = 1, 2, \ldots, N$

r_j^1 : release date for the planning unit procedures for patient j determined using Equation 6.2, $j = 1, 2, \ldots, N$

$$r_j^1 = a_j + \delta_j \tag{6.2}$$

r_j^2 : release date for the physics unit procedures for patient j, $r_j^2 \geq r_j^1$, $j = 1, 2, \ldots, N$

r_j^3 : release date for the pretreatment unit procedures for patient j, $r_j^3 \geq r_j^2$, $j = 1, 2, \ldots, N$

r_j^4 : release date for the treatment unit procedures for patient j, $r_j^4 \geq r_j^3$, $j = 1, 2, \ldots, N$

h_j : number of treatment phases prescribed by a doctor for patient j, $h_j \geq 1$, $j = 1, 2, \ldots, N$

h : treatment phase, $h \geq 0$. In this case, $h = 0$ represents the phase before the actual treatment starts on the treatment machines, $h = 0, 1, 2, \ldots, h_j$

f_{jh} : number of fractions prescribed by a doctor for patient j in treatment phase h, $j = 1, 2, \ldots, N$, $h = 0, 1, 2, \ldots, h_j$

$$f_{jh} = \begin{cases} 0 & \text{if } h = 0 \\ \geq 1 & \text{otherwise} \end{cases} \tag{6.3}$$

$\mathbf{TOTAL}_j$: the total number of fractions prescribed by the doctor for patient j determined using Equation 6.4, $j = 1, 2, \ldots, N$

$$TOTAL_j = \sum_{h=0}^{h_j} f_{jh} \tag{6.4}$$

G : set of treatment machines and facilities, $|G| = 7$

I : set of planning machines and facilities, $|I| = 3$

J : set of desks in the pretreatment unit, $|J| = 3$

K : set of desks in the physics unit, $|K| = 1$

M : set of all machine and facility resources, $M = G \cup I \cup J \cup K$. Hence,

$$|M| = |G| + |I| + |J| + |K| = 14 \tag{6.5}$$

c_k : capacity of machine or facility k for each day specified as number of slots, $k \in M$

o_k : number of overtime slots made available on a given machine or facility k, where $k \in M$

s_k : slot on a machine or facility k for each day $s_k = 1, 2, \ldots, c_k, c_k+1, \ldots, c_k+o_k$

l : doctor, $l = 1, 2, \ldots 13$, $l = 13$ represents a locum doctor who works only when $o_k > 0$

G_j^{type} : set of treatment machines of the type chosen by doctor l, $j = 1, 2, \ldots, N$

S_d : list of newly arrived patients for day d, $|S_d| = n_d$, $d = 1, 2, \ldots, H$

S_d^1 : list of patients, that arrived in the department on day d, for the planning unit procedures, $S_d^1 = S_d$, $d = 1, 2, \ldots, H$

S_d^2 : list of patients, that arrived in the department on day d, for the physics unit procedures, $S_d^2 \subseteq S_d$, $d = 1, 2, \ldots, H$

S_d^3 : list of patients, that arrived in the department on day d, for the pretreatment unit procedures, $S_d^3 = S_d$, $d = 1, 2, \ldots, H$

S_d^4 : list of patients, that arrived in the department on day d, for the treatment unit procedures, $S_d^4 = S_d$, $d = 1, 2, \ldots, H$

t_j : targeted waiting time for patient j as set by the JCCO shown in Table 2.6 in Chapter 2

D_j^{jcco} : JCCO target due date for patient j, $j = 1, 2, \ldots, N$

$$D_j^{jcco} = a_j + t_j \tag{6.6}$$

D_j^1 : due date for the planning unit for patient j, $D_j^1 \leq D_j^{jcco}$, $j = 1, 2, \ldots, N$ (determined using Algorithm B.1 in Appendix B)

D_j^2 : due date for the physics unit for patient j, $D_j^2 \leq D_j^{jcco}$, $j = 1, 2, \ldots, N$ (determined using Algorithm B.2 in Appendix B)

D_j^3 : due date for the pretreatment unit for patient j, $D_j^3 \leq D_j^{jcco}$, $j = 1, 2, \ldots, N$ (determined using Algorithm B.3 in Appendix B)

D_j^4 : due date for the first definitive treatment for patient j, $D_j^4 \leq D_j^{jcco}$, $j = 1, 2, \ldots, N$ (determined using Algorithm B.4 in Appendix B)

i : operation. Hereafter, each procedure involved in the EBT processes has been termed an operation

p_{jk} : processing time on machine or facility k on patient j, $j = 1, 2, \ldots, N$, $k \in M$

$$p_{jk} = |s_k| \tag{6.7}$$

where $|s_k|$ denotes the size of slot s_k on facility or machine k

u_{jk} : penalty for performing an operation for patient j on machine k after normal working hours (i.e. using slots $c_k + 1, c_k + 2, \ldots, (c_k + o_k)$)

$$u_{jk} = \begin{cases} p_{jk} & \text{if } c_k < s_k \leq (c_k + o_k) \\ 0 & \text{otherwise} \end{cases} \tag{6.8}$$

where $j = 1, 2, \ldots, N$, $k \in M$

Decision variables

C_{ijhk} : the completion date of operation i for patient j in treatment phase h on machine k, $j = 1, 2, \ldots, N$, $h = 0, 1, 2, \ldots, h_j$, $k \in M$

Parameters

μ_j : threshold of the time difference between completion of pretreatment and the JCCO due date target (in days)

$\upsilon_{1,j}$: threshold of the tolerated tardiness for patients requiring emergency treatment in the treatment unit

$\upsilon_{2,j}$: threshold of the tolerated tardiness for patients requiring palliative treatment in the treatment unit

$\upsilon_{3,j}$: threshold of tolerated tardiness for patients requiring radical treatment in the treatment unit

ω : threshold of the tolerated tardiness for patients in the planning unit

Performance measures

L_j : lateness of patient j, defined as the difference between the completion of the first fraction of the prescribed fractions on machine k and the JCCO due date, given in days

$$L_j = C_{1j1k} - D_j^{jcco} \tag{6.9}$$

where $j = 1, 2, \ldots, N$, $k \in G$

T_j : tardiness of patient j, $j = 1, 2, \ldots, N$

$$T_j = max\{0, L_j\} \tag{6.10}$$

$\overline{T}$: mean tardiness of the N patients given in Equation 6.11

$$\overline{T} = \frac{1}{N}(\sum_{j=1}^{N} T_j) \tag{6.11}$$

η : number of patients that do not meet their JCCO due date

$$\eta = \sum_{j=1}^{N} x_j \tag{6.12}$$

where x_j is defined as follows:

$$x_j = \begin{cases} 0 & \text{if } T_j = 0 \\ 1 & \text{otherwise} \end{cases} \tag{6.13}$$

RW_j : waiting time for patient j, that is the time difference between the date of completing the first fraction in the treatment unit and the date when the decision to treat by radiotherapy was made

$$RW_j = C_{1j1k} - a_j \tag{6.14}$$

where $i = 1$, $h = 1$, $j = 1, 2, \ldots, N$, $k \in G$

$\overline{RW}$: average waiting time of N patients processed within H

$$\overline{RW} = \frac{1}{N}(\sum_{j=1}^{N} RW_j) \tag{6.15}$$

where $j = 1, 2, \ldots, N$

$\overline{RW}^1$: average waiting time of the patients requiring emergency treatment determined using Equation 6.16, where A is a set of patients requiring emergency treatment

$$\overline{RW}^1 = \frac{1}{|A|}(\sum_{j \in A} RW_j) \tag{6.16}$$

$\overline{RW}^2$: average waiting time of the patients requiring palliative treatment determined using Equation 6.17, where B is a set of patients requiring palliative treatment

$$\overline{RW}^2 = \frac{1}{|B|}(\sum_{j \in B} RW_j) \tag{6.17}$$

$\overline{RW}^3$: average waiting time of the patients requiring radical treatment determined using Equation 6.18, where C is a set of patients requiring radical treatment

$$\overline{RW}^1 = \frac{1}{|C|}(\sum_{j \in C} RW_j) \tag{6.18}$$

U_j : total penalty for overtime required for patient j, $j = 1, 2, \ldots, N$

$$U_j = \sum_{k \in M} u_{jk} \tag{6.19}$$

$\overline{U}$: total overtime for N patients

$$\overline{U} = \sum_{j=1}^{N} U_j \tag{6.20}$$

6.3 Assumptions, constraints and objectives

The following assumptions, constraints and objectives of the radiotherapy scheduling problem were derived based on the insight into the simulation models discussed in Chapter 5.

Assumptions

(i) All appointments are scheduled daily at 9.00am.

(ii) There is no separation time between operations for two consecutive patients or treatment plans. Hence, the operations on the next patient can be started as soon as the one for the current patient has been completed.

(iii) The processing times (i.e. for each operation) for each machine considered are shown in Table 6.1. These processing times were suggested based on the averages obtained from the data collected. This assumption was based on the block scheduling approach that was reported in (Conforti *et al.* 2008).

(iv) There are no revisits on the planning unit machines before the patient proceeds to the next unit (either the physics or pretreatment unit). A patient visits a planning machine or facility at most once.

Constraints

(v) A patient's schedule of appointments for the procedures to be done in any of the four units cannot be altered once scheduled.

(vi) Machines and/or facilities are continuously available from Monday through Friday from 9.00am to 5.00pm except for weekends, planned machine breakdown times, bank holidays and days when overtime is considered.

(vii) Machines are under periodic service and maintenance according to a predetermined maintenance plan. During the maintenance period, the machines cannot be used for either planning or treatment.

(viii) Each doctor only examines the patient during the first five minutes of their procedures on the planning machines or facility. For example, if a patient takes up to 30 minutes on the simulator, the doctor must be available in the first 5 minutes.

(ix) The doctor takes up to 5 minutes to approve and sign the initial outlining and planning calculations completed by the technicians. Generally, in the physics unit, doctors are presumed to take the same amount of time as they take examining a patient in the operations in the planning unit.

(x) Each doctor is available in the radiotherapy department at specified time periods per week (see Table 2.10).

(xi) If a patient must have more than one procedure in the planning unit (if the patient has to visit the mould room before going to the CT scanner or simulator), all the procedures must be completed on the same day.

(xii) Treatment plan checks that are conducted in-between treatment phases must be done at most 3 fractions prior to the completion of each treatment phase.

(xiii) Some cancer cases, especially a) head and neck, b) gynaecological, c) respiratory, and d) urinary, must start treatment on Mondays.

(xiv) Precedence constraints are to be followed for patients that need to visit the mould room and either the simulator or CT scanner. Patients that require a mask must always visit the mould room before going to the planning machines (either the simulator or CT scanner).

(xv) Two consecutive fractions for a patient must be separated by up to one day, apart for cases when the treatment machine has been scheduled for service and maintenance.

Table 6.1: Sizes of slots for the machines and facilities

Unit	**Resource**	**Slot size** (in minutes)
Planning	Simulators	30
	CT scanners	20
	Mould rooms	20
	Doctors	5
Physics	Physics desks	75
Pretreatment	Pretreatment desks	30
Treatment	High energy linacs	15
	Low energy linacs	12
	DXRs	15
	Betatrons	110

Objectives

The foremost objective is to create schedules of appointments for all the operations for the N patients received within the period H. The created schedules of appointments should aim:

- to minimise the average waiting times: $\overline{RW}^1$, $\overline{RW}^2$, $\overline{RW}^3$ and $\overline{RW}$,
- to minimise the average percentage of patients that do not meet their JCCO due dates, and
- to minimise the total overtime penalty, $\overline{U}$.

In this thesis, the main aim was to minimise $\overline{RW}^1$, $\overline{RW}^2$, $\overline{RW}^3$ and $\overline{RW}$, and the other objectives were used in the analysis of the performance of the approaches proposed to solve the radiotherapy scheduling problems. The percentage of patients that fail to meet their JCCO targeted due dates has been widely used to analyse the performance of radiotherapy departments in the UK. Tables 2.7 and 2.8 shows such results reported in waiting times audits. Further, the total overtime penalty also helps in determining the extent of the use of additional capacity requirements for the proposed scheduling approaches.

6.4 Problem definition

This research concerns a radiotherapy scheduling problem which is essentially a complex real-world problem. The problem was divided into four subproblems denoting each unit of the radiotherapy department (i.e. planning, physics, pre-treatment and treatment units) which were termed: Subproblem 1, Subproblem 2, Subproblem 3, and Subproblem 4, respectively. In general, the entire radiotherapy scheduling problem considered n_d newly arriving patients to be scheduled. Details of the n_d patients are released on day d as list S_d, where $|S_d| = n_d$. The size of the list is uncertain and the pathways of the patients are predetermined by the doctor and included in the details. Each patient j goes through 3 or 4 units, beginning and ending in the planning and treatment units, respectively, visiting machines or facilities k, $k \in M$ to meet assigned due dates (i.e. D_j^1, D_j^2, D_j^3, D_j^4, and D_j^{jcco}).

Graham notation

Scheduling problems can be analysed using a three field notation (i.e. $\alpha|\beta|\gamma$) proposed in (Graham *et al.* 1979). The classification of scheduling problems in this thesis has been founded on the Graham notation which comprises symbols defined as follows. α describes the machine and facility environment considered by characterising them as the well-known shop scheduling problem models such as single machine, parallel machines, open shop and others. Graham *et al.* (1979) described the machine environment as $\alpha = \alpha_1\alpha_2$ where α_1 is a set of shop scheduling problem models described in Chapter 4 including the symbol $\circ$ for single machine environments. α_2 represents the number of the machines involved where $\alpha_2 = \circ$ means the number of machines varies.

The second field, β denotes the characteristics of the jobs that are processed in the system. This involves patient data which includes number of operations, processing times, release dates (e.g. r_j^1), due dates (e.g. D_j^1), treatment required and others. Graham *et al.* (1979) denoted this field as $\beta \subset \{\beta_1, \ldots, \beta_6\}$, where $\beta_1 \in \{pmtn, \circ\}$ means that there is preemption of jobs (i.e. $\beta_1 = pmtn$) or no preemption was permitted (i.e. $\beta_1 = \circ$). $\beta_2 \in \{res, res1, \circ\}$ denoted there are limited resources used (i.e. $\beta_2 = res$), single resource (i.e. $\beta_2 = res1$) or no resource constraints are considered (i.e. $\beta_2 = \circ$). $\beta_3 \in \{prec, tree, \circ\}$ denotes that there were precedence relations between jobs (i.e. $\beta_3 = prec$) derived from an acyclic graph. $\beta_3 = tree$ denotes that the acyclic graph was a rooted tree and $\beta_3 = \circ$ means that there were no precedence relations. $\beta_4 \in \{r_j, \circ\}$ denotes that release dates differ for the jobs (i.e. $\beta_4 = r_j$) or that release dates are zero (i.e. $\beta_4 = \circ$). $\beta_5 \in \{m_j \leq \overline{m}, \circ\}$ denotes that there is a constant upper bound on the number of operations to be performed (i.e. $\beta_5 = m_j \leq \overline{m}$) or no such bound is specified (i.e. $\beta_5 = \circ$). $\beta_6 \in \{p_{ij}, \underline{p} \leq p_{ij} \leq \overline{p}, \circ\}$ denotes that each operation has unit processing time (i.e. $\beta_6 = p_{ij}$), there are constant lower and upper bounds on p_{ij} (i.e. $\beta_6 = \underline{p} \leq p_{ij} \leq \overline{p}$), or no such bounds exist (i.e. $\beta_6 = \circ$).

The last field, γ denotes the optimality criteria chosen for the problem. For example, some of the shop scheduling problems discussed in Chapter 4 involved minimising the maximum completion time of jobs (i.e. denoted as C_{max}). In this case, C_{max} was the optimality criterion and $\gamma = C_{max}$.

Subproblem 1

The planning unit comprises 4 resources (i.e. both human and machine resources). The CT scanner, simulator, mould room and doctors are considered in such a way that the scheduling problem in the planning unit can be described as a dynamic (i.e. sequences of patients arriving every day), flexible *multi-resource* two-stage hybrid flowshop (HFS) problem. Multiple resources (i.e. doctor and machine) are required for each operation in the planning unit. For example, for the mould room, CT scanner and simulator, a doctor has to be available for the first 5 minutes (i.e. estimated processing time for each doctor) of each operation performed on each patient. Of the n_d patients, some may not visit the first stage of the planning unit according to their pathways as prescribed by their doctors but all the patients visit a machine in the second stage of the planning unit. Normally, the first stage of the problem involves the mould room which patients had to visit before going to the other planning unit machines.

The second stage involved the two parallel unrelated alternative planning machines, the CT scanner and simulator. Figure 6.1 illustrates the configuration of the machines and possible patient pathways for Subproblem 1 in the planning unit. Only the machines and facility, without the doctor resources are shown. Some patients do not visit the mould room but just the CT scanner or simulator only as shown by the arrows labelled (a) or (d) respectively. Patients that require a mask from the mould room can then visit either the CT scanner or simulator but not both in the second stage (i.e. pathways labelled (b) and (c) respectively).

The machine on which an operation is performed is predetermined by the doctor but the number of patients in the sequence of patients to be scheduled, S_d^1 is uncertain. Subproblem 1 can be described as a dynamic and flexible multi-resource two-stage HFS denoted as $FS_{m1,m2}$, where $m1 = 1$ and $m2 = 2$, where $m1$ and $m2$ denote the number of machines and/or facilities in the first and second stages, respectively. The main objective of this $FS_{1,2}$ problem was to minimise the number of late patients with respect to due date D_j^1 while also minimising the flowtime of each patient in the planning unit.

Subproblem 1 classification

The first field, $\alpha = \alpha_1\alpha_2$ of the Graham notation (Graham *et al.* 1979) can be denoted as follows.

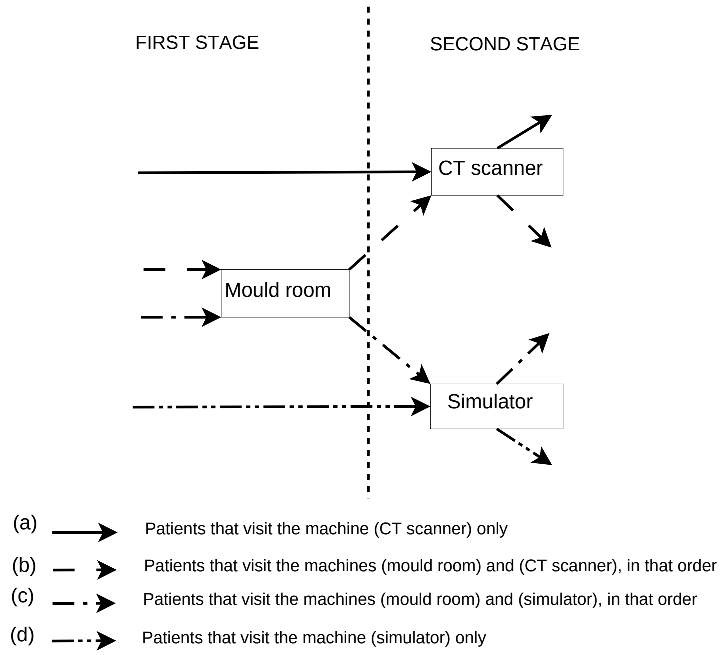

Figure 6.1: An illustration of the patient pathways in the planning unit

$\alpha_1 = FS_{1,2}$ is a two-stage hybrid flowshop problem in which the first stage comprises a single machine and the second stage has 2 unrelated parallel machines.

$\alpha_2 = 3$ because Subproblem 1 comprises three machines only.

The second field $\beta = \beta_1, \ldots, \beta_6$ defines the patient characteristics in Subproblem 1 as follows.

$\beta_1 = \circ$. No preemption is allowed in the operations performed on each patient j on any machine.

$\beta_2 = res1$. Only one doctor resource (either the patient doctor or the locum doctor) is used on each operation.

$\beta_3 = \circ$. No precedence relations exist between patients to be processed.

$\beta_4 = r_j^1$. Release dates for the patients are the same and $r_j^1 \neq 0$.

$\beta_5 = 2$. A maximum of 2 operations should be done on each patient in the two stages of the planning unit.

$\beta_6 = \circ$. The machines and facility have different processing times, where $k \in I$.

Lastly, the field represented by γ describes the objective function of Subproblem 1, denoted by X to represent the objectives of minimising the number of late patients with respect to due date D_j^1 and flowtime of each patient in the planning unit. Hence, Subproblem 1 can be stated as $FS_{1,2}|res1, r_j^1, 2|X$, where the second field β denotes that a resource (i.e. $res1$) is required on the machines whose processing times vary and only two operations must be performed.

Subproblem 2

In the physics unit, the procedures conducted by the technicians involve, first, creating the outlining and planning plans (i.e. the first calculation). After the doctor approves the outlining and planning plans, the second complex calculation is performed. Figure 6.2 shows the configuration of the physics facilities that are involved in the generation of complex treatment plans for the patients. Digital images arriving from the planning unit (i.e. arrow labelled (a)) are used to create outlining and planning plans on the physics desks (i.e. the area where the four technicians perform the operations as depicted in Figure 5.19). Treatment plans awaiting the doctor's approval take the pathway labelled (b). When the doctor has approved them, the treatment plans take the pathway labelled (c) for the technicians to perform the final operation, the complex calculations, on the physics desk before exiting the physics unit.

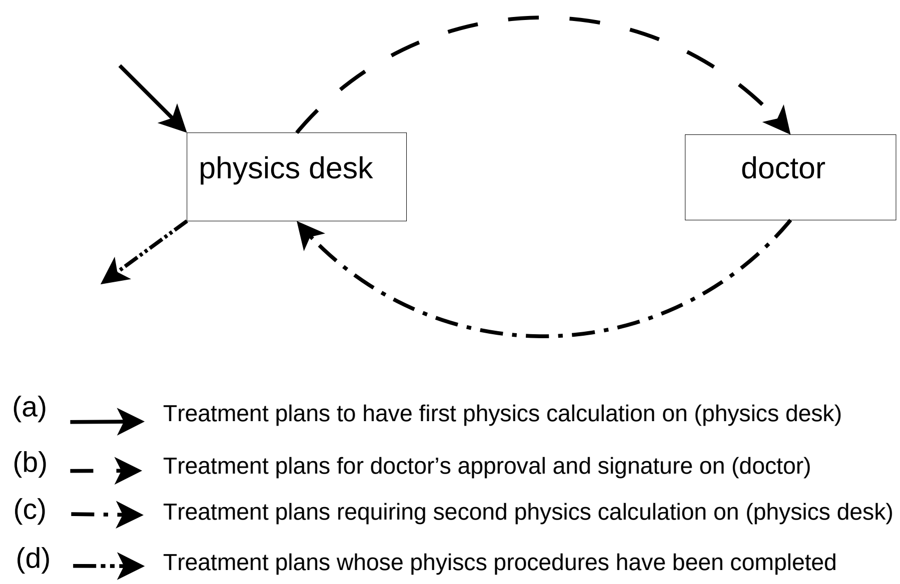

Figure 6.2: An illustration of the patient pathways in the physics unit

Subproblem 2 can be described as a flowshop problem that involves two facilities or resources (i.e. the physics desk and doctor). There are $|S_d^2|$ treatment plans, where $|S_d^2| \leq n_d$ and two resources (i.e. physics desk and doctor) are available to process the treatment plans. Each treatment plan has to be processed on these two resources in the same order: physics desk then doctor and then physics desk again, as shown in Figure 6.2. The two operations conducted on facility 1 have the same processing times. The resource (i.e. doctor) operations depend on the availability of doctor l in the department.

The main objective of Subproblem 2 is minimising the number of treatment plans that do not meet their D_j^2 due date and their flowtime in the physics unit.

Subproblem 2 classification

Subproblem 2 can be described using the classification scheme by Graham *et al.* (1979) as follows.

The first field about the physics desk and doctor resource configuration $\alpha = \alpha_1\alpha_2$ can be denoted as:

$\alpha_1 = F$ denoting that the use of the two facilities (i.e. the desk and doctor resource) represents a flowshop machine environment.

$\alpha_2 = 2$ because there are only two facilities involved in this unit.

The second field $\beta = \beta_1, \ldots, \beta_6$ defines the treatment plan characteristics in Subproblem 3 as follows.

$\beta_1 = \circ$. No preemption is allowed in the operations of the treatment plans.

$\beta_2 = res1$. Only one doctor resource is used and each treatment plan was allocated one doctor resource.

$\beta_3 = \circ$. No precedence relations exist between treatment plans to be processed.

$\beta_4 = r_j^2$. Release dates for the treatment plans can vary.

$\beta_5 = 3$. A maximum of 3 operations should be done on each treatment plan. One by the doctor and two on the physics desk.

$\beta_6 = \circ$. The desk and doctor have different processing times p_{jk}, where $k \in J$ and $p_{jk} \neq 1$.

Lastly, the field represented by γ describes the objective function of Subproblem 2 which has been denoted by X to represent minimising of the number of treatment plans that fail to meet the due date D_j^2 while also minimising the flowtime of each treatment plan in the physics unit. Therefore, Subproblem 2 can be denoted by $F|res1, r_j^2, 3|X$, where the second field β denotes that a resource (i.e. $res1$) is required on the machines whose processing times vary and only 3 operations must be performed.

Subproblem 3

Subproblem 3 for the pretreatment unit involves 3 desks. Each operation for each treatment plan must be performed on a different desk if the three calculations are required. If a treatment plan has been worked on in the physics unit, it requires a single operation which is performed on one of the desks. As previously discussed in Chapter 4, in open shop scheduling problems (OSP), the routes taken by jobs (i.e. patients) are immaterial but each job has to be processed on each machine once.

The configuration of the 3 desks and some of the possible pathways that treatment plans for the patients can take in the pretreatment unit are shown in Figure 6.3. The arrows represent some of the possible pathways taken by the treatment plans for each patient. Treatment plans whose digital images had been forwarded from the planning unit can take possible pathways with arrows labelled (a), (b), (c) or (d) before exiting the pretreatment unit. In these pathways, the treatment plans have operations performed on each of the 3 desks in a typical OSP manner. The arrow labelled (e) is for one of the possible pathways taken by treatment plans received from the physics unit. As discussed previously, only a single operation is performed on them. In this case, the pathways shows that the treatment plan received from physics unit can be processed on desk 3 and then exits the pretreatment unit. As shown in Table 6.1, it is imperative to note that the processing times of these desks are all equal. In addition, the treatment plans can be divided into two groups according to the number of operations to be performed on the desks: i) those that require a single operation, and ii) those that require three operations.

Subproblem 3 can be described as comprising two problems. The first problem involves the treatment plans that require one calculation and can be described as a multiple parallel machine (i.e. desks) scheduling problem involving three identical desks. The second problem concerns treatment plans that have to be processed once on each of the three desks using any route possible as in an open shop problem. Therefore, Subproblem 3 has characteristics of mixed shop scheduling problems.

There are $|S_d^3|$ treatment plans, where $|S_d^3| = n_d$ that arrived on date d. The $|S_d^3|$ treatment plans can be split into two sets of treatment plans, according to the number of operations to be performed on the plans. One set of treatment plans are to be processed as in a multiple parallel desk scheduling problem. The other set comprises treatment plans that are to be processed as in an open shop. Each treatment plan for patient j has a maximum of 3 operations performed on each of the $|J|$ desks.

The main objective of the problem is to minimise the number of treatment plans that fail to meet the due date D_j^3 while also minimising the flowtime of each plan in the pretreatment unit.

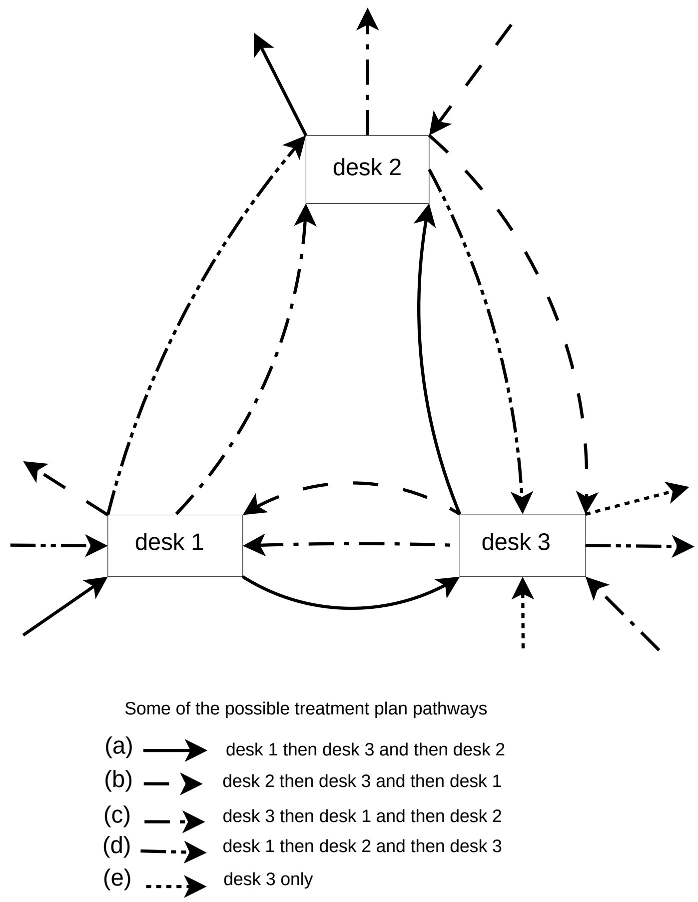

Figure 6.3: Patient pathways followed in the pretreatment unit

Subproblem 3 classification

Again, using the classification scheme by Graham *et al.* (1979), Subproblem 3 can be described as follows.

The first field about the pretreatment desk configuration $\alpha = \alpha_1\alpha_2$ can be denoted as:

$\alpha_1 = \mathscr{X}$, where $\mathscr{X}$ denotes a mixed scheduling problem which involves two problems: parallel machine and open shop scheduling problems.

$\alpha_2 = 3$ because the number of pretreatment desks in Subproblem 3 is constant.

The second field $\beta = \beta_1, \ldots, \beta_6$ defines the treatment plan characteristics in Subproblem 3 as follows.

$\beta_1 = \circ$. No preemption is allowed in the operations of the treatment plans on any of the pretreatment desks.

$\beta_2 = \circ$. No resource constraints are considered.

$\beta_3 = \circ$. No precedence relations exist between treatment plans to be processed on the desks.

$\beta_4 = r_j^3$. Release dates for the treatment plans can vary.

$\beta_5 = 3$. A maximum of 3 operations can be done on a given treatment plan.

$\beta_6 = p_{jk}$. All the desks have the same processing time p_{jk}, where $k \in J$ but $p_{jk} \neq 1$.

The last field γ describes the objective function of Subproblem3 which has been denoted by X to represent the minimising of the number of treatment plans that fail to meet the due date D_j^3 while also minimising the flowtime of each plan in the pretreatment unit.

Hence, using the notation $\alpha|\beta|\gamma$, Subproblem 3 can be described as $\mathscr{X}|r_j^3, 3, p_{jk}|X$, where the second field β denotes that all the desks have the same processing times (i.e. p_{jk}) and only 3 operations must be performed.

Subproblem 4

In the treatment unit, the patient j visits and/or revisits a treatment machine (i.e. $k \in G$) over several consecutive days. On each visit to the department, patient j has to be treated on the same machine. This machine must be of the machine type prescribed by the patient's doctor l. Therefore, when booking appointments for a patient, if there are more than one machines of the type prescribed by the doctor, only one machine should be used to treat the patient. This implies that all the prescribed fractions (i.e. TOTAL_j) for patient j must be received on that same machine.

The main objectives include minimising: the amount of time each patient takes from arrival in the unit to the time when the first fraction is to be done, amount of overtime accumulated by the machines and the number of patients that fail to meet their JCCO waiting time targets.

Subproblem 4 classification

Subproblem 4 can be analysed using the $\alpha|\beta|\gamma$ classification scheme as follows. The first field about treatment machines environment $\alpha = \alpha_1\alpha_2$ can be denoted as:

$\alpha_1 = P$ describes that the machines of the type chosen by doctor l considered are multiple identical parallel machines,

$\alpha_2 = \circ$ because the number of machines of the type chosen by the doctor varies. For example, $\alpha_2 = 3$, $\alpha_2 = 2$ and $\alpha_2 = 1$ for high energy linacs, low energy linacs, and DXR or betatron, respectively, The second field $\beta = \beta_1, \ldots, \beta_6$ defines the patient characteristics in Subproblem 4 as follows.

$\beta_1 = \circ$. No preemption is allowed in the treatment of patients on any of the machines

$\beta_2 = \circ$. Unlike Subproblem 1 which involves the constraint that a doctor resource must be available for the procedures in the planning unit, Subproblem 4 does not involve the requirement of any resource as a constraint.

$\beta_3 = \circ$. No precedence relation exist between patients being treated on the machines of the chosen machine type.

$\beta_4 = r_j^4$. Release dates for the patients can be different.

$\beta_5 = \circ$. No upper bound on the number of fractions prescribed to the patients.

$\beta_6 = p_{jk}$. The processing times (p_{jk} of the machines of a given type are always the same.

The last field γ describes the objective functions of the subproblem. It can be stated as follows.

Let X represent the objectives of Subproblem 4 which have been stated as i) minimising the amount of time each patient j takes from arrival in the unit to the time when the first fraction is to be done, ii) minimising the amount of overtime accumulated by the machines, and iii) minimising the number of patients that fail to meet their JCCO waiting time targets. Hence, Subproblem 4 can be described as $P|r_j^4, p_{jk}|X$.

6.5 Concluding remarks

This chapter has formulated four radiotherapy scheduling problems prevalent in departments in the UK and termed them: Subproblem 1, Subproblem 2, Subproblem 3 and Subproblem 4 for the planning, physics, pretreatment and treatment units, respectively. The subproblems have been characterised using the shop scheduling problem models considered intrinsically hard to solve by many researchers. Such models include the flexible two-stage hybrid flow shop, flowshop, mixed shop and parallel machine scheduling problems. One key aspect of the subproblems is that the processing times for the machines and/or facilities involved were estimated using averages of processing times reported in Chapter 5. This implies that the problems formulated are deterministic. Although in the real-world processing times for patients on a given machine vary, these deterministic problems can be considered as germinal ideas for future research on the subproblems.

It is imperative that scheduling methods be proposed with the aim to minimise the average waiting time for each treatment, the criterion normally used to measure performances of departments in the UK. However, other objectives have been included in order to help in the analysis and further improvement of the proposed approaches. Such objectives have also been used to compare the performances of radiotherapy departments in the waiting times audits conducted between 2000 and 2008 as discussed in Chapter 4.

Chapter 7

Constructive heuristics for radiotherapy scheduling

Contents

7.1 Introduction

Constructive heuristics can be defined as algorithms that can build up an approximate solution from the data provided in the problem to be solved using simple rules which determine the processing order of the arriving jobs (French 1982). In its entirety, the radiotherapy scheduling problem considered in this study is an intrinsically hard problem since it comprises four subproblems that can be typified as some of the complex scheduling problems treated in the literature. Therefore, approximate methods discussed in Section 4.3.3 can be proposed for the subproblems stated in Chapter 6.

The motivation for proposing constructive heuristics to solve the four subproblems are as follows.

- The shop scheduling problem models used to formulate the subproblems in Chapter 6 have been shown to be NP-hard (Drozdowski 1996, Oğuz *et al.*

1997, Oğuz *et al.* 2004, Low *et al.* 2008, Brucker and Knust 2009). When more constraints from the work practices of the department are introduced, the subproblems become more difficult to solve using methods such as exact enumerative methods as discussed in Chapter 4. Therefore, approximate methods such as heuristics can be considered to obtain good schedules of appointments on the machines.

- It is essential to quickly create good schedules of appointments for the n_d patients received. Approximate methods such as heuristics have been shown to be computationally efficient compared to some of the optimisation methods such as TS and GAs whose application on healthcare problems is growing. The approaches to the subproblem were preferred to be less computationally intensive so that the schedules of appointments can be created in the shortest time possible.

- The schedules of all the appointments (i.e. from planning to the treatment unit) were to be created so that patients would be informed about when they were to visit the department prior to the first visit for the planning operations. Heuristics were considered in order to quickly generate good schedules of appointments and hence, simplify the booking of appointments. The senior radiographers would then concentrate more on caring and treating the patients than creating or amending appointments.

- Approximate methods such as the heuristics are useful in the development of hybridised metaheuristics such as those proposed in (Burke *et al.* 1998, Petrovic and Leite-Rocha 2008). The constructive heuristics proposed can be used to generate initial solutions for the optimisation algorithms in future research.

The rest of the chapter is organised as follows. Section 7.2 discusses the four constructive heuristics developed for each subproblem representing each of the four units in the department. This includes the time complexities and interconnecting these four heuristics into one. Section 7.3 discusses the possible alternative pathways suggested for the treatment unit. Lastly, Section 7.4 gives the concluding remarks.

7.2 Proposed heuristics

Four constructive heuristics were developed for the four subproblems discussed in Chapter 6. The heuristic algorithms were based on the following framework.

1. Input and reorder sequence S of patients using priority dispatching rules.

2. Given the reordered S, find the schedules of appointments for the patients.

Such a framework can be considered as a *two-stage* constructive heuristic algorithm involve prioritising patients using PDRs and strategies to build the schedules of appointments for the patients in S inspired by established algorithms like those in (Moore 1968, Petrovic *et al.* 2006).

Four heuristic algorithms were developed and termed Heuristic H1, Heuristic H2, Heuristic H3 and Heuristic H4 for Subproblem 1, Subproblem 2, Subproblem 3 and Subproblem 4 respectively. In Heuristic H1 included strategies for making radiotherapy capacity available on the next immediate dates the doctor is available in the department for patients needing critical treatments. Heuristic H2 had a 'greedy' strategy for scheduling treatment plans on the immediately available slots. Heuristic H3 also comprised a strategy for fast-tracking and delaying patients requiring critical (i.e. emergency and palliative) and radical treatments respectively. Lastly, Heuristic H4 included a strategy that scheduled first patients whose earliest start date, C_{1j1k} was below the JCCO due date and those who had the earliest start dates that did not comply with the JCCO due dates by more than the threshold of tolerated tardiness for their treatment (i.e. parameters in Section 6.2). Those whose earliest start dates did not meet the JCCO due dates by days within the threshold of tolerated tardiness were then scheduled last.

7.2.1 Heuristic H1

It was imperative to synchronise doctor availability with each operation on the machines or facility in the planning unit since doctors have to be available to oversee the staging of the cancers in the planning unit. The doctor is scheduled to examine the patient in the first minutes (i.e. the processing time of each doctor) of the machine or facility's processing time. A good feasible schedule of the appointments for the planning unit resources (i.e. doctors, machines and facilities) that can be generated in the planning unit is exemplified in Table 7.1.

In Table 7.1, patient 1 is to be examined by the doctor in the mould room during slot 1 while the mask or shell is being cast. The doctor then leaves at the end of slot 1 but the technicians in the mould room continue moulding the mask until the end of slot 4. In this case, the same doctor oversees the taking of images for patient 2 on the CT scanner during slot 2 before going to the simulator room to examine patient 1 as the images are being taken by the radiographers.

The constructive heuristic algorithm developed to obtain such feasible schedules in Table 7.1, was termed Heuristic H1 and is given in Algorithm 7.1. The first step of the Heuristic H1 involved reordering the input sequence of patients S_d^1, using composite PDRs developed using the information about each patient as follows.

- Most urgent patient category (MUPC) prioritised using the patient categories (see Table 2.3). The category of patients that need the most immediate treatment had higher priority. Hence, the Arden Cancer categories

<table>
<tr><th>Resources \ Slots</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th><th>8</th><th>9</th><th>10</th><th>11</th><th>12</th><th>13</th><th>14</th></tr>
<tr><td>Doctor</td><td>1</td><td>2</td><td></td><td></td><td>1</td><td>4</td><td>3</td><td></td><td></td><td></td><td>3</td><td>6</td><td></td><td></td></tr>
<tr><td>Mould</td><td colspan="4">1</td><td></td><td></td><td colspan="4">3</td><td></td><td colspan="3">6</td></tr>
<tr><td>Simulator</td><td></td><td></td><td></td><td></td><td colspan="6">1</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Scanner</td><td></td><td colspan="4">2</td><td colspan="4">4</td><td></td><td colspan="4">3</td></tr>
</table>

Table 7.1: Example of a feasible schedule of appointments for the operations to be conducted in the planning unit

can be listed by the priorities assigned to the categories as follows: *Urgent*, *Emergency*, *Priority*, *Standard*, and *Elective*. The *Urgent* patient category had the highest priority and *Elective* had the least priority. In Table 2.4, most of the patients in the department were classified as *Standard* and *Elective* patients. These patients needed palliative or radical treatment. It was essential to further reorder the sequence of patients using the most urgent (i.e. critical) treatment (MUT) rule (see Table 2.2).

- Most number of units (i.e. steps) to be visited in the entire radiotherapy process (MNSRP). Some patients have to visit 3 or 4 units depending on the complexity of their treatment plans. Those to visit more units had the highest priority to those patients that visited less units.

- Most number of operations in the planning unit (MNOP). Patients considered to have the most number of operations to be completed in the planning unit (i.e. those who needed masks) had the highest priority.

- Least slack (LS). Slack for each patient j was calculated as the difference between the release date and due date for the planning unit procedures: slack=$D_j^1 - r_j^1$. For patients that had the submission of their request forms delayed (that is, $\delta_j > 0$), the slack can be small depending on the value of δ_j.

The PDRs were applied to the sequence of patients in the order: MUPC followed by MUT, MNSRP, MNOP and LS. In the second stage, a 'scattering' strategy was employed to schedule the patients on the machines. It aimed to ensure some slots on the schedule of the machines and doctors were available for the uncertain arrival of patients requiring critical treatments such as emergency and palliative treatments. It involved obtaining an initial date when the doctor for patient j was available for the planning unit operations starting from the release

Input: S_d^1

Output: planning unit schedule, S_d^2 and S_d^3

$S_d^2 \leftarrow \emptyset$ and $S_d^3 \leftarrow \emptyset$

Reorder sequence S_d^1 using the PDRs for the planning unit

Let $k = 1$ (mould room), $k = 2$ (CT scanner) and $k = 3$ (simulator)

for patient j in position 1 **to** n_d in S_d^1 **do**

  Take the date d_1, obtained using obtained using ScatterDoctorDates in Algorithm 7.2 and let $i \leftarrow 1$

  if j requires a mask from the mould room **then**

    Starting from date d_1, find the first available coinciding doctor and mould room slots and determine the completion date C_{1j01} using DoctorAndMachineSlots in Algorithm 7.3 and set $i \leftarrow i + 1$

    Starting from the date C_{1j01}, find the first available slot s_k, $k \in \{2, 3\}$ when doctor l is available and let date d_2 be the completion date C_{2j0k} using the DoctorAndMachineSlots procedure

    while $C_{1j01} \neq d_2$ **do** {All operations done on the same date}

      $d_1 \leftarrow d_2$ and $i \leftarrow 1$

      Starting from date d_1, find the first available slot when doctor l can be in the mould room and determine the completion date C_{1j01} using the DoctorAndMachineSlots procedure and set $i \leftarrow i + 1$

      Starting from the date C_{1j01}, find the first available slot s_k, $k \in \{2, 3\}$ when doctor l is available and let date d_2 be the completion date C_{2j0k} using the DoctorAndMachineSlots procedure

    end while

    If $C_{2j0k} - D_j^1 > \omega$, $k \in \{2, 3\}$, starting from r_j^1 and using $l = 13$, schedule the operations to be performed on j using OvertimeBookings in Algorithm 7.4. Otherwise, schedule j on slot s_1 and the corresponding slot for doctor l on the date C_{1j01} and also schedule j on the slot for the doctor l coinciding with s_k on the date C_{2j0k}, $k \in \{2, 3\}$

  else

    Set $i \leftarrow i + 1$ and starting from date d_1, determine the first available slot for doctor l, s_k and the completion date C_{1j0k}, where $k \in \{2, 3\}$ using the DoctorAndMachineSlots procedure

    If $C_{1j0k} - D_j^1 > \omega$, $k \in \{2, 3\}$, starting from r_j^1 and using $l = 13$, schedule the operations to be performed on j using the OvertimeBookings procedure. Otherwise, schedule j on the slot for the doctor l coinciding with s_k on the date C_{2j0k}, $k \in \{2, 3\}$

  end if

  If j requires complex plans, then $S_d^2 \leftarrow S_d^2 \cup \{j\}$ and $r_j^2 \leftarrow C_{2j0k}$, $k \in \{2, 3\}$. Otherwise, $S_d^3 \leftarrow S_d^3 \cup \{j\}$ and $r_j^3 \leftarrow C_{2j0k}$, $k \in \{2, 3\}$

end for

Algorithm 7.1: Constructive heuristic H1 for Subproblem 1

date, r_j^1 for the search of available slots to schedule the appointments as shown in the ScatterDoctorDates procedure in Algorithm 7.2.

ScatterDoctorDates determined the number of dates the doctor is available in the department between r_j^1 and D_j^{jcco} using details in Table 2.10. Since each doctor was available on one day of the week, patients with 2 or less number of dates their doctor can be available before the due date were assigned r_j^1 as the initial planning date. For the others, the initial planning date was determined by skipping some immediate dates when the doctor can be available in the department. This strategy was inspired by the just-in-time (JIT) and as-soon-as-possible (ASAP) algorithms in (Petrovic *et al.* 2006). Patients with fewer number of days their doctor is available before the JCCO due date should be considered for immediate planning unit appointments (i.e. ASAP) whilst those with the maximum possible (e.g. 5 days) number of days their doctor is available should be considered later but before their JCCO due dates (i.e. JIT).

Input: r_j^1, D_j^{jcco}, doctor l
Output: date when doctor l is available
Take the first date after r_j^1 when doctor l is available
Let $x \leftarrow 1$ $\{x$ is a counter of dates when doctor l is available$\}$
while the date is on or before D_j^{jcco} **do**
    $x \leftarrow x + 1$
    Advance date to the next date the doctor is supposed to be available
end while
if $x \leq 2$ **then**
    return r_j^1
else if $x = 3$ **then**
    return date after skipping 1 date the doctor is available from r_j^1
else
    return date after skipping 2 dates the doctor is available from r_j^1
end if

Algorithm 7.2: ScatterDoctorDates procedure for determining the initial date when the doctor is available

For each patient in the reordered sequence, an initial planning date was determined using ScatterDoctorDates. If the patient required a mask for their operations, starting from the initial planning date, slots for the doctor and the mould room were determined using a procedure called DoctorAndMachineSlots shown in Algorithm 7.3. Then, the mould room slot was the starting date used to determine available slots on the simulator or CT scanner. The first stage involving the mould room was not considered for patients who did not require a mask since it was assumed that the processing times for the doctor and mould room were all zero.

Input: $k \in I$, date d when doctor l is available
Output: slot for doctor l, s_k and completion date of the operation

Set *correspond*=**false**
while *correspond* =**false** **do**
  On the date d, find the first available slot when l is available
  if a slot for doctor l is available **then**
    Using the date d, find the first available slot s_k for the machine or facility k which corresponds to the determined slot for doctor l
    if s_k is obtained **then**
      correspond =**true**
      return Slot when doctor l is available, s_k and the date when these slots are available
    else
      Advance the date d to the next date the doctor l is available
    end if
  else
    Advance the date d to the next date the doctor l is available
  end if
end while

Algorithm 7.3: DoctorAndMachineSlots procedure for finding machine and the corresponding doctor slots

Use of overtime slots in Heuristic H1 was considered if the difference between completion date on the simulator or CT scanner and the due date for the planning unit operations was greater than the threshold of tolerated tardiness in the planning unit (i.e. parameter ω) as shown in Algorithm 7.1. Otherwise, the patient's doctor and machine and/or mould room slots were added to the appointments schedule. This is shown in the procedure called OvertimeBookings in Algorithm 7.4 used to find the date, slot for the doctor l and the corresponding slots on the machines and/or facility using the chosen number of overtime slots for planning unit machines and facility (o_k).

7.2.2 Heuristic H2

An example of a feasible schedule of operations conducted in the physics unit is shown in Table 7.2. The first slots (i.e. slots 1–7) on the physics desk schedule are booked for patient 3's first calculation (or outlining and planning operation) and the doctor l is expected to approve and sign the plans in slot 8. As the doctor examines the plan for patient 3, the physics technicians can start working on the outlining and planning of patient 6's treatment plan (i.e. slots 8–14). Upon completing the creation of the treatment plans for patient 6, the physics technicians immediately start working on the second operation of the approved

Input: locum doctor $l = 13$, j
Output: planning unit schedule for j

Let $d_1 \leftarrow r_j^1$
Let $k = 1$ (mould room), $k = 2$ (CT scanner) and $k = 3$ (simulator) and $i \leftarrow 1$
if j must have mask in the mould room **then**
  Consider $c_k + o_k$ slots for $k = 1$ and starting from date d_1, obtain coinciding doctor and mould room slots using the DoctorAndMachineSlots procedure on completion date C_{1j01} and set $i \leftarrow i + 1$
  Using date C_{1j01}, consider $c_k + o_k$ slots for $k \in \{2, 3\}$ to obtain coinciding doctor and machine slots on completion date C_{2j0k}, $k \in \{2, 3\}$ using DoctorAndMachineSlots procedure. Let $d_2 \leftarrow C_{2j0k}$, $k \in \{2, 3\}$
  while $C_{1j01} \neq d_2$ **do**
    $d_1 \leftarrow d_2$ and $i \leftarrow 1$
    Starting from date d, determine the coinciding slots for doctor l and the mould room considering $c_k + o_k$ slots using the DoctorAndMachineSlots procedure on completion date C_{1j01} and set $i \leftarrow i + 1$
    Using date C_{1j01} and considering $c_k + o_k$ slots, obtain the coinciding doctor and machines slots on completion date C_{2j0k}, $k \in \{2, 3\}$ using the DoctorAndMachineSlots procedure. Let $d_2 \leftarrow C_{2j0k}$, $k \in \{2, 3\}$
  end while
  Schedule j on slot s_1 and the slot for doctor l on the date C_{1j01} and also schedule j on the slot for the doctor l coinciding with s_k, on the completion date C_{2j0k}, $k \in \{2, 3\}$
else
  Set $i \leftarrow i + 1$ and starting from date d_1, consider $c_k + o_k$ slots and determine coinciding doctor and machine slots on completion date C_{2j0k}, $k \in \{2, 3\}$ using the DoctorAndMachineSlots procedure
  Schedule j on slot s_k, $k \in \{2, 3\}$ and the slot for doctor l on the date C_{2j0k}
end if
$r_j^3 \leftarrow C_{2j0k}$, $k \in \{2, 3\}$

Algorithm 7.4: OvertimeBookings procedure for scheduling patients on overtime slots in the planning unit

outlining and planning calculations for patient 3's treatment plans (i.e. from slot 15 onwards).

The flowtime of treatment plans in the physics unit is affected by the difference between r_j^2 and the next day the doctor is available. For example, if the first calculation (or outlining and planning procedures) for a treatment plan whose doctor is available on date d is done on the same date d but no doctor available slot can be found on date d for the plan's approval by the doctor, the treatment plan will be delayed by a week (i.e. according to Table 2.10). Therefore, a

<table>
<tr><th>Slots / Resource</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th><th>8</th><th>9</th><th>10</th><th>11</th><th>12</th><th>13</th><th>14</th><th>15</th></tr>
<tr><td>Doctor</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>3</td><td></td><td></td><td></td><td></td><td></td><td></td><td>6</td></tr>
<tr><td>Desk</td><td colspan="7">3</td><td colspan="7">6</td><td>3</td></tr>
</table>

Table 7.2: An example of a feasible good physics unit schedule of appointments

PDR termed the Least Doctor Delay (LDD), defined as the least number of days that elapse between the release date for the physics unit, r_j^2 and the next date immediately after r_j^2 on which doctor l is available in the department, was used to prioritise treatment plans.

The PDRs used in Heuristic H2 (see Algorithm 7.5) included LDD, MUPC, and MUT, in that order. Using the reordered sequence S_d^2 of treatment plans, Heuristic H2 schedules each treatment plan on the physics desk beginning from the head of the sequence. It starts from the release date for the physics unit r_j^2 and searches for the first available slot s_k for the desk. It determines if the available slot s_k coincides with any slot scheduled for a patient for the mould room operation. If the slots on the mould room that coincide with the slot s_k, where $k \in K$ are free, then the heuristics finds the first available doctor slot after slot s_k ($k \in K$) when the doctor is available. For the final operation, Algorithm 7.5 uses the found doctor slot to determine the slot on the physics unit desk if the mould room is free on that slot. The first and second operations, and the doctor slot are scheduled for the treatment plan on the physics unit desk. If the mould room is not free, Algorithm 7.5 searches the next immediate working day until an available slot is obtained.

7.2.3 Heuristic H3

An example of a feasible schedule of appointments for the pretreatment unit desks is shown in Table 7.3. In this schedule, the first slot is for the first calculation, the second is for the second calculation and the third is for the last calculation. The slots shown in Table 7.3 are not just over a single day but can be over several days. The order of processing the operations for treatment plan for patient 1 is as follows: Desk 1→Desk 3→Desk 2. The treatment plan for patients 2 and 4 undergo dosimetry calculations and accuracy checks on the desks in the following order, Desk 2→Desk 3→Desk 1 and Desk 3→Desk 1→Desk 2, respectively. For patients 3, 5, and 6, their calculations were done in the physics unit and hence, a single calculation was performed on Desk 2, Desk 1 and Desk 3 respectively.

Heuristic H3 in Algorithm 7.6 schedules treatment plans whose patients require immediate treatment on the earliest available slots on the desks. The first stage of the heuristic involves reordering the sequence of patients using the PDRs: Least Number of Pretreatment Operations (LNPO) to be performed, MUPC, MUT, and LS, in that order. The LS rule was defined using a priority index

Input: S_d^2
Output: physics unit schedule

Reorder treatment plans in S_d^2 using the PDRs for the physics unit
for treatment plan j in position 1 **to** $|S_d^2|$ **do**
    $i \leftarrow 1$ {first operation}
    Starting from the release date r_j^2, find the first available slot s_k and completion date C_{1j0k} for the desk, $k \in K$. Let date d_1 be C_{1j0k}
    Determine if the mould room is free during the slot s_k on the date d_1
    while $i \leq 2$ **do**
        if the mould room is free **then**
            if $i = 1$ **then**
                $i \leftarrow 2$ {second operation}
                Starting from the date d_1, find the first available slot for doctor l on date d_2
                Starting from the date d_2, take the first available slot s_k after the slot for doctor l and determine completion date C_{2j0k}
                Determine if the mould room is free during the slot s_k on date C_{2j0k}
            else
                Schedule treatment plan for patient j on slot s_k for the first operation on date C_{1j0k} and slot s_k for the second operation on the desk, $k \in K$ on date C_{2j0k}, and slot for doctor l on the date d_2
                $i \leftarrow 3$ {exit while loop}
            end if
        else
            Advance date d_i to the next date
            Starting from the date d_i, take the first available slot for the operation i on the desk, $k \in K$ and set the completion date C_{ij0k} to date d_i
            Determine if the mould room is free during the slot s_k on the date d_i
        end if
    end while
end for

Algorithm 7.5: Constructive heuristic H2 for Subproblem 2

determined the difference between the JCCO determined due date and the completion date of the last operation for the pretreatment unit (i.e. $D_j^{jcco} - C_{ij0k}$, where $i \in \{1, 3\}$) for complex and simple plans.

The first stage reorders the treatment plans received so that those in sequence S_d^2 are processed first and then followed by the treatment plans in the sequence S_d^3. Treatment plans processed in the physics unit, where they can be delayed due to the unavailability of the doctors were processed first (i.e. in Algorithm 7.6) to ensure their flowtime in the pretreatment is minimised. Heuristic H3 considers two sets, the set of all pretreatment desks J and another set κ which keeps track of

Desks	**Slots**			
Desk 1	1	4	5	2
Desk 2	2	3	4	1
Desk 3	4	1	2	6

Table 7.3: An illustration of a good feasible schedule of appointment slots for patients

the desks whose slots have been scheduled for treatment plan operations. For each calculation to be performed on the treatment plan in sequence S_d^3, the number of desks that can possibly be used to perform the calculation is determined using the difference between the two aforementioned sets, $J - \kappa$.

After a desk with the shortest amount of work on its schedule has been determined, the first available slot is determined and the desk added to the set κ. Determining the desk with the least amount of work on its schedule involved using a heuristic termed the Least Work In Queue (LWINQ) given in Algorithm 7.7 inspired by the study in (Holthaus and Rajendran 1997*b*). LWINQ employs a supplied set of pretreatment desks $\mathscr{E}$ and date to find the desk that has the earliest available slot. Heuristic H3 then schedules an operation for the treatment plan on this desk and the determined available slot.

Treatment plans for the patients that require critical (i.e. emergency) treatment need 3 operations in the pretreatment unit. This means that on a given date when an emergency patient arrives, there should be some free slots available on the pretreatment desks to accommodate them. Heuristic H3 employs a strategy of delaying some of the patients requiring non-critical treatments (i.e. those requiring radical treatment). In this strategy, treatment plans whose JCCO due date for treatment is more than μ_j days away from the determined completion date for the last operation are scheduled in such a way that each operation is processed on consecutive working days as shown in Steps 15 to 25 in Algorithm 7.6.

7.2.4 Heuristic H4

The first stage of the Heuristic H4 shown in Algorithm 7.8 involves reordering the sequence of patients S_d^4 using the PDRs: MUPC, MUT, Least Number of Prescribed Treatment Phases (LNPTP), Least Number of Prescribed Fractions (LNPF), and Earliest Treatment Due Date (ETDD), in that order. When the rules LNPTP and LNPF are combined, the total number of fractions, TOTAL_j,

Input: S_d^2 and S_d^3
Output: pretreatment unit schedule

Reorder $S_d^2 \cup S_d^3$ using PDRs for the pretreatment unit
for patient j in position 1 **to** $|S_d^2 \cup S_d^3|$ **do**
  $i \leftarrow 1$\{first operation\}
  if $j \in S_d^2$ **then** \{1 operation needed\}
    Starting from r_j^3, find the first available slot s_k on desk k on completion date C_{1j0k}, $k \in J$ using the LWINQ heuristic in Algorithm 7.7 and schedule the treatment plan for patient j on this slot s_k
  else \{3 operations needed\}
    $\kappa \leftarrow \emptyset$\{let κ be an empty set of desks\}
    Starting from r_j^3, find the first available slot s_k on desk k on completion date C_{1j0k}, $k \in J$ using the LWINQ heuristic
    Schedule treatment plan for patient j on the slot s_k on completion date C_{1j0k}, $k \in J$ and set $\kappa \leftarrow \kappa \cup \{k\}$
    Set $i \leftarrow 2$ and let date d_i be C_{1j0k}, $k \in J$
    while $i \leq 3$ **do**
      Starting from d_i, find the first available desk k, $k \in J - \kappa$ and slot s_k for operation i using the LWINQ heuristic such that s_k, $k \in J$ for operation i is after s_k, $k \in \kappa$ for operation $i-1$ and set $d_i \leftarrow C_{ij0k}$, $k \in J$
      Schedule patient j on the corresponding slot s_k, $k \in J$
      $\kappa \leftarrow \kappa \cup \{k\}$
      if $j \in C$ **and** $D_j^{jcco} - C_{3j0k} \geq \mu_j$ **then** \{scattering strategy\}
        Delete j from the current schedule
        Set $i \leftarrow 0$
        Set $d_i \leftarrow r_j^3$ and $\kappa \leftarrow \emptyset$
        for $i = 1$ **to** 3 **do**
          Set $d_i \leftarrow d_{i-1}$
          Starting from d_i, find the first available desk k and slot s_k on completion date C_{1j0k}, $k \in J - \kappa$ and set $d_i \leftarrow C_{1j0k}$ such that date d_i for operation i is after date d_{i-1} for operation $i-1$ (i.e. $d_i - d_{i-1} \geq 1, \forall i \geq 1$) using the LWINQ heuristic
          Schedule patient j on the corresponding slot s_k, $k \in J - \kappa$
          $\kappa \leftarrow \kappa \cup \{k\}$
        end for
      end if
      $i \leftarrow i + 1$
      $d_i \leftarrow d_{i-1}$
    end while
  end if
end for

Algorithm 7.6: Constructive heuristic H3 for Subproblem 3

Input: date d and $\mathscr{E}$ {Let $\mathscr{E}$ be any set of pretreatment desks}
Output: k, s_k and date when k is available

Choose a desk k from the set $\mathscr{E}$
Starting from the input date d, find the date d_1 when the first slot s_k is available
$k^1 \leftarrow k${Let k^1 be a desk}
$\mathscr{E} \leftarrow \mathscr{E} - \{k\}$
for each desk $k \in \mathscr{E}$ **do**
    Starting from the input date d, find the date d_2 when the first slot is available on k
    If $d_1 > d_2$, set $d_1 \leftarrow d_2$ and also $k^1 \leftarrow k$
end for
return d_1, slot s_{k^1} for desk k^1

Algorithm 7.7: LWINQ heuristic for finding the first available desk k on a given date

are considered. The patient with the least TOTAL_j has the highest priority. Since the fractions have to be delivered over several consecutive days, LNPF can be considered to be a processing time (i.e. in days) based PDR similar to the SPT. The performance of SPT in minimising mean flowtime and tardiness has been shown by several researchers in (Baker 1974, French 1982, Baker 1984, Raghu and Rajendran 1993, Holthaus and Rajendran 1997*b*, Holthaus and Rajendran 1997*a*, Holthaus 1997, Sule 1997, Mohanasundaram *et al.* 2002, Pinedo 2002, Rajendran and Alicke 2007).

For the LNPF rule, the processing time for each patient j can be considered to be greater than or equal to TOTAL_j, because weekends and bank holidays are not considered. Figure 7.1 shows a possible worst-case scenario where most of the slots on a given machine k have been already booked and are unavailable (i.e. the shaded boxes) and only one slot is left available on each of the six consecutive dates. Sequence $S^4_{(d-2)}$ has two patients j and $j+1$ whose release date in the treatment unit is $d-2$, TOTAL_j and $\text{TOTAL}_{(j+1)}$ are 4 and 2, respectively and the D^{jcco}_j and $D^{jcco}_{(j+1)}$ are on the same date $d-1$. Using the LNPF rule to reorder sequence $S^4_{(d-2)}$, gives a sequence with patient $j+1$ at the head followed by j to obtain Schedule2 while using the FCFS rule gives a sequence with patient j followed by $j+1$ that produces Schedule1 shown in Table 7.4.

The schedules of appointments shown in Figures 7.2 and 7.3 produced the mean waiting times (i.e. $\overline{MWT}$ defined in Equation 7.1) to the start of treatment for the patients j and $j+1$ in Table 7.4. Schedule2 obtained using the LNPF rule produced the best result of 1.0 compared to the 2.0 produced by the FCFS rule. Therefore, the use of the LNPF rule minimised $\overline{MWT}$ for Schedule2 shown in Figure 7.3. Another measure also used to compare Schedule1 and Schedule2 in Table 7.4 is $\overline{T}$. The two schedules, Schedule1 and Schedule2, produced 1.5 and

Input: S_d^4
Output: treatment schedule

Reorder the sequence S_d^4 using PDRs for the treatment unit
$R \leftarrow \emptyset$ and $h \leftarrow 1$ {let R be a set of 'retained' patients}
for patient j in position 1 **to** $|S_d^4|$ **do**
    If j requires initial plan verification, then starting from date r_j^4, find the first available slot s_k on completion date C_{1j1k}, $k \in I$ on the simulator and set $r_j^4 \leftarrow C_{1j1k}$
    Starting from date r_j^4, determine the first available slot s_k on completion date C_{1j1k}, $k \in G_j^{type}$ using EarliestTreatmentStart in Algorithm 7.9
    if $j \in (A \cup B)$ **then** {needs emergency or palliative treatment}
        if $j \in A$ **and** $C_{1j1k} - D_j^4 > \upsilon_{1,j}$ **then**
            Starting from r_j^4, determine the first available slot s_k on completion date C_{1j1k}, $k \in G_j^{type}$ considering overtime slots $c_k+1, c_k+2, \ldots, c_k+o_k$ and using the EarliestTreatmentStart procedure
        end if
        if $j \in B$ **and** $C_{1j1k} - D_j^4 > \upsilon_{2,j}$ **then**
            Starting from r_j^4, determine the first available slot s_k on completion date C_{1j1k}, $k \in G_j^{type}$ considering overtime slots $c_k+1, c_k+2, \ldots, c_k+o_k$ and using the EarliestTreatmentStart procedure
        end if
    else
        if $C_{1j1k} - D_j^4 > \upsilon_{3,j}$ **then**
            $r_j^4 \leftarrow D_j^4 + \upsilon_{3,j}$
            Starting from r_j^4, determine the first available slot s_k on completion date C_{1j1k}, $k \in G_j^{type}$ considering overtime slots $c_k+1, c_k+2, \ldots, c_k+o_k$ and using the EarliestTreatmentStart procedure
        else
            $R \leftarrow R \cup \{j\}$
        end if
    end if
    If $j \notin R$, schedule the TOTAL_j fractions on the determined slots
end for
for j in position 1 **to** $|R|$ **do**
    Starting from r_j^4, determine the first available slot s_k on completion date C_{1j1k}, $k \in G_j^{type}$ considering overtime slots $c_k + 1, c_k + 2, \ldots, c_k + o_k$ and using the EarliestTreatmentStart procedure
    Schedule the TOTAL_j fractions on the determined slots
end for

Algorithm 7.8: Constructive heuristic H4 for Subproblem 4

Input: set of identical machines G_j^{type}, date d
Output: k and C_{1j1k}, $k \in G_j^{type}$

for each $k \in G_j^{type}$ **do**
    $h \leftarrow 1$ {first treatment phase}
    $i \leftarrow 1$ {first fraction}
    while $i \leq$TOTAL$_j$ **and** $h \leq h_j$ **do**
        Determine the first available slot s_k, $k \in G_j^{type}$ on date d and denote this date as d_i
        if there is no available slot s_k **then**
            $i \leftarrow 1$ and advance d to the next working day
        else
            If $i = 1$ and $h = 1$, set the completion date C_{1j1k} to d_i and advance d to the next working day
            $i \leftarrow i + 1$
            If $i > f_{jh}$, increment h (i.e. $h \leftarrow h + 1$)
        end if
    end while
end for
Find the machine k with treatment start date d_1 in the set G_{type}
return machine k and the first fraction date d_1

Algorithm 7.9: EarliestTreatmentStart procedure for finding the machine with the earliest treatment start date

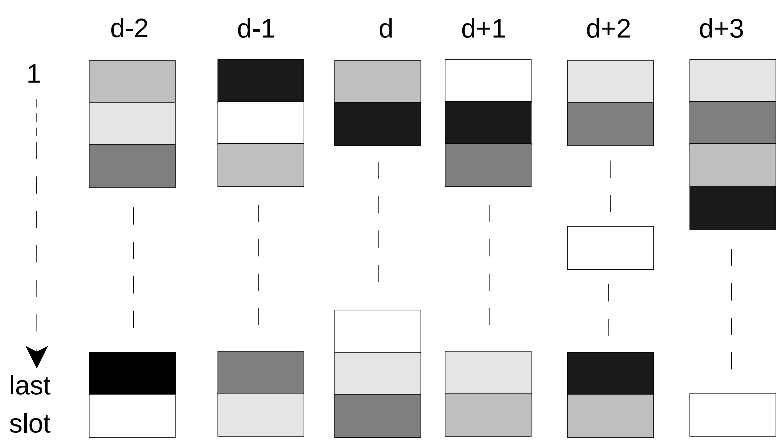

Figure 7.1: An illustration of how the LNPF rule resembles the SPT rule using slots on a given machine. Shaded boxes depict already booked slots

0.5, respectively. Schedule2 also produced the best result for $\overline{T}$.

$$\overline{MWT} = \frac{1}{N}\sum_{j=1}^{N}(C_{1j1k} - r_j^4) \tag{7.1}$$

Table 7.4: A comparison of the results obtained for *Schedule1* and *Schedule2* illustrating the performances of the LNPF and FCFS rules

Objective	**Schedule1**	**Schedule2**
T_j	0	1.0
T_{j+1}	3.0	0
$C_{1j1k} - r_j^4$	0	2.0
$C_{1(j+1)1k} - r_{j+1}^4$	4.0	0
$\overline{T}$	1.5	0.5*
$\overline{MWT}$	2.0	1.0*

$*$ *denotes the best result*

Heuristic H4 was developed based on the Moore's algorithm for solving a single machine scheduling problem whose objective was to minimise the number of tardy jobs as explained in (Moore 1968, French 1982). The strategy used by Heuristic H4 involved categorising patients in S_d^4 into 3 sets: 1) patients that meet their JCCO due date, 2) patients that cannot meet their JCCO due date by the threshold of tolerated tardiness for their treatment, and 3) patients that cannot meet their JCCO deadlines by the number of days that do not the threshold of tolerated tardiness for their treatment. Hence, Heuristic H4 employs a set, R, of 'retained' patients from the set of patients described in category 3. These patients are kept in a sequence that has to be scheduled later in the Steps 23 to 26 in Algorithm 7.8. If a patient requires an initial plan verification procedure on the simulator in the planning unit, the first available slot on this machine is obtained and the date on which this slot is available becomes the new release date for the treatment unit.

Heuristic H4 also employs the procedure termed EarliestTreatmentStart shown in Algorithm 7.9 to find the treatment machine k with the earliest treatment start date. EarliestTreatmentStart uses a set, G_j^{type}, of treatment machines of the same machine type as prescribed by the doctor in the request form. When $G_j^{type} = 1$, Subproblem 4 can be considered as a single machine problem. Otherwise, Subproblem 4 is a parallel identical machines problem. When $|G_j^{type}| > 1$, EarliestTreatmentStart chooses a treatment machine k and starting from a supplied date, it searches for the first available slot (i.e. within a given range of slots) on each date. If there are no slots available, the procedure restarts its search for available slots on the machine beginning from the next working date after the date that had no available slots. Upon determining the treatment start dates and slots for each machine in the set G_j^{type}, EarliestTreatmentStart then compares the treatment start dates to determine the machine k with the earliest start date and slot.

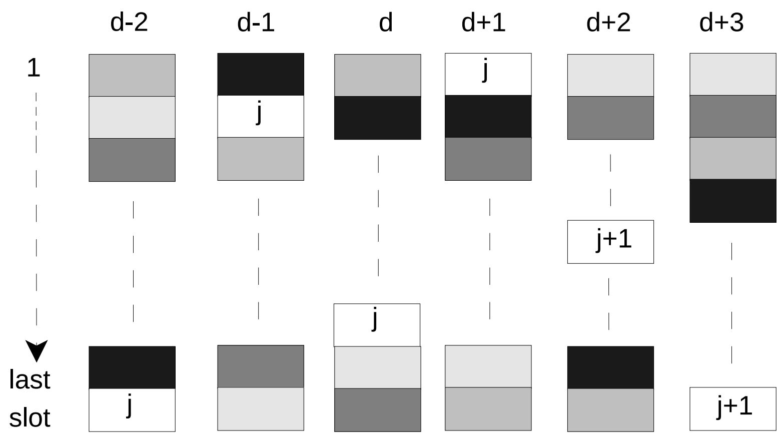

Figure 7.2: An illustration of how patients j and $j+1$ can be scheduled on a machine using to the FCFS rule

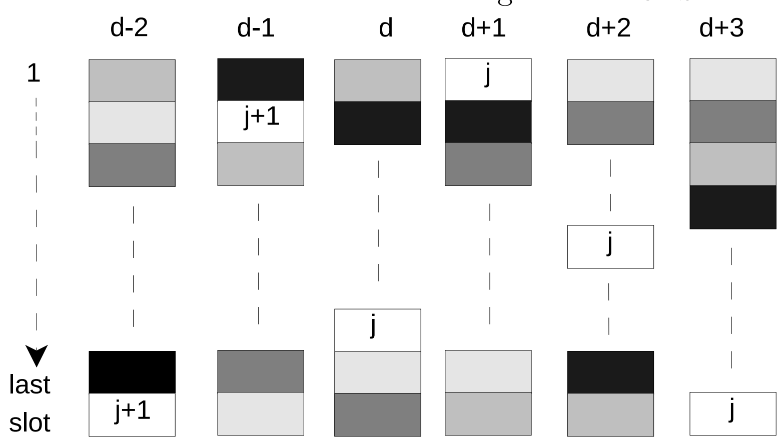

Figure 7.3: An illustration of how patients j and $j+1$ can be scheduled on a machine using the LNPF rule

Using the machine k and start date determined by the EarliestTreatmentStart procedure, Heuristic H4 determines if the patient j's completion date for the first fraction complies with the set treatment unit due date. If the patient j requires emergency treatment and the completion date for the first fraction exceeds the treatment unit due date by a number of days greater than $v_{1,j}$, a parameter denoting the maximum allowable number of days the patient can exceed the treatment unit due date, EarliestTreatmentStart is used again to determine the earliest start date by considering overtime slots on the machines. Similarly, if the patient j requires palliative treatment, a parameter $v_{2,j}$ is used to determine if EarliestTreatmentStart has to restart its search for the earliest start date using the overtime slots.

The most important part of Heuristic H4 deals with the patient j which requires radical treatment. If completion date for the first fraction determined using EarliestTreatmentStart in Step 5 of the Algorithm 7.8 exceeds the treatment unit due date by a number greater than $\upsilon_{3,j}$, Heuristic H4 updates the release date for the patient to $D_j^4 + \upsilon_{3,j}$ and restarts the search for the slots for the fractions by the EarliestTreatmentStart from this date. This strategy helps to minimise the $\overline{T}$ for these patients to values closer to $\upsilon_{3,j}$. In particular, if patients requiring radical treatments are allowed to use a given number of overtime slots, some of these patients can have starting dates closer to $D_j^4 + \upsilon_{3,j}$.

If patient j does not meet the due date D_j^4 by days less than $\upsilon_{3,j}$, the patient j is added to the set, R, of 'retained' patients. These 'retained' patients are the last to be scheduled as illustrated in Algorithm 7.8. The main purpose of this strategy was to reduce the number of days the appointments generated by the algorithm for patients that exceeded their due dates for the treatment unit by $\upsilon_{3,j}$ to a value closer to $\upsilon_{3,j}$. Furthermore, by 'retaining' some of the patients, the strategy aims to make some slots available for the next patient in the sequence since the 'retained' patients would already have missed their due dates.

7.2.5 Combined four heuristics

The four heuristic algorithms, Heuristic H1, Heuristic H2, Heuristic H3 and Heuristic H4 were interconnected into the framework in Figure 7.4. A sequence S, where $S = S_d^1$, is input into the system which begins with Heuristic H1 which generates two sequences of patients requiring treatment plans for the physics or pretreatment unit. Those requiring complex treatment plans are input into Heuristic H2. The sequence input into Heuristic H2 is also input into Heuristic H3 including the sequence of patients that needed simple treatment plans. Lastly, Heuristic H4 uses a sequence of patients which is the same as the input sequence. The results of the average waiting times, total overtime accrued on the machines and percentage of late patients are then collected from the schedules of appointments generated.

7.2.6 Time complexity of heuristics

The Heuristic H1 in Algorithm 7.1 takes as input a sequence of n_d patients. When S_d^1 is not ordered according to the planning unit composite rule, Step 2 in Algorithm 7.1 has to deal with the worst-case scenario. This step can be implemented using established sorting algorithms such as bubble sort, merge sort, quick sort and others for each PDR. Hence, the worst-case time complexity for Step 2 is of $\mathcal{O}(n^2)$ as demonstrated in the analysis of the time complexity of bubble sort and merge sort algorithms (Johnsonbaugh and Schaefer 2004).

One of the major steps in Heuristic H1 is Step 4 which is governed by the value of $|S_d^1|$. Assuming that $|S_d^1| = n$, Step 4 is executed $(n + 1)$ times. The other loops in the steps between Step 5 and 19 do not depend on the size n of the input sequence. Hence, for each patient j in the sequence, the Steps 5 to 19 may be executed a different number of times, but most of these steps are executed

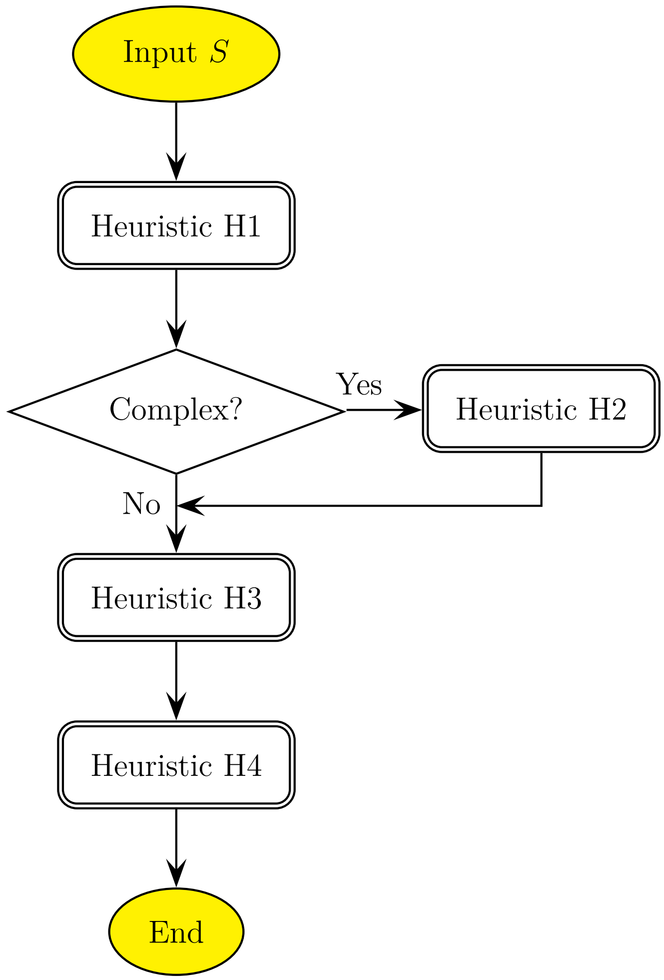

Figure 7.4: A flowchart illustrating how the four heuristic algorithms were combined

once for each patient j selected in Step 4. Therefore, the total time needed to run these steps can be given as a function of n, $f(n)$ as shown in Equation 7.2. In the worst case, $f(n) = \mathcal{O}(n)$ and thus, for Algorithm 7.1, the time complexity is $\mathcal{O}(n^2)$ because of the highest order terms given by Step 2 for the sorting of the input sequence.

$$\begin{aligned} f(n) &= (n+1) + b_1 + b_2 + b_3 + \ldots + b_n \\ &= n + (1 + b_1 + b_2 + b_3 + \ldots + b_n) \\ &\leq bn \end{aligned} \tag{7.2}$$

where $b_1, b_2, b_3, \ldots, b_n$ are constants representing the amount of time it takes to execute a step in the algorithm and b is a constant such that:

$$n + (1 + b_1 + b_2 + b_3 + \ldots + b_n) \leq bn \tag{7.3}$$

Like Heuristic H1, Heuristic H2 consists of just one sorting operation performed in Step 1 in Algorithm 7.5. All the other operations performed in the steps between Step 3 and 22 can be executed in a maximum of bn time units as shown in Equation 7.2. Therefore, the time complexity of the Heuristic H2 can also be expressed as $\mathcal{O}(n^2)$. Similarly, in Algorithm 7.6 the major steps for the Heuristic H3 include the Step 3 in which $\mathcal{O}(n^2)$ comparisons are made. The other steps including the loops are executed in bn times, where b is a constant. Hence, the time complexity of the Heuristic H3 can also be stated as $\mathcal{O}(n^2)$. The Heuristic H4 has one sorting operation done on the sequence S_d^4 in Step 1 in Algorithm 7.8. In the other steps, the sequence of patients (for example, R) is not resorted. Thus, the time complexity of the Heuristic H4 can also be estimated as $\mathcal{O}(n^2)$.

7.3 Alternative pathways

When the constraint that ensures a patient receives fractions on the same treatment machine is ignored, the machine environment is changed such that Subproblem 4 can be a typified as a different scheduling problem. The main motivation of ignoring this constraint involves determining the performance of the department with respect to the objectives such as average waiting time for patients received in a given period of time and the maximum number of times in the schedule of appointments that a patient has to be switched to different machines. Hence, it is necessary to examine some of the alternative pathways that can further complicate Subproblem 4. In this case, four alternative pathways were investigated which included:

1. Alternative pathway 1 (AP1): involves a scenario whereby it was presumed the doctor prescribed a specific treatment machine. The patient's appointments had to be scheduled on the available slots on this machine only.

2. Alternative pathway 2 (AP2): a scenario whereby the doctor prescribed the type of machine to be used to treat the patient. The patient's appointments were scheduled on several different machines of the same type.

3. Alternative pathway (AP3): same as AP1 but the patient was first scheduled on the specific machine prescribed by the doctor and other machines (i.e. of the same type) were considered only when the doctor prescribed machine was fully booked on a given date.

4. Alternative pathway (AP4): current scenario used at Arden Cancer Centre. Like AP2; however, the doctor prescribes the type of treatment machine and the patient's appointments for all the TOTAL_j fractions must be scheduled on one machine of this type.

In AP1, it was assumed that the doctor prescribed a specific treatment machine for a patient in the request forms. For example, the doctor may prescribe

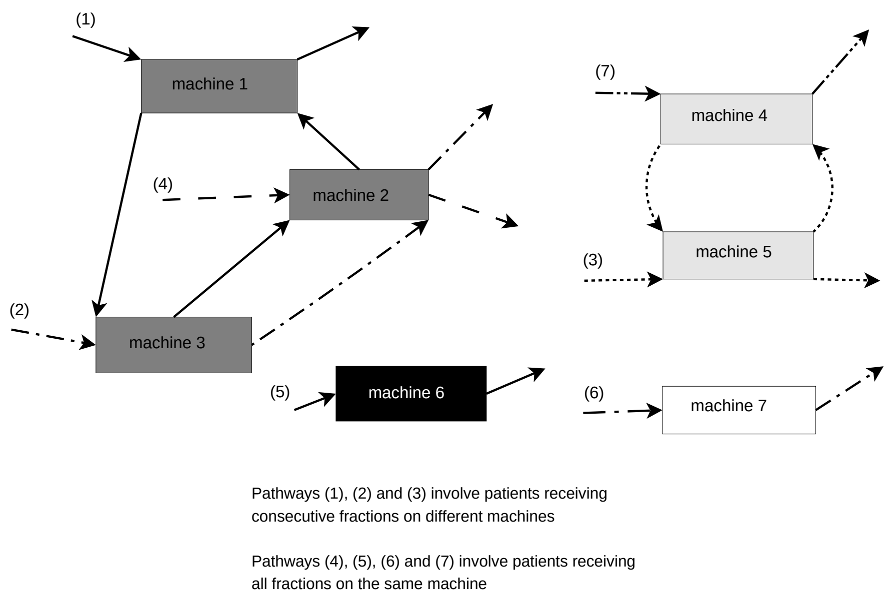

Figure 7.5: Possible patient pathways for AP2 which resemble an m-machine job shop, where $1 \leq m \leq 3$

HE linac 3 (i.e. HE3) for the treatment of patient j, meaning that all the fractions for j must be delivered on HE3. The procedure EarliestTreatmentStart in Algorithm 7.9 would then take as input the set $G_j^{type} = \{\text{HE3}\}$ whose cardinality (i.e. $|G_j^{type}|$) is always 1. In pathway AP1, Subproblem 4 can be considered as a single machine scheduling problem.

The second alternative pathway (i.e. AP2) considered involves a scenario whereby the doctor prescribed a treatment machine type, as is the current work practice at the Arden Cancer Centre, but with the constraint that all the fractions be delivered on the same machine relaxed. Thus, the patients can be switched on various treatment machines (i.e. of the specified machine type) to improve the quality of the schedules created with respect to the aforementioned performance measures. For example, if the doctor for patient j prescribed a HE linac for treatment, j can receive 6 of his or her fractions in the following pathway: HE3 $\rightarrow$ HE3 $\rightarrow$ HE1 $\rightarrow$ HE2 $\rightarrow$ HE3 $\rightarrow$ HE1. Figure 7.5 shows some of the pathways that can be taken by the patients when they are permitted to have consecutive fractions on different machines using different arrows.

The arrows labelled (1) denote the pathway which involves patients visiting machine 1 for some fractions then receive more fractions on machine 3 and then machine 2, before finishing the rest of the prescribed fractions on machine 1 again. Similarly, the pathway denoted by arrows labelled (2) involves patients visiting machine 3 for some fractions before finishing the rest of the fractions on machine 2. The arrows labelled (4), (5), (6) and (7) denote the pathways that involve patients visiting the same machine (i.e. machine 2, machine 6, machine

7 and machine 4, respectively) for all their prescribed fractions. In this context, Subproblem 4 becomes a m-machine n-patients JSP which can be classified using the Graham *et al.* (1979) classification scheme as follows.

The first field about treatment machine environment $\alpha = \alpha_1\alpha_2$ can be denoted as:

$\alpha_1 = J$ denotes that the environment resembles a job shop where a patient j can have fractions on several machines of the same type chosen by doctor l

$\alpha_2 = \circ$ because the number of machines of the type chosen by the doctor varies. For example, $\alpha_2 = 3$, $\alpha_2 = 2$ and $\alpha_2 = 1$ for high energy linacs, low energy linacs, and DXR or betatron, respectively,

In the second field $\beta = \beta_1, \ldots, \beta_6$ defines the patient characteristics for Subproblem 4 considering AP2 as follows.

$\beta_1 = \circ$. No preemption is allowed in the treatment of patients on any of the machines

$\beta_2 = \circ$. No requirement of any resource as a constraint.

$\beta_3 = \circ$. No precedence relation exist between patients being treated on the machines of the chosen machine type.

$\beta_4 = r_j^4$. Release dates for the patients vary.

$\beta_5 = \circ$. No upper bound on the number of fractions prescribed for the patients since patients can recirculate on any of the machines.

$\beta_6 = \circ$. There are no bounds on the processing times but p_{jk} is the same for all machines of $k \in G_j^{type}$.

The last field γ describes the objectives (i.e. X) of the subproblem which include minimising the amount of time each patient j takes from arrival in the unit to the time when the first fraction is to be done, amount of overtime accrued by the machines, and the number of patients that fail to meet their JCCO due dates. Hence, when AP2 is considered, Subproblem 4 can be described as $J|r_j^4|X$.

The problem $J|r_j^4|X$ can be solved using a modified Heuristic H4 which includes the function called EarliestTreatmentStart_AP2 shown in Algorithm 7.10. EarliestTreatmentStart_AP2 starts the search for a sequence of machines that give the earliest start date by selecting a machine k for each operation. From the Steps 1 to 22, the function uses each machine of that type including the one that would have been used for the previous fraction to search for the first available slot. EarliestTreatmentStart_AP2 then returns the sequence of machines for all the TOTAL$_j$ with their corresponding slots s_k and dates which are then used accordingly in the Heuristic H4.

Input: set of identical machines G_j^{type} and date d
Output: a sequence of machines with their available slots and dates

Set $G_j^{type^1} \leftarrow G_j^{type}$ {let $G_j^{type^1}$ be a set of the identical machines}
for each $k \in G_j^{type}$ **do**
  $h \leftarrow 1$ {first operation or fraction}
  $i \leftarrow 1$ {first treatment phase}
  while $i \leq$ TOTAL$_j$ and $h \leq h_j$ **do**
    Determine the first available slot s_k, $k \in G_j^{type^1}$ on date d and set $d_i \leftarrow d$
    $G_j^{type^1} \leftarrow G_j^{type^1} - \{k\}$
    while there is no available slot s_k **and** $G_j^{type^1} \neq \emptyset$ **do**
      Select a machine k from set $G_j^{type^1}$
      Determine the first available slot s_k, $k \in G_j^{type^1}$ on date d and set $d_i \leftarrow d$
      $G_j^{type^1} \leftarrow G_j^{type^1} - \{k\}$
    end while
    $G_j^{type^1} \leftarrow G_j^{type}$
    if there is no available slot s_k **then**
      Reset $i \leftarrow 1$, $G_j^{type^1} \leftarrow G_j^{type}$ and advance d to the next working day
    else
      Add machine k, $k \in G_j^{type}$ to the back of the sequence of machines with available slots on the dates $d_1, d_2, \ldots, d_i$
      If $i = 1$ and $h = 1$, set the completion date $C_{1j1k} \leftarrow d_1$
      Advance d to the next working day and increment i to the next fraction (i.e. $i \leftarrow i + 1$)
      If $i > f_{jh}$, then increment the treatment phases (i.e. $h \leftarrow h + 1$)
    end if
  end while
  Update the set of the sequences of the machines, slots and dates $d_1, d_2, \ldots, d_{TOTAL_j}$
end for
From the updated set of machine sequences, find the sequence of machines with the earliest start date C_{1j1k}, $k \in G_j^{type}$
return sequence of machines with their available slots and dates $d_1, d_2, \ldots, d_{TOTAL_j}$, where $d_1 = C_{1j1k}$, $k \in G_j^{type}$

Algorithm 7.10: EarliestTreatmentStart_AP2 procedure for finding a sequence of machines with the earliest treatment start date for TOTAL$_j$ fractions

When AP1 and AP2 pathways are combined, a case whereby the doctor prescribes a specific treatment machine but the patient is permitted to use other machines if the prescribed machine is not available can be considered. In such a case, the first fraction must always be scheduled on the specifically prescribed machine. Thereafter, the other fractions can be scheduled on other machines of the same type as the prescribed machine if the prescribed machine has no available slots. EarliestTreatmentStart_AP3 in Algorithm 7.11 is the heuristic used to determine the earliest treatment start date, C_{1j1k}, where k is the prescribed treatment machine. Subproblem 4 with this pathway (i.e. AP3) can also be classified as a $J|r_j^4|X$ problem and also illustrated using Figure 7.5.

Input: set of identical machines G_j^{type}, date d and k, where $k \in G_j^{type}$ prescribed by doctor l

Output: a sequence of machines with their available slots and dates

Set $G_j^{type^1} \leftarrow G_j^{type}$ {let $G_j^{type^1}$ be a set of the identical machines}
$i \leftarrow 1$ {first operation}
Starting from the date d, determine the first available slot s_k on the prescribed machine k, $k \in G_j^{type^1}$ to obtain date $d_i \leftarrow C_{1j1k}$
Add the machine k to the sequence of machines for the TOTAL$_j$ fractions
while $i \leq$TOTAL$_j$ **and** $h \leq h_j$ **do**
  $i \leftarrow i + 1$
  Advance date d_i to the next working day
  Determine an available slot s_k on the prescribed machine k on date d_i
  $G_j^{type^1} \leftarrow G_j^{type^1} - \{k\}$
  while there is no available slot s_k on machine k and $G_j^{type^1} \neq \emptyset$ **do**
    Select another machine k from set $G_j^{type^1}$
    Find the first available slot s_k on machine k, $k \in G_j^{type^1}$ on date d_i
    $G_j^{type^1} \leftarrow G_j^{type^1} - \{k\}$
  end while
  $G_j^{type^1} \leftarrow G_j^{type}$
  if there is no available slot s_k found on the machines **then**
    $i \leftarrow 0$ and set k to the prescribed machine k^1 {Restart from first fraction using k^1}
  else
    Add machine k to the back of the sequence of machines with available slots on the dates $d_1, d_2, \ldots, d_i$
    If $i = 1$ and $h = 1$, set the completion date of the first fraction on the machine k, C_{1j1k} to d_1
    If $i > f_{jh}$, increment the treatment phases (i.e. $h \leftarrow h + 1$)
  end if
end while
return sequence of machines with their available slots and dates $d_1, d_2, \ldots, d_{TOTAL_j}$, where $d_1 = C_{1j1k}$ and k is the prescribed machine

Algorithm 7.11: EarliestTreatmentStart_AP3 for finding the sequence of machines with the earliest treatment start date

7.4 Concluding remarks

This chapter has discussed the proposed constructive heuristics for each of the four Subproblems. The main motive for developing such approximate methods was to quickly build schedules of appointments for newly arriving patients using less computational effort. Prioritisation of patients using priority dispatching rules (PDRs), derived from the data on the request forms submitted by the doctors, can be useful in ensuring that those requiring critical treatment are at the head of the reordered list of patients. However, most of the PDRs devised can be considered as static rules (i.e. not time dependent) while some are dynamic rules (i.e. dependent on the changes in time).

Scheduling of patients in the reordered lists involved various strategies aimed at fast-tracking patients needing critical treatments. Some of these strategies were founded on some of the established algorithms for single and parallel machine scheduling problems in the literature. Four different pathways for Subproblem 4 were also identified (i.e. including the existing pathway) based on allowing patients to switch to other machines of the same type as prescribed by the doctors. Tests of the heuristics on such pathways can give indications of which ones can improve the performance measures. It is imperative to first determine the performance of the existing pathway (i.e. AP4) with regard to the performance criteria and also empirically determine values of the parameters in Section 6.2.

It can be noted that the four radiotherapy scheduling problems formulated can be adapted to any radiotherapy department in the UK because most departments use similar treatment processes and work practices to the ones discussed in Chapter 3. Some of the heuristics can be adapted to any such problems. For example, for a pretreatment unit problem comprising 5 desks where a maximum of 3 operations (i.e. calculations) have to be conducted, the Heuristic H3 can be applied. However, for the planning unit problem, as multiple CT scanners or simulators are added (i.e. more multiple unrelated machines in the second stage of the two-stage hybrid flowshop), the heuristics may need to be adjusted accordingly.

Chapter 8

Results

Contents

8.1 Introduction

This chapter presents and analyses the results obtained in different tests conducted with the constructive heuristics described in the previous Chapter. In these tests, the heuristics were incorporated into the DES model of the department discussed in Chapter 5 so that details of the patients generated by the model were input into the scheduling heuristics.

The DES model was also modified to accept the schedules of appointments generated by heuristics so that the movement of patients can be visually depicted in the model and assess their viability. Further, the DES model was run for several multiple runs using different random number seeds and the results of the performance criteria collected. Using the DES model in this way, different tests were conducted which included:

1) evaluating the performance of each of the PDRs in each of the four proposed constructive heuristics,

2) evaluating the values of the parameters such as: maximum number of days emergency, palliative and radical treatments were allowed to breach the JCCO due date, number of days between the completion of pretreatment and the JCCO due date, and tardiness in the planning unit,

3) finding the number of reserved slots for each treatment, and

4) comparison of various alternative pathways (i.e. AP1–4) using the performance criteria.

The tests on the PDRs were based on four different separate DES models for each of the four units of the department (see Figures 5.18–5.23). Comparisons of the alternative pathways involves scenarios AP1–4, defined in Chapter 7 using the same values of empirically determined parameters listed in Section 6.2. Since increased radiotherapy demand is expected in the next decade, as explained in Chapter 2, it is imperative that the performance of the heuristics be tested with increased numbers of newly arriving patients. Such tests involved using new patient arrival rates increased by 10%, 20% and 40%.

In the next Sections, the results for the tests are presented. Section 8.2 gives the results of the tests on the PDRs used in the proposed constructive heuristics. Section 8.3 demonstrates the capacity usage on each machine or facility on each day, particularly during the transient period. In Section 8.4, different combinations of the values of the parameters used in the tests are presented. Section 8.5 then discusses and analyses the results obtained from different tests conducted using the combinations of values of the parameters presented in Section 8.4. Section 8.6 compares the performance of the heuristics using different alternative pathway scenario that can be implemented in the treatment unit. Finally, Section 8.7 gives the concluding remarks.

8.2 Evaluating dispatching rules

DES models of each unit of the department were used to generate the inputs (i.e. patients) for the four constructive heuristics. Since new PDRs were being used for each first stage of the constructive heuristics, it was essential to evaluate their performance with regards to criteria such as average flowtimes, tardiness and waiting time to first fraction. Therefore, the second stage of heuristics were stripped out to simplify and minimise their influence on the results.

A stripped version of the Heuristic H1 was incorporated into the DES model for the planning unit. It was used to test the performance of the PDRs for prioritising patients in the sequence S_d^1, input into Heuristic H1, while minimising the impact of its 'scattering' strategies. It was assumed that no locum doctors (i.e. doctor $l = 13$) examined patients implying that no overtime slots were used. The arrival rate of patients for each day of the week in the planning unit was modelled using Poisson distributions whose parameters (i.e. the average number of patients arriving) were 10, 10, 11, 11, and 7 for Monday through to Friday, respectively. No transient period was considered to ascertain the performance of the PDRs without necessarily having to bring the model to a 'steady' state when the DES model was run.

For Heuristic H2 and Heuristic H3, the patient arrival rates were assumed to be the same as the one used for the planning unit. The DES model for the physics unit was also set to collect results for a year with the transient period set to zero. It was assumed that the mould room was always free so that the physics technicians were always available for the calculations only. The stripped version of Heuristic H3 did not include the strategy for scheduling patients requiring radical treatments on separate consecutive working days. It was possible for Heuristic H3 to generate schedules which had all the 3 appointments on a single day.

Heuristic H4 was stripped-down by making the following changes. The patients generated had the same arrival date a_j. The number of treatment machines was not changed and they all had a maximum of 30 slots. The strategy involving the use of the set, R, of 'retained' patients was excluded. No initial and other plan checks during treatment were included. The DES model for the treatment unit comprised patient arrival rates modelled using Poisson distributions, that took an average of 24 patients per day, an estimated average number of patients that visited the treatment unit machines for their fractions. In these tests, only AP1 was included in Heuristic H4 to ensure that the performance of the PDRs was not distorted by allowing patients to be switched to other machines.

The mean flowtime and tardiness are given in Tables 8.1 and Table 8.2. Mean tardiness results were determined by considering due dates assigned to each unit using Algorithms B.1–B.4 in Appendix B. In Tables 8.1 and 8.2, combined rules: MUPC and MUT, and MNSRP and MNOP, performed best for Heuristic H1. The FCFS and LS rules had were the same results because all the patients considered in these tests arrived at the same time and thus, were assigned the same due dates. For Heuristic H2, MUPC and MUT, FCFS and LDD produced the best results for patients requiring palliative, radical and all treatments, respectively. The closeness of results for FCFS and LDD can be attributed to the fact that most patients that required treatment plans from the physics unit were assigned to the same doctor. Protracted mean flowtimes for Heuristic H2 are due to the long processing time for each operation on the physics unit desk which means only 7 appointment slots are available per day.

Most of the patients had their pretreatment appointments booked on their arrival date because the mean flowtimes for Heuristic H3 were less than 1. The rules MUPC and MUT, and LNPO produced the best mean flowtimes for palliative and radical treatments respectively. For the mean tardiness objective, LS performed better than the other rules in Heuristic H3. For patients requiring palliative treatment, LS, and MUPC and MUT rules produced the least mean tardiness of 0.001 days compared to LNPO and FCFS. Finally, for Heuristic H4, the MUPC and MUT, and LNPTP and LNPF produced the best results, that is, 38.1 and 39.8 days (i.e. for the $\overline{MWT}$ objective) for palliative and radical treatments respectively.

Table 8.1: Comparison of the PDRs in the heuristics using mean flowtime and $\overline{MWT}$ (in days)

Heuristic	FCFS	MUPC + MUT	MNSRP + MNOP	LDD	LNPO	LS	LNPTP + LNPF	ETDD	**Treatment**
$H1$	5.22	5.05∗	5.24	-	-	5.22	-	-	Palliative
	6.23	6.25	6.20∗	-	-	6.24	-	-	Radical
	5.86	5.81∗	5.85	-	-	5.86	-	-	All
$H2$	100.46	99.57*	-	100.43	-	-	-	-	Palliative
	101.88*	102.44	-	101.91	-	-	-	-	Radical
	101.25*	101.26	-	101.25*	-	-	-	-	All
$H3$	0.20	0.10*	-	-	0.14	0.16	-	-	Palliative
	0.21	0.27	-	-	0.13*	0.14	-	-	Radical
	0.20	0.20	-	-	0.13*	0.15	-	-	All
$H4$	39.15	38.09*	-	-	-	-	38.38	41.36	Palliative
	40.50	40.88	-	-	-	-	39.83*	43.67	Radical
	40.04	39.97	-	-	-	-	39.40*	43.87	All

∗ *denotes the best value for each row*

Table 8.2: Comparison of the PDRs in the four heuristic algorithms using $\overline{T}$ (in days)

Heuristic	FCFS	MUPC + MUT	MNSRP + MNOP	LDD	LNPO	LS	LNPTP + LNPF	ETDD	**Treatment**
$H1$	0.87	0.80$\ast$	0.87	-	-	0.87	-	-	Palliative
	1.25	1.27	1.22$\ast$	-	-	1.25	-	-	Radical
	1.11	1.09$\ast$	1.09$\ast$	-	-	1.11	-	-	All
$H2$	95.92	95.05*	-	95.89	-	-	-	-	Palliative
	97.52*	98.06	-	97.55	-	-	-	-	Radical
	96.83*	96.83*	-	96.83*	-	-	-	-	All
$H3$	0.03	0.001*	-	-	0.01	0.001*	-	-	Palliative
	0.03	0.05	-	-	0.01	0.002*	-	-	Radical
	0.03	0.03	-	-	0.01	0.001*	-	-	All
$H4$	37.37	36.32*	-	-	-	-	36.59	39.55	Palliative
	38.67	39.15	-	-	-	-	38.11*	41.87	Radical
	38.29	38.22	-	-	-	-	37.66*	41.11	All

$\ast$ *denotes the best value for each row*

8.3 Used capacity in the transient period

It was imperative to determine the extent of capacity usage over the transient period. The usage of machines and facilities during the transient period can influence the results obtained during the results collection period. In this case, the DES model of the entire department with a transient period of 3 months and results collection period of a year was used. Less days were used for the transient period due to the heuristics incorporated in the DES model compared to the tests in Chapter 5. The transient period and results collection period used in the tests were determined with the help of the Simul8 which issues warnings if it deems a short or overlong transient period or results collection period were set.

The transient and results collection period included weekends, and service and maintenance dates for the machines. In Figures 8.1–8.6, the percentages of slots used on the machines and facilities over the transient period excluding weekends and/or service and maintenance dates are shown. The average percentage of used slots per given date were obtained from 10 different runs of the DES model using different random number seeds. CT scanner capacity utilisation is shown in Figure 8.1. Utilisations varied between peaks of 18% and lows of about 6%. Such utilisations of CT scanner capacity can be explained by its low usage for the 15 cancer diagnosis compared to the simulator as presented in Chapter 5.

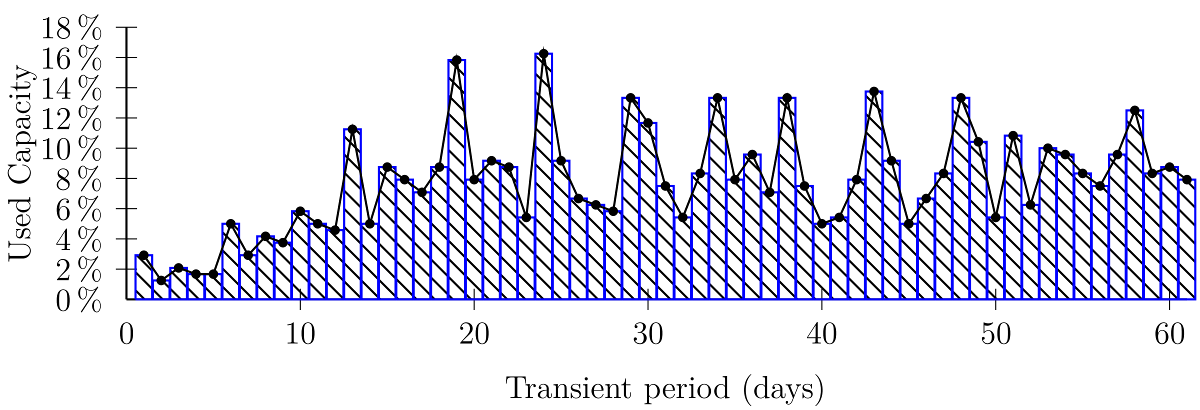

Figure 8.1: A plot of the percentage of capacity used on the CT scanner

Capacity usage on the simulator over the transient period is shown in Figure 8.2. Utilisation of the slots on the simulator during the transient period generally rises to about 50% with several peaks of between 80 and 90%. Data collected showed that more patients visited the simulator than the CT scanner. Hence, the average percentages of slots used on the dates were more than the CT scanner. Capacity usage of between 80 and 90% in Figure 8.2 can be explained by the use of overtime appointment slots for some patients when Heuristic H1 failed to obtain available slots during normal working hours.

For the DXR, capacity usage during the transient period is shown in Figure 8.3. By the end of the transient period, between 30% and 40% of its slots are

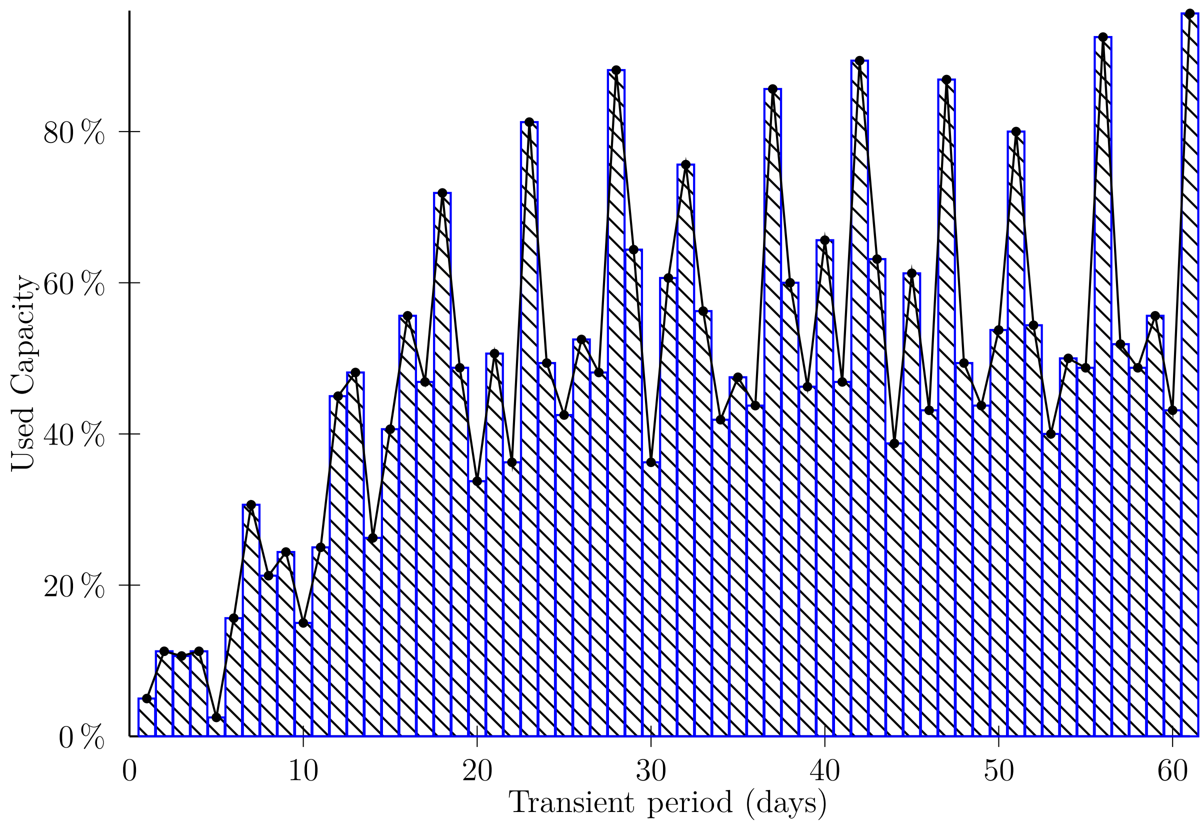

Figure 8.2: A plot of the percentage of capacity used on the simulator

booked. Although it is not the most visited machine as shown in Table 5.11 (i.e. except skin cancers), when results collection starts, the DXR has at least a third of its slots already booked. From about 0%, the total available slots used on the LE linacs rises to about 60% with several dates that peak at around 90% as shown in Figure 8.4. The peaks of up to 90% capacity usage represent some dates for weekly service and maintenance. LE linacs had half their normal capacity because they were out of service in the afternoon for the maintenance work.

Usage of capacity on HE linacs generally rises as the transient period progresses as shown in Figure 8.5. When the transient period terminates, the HE linacs have about 40% of the slots available for the day while the rest would be already booked for the patients that arrived earlier. Capacity usage pattern for LE and HE linacs is similar as shown in Figures 8.4 and 8.5. Like on LE linacs, the peaks of over 80% usage can be attributed to the weekly service and maintenance dates for the HE linacs which had almost half the capacity of a normal day. The mould room facility was rarely used compared to the CT scanner and simulator. Hence, in Figure 8.6, between 2 and 8% of the mould room slots were booked for patients during the transient period.

It can be concluded that when the results collection period commenced, ma-

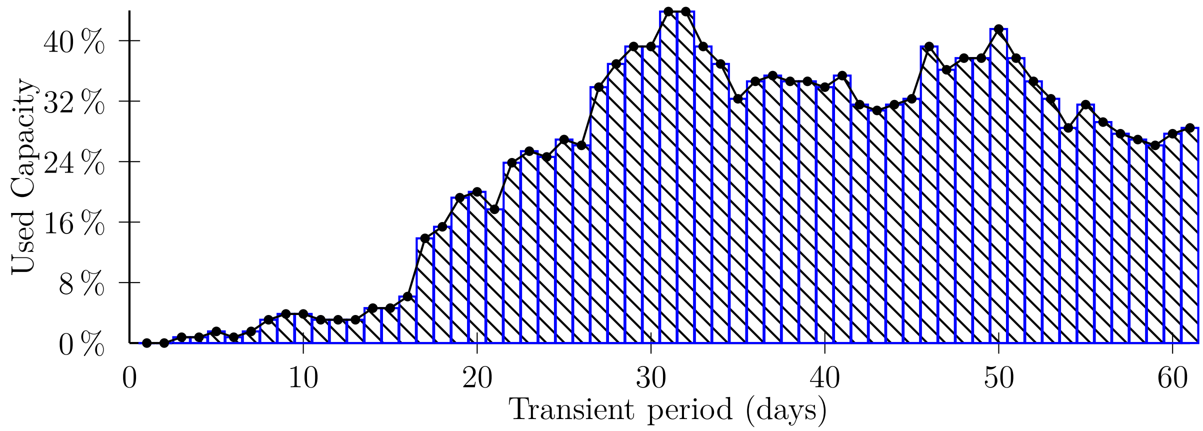

Figure 8.3: A plot of the pattern of capacity usage on the DXR during the transient period

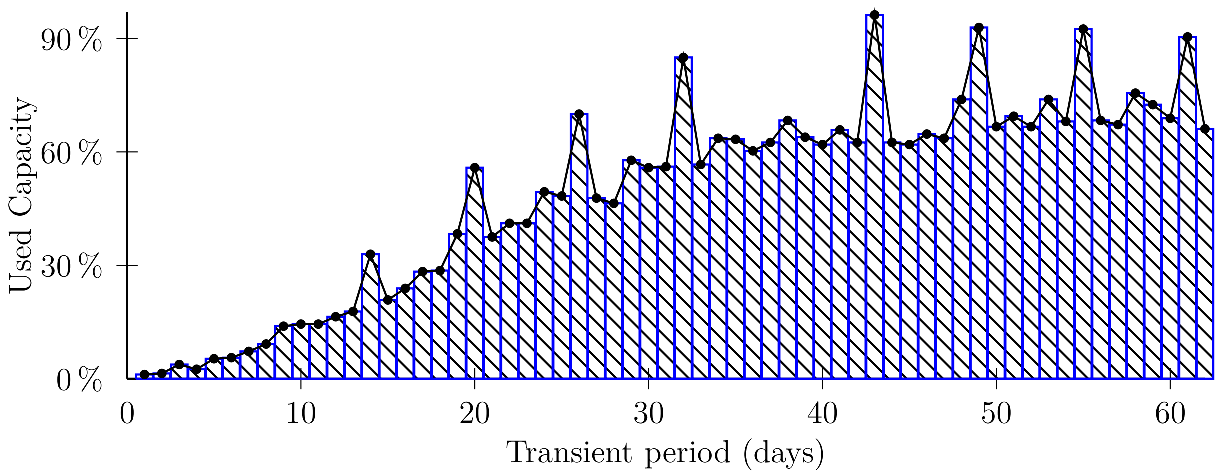

Figure 8.4: A plot of the pattern of capacity usage on one of the LE linacs

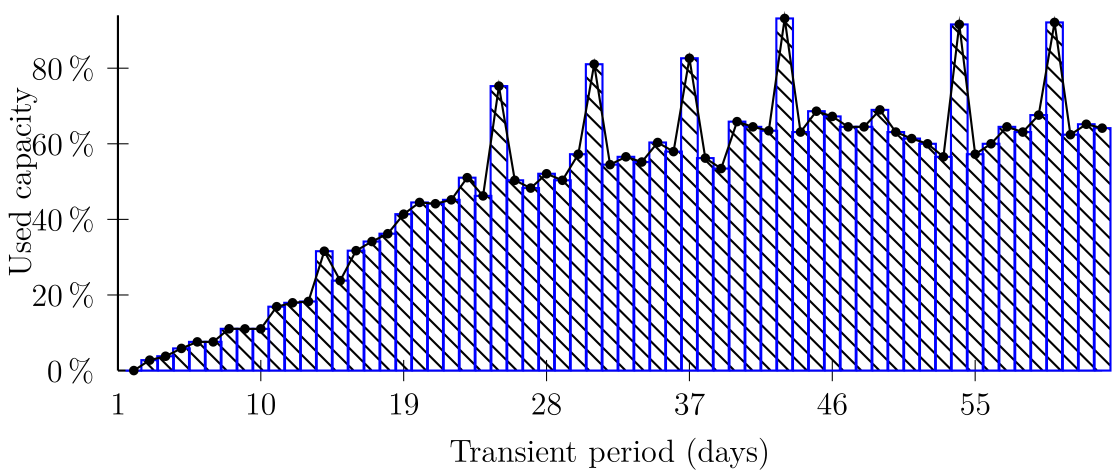

Figure 8.5: A plot of the percentage of used capacity for one of the HE linacs

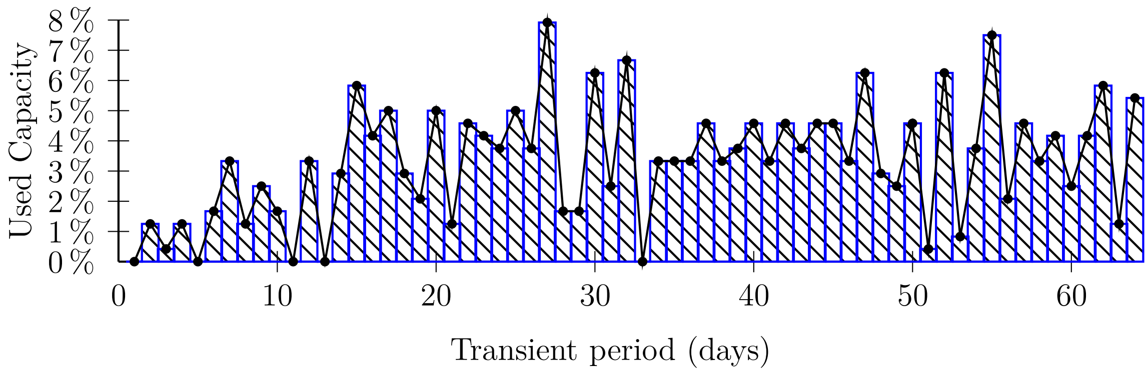

Figure 8.6: A plot of the pattern of capacity usage on the mould room

chines such as the linacs (i.e. HE and LE) and the simulator had about 40% of the slots on their schedule available for bookings. The CT scanner, DXR and mould room had more slots available for the bookings. Hence, the amount of slots that can be used to schedule patients on a given date on the machines after the transient period can be considered reasonable. The transient period was aimed at eliminating the bias caused by machines having completely available slots on a given date on their schedules.

8.4 Values of parameters

Parameters used by the heuristics include $\upsilon_{1,j}$, $\upsilon_{2,j}$, $\upsilon_{3,j}$, ω, μ_j and the number of reserved and overtime slots (o_k) for each of the treatments. $\upsilon_{1,j}$, $\upsilon_{2,j}$ and $\upsilon_{3,j}$ represent the maximum allowed number of days the JCCO target can be breached by a patient requiring either emergency, palliative or radical treatment, respectively. They were incorporated into Heuristic H4 to determine the members of the set, R (see Algorithm 7.8). ω was used in Heuristic H1 to determine if a patient had to be scheduled on overtime slots when the obtained planning date was not within the planning due date (see Algorithm 7.1). μ_j was used to spread appointments of patients requiring radical treatment over three consecutive working days (see Algorithm 7.6). It was essential that the values of these parameters be determined empirically, by setting them manually in the heuristics.

8.4.1 *Maximum allowed target breach*

There is no medically established threshold below which treatment delays are safe (Mackillop 2007). Hence, the waiting time targets recommended by the JCCO can be deemed to be short, but reasonably achievable (Joint Council of Clinical Oncology 1993). Literature on the treatment of various cancers (including those treated at the Arden Cancer Centre) showed that some studies have reported that waiting times of within 6 and 8 weeks (i.e. up to 42 and 56 days, respectively) for head and neck carcinomas, and breast cancers respectively, had lower local recurrence rates (Huang *et al.* 2003, León *et al.* 2003).

These studies reported positive effects of waiting times longer than the JCCO targets. It can be deemed that the JCCO targets are much tighter targets. In this context, a constraint which set the maximum allowed JCCO target breach (i.e. threshold of tolerated tardiness) was included in Heuristic H4 together with the strategy which involves the set, R. The purpose of this parameter was to prevent creating schedules in which a patient may have an unacceptably long waiting time before the start of treatment. Based on the waiting times more than the JCCO targets for certain cancers (i.e. treated at the Arden Cancer Centre) reported in (Huang *et al.* 2003, León *et al.* 2003), different combinations of the threshold of tolerated tardiness for each treatment were proposed, as shown in Table 8.3.

Table 8.3: Proposed maximum allowed JCCO target breaches (in days)

$\mathcal{T}$	$\upsilon_{1,j}$	$\upsilon_{2,j}$	$\upsilon_{3,j}$
1	0	0	0
2	0	3	7
3	0	3	14
4	0	7	14

$\mathcal{T}$ refers to combinations of $\upsilon_{1,j}$, $\upsilon_{2,j}$ and $\upsilon_{3,j}$

In Table 8.3, $\mathcal{T} = 2$ represents the scenario whereby patients requiring emergency treatments had to strictly adhere to the targeted JCCO waiting time always (i.e. $\upsilon_{1,j} = 0$), while 3 and 7 days (i.e. $\upsilon_{2,j} = 3$ and $\upsilon_{3,j} = 7$) were set to be the maximum number of days allowed to breach the waiting time targets for palliative and radical treatments, respectively.

8.4.2 *Reserved slots on treatment machines*

The department uses the block/slot approach to create schedules of appointments for the planning and treatment unit operations. In this study, the size of a slot for a machine or facility was estimated as the mean time taken to treat a patient on the machine or facility (see Chapter 6). It takes 15 and 12 minutes (see Table 6.1) to treat a patient on HE and LE linacs, respectively. Hence, the total number of available slots for booking treatment appointments of the high and low linacs on a normal working day are 29 and 36 respectively, since work (i.e. clinical treatments) starts at 9.20am and ends at around 4.30pm. For a machine such as the DXR whose normal working hours are between 9.20am and 12.40pm, there were 13 appointment slots on its schedule each day.

In Table 8.4, combinations of reserved slots applied to each of the three types of treatment machines namely, DXR, high and low energy linacs, for emergency, palliative and radical treatments are shown. The other machine type, betatron, was not included because it was rarely used (see Table 5.11). These combinations of reserved slots were only used in Heuristic H4 to hold a given number of available slots for the patients that need critical treatments such as emergency and palliative treatments that may arrive in the following dates.

Table 8.4: Proposed reserved slots on the treatment machines

$\mathcal{R}$	Emergency		Palliative		Radical		
	DXR	Linacs	DXR	Linacs	DXR	Linacs High	Linacs Low
1	0	0	0	0	0	0	0
2	1	1	3	3	9	25	32
3	1	1	3	6	9	22	29
4	1	1	6	6	6	22	29
5	1	1	6	12	6	16	23

$\mathcal{R}$ refers to combinations of the number of appointment slots reserved for each treatment

The allocation of reserved slots involved the use of three blocks of slots for the three treatments as depicted in Figure 8.7. Each block of slots only comprised a given number of slots which were not restricted to any particular time of the day. Patients requiring emergency treatment had access to all the slots on a machine on a given date. For example, in Figure 8.7, there were 29 slots available for the emergency treatments. For the patients that require palliative treatment, Heuristic H4 considered all slots on the machine excluding the number of slots in the block of slots reserved for emergency treatments, for each given date. Lastly, patients requiring radical treatment only had access to the number of slots in the block of slots reserved for radical treatments as illustrated in Figure 8.7.

The motivation of allocating slots available on a machine in this manner was the fact that 2%, 31% and 67% of all the patients treated in the department required emergency, palliative and radical treatments, respectively. Tests on Scenarios 2–4 in Chapter 5 showed that more patients requiring radical treatments arrive on each day and they tend to benefit when more capacity is made available. Therefore, if the available slots on a given date on a treatment machine are not reserved and or restricted, most of the slots on a given date can all be scheduled for patients requiring radical treatment.

8.4.3 *Number of overtime slots*

The practice of extending the working day can allow the machines to be used to full capacity to meet increased demand for radiotherapy. However, such practices may negatively impact the quality of service because of increased staff exhaustion and limited availability of other hospital services such as pharmacy, portering, medical and nursing cover, and transportation during these extended hours.

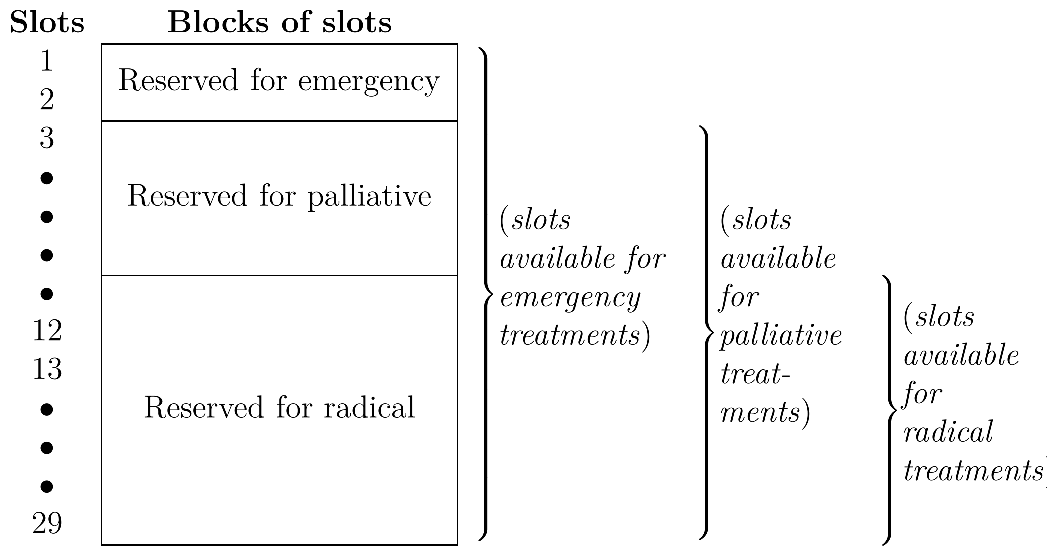

Figure 8.7: Reserved slots usage on the treatment machines in Heuristic H4

Generally, anytime outside the usual core working hours of a hospital department may affect patient care quality because the aforementioned hospital services are limited or unavailable. In such circumstances, most of the patients have to be seen and treated during the normal working hours.

Research on the use of overtime hours using data from some cancer centres showed that extending working days is cheaper than investing in new linacs (Routsis *et al.* 2006). It has also been shown that most patients prefer to be treated between 9.00am and noon; some departments have extended their working days to include the hours between 7.00am and 9.00am, and/or 5.00pm and 8.00pm to meet the increasing demand for radiotherapy (Calman *et al.* 2008). Hence, in this study it was assumed that the use of overtime slots offered a short-term practical approach to minimise the average waiting times.

The effects of using overtime slots on each treatment machine as well as the planning unit machines and facility were evaluated for each treatment. In Heuristic H1, overtime slots were used if no available slots were obtained on all the dates that the doctor would have been available to the department on or before the set planning due date. Heuristic H4 explores the overtime slots region if the obtained available treatment start date is greater than the treatment due date by values more than $\upsilon_{1,j}$, $\upsilon_{2,j}$ and/or $\upsilon_{3,j}$ for emergency, palliative and radical treatments, respectively.

As shown in Table 8.5, only patients needing emergency and palliative treatments have been permitted to access some of the overtime slots on a given date on the treatment machines. The purpose of permitting patients requiring emergency and palliative treatment to explore the overtime slots region for available slots in the cases were on a given date, the number of slots of the block of slots for radical treatments (see Figure 8.7) would have been already fully booked. In those cases, if Heuristic H4 is searching for available slots for patient j who requires emergency treatment and the number of slots of the block of slots reserved for palliative treatments is also fully booked, then Heuristic H4 explores the overtime slots region.

In Table 8.5, given a case where $\mathcal{O} = 2$, Heuristic H4 permitted the accruement of up to nearly thirty minutes of overtime on the treatment machines (i.e. the DXR, low and high energy linacs). In this case, translating the number of overtime slots into the time of the day shows that the treatment unit would be working until about 5.00pm. When $\mathcal{O} = 3$ and $\mathcal{O} = 4$, the machines would be working until about 5.30pm and 6.30pm, respectively.

Table 8.5: Proposed combinations of the amount of overtime slots for each treatment

$\mathcal{O}$	Emergency and Palliative			Radical
	DXR	Linacs		
		High	Low	
1	0	0	0	0
2	2	2	2	0
3	4	4	5	0
4	8	8	10	0

$\mathcal{O}$ is the combinations of number of overtime slots

8.5 Tests with parameter values

Using the entire system of the four heuristics, various tests with the parameters discussed in Section 8.4 were conducted. In these tests, the simulation model of the department included the number of arriving patients modelled using Poisson distributions for each of the seven days of the week. Poisson probability distribution was used to model new cancer referral rates in other research studies on radiotherapy waiting time issues (Thomas *et al.* 2001).

In the tests conducted, different combinations of the thresholds of tolerated tardiness for each treatment, reserved slots for the treatment machines and overtime slots to be used for the different treatments were used. In Tables 8.3, 8.4 and 8.5,

- $\mathcal{T}$ denotes combinations of the thresholds of tolerated tardiness from JCCO targets,
- $\mathcal{R}$ denotes combinations of the number of reserved slots for treatment machines, and
- $\mathcal{O}$ denotes combinations of overtime slots for each of the treatments.

The amount of time between the completion date for pretreatment unit operations and the JCCO due date for any patient j, μ_j was set to 7 and the number of days by which patient j could fail to meet the planning unit due date D_j^1, ω was set to 0. This means that the heuristics had to adhere to the due dates for the planning unit. Otherwise, patients had to be booked on overtime slots on the planning unit machines and facility.

In each test, the DES model of the department was run using the same transient and results collection period used in Section 8.3. Each experiment was repeated 10 times using a different random number seed for each run to increase the accuracy of the results and narrow the confidence limits. It was observed that more than 10 runs were tedious and time consuming since the simulation model developed can be considered a complex one.

8.5.1 Tests with maximum allowed target breaches

In these tests, the combinations of $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$ given in Table 8.3 were used to obtain the results of the average waiting times, average percentage of patients that would be late for the start of their treatment and the average penalty accrued for the use of overtime slots during the period when the DES model and scheduling system of heuristics was run.

The combination $(1, 1, 1)$ in Table 8.6 meant that Heuristic H4 did not consider maximum allowed time to breach the JCCO targets, no slots were reserved for each of the treatments and no overtime slots were made available. It produced the worst average waiting time results by 20% and 3% for $\overline{RW}^1$ and $\overline{RW}^2$, respectively. Some dates had patients requiring radical treatment scheduled on all the available slots. Hence, when those requiring emergency and palliative treatment arrived, there were no slots available on some immediate dates and consequently, their waiting times were prolonged. In Table 8.7, combination $(1, 1, 1)$ produced the worst average percentage of late patients for each treatment since the difference between the result for those who were late using $(1, 1, 1)$ and the other combinations was at least about 2% and 3% for emergency and palliative treatments, respectively.

Table 8.6: Average waiting times (with standard deviations) obtained from tests with combinations of $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$

$(\mathcal{T}, \mathcal{R}, \mathcal{O})$	$\overline{\mathbf{RW}}^{\mathbf{1}}$	$\overline{\mathbf{RW}}^{\mathbf{2}}$	$\overline{\mathbf{RW}}^{\mathbf{3}}$	$\overline{\mathbf{RW}}$
(1,1,1)	$1.2^\dagger$ (0.2)	$10.0^\dagger$ (0.2)	20.5 (0.1)	$16.8^\dagger$
(2,1,1)	1.0 (0.2)	9.7 (0.2)	20.5 (0.1)	16.6
(3,1,1)	1.0 (0.2)	9.7 (0.2)	20.5 (0.1)	16.6
(4,1,1)	1.0 (0.2)	9.7 (0.2)	20.5 (0.1)	16.6

† *denotes the worst results obtained*

Table 8.7: Average percentages (with standard deviations) of late patients obtained from tests with the combinations of $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$

$(\mathcal{T}, \mathcal{R}, \mathcal{O})$	**Emergency**	**Palliative**	**Radical**	**All**
(1,1,1)	25.0† (7.9)	17.0† (2.1)	1.0† (0.5)	7.0†
(2,1,1)	22.9 (8.8)	13.5 (1.6)	1.1 (0.2)	5.5
(3,1,1)	22.9 (8.8)	13.7 (1.8)	1.0 (0.2)	5.5
(4,1,1)	22.9 (8.8)	13.8 (1.9)	1.1 (0.1)	5.6

† *denotes the worst results obtained*

Patients requiring radical treatment occupied most of the slots on the machines such that there were no available slots for those requiring palliative treatment that arrived on later dates. The average percentage of the patients for emergency and palliative treatment were more than 20 and 13%, respectively compared to 1% for those needing radical treatment. The tests with combinations $(2, 1, 1)$, $(3, 1, 1)$ and $(4, 1, 1)$ produced the same average waiting times (i.e. for all treatments) which were 20% and 3% better for emergency and palliative treatments. This implies further changes to $\mathcal{T}$ (i.e. $\mathcal{T} = 3 or 4$) combinations had the same effect as strictly adhering to JCCO targets for emergency treatment but allowing patients to breach them by 3 and 7 days for palliative and radical treatments, respectively. Due to the fact that the radiotherapy department receives between 2500 and 3000 new patients (i.e. considered a large department) in a year, small increases or reductions in the average waiting times and percentage of patients for each treatment who were late can be considered to be significant.

Allowing patients to breach the JCCO targets by these values of $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$ enabled Heuristic H4 to ensure that some available slots that would have been booked for patients needing radical treatment became available for the patients requiring critical treatments (i.e. emergency and palliative) that arrived on the later dates. This improved the average percentage of late patients requiring emergency and palliative treatment by about 2 and 4%, respectively. The use of parameters $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$ also helped to minimise the tardiness of patients requiring radical treatment to about 7 or 14 days set in Table 8.3. Noticeably, the high standard deviations of the average percentages of late patients requiring emergency treatment in Table 8.7 were the result of the small number of patients scheduled differently depending on the available slots. High percentages of late patients for emergency treatments can be explained by the fact that most patients arrived on a Friday when no planning slots were available and hence, they were late for treatments because no there were no bookings for the weekends allowed.

8.5.2 Tests with reserved slots

The best results for the performance measures (i.e. average waiting times and percentage of late patients for each treatment) were obtained in the tests using combination $(2,1,1)$ (see Tables 8.6 and 8.7). This combination had the same average waiting times for each treatment, as combinations $(3,1,1)$ and $(4,1,1)$, but slightly better percentage of patients for palliative treatment who were late (13.5%). Therefore, further tests which involved the combinations of reserved slots for each treatment used the values of the parameters $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$ determined when $\mathcal{T}=2$ (see Table 8.3).

Tests with reserved slots involved using the combinations of reserved slots given in Table 8.4 and the results shown in Tables 8.8 and 8.9. Introducing the pattern of reserving slots in Figure 8.7 (i.e. in combinations (2,2,1) and (2,3,1)) marginally increased $\overline{RW}^2$ and $\overline{RW}^3$ by about 1 and 2%, respectively from the results obtained in combination $(2,1,1)$. No improvements in $\overline{RW}^1$ were made due to the patients received on Fridays when the planning unit machines were fully booked and had to be booked for treatment on Mondays or Tuesdays. For combinations (2,2,1) and (2,3,1), the strategy of reserving slots introduced had the effect of fully booking the patients requiring radical treatment on all the slots reserved for them on most of the dates during the year. This implies that when patients needing palliative treatment arrived, they were restricted to the block of slots reserved for palliative treatments only (see Figure 8.7). If this block of slots was also fully booked, the arriving patients needing palliative treatments had to be scheduled on further dates.

Combination $(2,4,1)$ improved $\overline{RW}^2$ by about 3% to 9.4 days and $\overline{RW}^1$ to 0.9 days. Tests with combination $(2,5,1)$ obtained good results for $\overline{RW}^1$ and $\overline{RW}^2$ but $\overline{RW}^3$ worsened to 21.5 days. This was a result of reserving more slots for palliative treatments at the expense of radical treatments as shown in Table 8.4. The number of slots available for radical treatments was reduced meaning that fewer patients requiring radical treatment could be scheduled on a machine on a given date. Tests with combination $(2,4,1)$ produced the best average percentage of the patients who were late results for all the three treatments. The average percentage of late patients needing radical treatment improved by more than 40% from the results obtained for combination (2,1,1).

Table 8.8: Average waiting times (with standard deviations) obtained for tests with reserved slots when $\mathcal{T}=2$

$(\mathcal{T},\mathcal{R},\mathcal{O})$	$\overline{\mathbf{RW}}^{\mathbf{1}}$	$\overline{\mathbf{RW}}^{\mathbf{2}}$	$\overline{\mathbf{RW}}^{\mathbf{3}}$	$\overline{\mathbf{RW}}$
(2,1,1)	1.0 (0.2)	9.7 (0.2)	20.5 (0.1)	16.6
(2,2,1)	1.0 (0.2)	9.8 (0.2)	20.8 (0.04)	16.9
(2,3,1)	1.0 (0.2)	9.8 (0.2)	20.9 (0.04)	17.0
(2,4,1)	0.9∗ (0.2)	9.4∗ (0.2)	20.8 (0.1)	16.8
(2,5,1)	1.0 (0.2)	9.4 (0.1)	21.5 (0.3)	17.2

∗ *denotes the best results obtained*

Table 8.9: Average percentages (with standard deviations) of late patients obtained from tests with reserved slots when $\mathcal{T} = 2$

$(\mathcal{T}, \mathcal{R}, \mathcal{O})$	**Emergency**	**Palliative**	**Radical**	**All**
(2,1,1)	22.9 (8.8)	13.5 (1.6)	1.1 (0.2)	5.5
(2,2,1)	22.9 (8.8)	15.5 (2.3)	1.1 (0.2)	6.2
(2,3,1)	22.9 (8.8)	15.4 (1.9)	1.2 (0.2)	6.2
(2,4,1)	22.5∗ (8.8)	13.0∗ (1.6)	0.6∗ (0.2)	5.0∗
(2,5,1)	22.9 (8.8)	13.0 (1.6)	1.1 (0.4)	5.3

∗ *denotes the best results obtained*

8.5.3 Tests with overtime slots

Tests on the number of overtime slots given in Table 8.5 when $\mathcal{T} = 2$ and $\mathcal{R} = 4$ were conducted and the results are shown in Tables 8.10 and 8.11. These tests were aimed at finding the minimum amount of time that can be added to normal working hours of the treatment unit in order to improve the performance of the heuristics. The results obtained showed a marginal increase in $\overline{RW}^1$ to 1.0 days. When overtime slots were used in Heuristic H4, most of the patients requiring palliative treatment were booked on them before the those patients needing emergency treatment arrived. The strategy for reserving slots used meant that most overtime slots were booked for the palliative treatments leaving only the block of slots reserved for emergencies available (see Figure 8.7). If this block did not have sufficient slots to cover the number of arriving patients requiring emergency treatment, Heuristic H4 had to advance its search for available slots to the next dates.

Tests with combination $(2, 4, 2)$ worsened average waiting times (i.e. by about 1, 4 and 1% for $\overline{RW}^1$, $\overline{RW}^2$ and $\overline{RW}^3$, respectively) and percentages of patients late for each treatment (i.e. about 3% for palliative treatment) as shown in Tables 8.10 and 8.11. This behaviour of the scheduling heuristics is different from that observed in Chapter 5 in the scenario tests whereby more capacity added resulted in improvements in the performance criteria for one of the treatments. It is essential to determine the necessary number of overtime slots because adding a few such as just 2 additional slots on each machine resulted in the worsening of the performance criteria. There are dates when most patients needing emergency or palliative treatments arrived. When more patients needing palliative treatment arrived, the strategy of reserving slots enabled these to be booked on most of the day. Hence, forcing those needing radical treatments to be booked on later dates and also restricting those for emergency treatment to the block of slots reserved for them.

The results obtained using combination $(2, 4, 4)$ were slightly better than those for combination $(2, 4, 3)$ because the average percentage of late patients for palliative and radical treatments improved to 12.9 and 0.6%, respectively. Further,

Table 8.10: Average waiting times (with standard deviations) obtained from tests with overtime slots, when $\mathcal{T} = 2$ and $\mathcal{R} = 4$

$(\mathcal{T}, \mathcal{R}, \mathcal{O})$	$\overline{\mathbf{RW}}^1$	$\overline{\mathbf{RW}}^2$	$\overline{\mathbf{RW}}^3$	$\overline{\mathbf{RW}}$
(2,4,1)	0.9∗ (0.2)	9.4 (0.2)	20.8 (0.1)	16.8∗
(2,4,2)	1.0 (0.2)	9.8 (0.2)	21.1 (0.1)	17.2
(2,4,3)	1.0 (0.2)	9.3∗ (0.2)	20.8∗ (0.1)	16.8∗
(2,4,4)	1.0 (0.2)	9.3∗ (0.2)	20.8∗ (0.1)	16.8∗

∗ *denotes the best results*

Table 8.11: Average percentages (with standard deviations) of late patients obtained from tests with overtime slots, when $\mathcal{T} = 2$ and $\mathcal{R} = 4$

$(\mathcal{T}, \mathcal{R}, \mathcal{O})$	**Emergency**	**Palliative**	**Radical**	**All**
(2,4,1)	22.5 (8.8)	13.0 (1.6)	0.6 (0.2)	5.0
(2,4,2)	23.8 (7.9)	15.5 (1.9)	1.5 (0.3)	6.4
(2,4,3)	22.9 (8.8)	13.0 (1.7)	0.7 (0.2)	5.0
(2,4,4)	22.9 (8.8)	12.9∗ (1.8)	0.6∗ (0.2)	4.9∗

∗ *denotes the best results*

for combinations (2,4,3) and (2,4,4), the average waiting times obtained were the same. In other words, the results can be translated as follows. If the treatment machines are allowed to continue treating patients until 5.30pm, the average waiting times obtained would be the same as when the working hours are extended to about 6.30pm. Therefore, given the costs incurred when staff work longer overtime working hours, combination $(2, 4, 3)$ can be considered to have produced the best results with respect to the average waiting times for each treatment.

8.5.4 Tests with increased arrival rates

Research studies conducted between 2000 and 2010 reported an expected rise in cancer incidences by about 20% in the UK due to changes in demographics and other reasons (Royal College of Radiologists 2003, Ash *et al.* 2004, Dodwell and Crellin 2006). Further tests were conducted to ascertain the performance of the heuristics with increased patient arrival rates. To mimic increased demand, the DES model had its arrival rates (i.e. parameters of the Poisson distributions) changed by various percentages. Using some of the expected percentage rises in cancer incidences given in Table 2.5, increases in arrival rates by 10% and 20% (i.e. greater than expected in (National Radiotherapy Advisory Group 2007*b*)) were chosen. To further ascertain the performance of the heuristics, tests with the 40% increase were also performed. Combinations of the values of the parameters $\upsilon_{1,j}$, $\upsilon_{2,j}$, and $\upsilon_{3,j}$, number of reserved and overtime slots for each treatment were set to $\mathcal{T} = 2$, $\mathcal{R} = 4$ and $\mathcal{O} = 3$, respectively.

Generally, as the arrival rates of new patients were increased, $\overline{RW}^1$ gradually worsened by between 10 and 20% (see Tables 8.12 and 8.13 for results). For $\overline{RW}^2$, the results showed an aspect akin to one observed in Table 8.10 whereby after an increase of arrival rates by 20%, $\overline{RW}^1$ marginally improved to 9.9 days. An increase in the arrival rates, increased the number of patients requiring emergency treatments especially those arriving on Fridays. Most of these patients were late for their treatment due to the limited capacity available on the planning machines due to the availability of their doctors.

Table 8.12: Average waiting times (with standard deviations) obtained for tests using increased arrival rates

Increase (%)	$\overline{\mathbf{RW}}^{\mathbf{1}}$	$\overline{\mathbf{RW}}^{\mathbf{2}}$	$\overline{\mathbf{RW}}^{\mathbf{3}}$	$\overline{\mathbf{RW}}$
0	1.0∗ (0.2)	9.3∗ (0.2)	20.8∗ (0.1)	16.8∗
10	1.2 (0.2)	10.1 (0.1)	21.5 (0.4)	17.3
20	1.3 (0.2)	9.9 (0.2)	21.5 (0.3)	17.2
40	1.5 (0.3)	10.4 (0.4)	22.7 (0.3)	18.2

∗ *denotes the best result*

Table 8.13: Average percentages (with standard deviations) of late patients obtained for tests using increased arrival rates

Rise (%)	**Emergency**	**Palliative**	**Radical**	**All**
0	22.9∗ (8.8)	13.0∗ (1.7)	0.7∗ (0.2)	5.0∗
10	22.9∗ (5.9)	17.5 (0.5)	2.2 (1.3)	7.6
20	23.6 (6.2)	14.8 (2.0)	1.2 (0.4)	6.2
40	25.2 (5.1)	16.6 (2.0)	4.3 (1.4)	8.8

∗ *denotes the best result*

After increasing the arrival rates by 20%, $\overline{RW}^2$ showed the aforementioned nonlinear increase effect. The increase in arrival rates resulted in more patients requiring palliative arriving on some dates such that they were booked on most of the slots on subsequent dates to the detriment of those needing emergency and radical treatments. However, after increasing the arrival rates by 20%, such patients requiring emergency treatment were affected more than those requiring radical treatments because of the improvement to 1.2% by the average percentage of late patients for radical treatments.

The result for $\overline{RW}^3$ remained the same (i.e. for 10% and 20% increments to arrival rates. It can be concluded that when more patients requiring palliative treatment arrive, the heuristics books them on more immediate slots to the detriment of those requiring radical treatments. There were more dates when more patients needing palliative treatment arrived compared to those needing radical treatment. About a quarter of the patients who needed emergency treatment when arrival rates were adjusted by 40% were late for their treatment. In this case, there were more late patients that needed radical treatment than in any other case (i.e. of increased arrival rates) tested. The average waiting times produced by the heuristics in these tests were all below the targeted JCCO targets. This implies that even after increasing the arrival rates by 40%, the heuristics still produced results that can be considered good and within the JCCO targets.

8.6 Tests with pathways

The heuristics were tested using the 3 other pathways: AP1, AP2, and AP3 with the parameters set to the values determined by the tests with AP4 (i.e. existing pathway). This means that in these tests, $\mathcal{T} = 2$, $\mathcal{R} = 4$ and $\mathcal{O} = 3$. Figures 8.8 and 8.9 show the results of the tests with the pathways. All the four pathways obtained $\overline{RW}^1$ results within the JCCO target of 2 days. The worst result of 1.6 days for $\overline{RW}^1$ was obtained with AP1 while the best result was obtained with AP4. For $\overline{RW}^2$, AP1 did not meet the JCCO target of 14 days while AP2 and AP3 had the same result of about 10 days. The best result of about 9.3 days was obtained with AP4. The best $\overline{RW}^3$ was obtained with AP2 while the AP1 had the worst result. However, AP2–4 had $\overline{RW}^3$ results which were within the JCCO target of 28 days.

AP2 improved $\overline{RW}^3$ by nearly 35% from the results obtained with AP4. Since most of the patients treated in the department needed radical treatment, the number of slots in the block of slots reserved for radical treatments (see Figure 8.7) are quickly fully booked on most immediate dates on the machines of the type chosen by the doctor. This restricted most patients requiring palliative treatment to the number of slots reserved for them and overtime slots only on most of the machines. Hence, AP4 performed better than AP2 with respect to $\overline{RW}^2$ because the patients requiring radical treatments were booked in a manner that made slots available on the immediate dates for those requiring palliative treatment.

The pathway scenario AP3 improved the performance of AP1 with respect to $\overline{RW}$, $\overline{RW}^1$, $\overline{RW}^2$ and $\overline{RW}^3$. When the machine prescribed by the doctor is fully booked, the patients are scheduled on other machines of the same type and thus, making slots that would have been used on later dates available for other patients that arrive on the next dates. In Figure 8.9, all the four pathways had relatively large average percentage of patients late for their emergency treatments due to the patients such treatment who mostly arrived on Fridays as discussed earlier. The targeted waiting time for those requiring emergency treatment was 2 days but in this case their treatment was expected at least after 3 days. Further, $\mathcal{R} = 4$, comprised one slot reserved for emergency treatments and thus, on a Friday, if two or more such patients arrived and the machines were fully booked, then some of these patients would be late by more than 3 days.

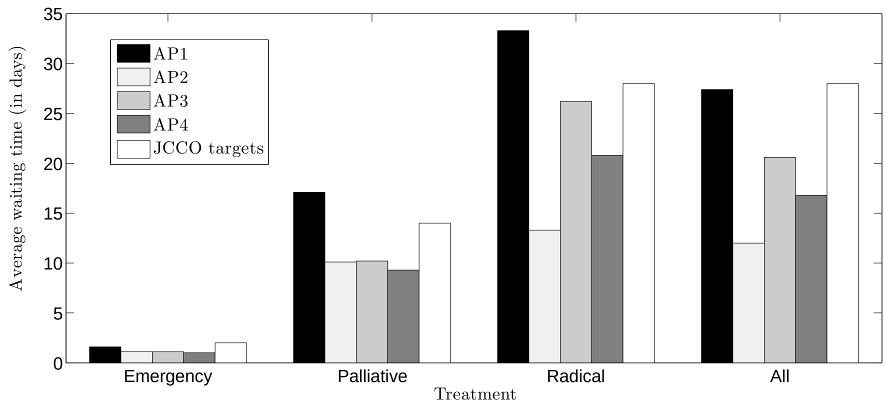

Figure 8.8: A plot of the average waiting time results obtained from tests with the four pathways

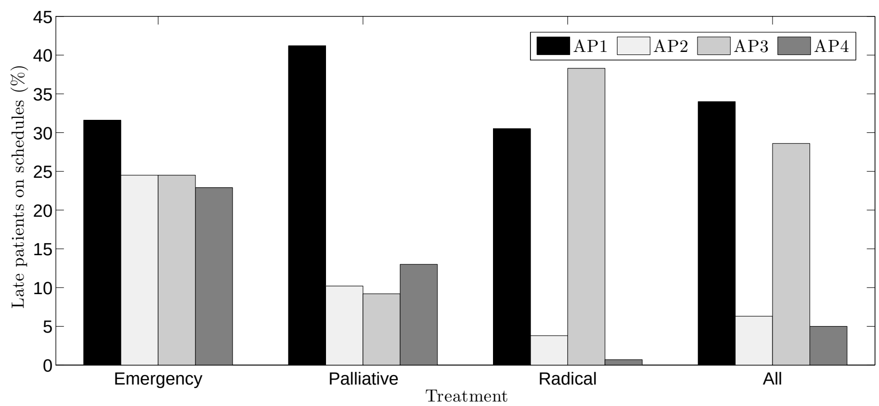

Figure 8.9: A plot of the average late patients (%) obtained from tests with the four pathways

For palliative treatments, AP1 had the worst result with about 40% expected to be late for treatment. AP3 was marginally better than AP2 for palliative treatment. For radical treatment, AP4 had the best result of less than 2% AP4 while AP3 had the worst result (i.e about 40%). AP4 had problems with the uncertain arrival of patients needing palliative treatment. Most of the time when some of these patients arrived there were fewer slots available to book all of their appointments within the targeted waiting times. However, for AP2 and AP3, some of these patients had more slots available on which they were booked for treatment.

AP1 accumulated the highest number of overtime slots (i.e. converted into days) compared to the other three pathways as shown in Figure 8.10. It is worth noting that the overtime incurred in the 3 pathways (i.e. AP2, AP3 and AP4) was from the planning unit where patients could not meet their planning unit deadlines and thus, exceeded the values of the parameter ω (which was set to 0) and had their appointments scheduled on overtime slots. In the case of AP1, most of the overtime was from the treatment unit where patients requiring emergency and palliative treatment made use of the overtime slots. Hence, it can be concluded that the pathways AP2, AP3 and AP4 minimise the use of overtime slots in the treatment unit and also improve the average waiting time of the patients.

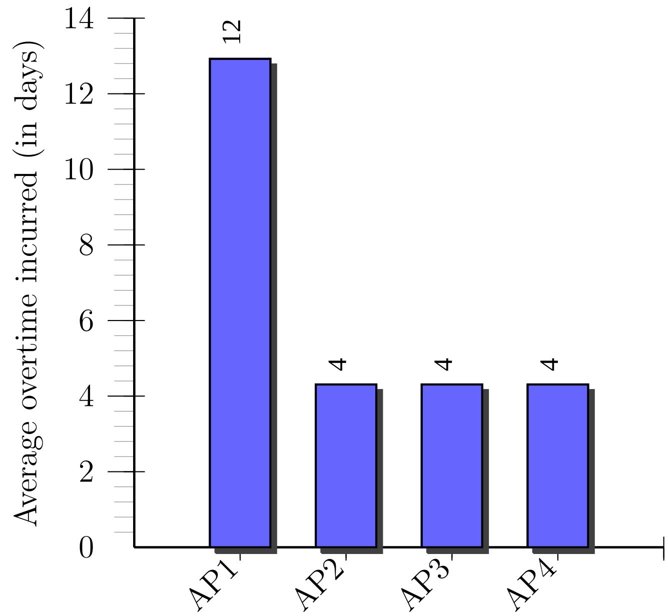

Figure 8.10: A plot of the average amount of overtime ($\overline{U}$) for each of the four pathways

8.7 Concluding remarks

This chapter discussed results of several tests performed to determine values of the parameters in Section 6.2 and compare the heuristics using the four pathways (i.e. AP1–4) of the treatment unit stated in Section 7.3. Tests on the PDRs for reordering the list of newly arriving patients demonstrated that rules such as the most urgent patient category (MUPC), most urgent treatment (MUT), least number of pretreatment operations (LNPO), least doctor delay (LDD), least number of prescribed treatment phases (LNPTP) and least number of prescribed fractions (LNPF) produced good results for the mean flowtime and/or mean tardiness objectives. Using the existing pathway (i.e. AP4), the heuristics improved the average waiting times of obtained from the historical data discussed in Chapter 5 by 50%, 34% and 41% for the emergency, palliative and radical treatments, respectively. Generally, it can be expected that as more patients arrive, the heuristics performances worsen. Even after 40% increase in the newly arriving patients (i.e.

to mimic increased demand), the heuristics produced average waiting times below the JCCO targets for each treatment.

It can be concluded that the strategy of reserving slots by ensuring that patients requiring emergency and palliative treatments had access to more slots on a given date on the machines did not hugely affect average waiting times for those who requiring radical treatment. This implies that the uncertain arrival of patients and notably, the fact that the greater proportion of these patients need radical treatment, poses challenges to strategies of scheduling their appointments. Therefore, it is essential that further studies consider applying intelligent algorithms such as the metaheuristics briefly discussed in Chapter 4 to outwit such aspects of the radiotherapy scheduling problems.

Chapter 9

Conclusions and suggestions for further work

Contents

9.1 Summary and conclusions

This thesis was founded on the treatment processes in the radiotherapy department at the Arden Cancer Centre located at the University Hospitals Coventry and Warwickshire NHS Trust, UK. The elaborate steps of the radiotherapy process in the UK are conducted in four units which are generally termed: planning, physics, pretreatment, and treatment units. Insight into the entire radiotherapy problem was gained by developing and using discrete-event simulation (DES) models of the radiotherapy department helped to characterise four subproblems from the four units. Although the DES models helped in identifying bottlenecks and other issues from the treatment processes, it was imperative to propose an approach for scheduling newly arriving patients in order to minimise waiting times and the number of patients expected to fail to meet their targeted due dates.

To solve the entire radiotherapy scheduling problem using the scheduling approach, four subproblems for each of the four units have been characterised as shop scheduling problems. These problems have been solved using constructive heuristics based on two-steps: 1) reordering the list of newly arriving patients using priority dispatching rules (PDRs), and 2) applying strategies for freeing slots so that patients requiring critical treatments can be booked on them. These heuristics have been incorporated into the DES model to schedule patients generated daily in several tests aimed at minimising the average waiting times for each treatment, average percentage of patients late for their treatments and the amount of overtime slots used on the machines. Amongst these tests, it was imperative to test the performance of the heuristics on the different pathways patients can follow in the treatment unit.

The following conclusions can be drawn:

- The entire radiotherapy scheduling problem which includes all the four units of a typical radiotherapy in the UK was considered.
- As proposed by some researchers, this study has shown that the radiotherapy scheduling subproblems can be typified as production scheduling problem models with several unique attributes that enable them to be classified as intrinsically hard problems. This study has broadened the research on the radiotherapy scheduling problem by characterising the subproblems as two-stage hybrid flowshop, flowshop, mixed shop and multiple identical parallel scheduling problems.
- The new constructive heuristics developed for the subproblems generated schedules whose average waiting times for emergency, palliative and radical treatments improved considerably by about 50%, 34% and 41%, respectively, compared to the historical data collected in 2008.
- The constructive heuristics achieved such improvements in the average waiting times, the average percentage of patients late for each treatment were about 23%, 13% and 1% for emergency, palliative and radical treatments respectively. Such results for emergency and palliative treatments can be considered high relative to the number of patients that require these treatments received (i.e. only 2% and 31% for emergency and palliative treatment respectively).
- Strategies for ensuring patients requiring critical treatment are treated quickly upon arrival at the radiotherapy department are essential. In this context, the constructive heuristics included strategies for ensuring that slots were available for patients needing emergency and palliative treatments. These include:
  - allowing maximum breaches on the targeted due dates for patients requiring palliative and radical treatments respectively.
  - reserving some slots on the treatment machines for a given day for the patients requiring emergency and palliative treatments respectively, to reduce the number of patients requiring radical treatment that can be booked on a given date for a machine since 67% of the patients received at the Arden Cancer Centre required radical treatment.
  - allowing overtime slots to be used on the treatment machines.
- It has been shown that the list of newly arriving patients can be prioritised using more composite priority dispatching rules (PDRs) based on the details on the request forms which include: the least number of pretreatment

operations, least number of prescribed treatment phases and least number of prescribed fractions.

- This study has also shown that extent of historical data requirements for the development of the DES models. Further, unlike other DES studies of the radiotherapy treatment processes, in this study, the DES models were for all the treatment processes of a radiotherapy department (i.e. external beam therapy, brachytherapy and unsealed sources therapy).

- The development of DES models also helped in determining several probability distributions for estimating uncertain data such as the processing time of the machines.

9.2 Suggestions for further work

This study has broadened the radiotherapy scheduling problem discussed in the literature by including all units in a typical radiotherapy department in the UK. The few papers on the problem from one of the units applied constructive heuristics and mathematical programming methods. Since the four radiotherapy scheduling problems from the units have been characterised as shop scheduling problem models, there are many methods amenable them. There are several OR optimisation methods that can be used to solve the four subproblems, either separately or as a whole. To contribute more to the theory and practical aspects of solving radiotherapy patient scheduling problems, there are directions for further work that can be suggested.

- The constructive heuristics proposed in this study did not include several aspects of the real-world radiotherapy scheduling problem such as:

  - anticipating that a given patient may fail to attend an appointment,
  - elective patient's preference for being treated in morning, afternoon, or on certain days of the week, and/or
  - rescheduling of the patients that missed appointments.

  When these aspects of the real-life problem are included, the subproblems become more complex. Therefore, it can be suggested that these aspects be included in one subproblem after the other. Further, this study involved the use of a DES model to generate newly arriving patients each day using probability distributions derived from the collected data. It can be noted that the heuristics proposed generate schedules for patients without the use of look ahead techniques for anticipating how many patients of each treatment might arrive in the succeeding days.

- Future research on the radiotherapy scheduling problem should consider using actual time rather than slots from the start of the day to the time the machine is supposed to be shutdown (i.e. for the end of the day or service and maintenance). The use of actual processing times for the machines and facilities helps to create more compact schedules compared to the use of slots which may lead to unused slots. It can be interesting if the radiotherapy scheduling problem is considered as an economic lot scheduling problem whose main objective is to minimise waiting times and solved using lot-sizing techniques. Lot-sizing techniques have been used in manufacturing to minimise inventory holding costs. In this context, the patient waiting times can be likened to the inventory holding costs.

- The constructive heuristics used in this study can be considered as an important starting point. Frontiers of the research on aspects of the radiotherapy scheduling problem should consider the application of meta-heuristics that are computationally efficient to generate the schedules of appointments for each sequence of patients that is submitted for booking. As a starting point, the metaheuristics can be applied to each of the four subproblems and then the entire radiotherapy patient scheduling problem. When considering the entire problem, it is imperative that the complexity of the problem be reduced by including certain assumptions. Depending on the efficiency of the metaheuristics, it would interesting to determine how much time it takes to solve large instances of the problem. These instances may involve more patients arriving daily than expected or more fractions prescribed to patients diagnosed with particular types of cancers. A comparison of the quality of schedules obtained by using the meta-heuristics with the constructive heuristics as a starting point and the results reported in this research will be important for the radiotherapy patient scheduling problems.

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Journal papers

- Kapamara, T. and Petrovic, D. 'Constructive heuristics for scheduling of radiotherapy patients'. *Journal of Operational Research Society* (Accepted subject to revisions)
- Kapamara, T., Petrovic, D., Haas, O.C.L. and Kelly, B. 'An approach to improving the management of radiotherapy patient flow'. To be submitted to an OR journal soon

Conference papers

- Kapamara, T., Sheibani, K., Haas, O. C. L., Petrovic, D. and Reeves, C. R. (2006) 'A review of scheduling problems in radiotherapy'. *In Proc. International Control Systems Engineering Conference (ICSE 2006)*, Coventry, U.K. Coventry University Publishing IBSN:1-84600-013-0.
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Appendices

A Distributions of the fractions

A.1 Prescribed fractions by cancer diagnosis

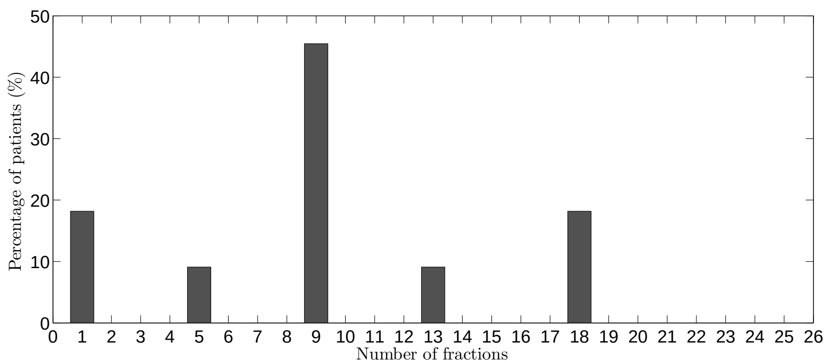


Figure A.1: A plot of the number of fractions prescribed to benign cancer patients

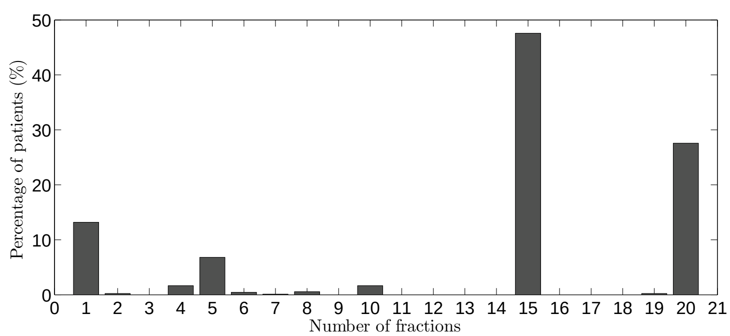


Figure A.2: A plot of the number of fractions prescribed to breast cancer patients

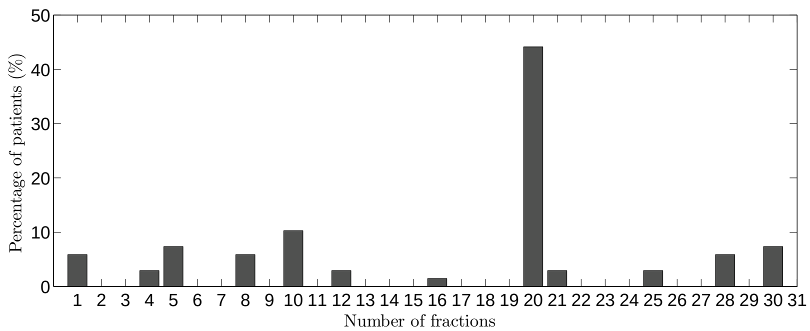


Figure A.3: A plot of the number of fractions prescribed to CNS cancer patients

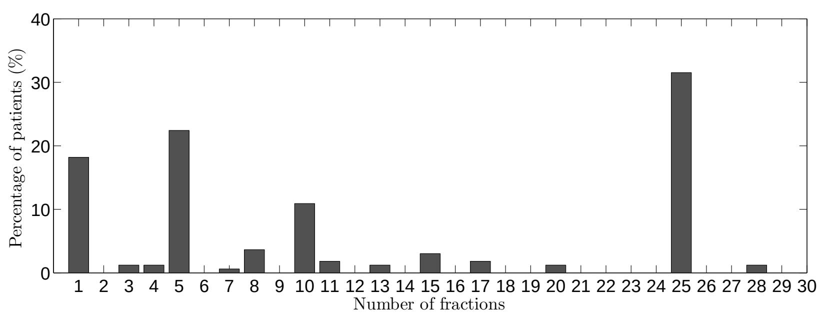


Figure A.4: A plot of the number of fractions prescribed to digestive system cancer patients

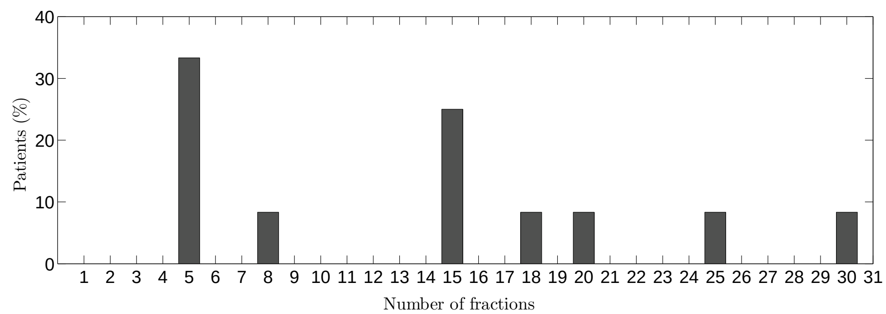


Figure A.5: A plot of the number of fractions prescribed to endocrine gland cancer patients

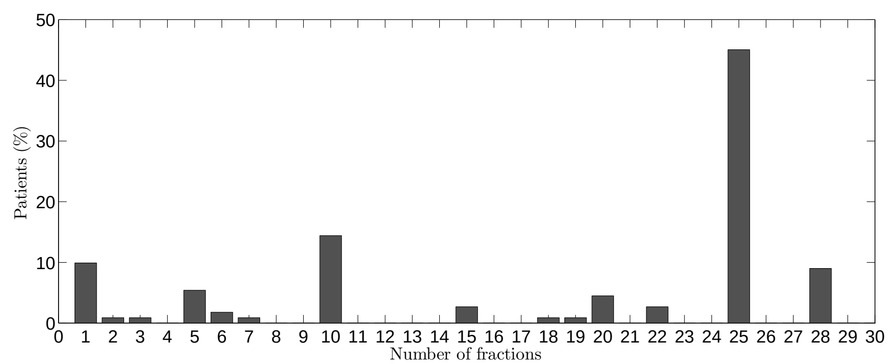


Figure A.6: A plot of the number of fractions prescribed to gynaecological cancer patients

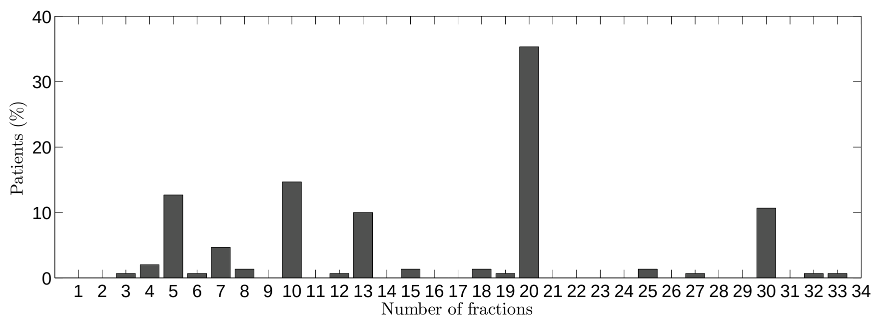


Figure A.7: A plot of the number of fractions prescribed to head and neck cancer patients

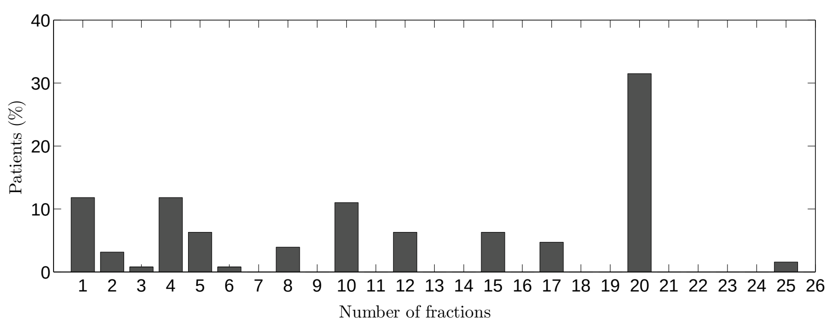


Figure A.8: A plot of the number of fractions prescribed lympho-reticular cancer patients

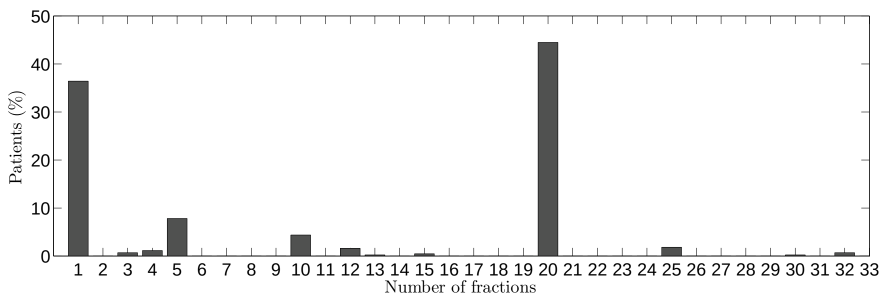


Figure A.9: A plot of the number of fractions prescribed to male genital cancer patients

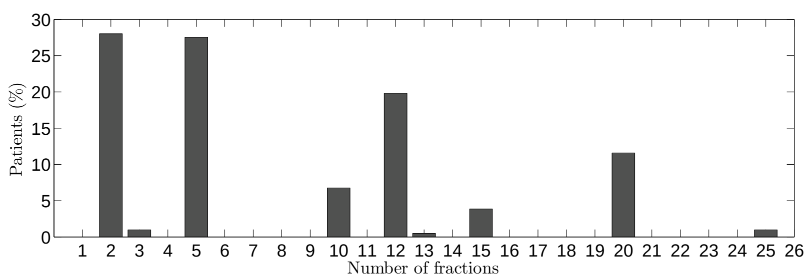


Figure A.10: A plot of the number of fractions prescribed to respiratory cancer patients

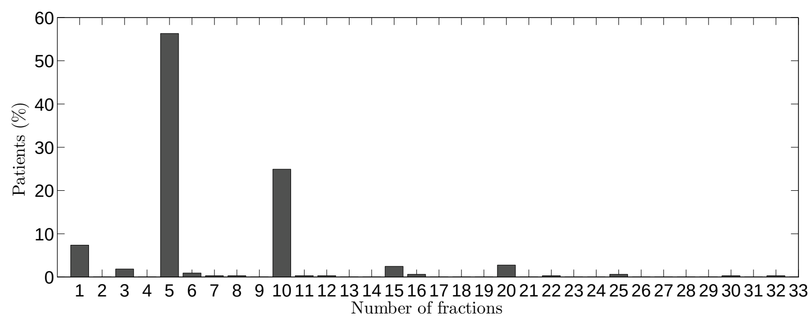


Figure A.11: A plot of the number of fractions prescribed skin cancer patients

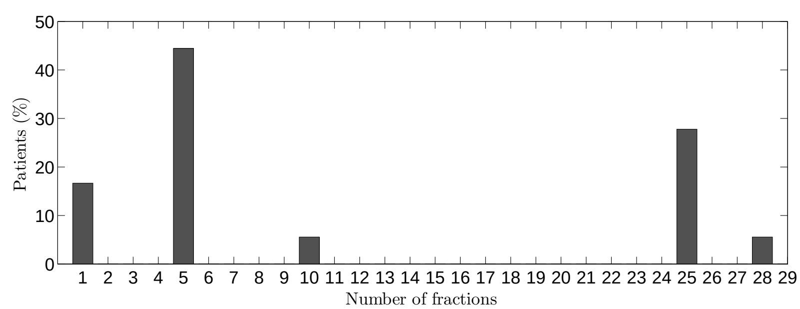


Figure A.12: A plot of the number of fractions prescribed to soft tissue and bone cancer patients

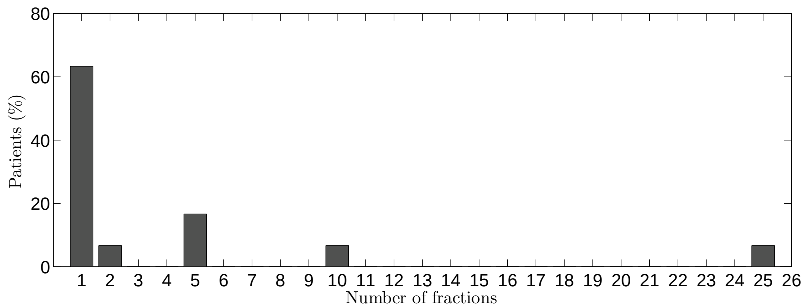


Figure A.13: A plot of the number of fractions prescribed to unspecified or other cancer patients

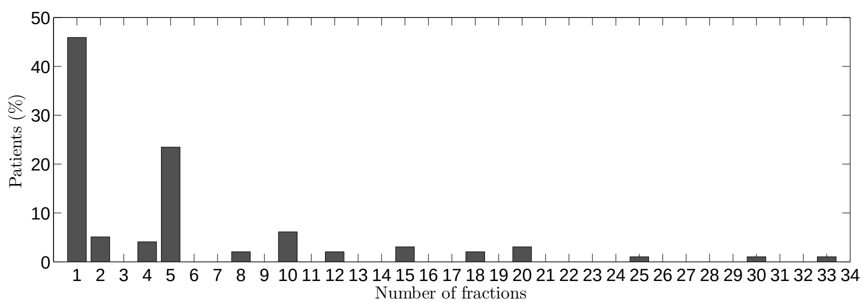


Figure A.14: A plot of the number of fractions prescribed to unknown primary cancer patients

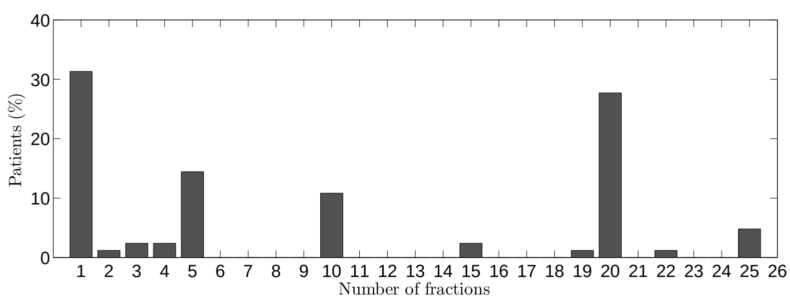


Figure A.15: A plot of the number of fractions prescribed to urinary cancer patients

B Due dates for each unit

B.1 Assigning due dates

Input: j
Output: D_j^1

if j belongs to the *Urgent* category **then**
  return r_j^1
else if j belongs to the *Emergency* category **then**
  return $r_j^1 + 1$
else if j belongs to the *Priority* category **then**
  return the next date the doctor l is available after a_j
else if j belongs to the *Standard* or *Elective* category **then**
  if j needs palliative treatment **then**
    return the next date the doctor l is available after a_j
  else
    return the date of the 4^{th} day when the doctor l is available after a_j (i.e. for the Arden Cancer Centre radiotherapy department, $D_j^1 = a_j$+21days)
  end if
end if

Algorithm B.1: Algorithm for determining the planning unit due date for patient j

Since, patients categorised as *Urgent* or *Emergency* do not need complex treatment plans, they do not visit the physics unit. Therefore, these patient categories where not included in the procedure which determined physics unit due dates shown in Algorithm B.2.

Input: j
Output: D_j^2

```
if j belongs to the Priority category then
    return the next date the doctor l is available after D_j^1
else if j belongs to the Standard or Elective category then
    if j needs palliative treatment then
        return the next date the doctor l is available after D_j^1
    else
        return the date of the 2^th day when the doctor l is available after D_j^1
    end if
end if
```

Algorithm B.2: Algorithm for determining the physics unit due date for patient j

Input: j
Output: D_j^3

```
if j belongs to the Urgent category then
    return D_j^1 + 1
else if j belongs to the Emergency category then
    return D_j^1 + 1
else if j belongs to the Priority category then
    return D_j^2 + 1 or D_j^1 + 1 depending on whether the patient required
    complex plans or not
else if j belongs to the Standard or Elective category then
    if j needs palliative treatment then
        return D_j^2 + 1 or D_j^1 + 1 depending on whether the patient required
        complex plans or not
    else
        return D_j^2 + 3 or D_j^1 + 3 depending on whether the patient required
        complex plans or not
    end if
end if
```

Algorithm B.3: Algorithm for determining the pretreatment unit due date for patient j

Input: j
Output: D_j^4

if j belongs to the *Urgent* category **then**
  return D_j^{jcco}
else if j belongs to the *Emergency* category **then**
  return D_j^{jcco}
else if j belongs to the *Priority* category **then**
  return D_j^3
else if j belongs to the *Standard* or *Elective* category **then**
  return $D_j^3 + 1$ (i.e. the next date after pretreatment due date)
end if

Algorithm B.4: Algorithm for determining the treatment unit due date for patient j

C Arden Scheduler

C.1 Introduction

This chapter discusses the features of the software called Arden Scheduler which was developed based on the four heuristics discussed in Chapter 7. The software comprises a booking form which is an electronic form of the request booking form used in the radiotherapy department at the Arden Cancer Centre. The Arden Scheduler has two modes in which it generates schedules of appointments: i) normal, and ii) simulation mode. When in the normal mode, the booking form is active to be used to capture details on the request forms submitted by the doctor to the planning unit booking desk. The simulation mode deactivates the booking form and ensures that the Arden Scheduler is active to simulate the arrival of request forms (i.e. patients) and creation of the schedules of appointments for a period of time specified in the simulation mode settings. The software was developed on a Windows Vista operating system using Java 1.6 and MySQL v5 database software (Oracle Corporation 2010). A database was created using the MySQL software to hold all the appointments generated by the Arden Scheduler.

In Section C.2, some of the features of the Arden Scheduler in normal and simulation modes are discussed. Section C.3 then briefly discusses the future upgrades to the software to be made after a trial by the radiotherapy department at the Arden Cancer Centre.

C.2 Features of the software

The main interface of the Arden Scheduler is the electronic booking form for capturing the details of the patients needed by the four heuristics. Figure C.1 is a screenshot of the booking form which is the main interface of the software. Other features of the software can be accessed using the menus labelled: i) 'Edit', ii) 'View', iii) 'Options', and iv) 'Run'.

On the booking form, details of each patient such as the name, number, cancer diagnosis, treatment, Arden Cancer Centre patient category, targeted due date, machine to be used in the planning unit, machine to be used in the treatment unit, prescribed fractions, perceived complexity of the treatment plan (classified as simple, intermediate and complex in Chapter 5) and the name of their Arden Cancer Centre doctor can be entered and saved. When the Arden Scheduler is running in normal mode, the details of each patients can be added one after the other into the database system or uploaded from a comma separated values (CSV) file. Using a command under the 'Run' menu, these details are used to create schedules of appointments the patients. The 'Run' menu has commands for building the schedules of appointments in the normal and simulation mode. If the software is switched to the simulation mode, the commands for the normal mode are deactivated and vice versa.

Under the 'Options' menu, the mode in which the software runs can be toggled between normal and simulation mode. In the simulation mode, the electronic booking form in Figure C.1 and other menus used only in the normal mode are deactivated.

Different parameters used by the heuristics can be set using the form whose screenshot is shown in Figure C.2 which is launched from the 'Options' menu. These parameters include the number of overtime slots, reserved slots, alternative pathways, processing times, maximum JCCO target breaches, treatment plan verification (i.e. on the simulator) settings and the delays between pretreatment and treatment unit shown as separate tablets of the form in Figure C.2.

The other settings required by the software are shown in the screenshot in Figure C.3. The pages of the form in Figure C.3 show that the settings include: i) the number of machines and facilities available in the radiotherapy department, ii) maintenance and service dates, iii) bank holidays, iv) doctors, v) working hours for each machine or facility, and vi) other settings needed by the heuristics. The form in Figure C.3 is accessed from the 'Options' menus. The heuristic parameters and settings were used in the normal and simulation modes. The default values of these settings and parameters are the values obtained based on the data collected from the radiotherapy department.

The form for changing simulation settings can be accessed from the 'Options' menu. On this form, the values of settings such as the probability distributions of fractions prescribed to patients, radiotherapy (i.e. emergency, palliative and radical treatments), request form delays, cancer diagnosis, perceived complexities of treatment plans, patient arrival rates and the different options for simulation runs are input. When in the simulation mode, the values of these settings can be viewed using graphs and charts such as the pie chart of the percentages of the total patients received that each doctor examined shown in Figure C.5, and the bar chart of the percentage of the total patients prescribed various numbers of fractions by their doctors, shown in Figure C.6. These graphs and charts can be accessed from the 'View' menu. When the software is run in the normal mode, such pie charts and bar charts can be plotted for the cumulative number of patients entered into the system.

The software creates several reports (i.e. text files) with details of waiting times, machine utilisations and overtime slots usage. Figure C.7 shows a screenshot of a text file with details of waiting times obtained after running the software in the normal mode. Such text files can be created and launched from the com-

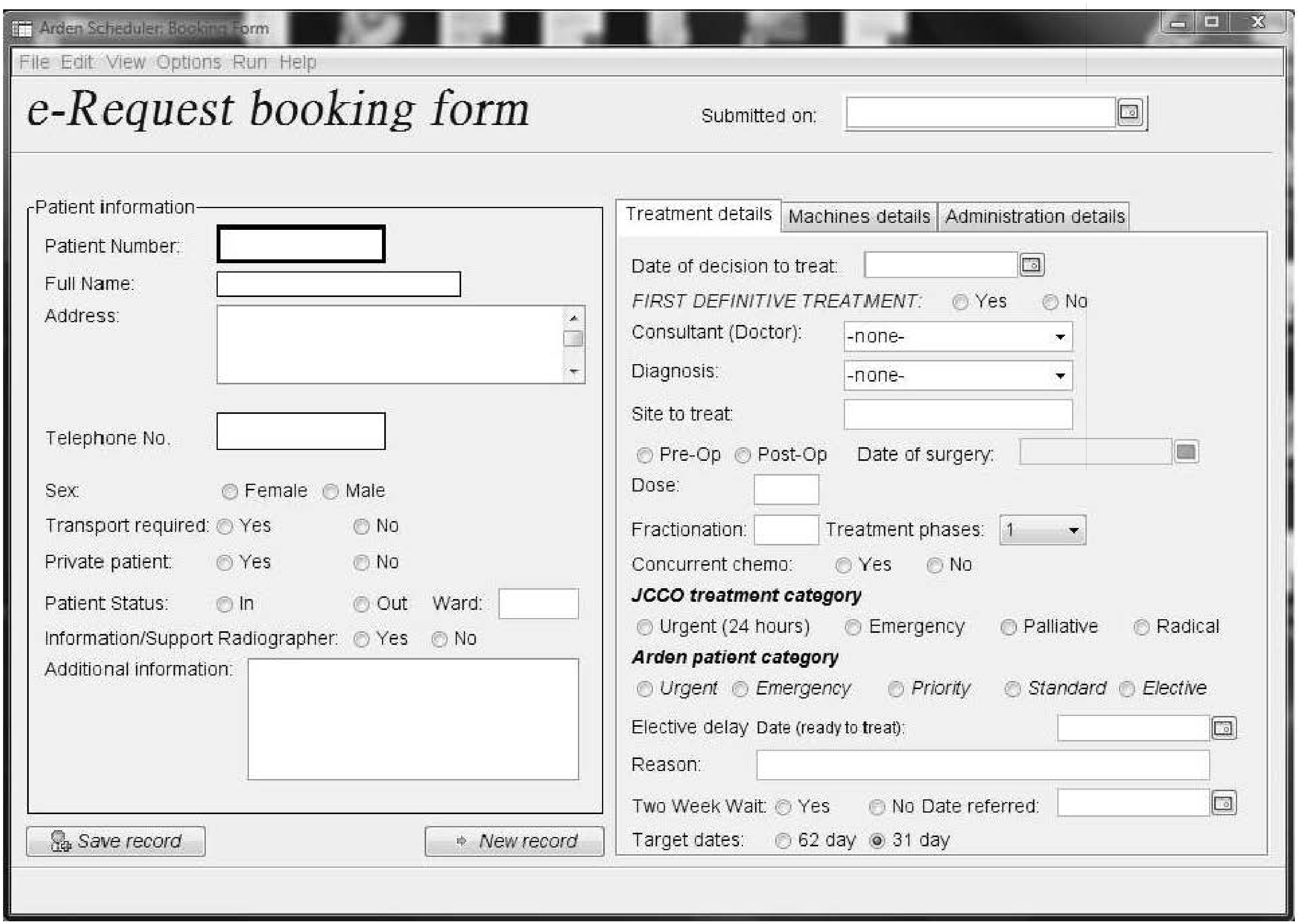


Figure C.1: A screenshot of the Arden Scheduler electronic booking form

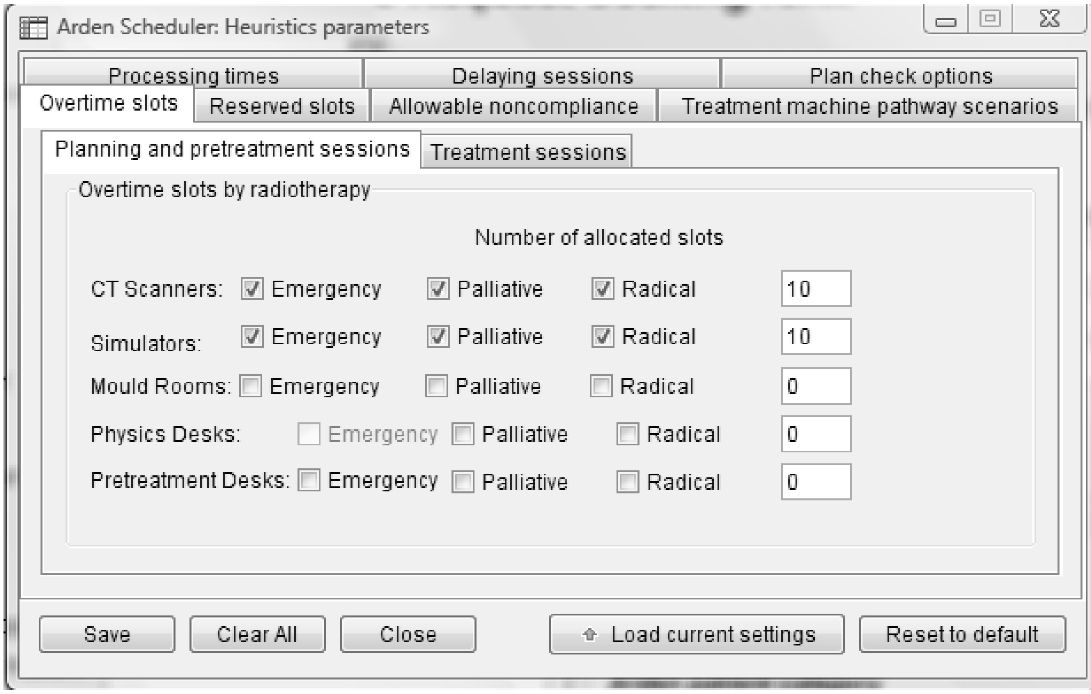


Figure C.2: A screenshot of the form for changing settings of heuristic parameters used by the Arden Scheduler

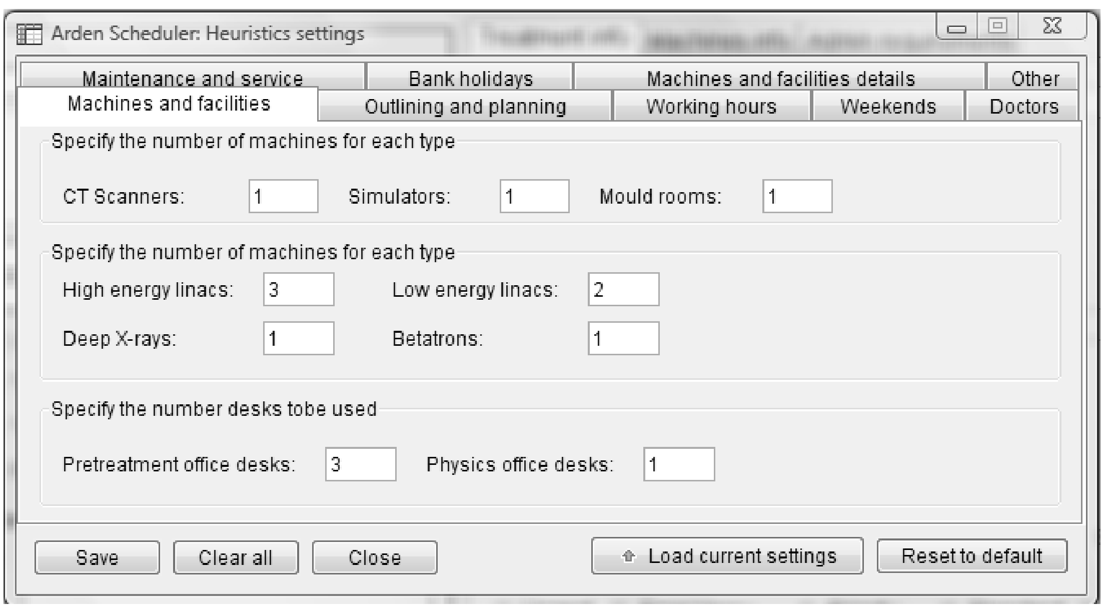


Figure C.3: A screenshot of the form for changing the settings of the heuristics used by the Arden Scheduler

mands under the 'View' menu. When the schedules of appointments are created in the normal or simulation mode, the schedules of appointments can be viewed

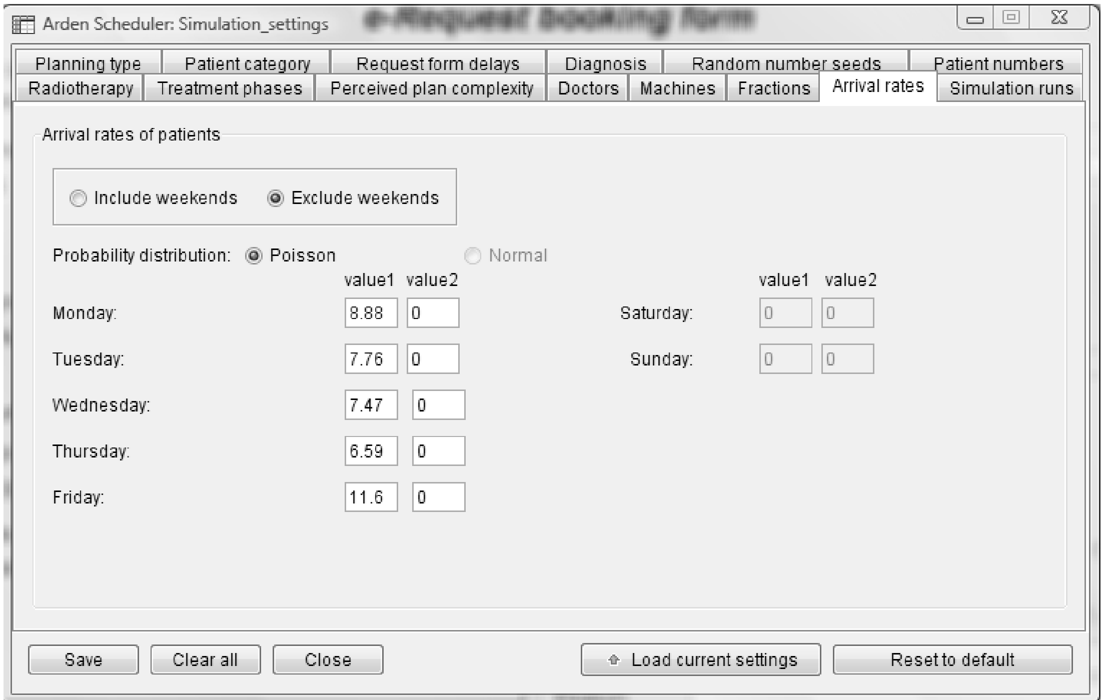


Figure C.4: A screenshot of the form for changing the simulation settings used by the Arden Scheduler

from the 'View' menu using commands for launching a coloured table of the appointments for scheduled on each slot on each machine. Figure C.8 shows an example of such a table that has been coloured using five different colours representing the Arden Cancer Centre patient categories. This feature should show the department how the different patient categories are scheduled on the slots of the machines for a given date. It can be an easy way of visually portraying the dates when the slots on a machine are fully or nearly-fully booked.

If changes to the created schedule have to be made, the interface for changing a patient's appointments for planning, physics, pretreatment or treatment, which is launched from the 'Edit' menu, is shown in Figure C.9. This feature was included to allow the radiotherapy department to manually create schedules of appointments to some patients when they deem necessary to do so.

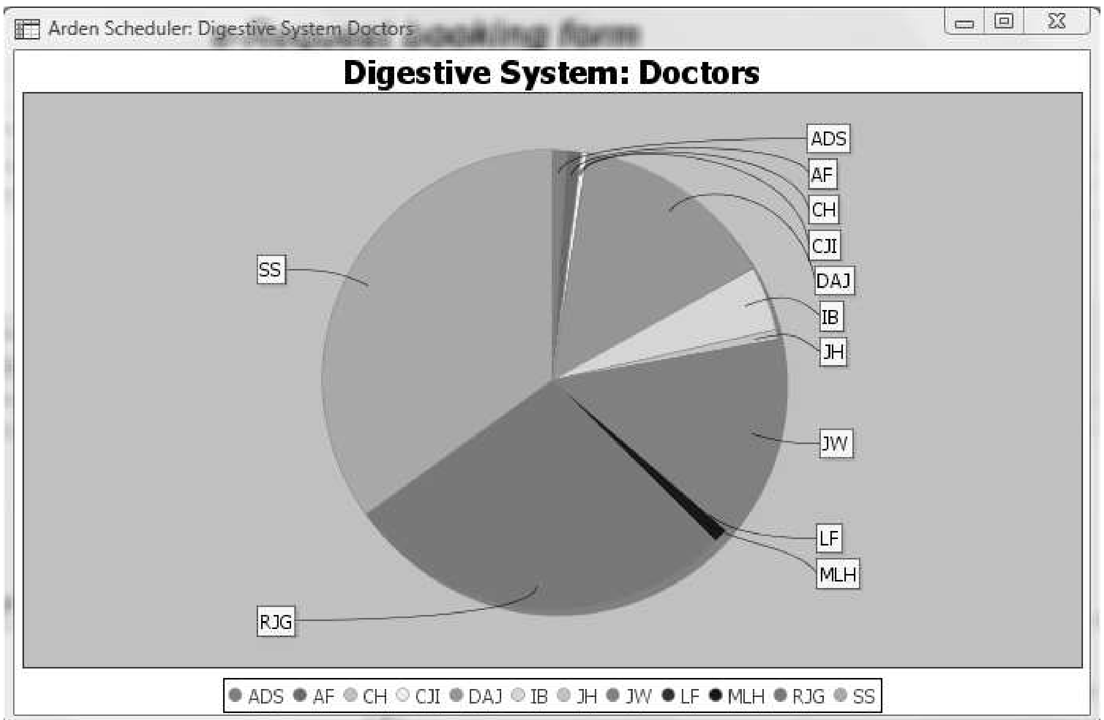


Figure C.5: A screenshot of the pie charts for the data input as simulation settings used by the Arden Scheduler

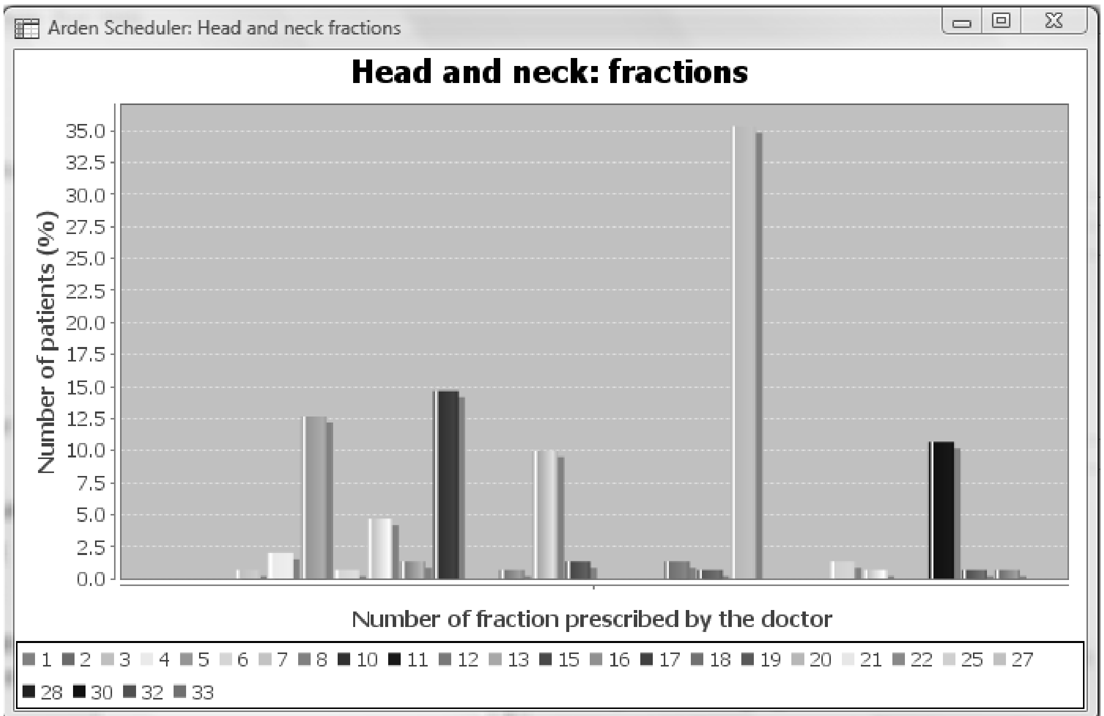
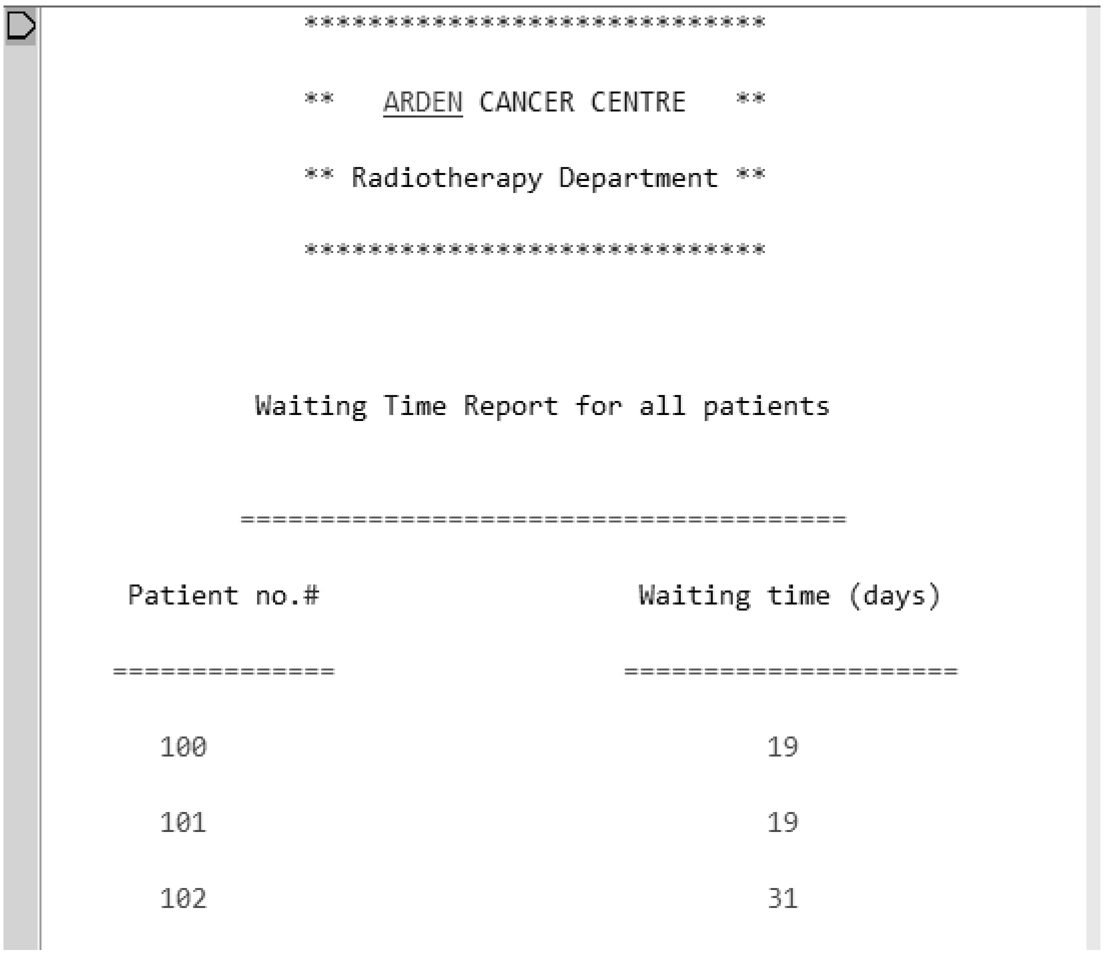


Figure C.6: A screenshot of the bar charts for the data input as simulation settings used by the Arden Scheduler



```
*****************************

**   ARDEN CANCER CENTRE   **

** Radiotherapy Department **

*****************************


Waiting Time Report for all patients


======================================

Patient no.#                    Waiting time (days)

==============                  =====================

100                                     19

101                                     19

102                                     31
```

Figure C.7: An example screenshot of one of the text files created by the Arden Scheduler

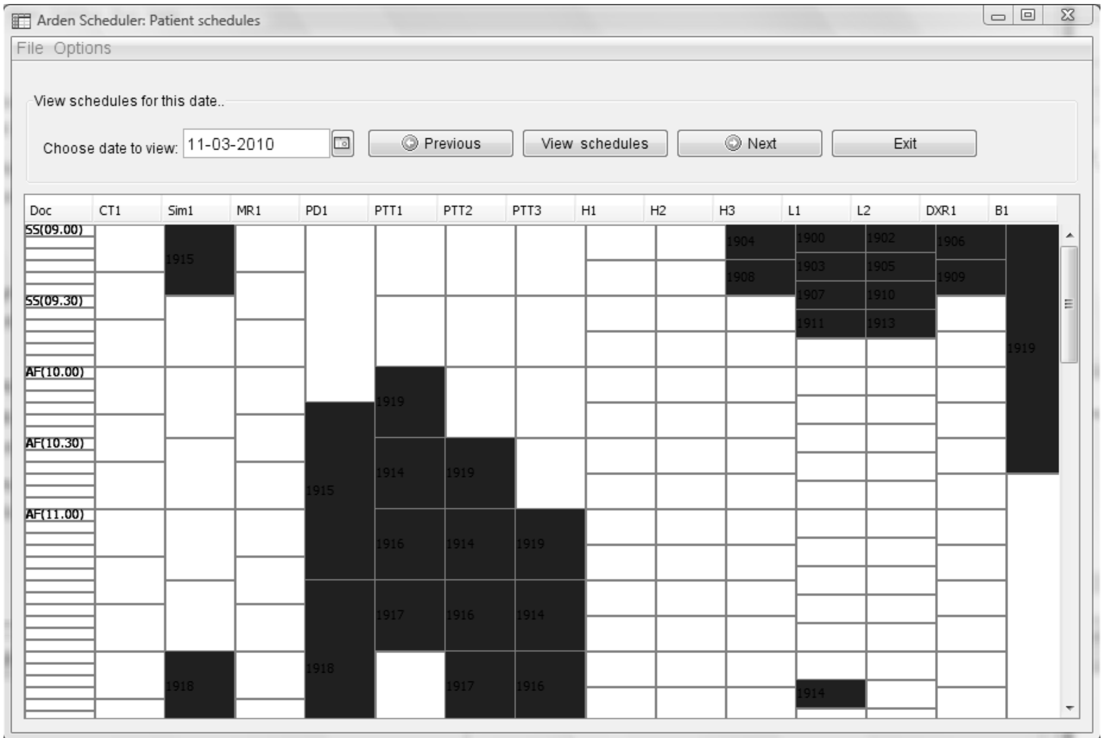


Figure C.8: An example screenshot of the schedules for a given date created by the heuristics in the Arden Scheduler

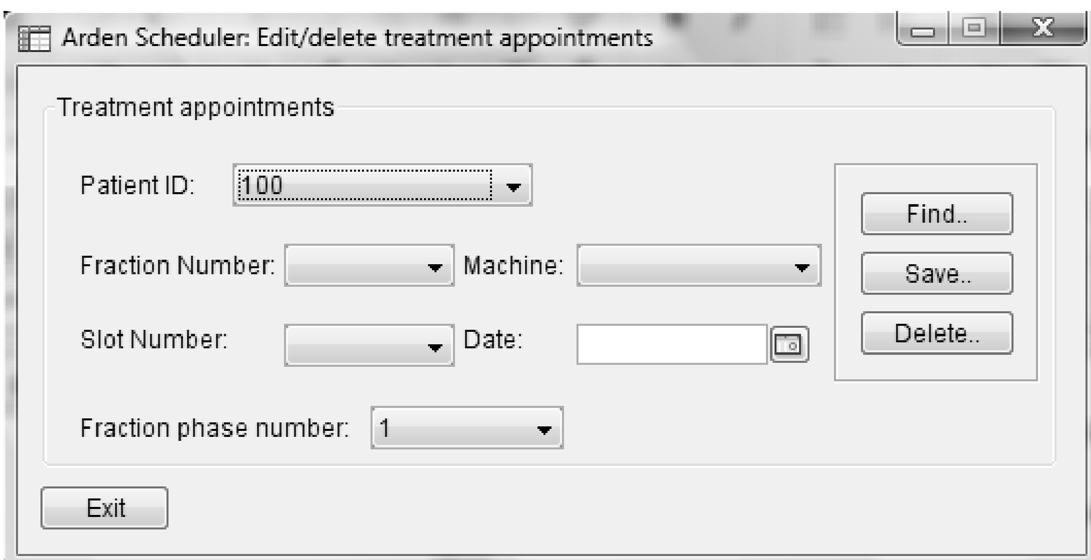


Figure C.9: An example screenshot of one of the forms used to manually edit schedules created by the Arden Scheduler

C.3 Future software upgrades

The radiotherapy department at the Arden Cancer Centre will trial the Arden Scheduler at the end of this project. The main features to be tested include the creation of schedules of appointments in the normal and simulation mode. The upload features will be used to load the department's current schedules of appointments into the database system from supplied CSV files. Furthermore, the efficiency of the software will be accessed against the schedules of appointments created by hand by the radiographers that book patients in the planning unit. Upgrades to the software should entail all the improvements and suggestions from the department after the trial.

Glossary

3D Three dimensional.

ACO Ant colony optimisation.

Adjuvant additive therapy to enhance the effectiveness of another treatment modality.

A&E Accident & Emergency.

Airway obstruction Blockage of the breathing tubes to the lungs.

Ansari-Bradley test A statistical test which tests if two independent samples come from the same distribution, against the alternative that they come from distributions that have the same median and shape but different variances.

AP1 Alternative pathway 1 scenario.

AP2 Alternative pathway 2 scenario.

AP3 Alternative pathway 3 scenario.

AP4 Alternative pathway 4 scenario.

Bank holiday Public holiday.

BB Branch and bound algorithm.

Betatron Machine that produces high energy X-ray beams used to treat certain types of cancers.

BIP Binary integer programming.

Brachytherapy Involves inserting radioactive seeds next to tumour inorder to maximise its destruction.

Bronchoscopy Examination of the passage of air in the lungs using a bronchoscope.

BT Brachytherapy.

Cancer Malignant tumours that uncontrollably grow, spread and invade healthy tissue.

Capacity Hours per unit time that a machine is available for the treatment of patients.

Carcinoma Cancerous tumours arising in the epithelial tissues of the skin and mucuous membrane in the glands, bladder, lungs, nerves, glands and other OARs. Carcinomas make-up 80–90% of all cancers.

Chemotherapy Treatment of cancer using anticancer drugs, highly toxic medications taht destroy cancer cells by interfering with their growth or preventing their reproduction.

Chi-Squared test A goodness-of-fit test which tests if a sample comes from a specified distribution, against the alternative that it does not come from that distribution.

CNS Central nervous system.

CSV Comma separated values.

CT Computed axial tomography.

CT scanner Machine used to take three dimensional images of tumour volume.

Date of booking request The date when the doctor completes a booking request or logs an electronic request for radiotherapy after agreeing on a course of radiotherapy that a patient has to take.

Date of decision to treat The date fo the consultation in which the patient and the oncologist agree the treatment plan for first treatment. It may be the same date when the booking request is done.

DES Discrete-event simulation.

Dietician Specialist in nutrition.

DoctorAndMachineSlots A procedure for determining finding the corresponding doctor and machine slots for a given operation.

Dosimetry Calculation of the absorbed dose in tissues after exposure to ionising radiation.

DXR Deep X-Ray machine.

EarliestTreatmentStart A procedure that finds the machine with the earliest treatment start date for a given set of identical machines.

EarliestTreatmentStart_AP2 A procedure that finds a sequence of machine which produces the earliest treatment start date for a given set of identical machines in the Alternative Pathway 2.

EarliestTreatmentStart_AP3 A procedure that finds a sequence of machine which produces the earliest treatment start date for a given set of identical machines in the Alternative Pathway 3.

EBT External beam therapy.

EDD Earliest Due Date.

Endoscopy Examining the inside of the digestive system using an endoscope.

Entity An element in a system that has to be simulated.

ETDD Earliest Treatment Due Date.

FCFS First-come first-serve.

FDT First definitive treatment.

First definitive treatment The first clinical intervention intended to manage a patient's disease, condition or injury. In this case,it is meant to remove or shrink the tumour. Where there is no definitive treatment, patients receive palliative intervention or palliative care.

Fraction Treatment session attended by patient.

Fractionation Division of the total therapeutic dose of radiation into small doses to be administered over a period of days or weeks.

Fri Friday.

FSP Flow shop problem.

GA Genetic algorithm.

Glioma Tumour of the brain.

GP General practitioner.

GRASP Greedy randomised adaptive search procedure.

GSP Group shop problem.

HDR High dose rate machine.

HE High energy.

HFS Hybrid Flow Shop.

High energy linac Linear accelerator that produces 25 MeV electron beams.

HIV Human immunodeficiency virus.

Hormonal therapy Involves using hormones in medical treatment.

Hybrid Flow Shop a shop scheduling problem involving jobs being processed in a series of production stages, eahc of which has several machines operating in parallel.

IBU Integrated brachytherapy unit.

IP Integer programming.

JCCO Joint Council of Clinical Oncology.

JSP Job shop problem.

LDD Least doctor delay.

LE Low energy.

Lean Involves removing wastes to add more value to product and work less.

Leukemia Cancerous tumours from blood forming cells.

Linac Linear accelerator.

LNPF Least number of prescribed fractions.

LNPO Least number of pretreatment operations.

LNPTP Least number of prescribed treatment phases.

Locum doctor Is a doctor who replaces a regular doctor when that doctor is absent.

Lognormal distribution A continuous probability distribution bounded on the lower side and has 3 parameters: minimum, μ (mean) and σ (standard deviation).

Low energy linac Linear accelerator that produces 6 MeV electron beams.

LP Linear programming.

LS Least slack.

LWINQ Least Work in Queue heuristic.

Lymphoma Cancerous tumour orignating in the lymph system.

MacMillan radiographer people working for the MacMillan Cancer Support.

Max. Maximum.

Megavoltage Refers to megavoltage gamma rays, X-rays or electrons that are capable of penetrating several centimetres of tissue.

Metaheuristics Method of solving complex combinatorial problems using robust procedures.

Min. Minimum.

Mins Minutes.

MIP Mixed-integer programming.

Mitosis Cell division.

MNOP Most number of operations in the planning unit.

MNSRP Most number of steps in the radiotherapy process.

Mon Monday.

MUPC Most urgent patient category.

MUT Most urgent treatment.

MWT Mean waiting time.

Myeloma Cancerous tumour originating from cells in the bone marrow.

Negative Binomial distribution A discrete probability distribution bounded on the low side and unbounded on the upper side. Its parameters include: x (number of trials), p (probability of event) and k (number of desired events).

Neoadjuvant chemotherapy Treatment given to cancer patients prior to surgery or radiotherapy.

Neoadjuvant radiotherapy Treatment given to cancer patients prior to surgery or chemotherapy.

NHS National Health Service.

NRAG National Radiotherapy Advisory Group.

OSP Open shop problem.

OTR On-treatment review.

Outlining and planning Involves determining the angles and intensity of radiation beams.

Palliative Treatment given to control or prevent symptoms of a disease.

PDR Priority dispatching rule.

Pearson VI distribution A continuous probability distribution which normally has 4 parameters: minimum, β, p and q.

Phlebotomy Involves opening a vein by surgical incision to remove blood as a treatment to conditions such as hemochromatosis.

Physicist Generally known as clinical scientist or physics scientist, uses his or her understanding of mathematics and radiation physics to design, develop and optimise treatment plans for radiotherapy patients. Physics scientists are also involved in the management of the radiotherapy department' infrastructure, especially the treatment machines.

Polycythemia Net increase of red blood cells in the body.

Postoperative radiotherapy Delivering the ionising radiation after a surgical operation.

Radical Treatment given to eradicate tumours and prolong survival.

Radiographers Deliver radiotherapy treatments and care to patients.

Radioisotope A radioactive isotope of an element.

Radionuclide A radioactive isotope of an element.

Radiotherapy Involves using carefully measured doses of ionising radiation to treat cancers.

Radiotherapy course Set of fractions prescribed for a patient.

Radiotherapy demand Total number of fractions required per year for a given population.

RCR Royal College of Radiologists.

SA Simulated annealing.

Sarcoma Cancerous tumour originating in the bone, cartilage, muscle, fibrous connective tissue or fatty tissue.

Sat Saturday.

ScatterDoctorDates A procedure for determining an initial date for the planning unit using r_j^1, D_j^{jcco}, and the patient's doctor l availability times.

Scheduling Involves allocating scarce resources.

SD Systems dynamics.

Session An attendance for a procedure in the treatment journey for a patient.

Simulator Machine used to take radiographs of the lesion and verify that the treatment plan is correct prior to administering the ionising radiation.

Spinal cord compression When tumour growths in or near the spine press the spinal cord and nerves. This results in swelling and reduction in blood supply to the spinal cord and nerves.

SPT Shortest processing time.

SSM Soft system methodology.

Sun Sunday.

Surgery Removal of tissue using cutting devices in order to treat a disease.

Targeted therapy is a type of medication that blocks the growth of cancer cells by interfering with specific targeted molecules needed for tumour growth.

TB Tuberculosis.

Teletherapy Involves delivering the radiation from a source at a distance from the patient.

Thrombocythemia Disorder in which excess platelets are produced causing blood clotting or bleeding.

Thrombocytosis Excess platelets in the blood caused by disease.

Thurs Thursday.

Thyrotoxicosis Thyroid gland producing excess hormones and affecting the body.

TS Tabu search.

Tue Tuesday.

Tumour Lesion formed by abnormal growth of cells. A tumour can be benign, pre-malignant, or malignant. A malignant tumour is a cancer.

Tumour volume Malignant tumour growth targeted targeted by cancer treatment modalities.

Two-sample Kolmogorov-Smirnov test A statistical technique which tests if a sample comes from a specified distribution, against the alternative that it does not come from that distribution.

UHCW University Hospitals Coventry and Warwickshire.

UK United Kingdom.

Unsealed sources therapy Involves delivering radiation by ingestion or injection of soluble radioisotopes.

UST Unsealed sources therapy.

Vena caval obstruction Blockage of the human heart's superior vena cava walls by tumours.

Waiting time Time difference between the date when the decision to treat by radiotherapy is made and when the first fraction is delivered. Waiting time is measured in consecutive days and includes weekends and bank holidays.

Wed Wednesday.

Weibull distribution A continuous probability distribution bounded on the lower side and has 3 parameters; minimum, α and β, where $\alpha > 0$ is the shape parameter and $\beta > 0$ is the scale parameter.

Wilcoxon rank sum test A statistical technique used to test if two independent samples come from identical continuous distributions with equal medians, against the alternative that they do not have equal medians.

X-rays Electrically produced penetrating ionising radiation (also called Röntgen rays).