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A REVIEW OF SCHEDULING PROBLEMS IN RADIOTHERAPY

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Abstract

This paper describes the radiotherapy patient scheduling problem of minimising waiting times. Like many other service industry problems, radiotherapy patient scheduling may be solved by first modelling and formulating it into a shop scheduling problem. Over the years, these shop scheduling models have been researched and solved using various approaches. This paper typifies radiotherapy patient scheduling into a job shop problem. In addition, exact and metaheuristic approaches of solving job shop scheduling problems are also reviewed and comparatively analysed.

1 Introduction

Scheduling can be defined as organising resources in order to meet objectives and requirements [1]. This field has been studied for over forty years, resulting in the conception of different shop scheduling models and a variety of approaches to solve them. Examples of these scheduling models are job shop problem (JSP), flow shop problem (FSP), open shop problem (OSP), and group shop problem (GSP) discussed in [1–4]. 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 a FSP all jobs follow a similar route while in an OSP, jobs do not have a defined point of entry into the system [3]. The GSP is a generalisation of the JSP and OSP [5].

This paper discusses a real-life radiotherapy patient scheduling problem (RTPS) defined in collaboration with the Arden Cancer Centre (ACC) at the University Hospitals Coventry and Warwickshire NHS Trust, UK. The main objective is to minimise patients (jobs) waiting time from diagnosis to the first definitive treatment and the overall completion of treatment.

The terminology used in scheduling is from the manufacturing environments. Thus, problems from the service industry, have been solved by modelling them into different manufacturing types (i.e. JSP, FSP, or OSP). In [5], it was noted that JSP and OSP are NP-hard problems from the works of Gonzalez and Sahni 1976, and Lenstra et al. 1977, respectively. Due to this combinatorial nature, the JSPs, FSPs, and OSPs are complex and difficult to optimaly solve. As a result, there has been much research on specialising exact methods or metaheuristics to solve them. Jain and Meeran [6], presented a comprehensive review of these meta-solvers and concluded that not all of them are effective and efficient on large instances of JSPs. A fair comparison of approaches is necessary in order to choose the one that performs well since RTPS can be considered a large problem. Amongst the reviewed approaches are branch-and-bound (B&B), simulated annealing (SA), tabu search (TS), greedy randomised adaptive search procedure (GRASP), and genetic algorithms (GA).

The remainder of the paper is organised as follows. Section 2 introduces the radiotherapy treatment process. Section 3 formulates a JSP from the treatment process and discusses its characteristics. Section 4 reviews some of the approaches that are potentially useful in solving such complex problems. Lastly, Section 5 provides comments and concluding remarks.

2 Radiotherapy treatment process

The radiotherapy treatment process at ACC is a complex process. This process has been simplified to facilitate the initial analysis. It can be divided into four phases (see Figure 1): consultation, planning, pre-treatment, and treatment. In the consultation phase, a patient meets a consultant who recommends the form of treatment (e.g. chemotherapy, radiotherapy). If radiotherapy is recommended and the patient consents, then they join a 'queue' for the planning phase after establishing a treatment regimen (i.e. a treatment path to be followed by a cancer patient).

In the planning phase, there are several machines used for 'virtual' planning of a patient's treatment. These are CT (computed axial tomography) scanner, simulator, and mould room. All patients receiving radiotherapy treatment are required to be positioned accurately at each treatment session. To improve the accuracy and reproducibility of the positioning, casts and immobilisation devices are used.

The type of the immobilisation devices depends on the location of the lesion. Some are required to be manufactured in the mould room for each patient (e.g. casts for head and neck cancers). All these immobilisation devices require additional time to be installed in the treatment room.

The pre-treatment phase deals with scheduling patients on treatment machines depending on the dose (low or high energy) to be delivered and machine availability. Additionally, it deals with calculations of patient information in preparation for the treatment sessions using data provided by the physics division. The physics division provides essential services such as commissioning, calibration, repair, and maintenance of planning and treatment machines.

The treatment phase involves radiation delivery performed using a range of equipment (five machines). These machines are the high and low energy linear accelerators (linacs) and the high dose radiation (HDR). Low energy linacs are for patients whose fractionation scheme requires doses of low energy radiation. High energy linacs treat patients that require radiation doses of high energy.

The approach adopted to solve the RTPS is to map it into a manufacturing problem by identifying resources (machines), constraints, and objectives as well as the relationship between the different stages of the process. Such an approach deduces the most appropriate type of shop scheduling model (see Figure 2) to represent the RTPS.

3 Problem formulation

Shop scheduling models exist in two categories, that is, static and dynamic. Static problems have the number of jobs and their ready times known and fixed [7]. Dynamic problems involve considerations of possible dynamic disturbances. There can be many types and occurrences of disturbances affecting radiotherapy delivery such as the random arrival of new patients, ambulances arriving late with patients for treatments (due to the huge catchment area and nationalisation of ambulance services), patients failing to come to their appointments, patient demise, machine breakdowns, unanticipated unavailability of staff, delays in the chemotherapy department (i.e. for patients requiring both chemotherapy and radiotherapy), and or patient delays in signing of conformation forms. Therefore, the RTPS can be classified as a dynamic problem, see Figure 2.

Dynamic disturbances compound the complexity of scheduling problems, affecting the choice of approaches to solve them. One way of reacting to the disturbances is the event-driven rescheduling approach. Several researchers (e.g. Church and Uzsoy 1992, Muhleman et al. 1982, Sabuncuoglu and Karabuk 1997) have worked on reactive rescheduling approaches and concluded that frequent revision is necessary for better scheduling results although it is not always beneficial to reschedule after every unexpected event [4, 8]. This helps to further define RTPS as a patient scheduling/rescheduling problem.

Furthermore, shop scheduling problems also exist in two forms; stochastic and deterministic. In deterministic models, job information such as processing times, setup times, due dates is known prior to processing while in stochastic models it is uncertain. Most manufacturing and service industry scheduling problems are deterministic [1] save for a few cases of stochastic problems (such as the Sherwood printing company problem discussed in [9, 10]).

RTPS is characterised by uncertainties on machine processing and setup times. Although averages of machine processing and setup times have been determined from historical data, they are likely to vary because of the differences in severity of cancers. Hence, the RTPS can be considered a stochastic dynamic JSP based on the fact that all patients do not follow the same predefined route in the treatment process and the uncertainty or variability of factors such as the setup times, processing times and disturbances, as discussed above.

The dynamic nature of the above problem is intensified by the possibility of existence of recirculation on the treatment phase. Recirculation is whereby a job undergoes processing on one machine more than once before being processed on others [1, 3]. If a patient's fractionation scheme involves treatment on high energy linacs, it is likely that the patient would visit the same treatment machine for several subsequent treatments after the first definitive one. Another elaborate example of recirculation shows if a patient's physique changes (e.g. after failing to attend the treatment appointments), they may revisit the mould room for a new cast or imprints for treatment.

The following notation is used in the problem statement and objective and constraint functions definition.

j	job, where $j = 1, 2, 3, \ldots, n$
i	machine, where $i = 1, 2, 3, \ldots, m$
M	set of all machines, $\|M\| = m$
P	set of job priorities, P = {urgent radical, non-urgent radical, urgent palliative, non-urgent palliative}
N_T	number of tardy jobs (i.e. jobs that fail to meet the first definitive due date)
p_{ij}	processing time of job j on machine i where $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$
d_j	due date of job j, $j = 1, 2, 3, \ldots, n$
r_j	release date of job j, $j = 1, 2, 3, \ldots, n$
C_j	completion date of job j, $j = 1, 2, 3, \ldots, n$
$\overline{d}_j$	due date of the first definitive treatment of job j, given by $\overline{d}_j = r_j + 31$ days (a month)
$\overline{C}_j$	completion date of first definitive treatment of job j
$\overline{F}$	mean flow time of all n jobs given by $\overline{F} = \frac{1}{n} \cdot \sum_{j=1}^{n} C_j - r_j$
$\overline{f}$	mean flow time of all n jobs to the first definitive treatment given by $\overline{f} = \frac{1}{n} \cdot \sum_{j=1}^{n} \overline{C}_j - r_j$
C_{max}	makespan, the completion time of the last job to be processed, C_{max} = max$\{C_j \| j = 1, 2, 3, \ldots, n\}$

3.1 Objective functions formulation

An objective function can be defined as a mathematical formula derived from an operational statement [11]. Most of the targets and constraints covered in this initial study of the process can be modeled mathematically. According to [11], objectives such as 'to provide an efficient service to cancer patients', are referred to as 'ideals', which cannot be derived into a mathematical expression. Further examination and combining these 'ideals' with other targets or constraints, produces operational statements that could be modelled mathematically.

The most important objective functions for the RTPS are concerned about meeting the first definitive treatment due dates, ($\overline{d}_j$). This is in accordance with the UK government's target for cancer centres that patients should wait a maximum of one month before the first definitive treatment [12]. Static scheduling problem objective functions depend on the performance measure, C_{max}, which predominantly relies on release times of the latest jobs [13]. The dynamic JSP for RTPS involves new jobs arriving at intermittent uncertain times. Hence, the mean flow times, $\overline{f}$ and $\overline{F}$, together with N_T, and or C_{max} could be used as the objective functions subject to the constraints on $\overline{f}$ for urgent or non-urgent radical and palliative patients indicated in [12].

The following mathematical functions are some of the objectives identified in the initial study of the RTPS problem.

minimise N_T
minimise $\overline{f}$
minimise $\overline{F}$
minimise $(\overline{F} - \overline{f})$
subject to $\overline{C}_j \leq \overline{d}_j$

The first definitive treatment due date, $\overline{d}_j$, introduces a time window constraint to the radiotherapy scheduling problem. Other constraints include the number of consultants to attend to a patient at each phase, number of consultants available at the centre at any time (at least one), number of radiographers needed in the treatment units, and or number of patients to be treated on a machine per day. Given these constraints and others to be uncovered in further research work, the RTPS problem may be transformed into a JSP with n jobs (j) to be scheduled on m machines (i). Each job j with priority in P, can be processed on a set of machines A, where $A \subseteq M$, with $|A| \leq m$, and aims at a feasible schedule which minimises $\overline{f}$, $\overline{F}$, and N_T.

The objectives and constraints of the JSP model could be translated into a multiobjective shop scheduling problem of minimising waiting times. Researchers have solved multiobjective optimisation problems using exact methods and metaheuristics. Section 4 overviews B&B approach, GRASP, TS, SA, and hybrid GA algorithms based on their performances on shop scheduling problems.

4 Approaches to solving scheduling problems

RTPS is a complex type of dynamic scheduling problem. Therefore, careful consideration of approaches to use in solving the problem is essential. This includes critically analysing the performance of both exact and metaheuristic approaches on shop scheduling problems such as JSP or FSP. This Section discusses some of the approaches applied to such shop scheduling problems.

One of the earliest approaches to solving machine scheduling problems is dispatching rules. The earliest dispatching rules were developed by Jackson 1955, Smith 1956, Giffler and Thompson 1960, and Gere 1966 [6]. They are considered to be easy to use and have reduced computational requirements [2, 7, 14]. They have been used for finding good schedules for a single objective such as makespan, total completion time, tardiness, and or lateness. Some of the examples of elementary dispatching rules are Earliest Due Date (EDD), Shortest Processing Time (SPT), Longest Processing Time (LPT), Cost Over Time (COVERT). Dispatching rules procedures differ due to their different priorities. For example, EDD considers job due dates while SPT uses processing times. Thus, for EDD, jobs with earliest due dates are scheduled first on a machine.

In [2], dispatching rules procedures are comprehensively reviewed and compared to each other on small instances of shop scheduling problems. Experimental results in [6], suggest that dispatching rules perform better when they are combined with other rules or methods. A good example of such combinations is in [10], when the longest processing time (LPT) was combined with fuzzy concepts to specialise a genetic algorithm for dynamic JSP in a printing company. For real world problems such as RTPS that consist of several complex objectives, dispatching rules could be useful in proposing a hybridised algorithm to solve them. Besides the dispatching rules, B&B, a constructive exact approach has been used to solve many classes of scheduling problems [2, 3, 7].

B&B involves building a conceptual decision tree through its two main procedures; branching and bounding. The most important ingredient of B&B is finding the bounds for branching. This involves continuing the search for job operations on nodes using an estimated lower bound (LB) and the best achieved upper bound (UB). B&B creates a conceptual decision tree with n branches (for the n jobs) for the first job to be scheduled [2]. This means for the entire problem, it creates a decision tree with $n!$ nodes. Literature shows that B&B was improved in several ways by different researchers. Carlier and Pinson 1989, found ways of calculating the LB using Jackson's Preemptive Schedule (JPS) [6]. These modifications were meant to improve the branching and bounding procedures. However, B&B shortcomings are that they cannot be applied to large instances of scheduling problems (such as the 10x10 problem instance by Muth and Thompson 1963 [7]) and their use requires a good understanding of JSP in order to create procedures to fathom nodes at high levels in the conceptual decision tree [1, 2, 6]. The greater the number of jobs, the more branches for the decision tree and the higher the computational time to resolve the problem. There are approximate and constructive methods which can manipulate the constructed schedules to produce improved solutions. These methods are called metaheuristics.

B&B constructs an exact solution by creating a conceptual decision tree but metaheuristics use complete schedules and manipulate them into better schedules. They start with a pool of schedules known as the neighbourhood structure. This structure is defined by a series of perturbations from one solution to the other. The solutions, in the JSP case can be represented as permutations of the n jobs. Thus, there would be m arrays of the permutations of n jobs. The following is a brief review of such metaheuristics widely used in shop scheduling.

GRASP is a metaheuristic for combinatorial optimisation problems developed by Feo and Resende [15]. It consists of a construction phase and local search phase. The construction phase builds a schedule one element at a time using a greedy function and a restricted candidate list (RCL) of operations.

The local search phase improves the constructed solution iteratively. This metaheuristic was used on a JSP in [16] using disjunctive graphs to evaluate schedules and showed poor results. GRASP also showed poor results compared to TS, SA, and GA in [6]. However, Binato et al. [16] included in their GRASP a Proximate Optimality Principle (POP) that ensures partial schedules maintain good solutions. This improved the results of the GRASP on JSP but in this case, Binato et al. did not compare it to other metaheuristics. Thus, it can be concluded that such modification to GRASP improves its efficacy.

The fuzzy greedy evaluation concept in the field of combinatorial optimisation problems was devised by Sheibani [17]. The initial applications of this idea in the development of approximate methods, for example, on the travelling salesman problem (TSP) and the FSP performed very well. For a particular case, the developed fuzzy greedy heuristic (FGH) for the FSP significantly improved the well-known Nawaz, Enscore, Ham (NEH) heuristic [18] which has dominated the field for many years.

Simulated annealing was developed during a study of the cooling and recrystallisation of materials in a heat bath. It was first presented as a local search algorithm for combinatorial optimisation by Kirkpatrick et al. in 1983 [19]. SA is an iterative local search method that avoids local optima by accepting worse solutions than the current one. From an initial solution, the algorithm moves from one neighbour to another. If the proposed new solution is better than the current, it is accepted. If it is worse than the current, it is accepted with some probability. A variety of experiments have been conducted using this metaheuristic. In [6], Potts and Wessenhove, found that it performed better than other heuristics on single machine weighted tardiness problems. It was found that TS performed better than SA specialised with large-step optimisation since SA required huge computational times and involved a large amount of parameters that were difficult to tune [20]. On the GSP in [5], SA results compared very well to other algorithms though TS performed better. It can be concluded that the randomised diversification strategies of searching the neighbourhood in SA enhance its performance. Another local search algorithm which uses a different inspiration and has proven to be effective is tabu search.

Tabu Search (TS) was first proposed by Fred Glover [21]. It is a local neighbourhood search metaheuristic that avoids local optimality by storing search schedules in memory (i.e. a tabu list). The tabu list forbids moves with certain attributes and guides the algorithm by accepting worse schedules if it encounters duplicate schedules or previously achieved schedules [6]. The length of the tabu list (tabu tenure, L) is an important parameter for the algorithm as discussed in [22]. If L is too small, the algorithm only explores a small solution space. TS has been applied to a wide variety of shop scheduling problems which include FSP, JSP, and OSP. Liu et al. [4], used TS on a dynamic JSP and concluded that the algorithm can compete with other known metaheuristics because of its flexibility and efficiency. In [23], it was concluded that TS holds an impressive record when applied to machine sequencing problems after a series of experiments. Experiments by Sampels et al. [5] on Fisher-Thompson 15x15 JSP instance, showed that the TS approach yields the best results on all problem instances compared to ant colony optimisation (ACO), evolutionary algorithms, and SA.

Genetic algorithms (GA) were first proposed by John Holland in 1975 and they are inspired by nature (i.e. the theory of evolution) [24]. Given a generation of possible schedules to a scheduling problem, a generation is reproduced from the most ‘fit’ parents (schedules) using crossover and mutation. This is repeated until the algorithm converges to an optimal solution. Crossover and mutation are two important ingredients of these algorithms. They determine how genes from two parents’ chromosomes are exchanged to produce offsprings without losing their fitness. GAs are known to be robust and problem independent. Thus, research on GAs has been at the forefront and led to the development of hybridisation (with local search techniques) to enable them to converge on the best schedules for a problem. Hybridisation is a trade off between specialising GAs for a problem and keeping their problem independence attributes [25]. A hybridised GA was used in radiotherapy treatment studies in [25] and it performed better than its standard version. Some examples of using GAs on JSP and FSP include [13, 17, 26]. Experiments with dynamic JSP discussed in [13] concluded that their ability to converge to the best schedules diminishes as the problem size increases. In [6], it was shown that without hybridisation, GAs are the worst metaheuristics compared to TS and SA. One of the shortcomings of hybridised GAs is their inability to provide near optimal solutions in an acceptable time (on a JSP [6]).

Experiments in the reviewed literature show that TS is an efficient and effective approach on the JSPs. SA and GAs perform comparably well despite their shortcomings but the performance of GRASP in [16] shows it can obtain good results when specialised with certain techniques (such as the Proximate Optimality Principle). Further work on the RTPS will help determine the best approach to tackle the problem.

Whilst the ultimate aim is to find an algorithm able to solve any problem, practicality requires algorithms to be adapted to the problem by exploiting expert knowledge. A fair analysis and comparison of the approaches discussed shows that they are all important depending on the size and complexity of the problem instance. Therefore, the RTPS might be best tackled by a hybrid metaheuristic that combines certain features of the discussed approaches. From the discussion, the hybrid metaheuristic might best be built around the TS (due to its effectiveness and efficiency compared to other approaches) or hybrid GAs which allow further specialisation.

5 Conclusion

This paper has described the main elements of the radiotherapy patient scheduling (RTPS) problem. It was found that the RTPS can be expressed as a stochastic and dynamic job shop problem. Since job shop problems are known to be NP-hard, the RTPS problem is complex and requires approaches capable of solving large problem instances. Having identified the characteristics of the problem to be solved, the other part of the issue involves a review of the different methods that could be adapted to solve RTPS. Amongst these methods are tabu search, simulated annealing, GRASP, and evolutionary algorithms. Experiments with these algorithms on JSP instances suggest that tabu search outperforms the others (particularly on dynamic JSPs).

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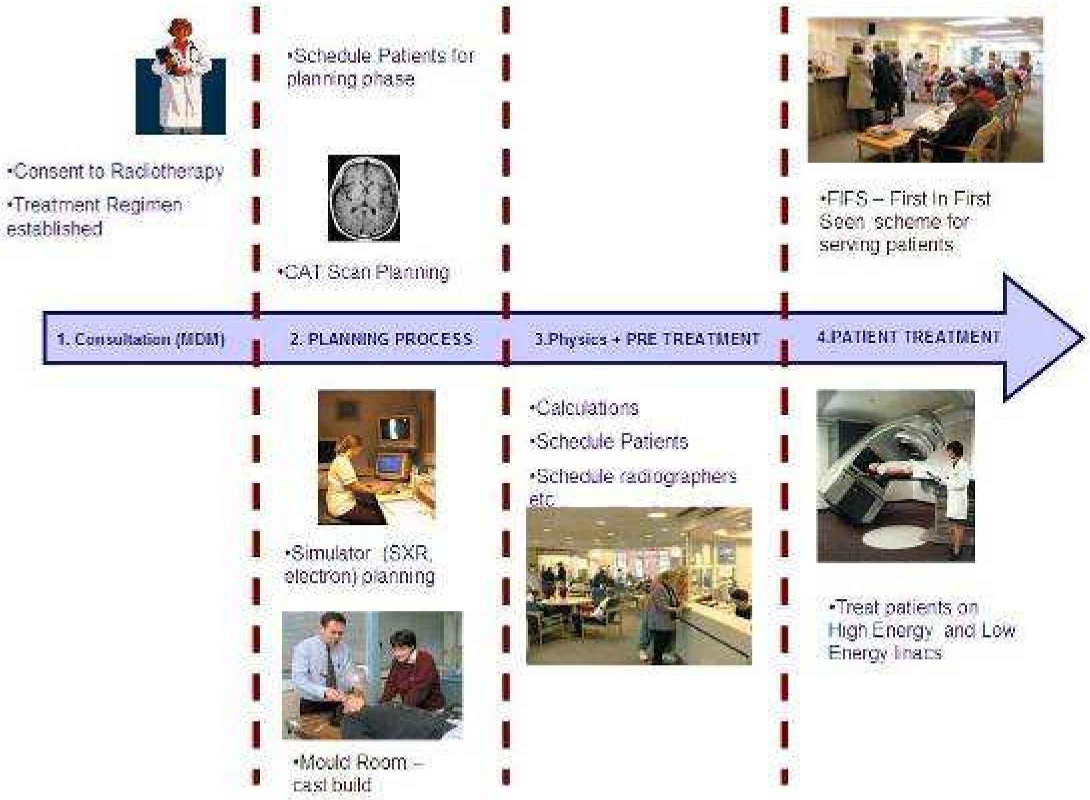

Figure 1: Radiotherapy treatment process flow

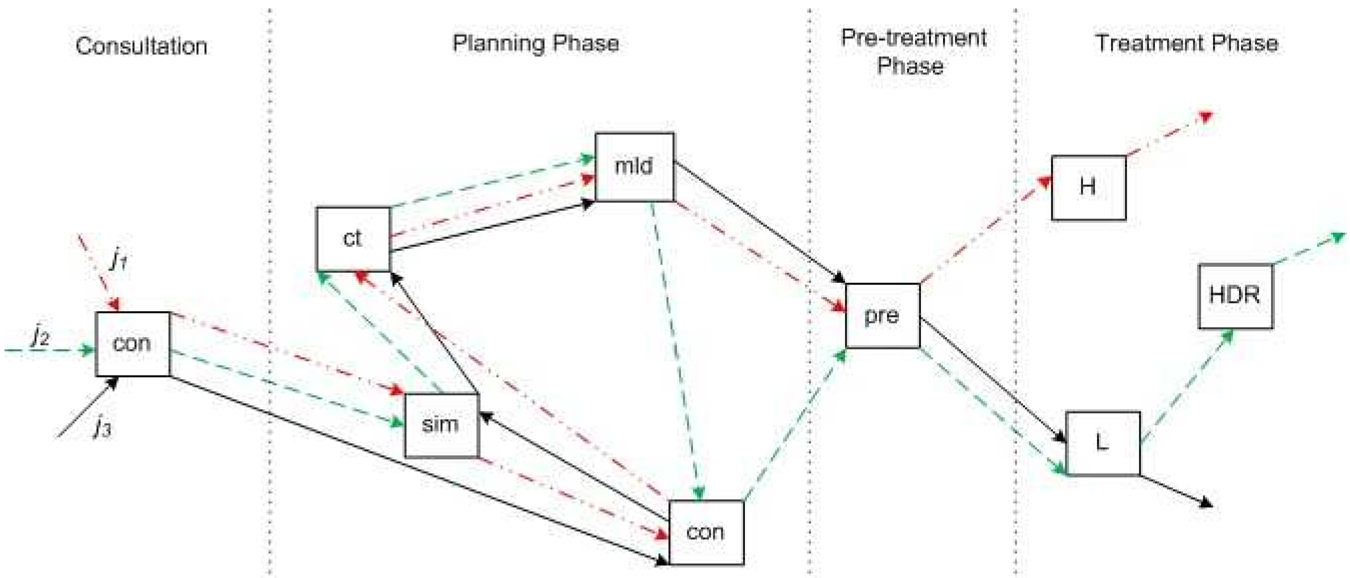

Figure 2: Simplified radiotherapy patient scheduling model. con=Consultant; sim=Simulator; ct=CT Scanner; mld=Mould Room pre=Pre-treatment resource; H=High energy machines; L=Low energy machines; HDR=High Dose Radiation machine