UNIVERSITÉ DE MONTRÉAL

SCHEDULING OF PHYSICIANS TO MINIMIZE PATIENTS' WAITING TIME

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SCHEDULING OF PHYSICIANS TO MINIMIZE PATIENTS' WAITING TIME

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DEDICATION

I would like to dedicate this thesis to
my parents,
for all their love and supports. . .

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RÉSUMÉ

Chaque phase du processus de soins en radiothérapie se compose de plusieurs étapes. Le patient est d'abord référé au centre de radiothérapie. Après une consultation avec le médecin, un scan permettra de délimiter les contours de la tumeur à soigner afin d'établir le plan de traitement. Les doses sont calculées par des dosimétristes et ensuite validées par le médecin. La phase de prétraitement commence donc par la consultation avec le médecin et se termine lorsque le traitement en tant que tel peut commencer. Dans cette étude, notre objectif est de minimiser la durée de la phase de prétraitement.

Bien que plusieurs ressources (humaines et matérielles) soient impliquées dans la phase de prétraitement, nous nous concentrons dans ce projet sur les médecins. En effet, à chacune des étapes du prétraitement le médecin est impliqué et doit donner son aval avant de passer à l'étape suivante. Notre objectif est de déterminer un horaire cyclique et hebdomadaire des tâches à affecter aux médecins, dans le but d'améliorer le flux des patients et de réduire la durée de la phase de prétraitement des patients. Bien que cet objectif soit primordial, nous incluons la satisfaction des médecins quant au choix des tâches affectées chaque jour lors de l'élaboration de l'horaire.

Le défi de ce problème réside dans l'incorporation d'éléments incertains (tels que l'arrivée des patients au centre de radiothérapie et leur profil). L'horaire des médecins est identique semaine après semaine tandis que la distribution de l'arrivée des patients varie au courant de l'année. Deux types de patients sont traités par le centre : les patients curatifs et palliatifs. Ces patients n'ont pas le même objectif de traitement, et surtout n'ont pas les mêmes délais d'attente.

Afin de résoudre ce problème nous avons développé une méthode de recherche Tabou basée sur trois types de mouvements. Dans un premier temps nous validons la performance de notre algorithme en nous basant sur des instances déterministes. Nous montrons qu'en moyenne, notre méthode est à 0.67% de la solution obtenue par CPLEX dans un temps de calcul raisonnable. Dans un deuxième temps nous incluons les paramètres stochastiques du problème. La fonction d'évaluation du coût des mouvements dans l'algorithme tient désormais compte du fait que l'arrivée et le profil des patients ne sont pas connus d'avance. Nous montrons que l'horaire obtenu par notre algorithme est de meilleure qualité que celui utilisé en pratique sur une cinquantaine de scénarios générés.

ABSTRACT

Patients are interacting with many different types of healthcare resources. At the same time, new technologies in laboratories, radiology departments and surgeries have increased the number of procedures in diagnosing and curing diseases. Due to financial issues, healthcare organizations are trying to provide the best quality services with reasonable cost by improving the utilization of existing resources. The variability in demand and uncertainty in treatment as well as test duration can cause situations that some resources may not be available at the time they are required which create bottlenecks. Various factors, such as the lack of physical capacity, staff, proper scheduling method, equipment, supplies and sometimes even information, can cause bottlenecks which result in a delay for patients who are receiving the treatment.

According to the Canadian Cancer Society reports, every three minutes one person is diagnosed and every seven minutes one person dies from cancer, Canadian Cancer Society (2013). Besides, long waiting times for radiotherapy treatments can cause serious effects on the treatment process. In Quebec, the waiting time for radiation oncology (the time between the patient becomes ready for the treatment and the starting day of treatment) is 4 weeks, Ministère de la santé et des services sociaux (2010). However, time has a major impact on the treatment process and delay in starting radiotherapy has negative effects on treatment progress. The optimal use of existing resources along with keeping the quality of treatment can be the best possible option. In cancer facilities and radiotherapy centers, the sooner the disease is recognized and the treatment is started, strengthen the chance of success in treatment. Since a patient is referred to a radiotherapy center till the start of the treatment, the patient should go through a sequence of tasks. Therefore, reducing the time for the pre-treatment phase becomes crucial, which again explains the importance of this study in making the patient ready for the treatment, thus shortening the pre-treatment phase to less than a week.

The objective of this study is determining a task schedule for physicians in a radiotherapy center. Attempts were made to find a scheme for physicians in order to minimize the pre-treatment phase for patients, which would help them to start their treatment earlier by preventing physicians from being bottleneck. Satisfaction of physicians was also considered. To reach this objective, some uncertainty items such as arrival rate of patients and their profiles were considered.

A meta-heuristic approach, Tabu Search algorithm, was developed and then compared with two mathematical models, one based on patterns and the other based on tasks of physicians. Due to the size of the problem and different conditions, either task-based model or pattern-based one could be used. It is shown that the method developed in this project is compatible with different situations. In addition, two heuristic approaches were developed based on physicians' tasks.

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CHAPTER 1 INTRODUCTION

A medical procedure to a patient often includes sequences of tasks performed by different individuals. Each task is in combination with equipment, supplies and specialized staff. The movement of patients through different departments in a healthcare center is a part of the patient flow, where long waiting lists, uncertainty and emergency admissions are common. An efficient and coordinated patient flow would result in improving the quality of treatment, shortening hospital lengths of stay and decreasing wait times for patients. Patient flow has been defined in different settings. For example, in an emergency department, the efficiency of patient flow is measured where a patient is treated immediately after arrival while in a walk-in clinic the patient can be seen in 30 minutes. In Canada, reducing the waiting time of patients to receive services and improving the availability of healthcare resources has received more attention. However, medical centers are challenged to provide highly complex and specialized services to ensure that patient flow will be smoothed from one step to the next.

Although a fast service with few disruption result in an effective patient flow, various challenges exist in patient flow optimization, (i.e., different resources, uncertainty in patient arrival, profile and service). Patients are interacting with different types of healthcare professionals and services, along with new technologies in laboratory, radiology and surgeries that increased the number of tests and procedures. Even though a resource may not be available at the time it is needed due to variability in demands and uncertainty in different factors (i.e., treatment and test duration), healthcare organizations are trying to provide high quality services with utilization of existing resources and eliminating waste and time. These bottlenecks and disruptions in patient flow can cause a delay in patients' treatment, poor patient satisfaction and even delays in the start or completion of medical treatment. Various items can cause bottlenecks, such as : physical capacity, staff, equipments and supplies, information and scheduling. The managing system in healthcare focuses on making a balance between keeping the capacity investments as low as possible and handling the patient demand without experiencing bottlenecks.

This study focuses on patient flow in cancer treatment centers, since aside from various needs for medical services, the number of patients diagnosed with cancer has increased significantly. In Canada, cancer is the major cause of death and almost half Canadians experience this disease in their lifetime. Figure 1.1 represents different causes of death in Canada and shows cancer as a leading one.

Based on Canadian Cancer Society reports, every 3 minutes one patient is diagnosed and

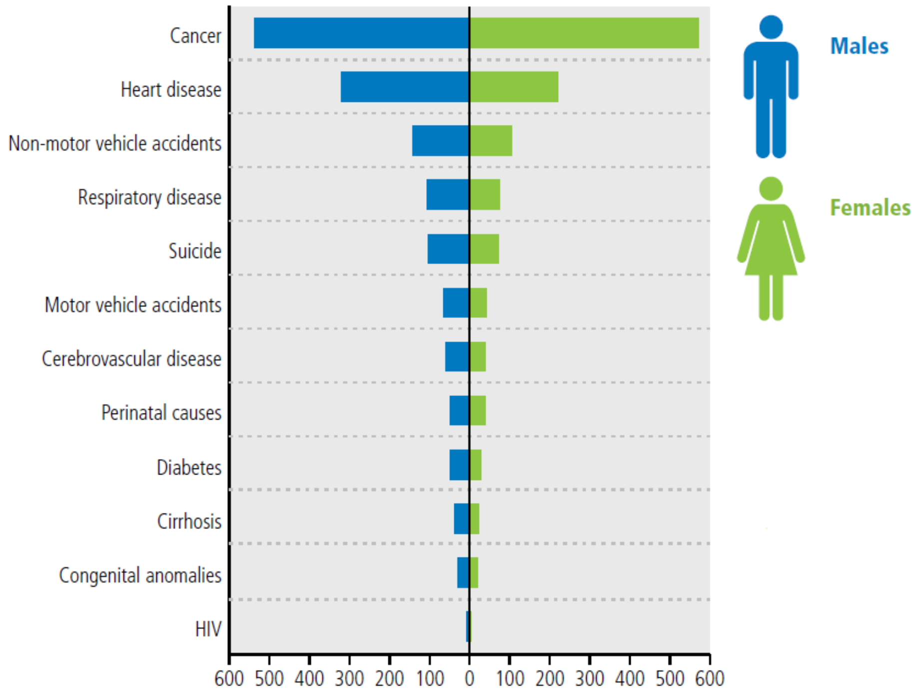

Figure 1.1 Selected causes of death and their associated potential years of life lost (PYLL), Canada, 2010.

every 7 minutes one patient dies from cancer and besides to the few resources, it is crucial to ensure that everyone has good access to cancer care facilities, Canadian Cancer Society (2013). Surgery, chemotherapy and radiation therapy are three most effective and standard cancer treatments. In the U.S., approximately 300,000 newly patients diagnosed with cancer benefited from radiation therapy, American Cancer Society report (2006), and approximately 52% of cancer patients experience radiotherapy at least once in their treatment process, Delaney (2005).

The radiotherapy treatment consists of different stages and each has different steps. Pretreatment and treatment are two phases of radiotherapy. In the pretreatment phase, the area that must be treated with radiation, the doses of radiation and a treatment plan would be defined and prepared. When a patient is referred to a radiotherapy center, before starting the treatment, he/she needs to go through some steps, including a consultation with a physician, a CT scan and indicating the dosage of treatment. After verifying the radiation doses, the treatment plan can be prepared. After completing this pre-treatment phase, patients can start their treatment.

Cancer patients are classified based on their treatment purpose and waiting list status to two categories of palliative and curative. The treatment for palliative patients is aiming to relieve the pain and symptoms of cancer while in curative patients, the purpose is curing. In cancer facilities and radiotherapy centers, time plays a significant role. The sooner the disease is recognized and treatment is started, the better are the chances of success in treatment. Almost all resources are a bottleneck in the patient flow of cancer patients : availability of slots on the treatment machines, availability of dosimetrists and physicians, etc. Given the fact that in a hospital physicians play a significant role in providing healthcare services for patients, we focus on the physicians schedule.

In this research, the main objective is to shorten the pretreatment phase for patients who are referred to the oncology department. Besides, attempts are made to maximize the satisfaction and preferences of physicians on performance of tasks. We developed a meta-heuristic method in order to propose an efficient weekly cyclic schedule for physicians in a radiotherapy center, which is proved to perform very well compared to a commercial solver, CPLEX. It considers uncertainty and should be easy to transfer to a cancer treatment facility.

The thesis is organized as follows. A brief review of related literature is given in the next chapter, which is followed by the problem statement and definition in chapter 3. In chapter 4, the methodology of solving the problem is given and it is followed by defining given instances and results in chapter 5. Finally, the conclusion is discussed in chapter 6.

CHAPTER 2 LITERATURE REVIEW

The objective of this chapter is to place our contribution in the context of previous works.

Management in healthcare organization has got great attention in recent years. Various concepts have been studied in this area, either with the objective of decreasing the processing and waiting times or decreasing the cost. Scheduling is one of the main topics that has been studied in different contexts, specifically in nurse rostering, appointment scheduling, operating room scheduling and outpatient appointment planning, (Burke (2004), Gupta (2008), Cayirli (2003), Cardoen (2010)). However, to the best of our knowledge, only few works have been done on physicians' scheduling. A large number of rules should be taken into account in generating a physician roster, such as the availability of physicians, the consecutive shifts or nights, and weekend shifts that one can work. Rousseau (2002) presented a hybridization of a constraint programming (CP) model and local search techniques in the context of physician rostering problem based on shifts scheduling.

Our attempts are made to find a task schedule for physicians in a radiotherapy center with maximising their preferences and minimising the patients' pre-treatment phase at the same time. We are proposing a meta-heuristic approach, which can be used in different situations and helps to avoid using commercial solvers. The arrival rate of patients and their profiles are not known in advance and has been considered through the proposing method.

The related literature can be divided into three categories of task scheduling, patient flow, and uncertainty conditions.

2.1 Task scheduling

The physician scheduling problem may be placed in the context of job-shop scheduling which is defined as processing a known set of jobs on a known set of machines. The goal in the job-shop scheduling problem is to assign each job to a relevant machine by considering a variety of conditions, Nowicki (1996).

In this problem, physicians are treated as machines and their tasks are considered as jobs. The goal is to minimize the total length of pre-treatment time for patients.

Sawik (2000) studied the scheduling of a flexible flow line problem. In a flexible flow line, several processing stages were separated by finite intermediate buffers. At each stage, each product must be processed by one machine among different ones. The buffer would prevent another product from being processed on the blocked machine. Sawik proposed a mixed integer programming model to find a production schedule in order to minimize the completion time of products. Bard (2005) introduced overtime for regular shifts in a week for regular workers and added shifts for temporary employees in the problem of adjusting the overall schedule at USPS. A large-scale MIP was solved by a MIP solver. In order to speed up the solution process, they used the linear relaxation solution. Assigning breaks to shifts and days off to the temporary employees were also post-processed by heuristic algorithms. A similar problem was also addressed by Zhang (2009) in rescheduling the equipments to adjust the activity demands. A multi-criteria MIP was composed to three modules of : scheduling the operations on each equipment by a multi-level lot sizing problem ; scheduling the shifts ; and assigning the breaks to shifts.

An extensive review of genetic algorithms applied to job-shop scheduling problems was given by Cheng (1996). They first represented the schemes proposed for job-shop problems and then discussed different hybrid approaches of genetic algorithms which could be applied to scheduling problems in various manufacturing systems and other combinatorial optimization problems. A hybrid framework integrating a heuristic and a genetic algorithm (GA) was presented by Zhou (2009) in job-shop scheduling to minimize weighted tardiness. In their approach, for each new generation, the GA finds the first task of each machine and the assignment of the remaining tasks was determined by the heuristic. Their attempts were to improve the performance of a heuristic with a GA and to improve the computational efficiency of a GA with a heuristic. They also developed a generalized hybrid framework that can solve different job-shop problems with multi-objective scheduling problems. They concluded that their hybrid framework performs significantly better results than either a heuristic or GA alone.

Staff is one of vital resources in hospitals who has great impact on the quality of services they give, so providing a flexible schedule with considering their preferences is important in health services. However, employees' satisfaction have been mostly studied in airline crew scheduling, rail crew scheduling, operating room scheduling, nurse rostering and timetabling problems.

Demassey (2005) proposed a hybrid constraint programming-based method to solve the Employee Timetabling Problem which is determining a set of work shifts to cover each activity with a sufficient number of employees. A set of additional constraints takes into account the preferences and qualifications of employees in assigning activities. A different cost is associated to the priority of each employee for the same assignment which is considered with the coverage costs in a single objective function. The ability of constraint programming in modeling the complex constraints is its advantage.

In this thesis, the preferences of physicians is defined as their priority of performing tasks on days over the planning horizon.

A review of literature on different contexts and approaches to improve the patient flow is also given in the following.

2.2 Patient flow

In our study, the physicians' tasks or stages of pretreatment phase are the steps of patient flow that should be smoothed. We had a look into the literature to find out how others took this context into account.

Improving the patient flow has been studied in various contexts. For example, the influence of different factors on patient flow in the emergency department was evaluated by Miro (2003). They broke down the main reasons of remaining each patient at ED into four categories, ED internal factors, hospital interrelation factors, factors related to hospital and factors related to neither of ED and hospital. They measured the number of patients, whom has been arrived between three hours, waiting to be seen. They concluded that the ED effectiveness can be determined by some ED and hospital internal factors.

Health care would be provided as either inpatient or outpatient systems. Inpatient care is defined as providing health care for patients who need to stay at a hospital for the duration of their treatment while in an outpatient clinic patients are treated on the day that they visit the clinic.

Hashimoto (1996) investigated the influence of staff number on the patients' length of stay in an appointment-based outpatient clinic through a computer simulation. It can be concluded from their study that increasing the number of providers in any group, increased the patient total time in clinic. For example, when the number of physicians working during a session increased, because the number of other servers was not proportionately increased, patient waiting time to see those servers would be increased. Thus patients spent more time in the clinic on the average. A discrete-event simulation model on physician's activities, is developed by Cote (1999) to examine the impacts of examining room capacity on the patient flow in an outpatient clinic. Their application developed for known paths for patient flow and necessary service distributions which proved the fact that simulation models cannot only apply on large projects but also its application on a much simpler and straightforward system can express meaningful analyses. Chand (2009) developed a simulation model to reduce both the patient wait times and physicians' finish times in an outpatient clinic. They believe that identifying the sources of variability at different stages can significantly improve the process performance. Two stages of registration and see-the-Doctor were considered in their patient flow process in which long wait times and variability can occur at any stage. However, their system could not achieve a steady state.

Lummus (2006) applied lean principles on a small medical center by a value stream mapping. They draw a set of scheduling guidelines to decrease patient wait time and increase patient throughput. At the current state of the center, patients are being scheduled by a scheduling department and pushed to a scheduling list, despite the current situations of the offices. Hence, the patients waiting time to be processed vary extremely from each other. This would even get worse, if a physician is called from the emergency department. They suggested some modifications which they summarized as :

1. "A ‘pass-through’ lane must be available to handle acute cases that arrive, without adding significant work-around steps to the support staff."
2. "The physician’s time is similar to a hotel room or airline seat – once it has passed without creating revenue – that potential revenue is lost."
3. "All in-process inventories must be processed by the end of the day."
4. "The time with the physician is by far the bottleneck in the system, while the average time of a 15 minute cycle is viewed as highly accurate."

A discrete-event simulation was developed by White (2011) to examine the influence of integrated scheduling and capacity allocation policies on reducing patient waiting times and improving resource utilization. Two decision factors of appointment scheduling rules and exam rooms allocation have been considered int their study. As a conclusion, they concluded that their given policy perfectly optimized the resources by minimizing waiting time and mean clinic duration among maximizing physician utilization.

Besides to reducing patients’ waiting time, some other factors has been also considered as a measurement for patient flow. Abraham (2010) studied two clinical and one non-clinical department of an academic hospital to evaluate the socio-technical requirements in order to improve the patient flow. They identified ineffectiveness of interdepartmental interactions, information handoffs and information technologies as the three major challenges in coordinating the patient transfer process.

A method was proposed by Pickard (2007) to evaluate the impact of staffing and demand management on patient flow. They predicted the number of staff needed for the near future by adding the patient progress in scheduled admissions and a prediction of unscheduled ones, which would effectively manage the staff.

For improving the patient flow in cancer care facilities, Santibáñez (2009) analyzed the simultaneous impact of several operational characteristics of a cancer care outpatient service by simulation. They presented the important factors in the appointment process that can help reduce patient wait time and improve resource utilization. Besides, radiotherapy process consists of several stages, therefore, Kapamara (2007) studied the treatment process and identified the the bottlenecks in the process using discrete-event simulation. Proctor (2007) also identified and quantified the factors that affect the number of days since the patient is referred to a radiotherapy center till the date the patient receives the first treatment. A simulation model was developed after a series of discussions and interviews with staff to represent the way a patient moves from a referral till starting the treatment.

By opposition to the presented studies, we want to improve the patient flow through more efficient physician task scheduling. However, healthcare processes consists of many variability items. A state of arts is presented in the following section to identify uncertainty factors and the proposed solutions for them.

2.3 Uncertainty situations

In real world problems, many factors are not fixed and known in advance. We review the literature to identify uncertainty factors in different problems and find out how others dealt with this problem. The concept of stochastic parameters has been studied in different areas through simulation and optimization methods. In the following subsections, different solution approaches are explained.

2.3.1 Simulation methods

Jongbloed (2001) showed how to compute a prediction of the arrival rates by proposing a queueing model for a call center with unknown arrival rates. They applied their model to the call centre of a Dutch insurance company.

A dynamic task scheduling scheme is proposed by Kong (2011) for virtualized data centers with uncertain workloads in which a two-objective optimization of the availability and responsiveness performance is modeled through a fuzzy prediction method. They concluded that their dynamic task scheduling algorithm can improve the total availability of the virtualized data centers and their responsiveness performance.

Vermeulen (2008) proposed an adaptive scheduling method with dynamic capacity usage for scheduling of outpatients appointments. They simulated the stochastic arrival process considering busier periods of weeks by means of a random walk. In their multi-agent approach the local department scheduling objectives was represented by departments agents whom were interacting with patient agents in coordinating scheduling of patient appointments.

2.3.2 Optimization methods

The literature in radiotherapy scheduling is mainly focused on the short term planning and mainly on specific parts of the care process, such as appointment scheduling on linac machines, which customize high energy x-rays to destroy cancer cells. Legrain (2014) developed a hybrid method combining stochastic optimization and online optimization to schedule patients on these machines. Conforti (2008) developed an optimization model to determine an efficient outpatient scheduling in a radiotherapy department. They evaluated their model on randomly generated instances and a real case study. Their constraint-based model for optimizing the sequencing of outpatients in radiotherapy treatment planning maximized the number of patients that begin the radiotherapy treatment in dynamic environment where future arrivals are considered continuously over the week. Conforti (2011) extended the models proposed in Conforti (2008) by considering patient availability.

A linear programming model solved by Saure (2012) through column generation to obtain an efficient allocation of available treatment capacity while reducing wait times in radiation therapy units. In their approach, an approximated value of linear programming formulation of Markov decision process is estimated and then column generation would solve its dual which gives an approximate optimal booking policy.

2.3.3 Simulation - Optimization methods

A two-stage algorithm was developed by Robbins (2008) in scheduling call centers with uncertain arrival rates. Using a constructive heuristic, the first schedule is developed in less than a minute and then improved by a simulation-based optimization approach. They claimed that the rapid scheduling process helps the managers to have a quick evaluation of multiple schedules. However, they could not have any claim on optimality, since their approach is based on heuristics.

A simulation-optimization approach is presented by Klassen (2009) to determine a scheduling of appointments in stochastic environment. Contrary to its similar studies, their approach provide more flexibility over different problem settings. In the simulation part, for each candidate solution, they calculated the relevant statistic and passed it to a heuristic to be optimized and the solution obtained through the heuristic, would be returned to the simulation to be evaluated.

De Angelis (2003) also studied the integrating of simulation and optimization in a transfusion centre. They used the simulation tool to generate observations and the optimization is then used to identify the optimal estimation methods. In case that the gap between the solution value of the optimization model and the simulated one was large, they would set a new configuration and produce a more accurate estimation. The combination of estimation and optimization makes their approach more effective in finding good configurations.

2.3.4 Heuristics

Bianchi (2009) presented a survey on meta-heuristics approaches and their application to stochastic combinatorial optimization problems.

A TS algorithm for solving the vehicle routing problem, was proposed by Gendreau (1996), in which they considered stochastic demands and customers. They developed an approximation objective function to use the evaluation of potential moves in their objective function. They solved the VRPSDC problem as a two stage objective in which they evaluated the expected value of the second stage objective function associated with a first stage solution, x^ν, by T(x^ν) for k^{th} route of x^ν. T(x^ν) is defined as :

$$T(x^\nu) = \sum_{k=1}^{m^\nu} T^k(x^\nu)$$

where m^ν is the number of routes at iteration ν, $T^k(x^\nu)$ was defined as the expected cost of route k in which the probability of the demands are considered. The proposed TS was successful to solve instances up to about 50 customers.

The uncertainty in TS has mainly studied over VRPSD and TSP problems. In Bianchi (2004) and Bianchi (2006) a simple TS algorithm has been compared with other meta-heuristics (ACO, EC, SA, and Iterated Local Search) and concluded that TS obtained results better than ACO and SA, but worse than EC.

The uncertainty has been solved through various methods in scheduling problems, however, to the best of our knowledge, it has not been studied through the Tabu Search method. We are applying the concept of uncertainty in task scheduling problem in the procedure of proposing Tabu Search method.

CHAPTER 3 PROBLEM DEFINITION

This chapter presents a complete description of the problem, including definition, characteristics and evaluation methods.

3.1 Definition

The goal of physician scheduling problem is to find a weekly cyclic scheme for physicians of radiation department and assigning the arriving patients to the best possible physician in their cancer type. It means that, the number of arriving patients and their cancer type cannot be known in advance. Figure 3.1 shows a schematic diagram of stages in the pre-treatment phase in a radiotherapy center. However, for patients with different types of cancer, some stages may vary.

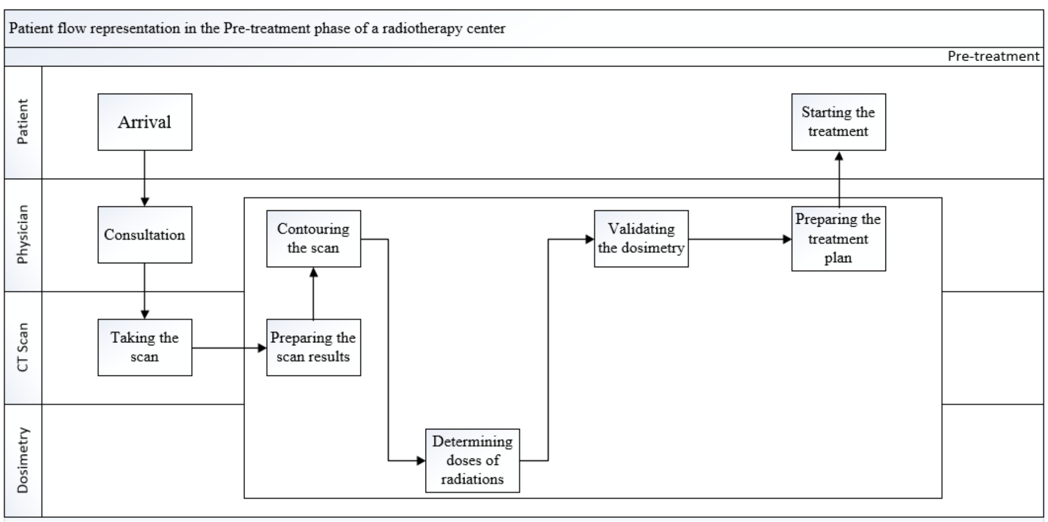

Figure 3.1 Stages of pre-treatment phase in a radiotherapy centre.

At the arrival of a patient, a consultation will be scheduled with a physician with considering the physician's availability and specialization in cancer type. Then, the patient is sent to take a CT-scan. After preparing the scan results and contouring them by the physician, a dosimetrist would determine the doses of radiation that the patient needs. At this step, the physician can validate the dosimetry and prepare the treatment plan, so the patient can start his/her treatment on linacs. In this thesis, we are focusing on the pre-treatment phase. The attempts are to decrease the time that a patient spends in this phase by determining a task schedule for physicians with these four main tasks.

3.2 Characteristics

The main characteristics of the physicians scheme which were considered are as follows :

— A weekly cyclic schedule is being proposed.

— All physicians should perform all tasks in a planning horizon.

— Two different categories of patients (curative and palliative) are considered.

— Each patient is assigned to one physician.

— The pre-treatment phase includes four sequential stages of Consultation, CT scan, Scan contouring and Treatment plan.

— Each physician specified his/her priority to perform a task on different days of a week by weighting task/day between 1-9.

In the rest of this work, each step of the patient flow is aligned with a task for the physician in which "Consultation " is addressed as task "A", CT-Scan" as task "B", "Scan Contouring" as task "C" and "Treatment Plan" as task "D". An example of the scheme that we are looking for is shown in table 3.1.

Table 3.1 An example of a schedule for 4 physicians in a week.

	Monday	Tuesday	Wednesday	Thursday	Friday
Phys. 1	B	C	A	A	D
Phys. 2	A	B	B	C	D
Phys. 3	B	D	C	B	A
Phys. 4	C	D	A	B	C

3.3 Mathematical models

In order to evaluate the quality of our proposing method and compare its results with the optimum solution, two mathematical models are presented as a solution of this problem to evaluate it in different situations. Due to the characteristics of this problem, either of the models can be used. Some parameters in these two models are similar.

Let I be the set of physicians, J be the set of patients and D be the set of days. Moreover, d_j indicates the arrival day of patient j and Cap is considered as the capacity of each physician which is the number of patients each physician can accept in a week.

Each model has also some more parameters which will be explained particularly.

3.3.1 Pattern-Based

A pattern is defined as a possible sequences of tasks for a physician in a planning horizon. In this model, all feasible patterns were generated and each physician and arriving patient was allocated to one of the patterns. The allocation respects the capacity of each pattern and ensures that a patient is assigned to a pattern which has already been assigned to a physician. Figure 3.2 represents this concept.

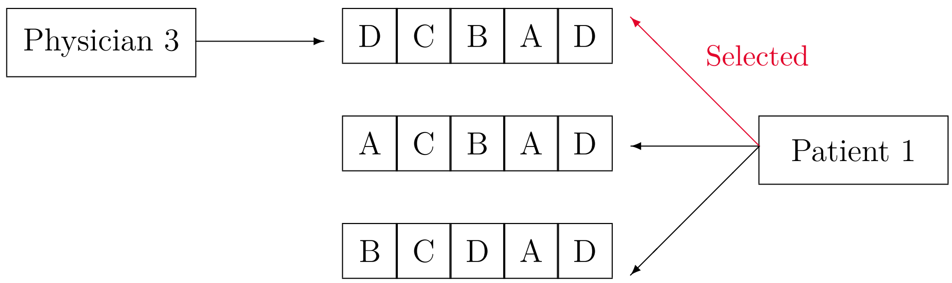

Figure 3.2 Pattern selection

In this figure, since only the first pattern is assigned to a physician, considering the capacity of physician for accepting patients, patient 1 can be assigned to the first pattern, therefore the patient is assigned to physician 3.

In addition to the defined sets and parameters, P is defined as the set of feasible patterns and for parameters, S_{ip} is defined as the preference of physician i for pattern p and W_{d_jp} is defined as the pre-treatment duration time for patient j arrives on day d with pattern p.

We used binary variables as :

$$x_{ip} = \begin{cases} 1, & \text{if Physician } i \text{ is assigned to pattern } p \\ 0, & \text{otherwise} \end{cases}$$

$$y_{jp} = \begin{cases} 1, & \text{if Patient } j \text{ is assigned to pattern } p \\ 0, & \text{otherwise} \end{cases}$$

The complete model can be written as :

$$\text{maximize} \quad \sum_{i \in I} \sum_{p \in P} S_{ip} x_{ip} - \sum_{j \in J} \sum_{p \in P} W_{d_jp} y_{jp},$$

The objective is divided into two parts : maximizing the weight of physicians' preferences and minimizing the patients' pre-treatment duration.

$$
\begin{aligned}
\text{subject to} \quad & \textstyle\sum_{j\in J} y_{jp} \leq Cap \times \sum_{i\in I} x_{ip}, && \forall p \in P && (3.1)\\
& \textstyle\sum_{p\in P} y_{jp} = 1, && \forall j \in J && (3.2)\\
& \textstyle\sum_{p\in P} x_{ip} = 1, && \forall i \in I && (3.3)\\
& x_{ip} \in \{0,1\}, && \forall i \in I \ , \forall p \in P && (3.4)\\
& y_{jp} \in \{0,1\}, && \forall j \in J, \forall p \in P && (3.5)
\end{aligned}
$$

Constraint (3.1) ensures that a patient would be assigned to pattern p only if a physician has been assigned to p with considering its capacity. Constraint (3.2) ensures that all patients are assigned to a pattern. Constraint (3.3) ensures that all physicians are assigned to a pattern. Constraints (3.4) and (3.5) enforce the integrality of decision variables.

This model will be denoted as model P1 in the rest of this thesis.

3.3.2 Task-based

The task-based model (denoted as model P2) concentrates on the physicians' daily schedule. In the following, the definition of additional sets and parameters that are used in this model are explained.

Let T be the set of tasks. The parameters are also defined as :

Parameters :

d_j : The arrival day of patient j

S^d_{ti} : Score/Preference of physician i for task t on day d.

b_t : Duration of task t.

Moreover, the binary variables are defined as :

$$
x^d_{ti} = \begin{cases} 1, & \text{if Physician } i \text{ perform task } t \text{ on day } d \\ 0, & \text{otherwise} \end{cases}
$$

$$
y_{ij} = \begin{cases} 1, & \text{if Patient } j \text{ is assigned to physician } i. \\ 0, & \text{otherwise} \end{cases}
$$

The integer variable of p_{jt} is also defined as the completion time of task t for patient j.

The task-based model is more complicated since the schedule of physicians on each day is not known on the arrival day of patients and minimizing the pre-treatment process for patients depends on physicians' schedule. The attempts are made to avoid presenting a non-linear programming (NLP) model. Thus, the horizon is extended to 20 days which is maximum processing time for each patient and the schedule of physicians is repeated every 5 days. In the following the proposed model and its complete description can be found.

$$\text{maximize} \quad \sum_{i\in I}\sum_{t\in T}\sum_{d\in D} S^d_{ti}x^d_{ti} - \sum_{j\in J}\sum_{t_n\in T}(p_{jt_n} - d_j)$$

The objective is divided into two parts : Maximizing priorities of physicians to perform tasks on different days and minimizing the patients' pre-treatment duration which is the difference between their arrival day and the ending time of their last task.

$$\begin{array}{llll}
\text{subject to} & \sum_{t\in T} x^d_{ti} = 1, & \forall i \in I\ ,\ \forall d \in D & (3.6)\\
& \sum_{d\in D} x^d_{ti} \geq 1, & \forall i \in I\ ,\ \forall t \in T & (3.7)\\
& x^d_{ti} = x^{d+5}_{ti}, & \forall i \in I\ ,\ \forall t \in T,\ \forall d \in D & (3.8)\\
& \sum_{i\in I} y_{ij} = 1, & \forall j \in J & (3.9)\\
& \sum_{j\in J} y_{ij} \leq Cap, & \forall i \in I & (3.10)\\
& w^d_{ijt} \leq x^d_{ti}, & \forall i \in I\ ,\forall j \in J\ ,\forall t \in T\ ,\ \forall d \in D & (3.11)\\
& w^d_{ijt} \leq y_{ij}, & \forall i \in I\ ,\forall j \in J\ ,\forall t \in T\ ,\ \forall d \in D & (3.12)\\
& \sum_{d'\in D} w^{d'}_{ijt} + 1 \geq x^d_{ti} + y_{ij}, & \forall i \in I, \forall j \in J\ , \forall t \in T, \forall d \in D & (3.13)\\
& \sum_{d\in D} w^d_{ijt} \leq 1, & \forall i \in I, \forall j \in J,\ t \in T & (3.14)\\
& p_{jt} \geq d w^d_{ijt} + b_t, & \forall i \in I, \forall j \in J, \forall d \in D,\ \forall t \in T & (3.15)\\
& d w^d_{ijt_1} \geq d_j w^d_{ijt_1}, & \forall j \in J, \forall d \in D, t_1 \in T & (3.16)\\
& \sum_{i\in I}\sum_{d\in D} d w^d_{ijt_{k>1}} \geq p_{jt_{k-1}}, & \forall j \in J, \forall t_{k>1} \in T & (3.17)\\
& x^d_{ti} \in \{0,1\}, & \forall i \in I\ ,\ \forall t \in T,\ \forall d \in D & (3.18)\\
& y_{ij} \in \{0,1\}, & \forall i \in I\ ,\ \forall j \in J & (3.19)\\
& P_{jt} \in N, & \forall j \in J\ ,\ \forall t \in T & (3.20)
\end{array}$$

Constraint (3.6) ensures that only one task t is assigned to a physician on each day. Constraint (3.7) ensures that all tasks are performed by all physicians during a week. Constraint (3.8) repeats the same schedule every 5 days for all physicians. Constraint (3.9) assigns all patients to a physician and constraint (3.10) tries to satisfy the capacity of each physician in accepting patients. In order to determine the pre-treatment days, there is a need to understand which patient is assigned to which physician as well as the task that the physician is performing on each day. An auxiliary binary variable is declared as w_{ijt}^d which takes value *1*, when physician i performs task t for patient j on day d. w_{ijt}^d helps to track patients' assignments and physicians schedules. Constraints (3.11), (3.12) and (3.13) are tracking this issue. These three constraints ensure that w_{ijt}^d takes value 1 only when x_{ti}^d and y_{ij} equal to 1. Constraint (3.13) allows to find all $d \in D$ that satisfy the constraint. Besides, constraint (3.14) ensures that each task is performed once for each patient. Thus, the best $d \in D$ will be chosen.

Now that we are tracking the schedule of physicians with w_{ijt}^d, $\mathrm{d}w_{ijt}^d$ denotes the day that task t is performed for patient j. Constraint (3.15) finds the ending time of task t for patient j. Constraint (3.16) ensures that the ending time of the first task for each patient is considered after his/her arrival day and constraint (3.17) ensures that the ending time of tasks are based on their order. Constraints (3.18)-(3.20) enforce the integrality of decision variables.

3.4 Extension

So far we explained the case for one block per day shift for physicians. However, doing the same activity during a day may not be desirable. Moreover, a patient needs to wait to be processed the next task until the following day. Thus, in order to smooth the flow of patients and help them to be processed as soon as possible, the number of time slots per day can be increased. A physician can perform different tasks during different time slots in a day and his preferences may be better satisfied. Two time slots per day are considered for physicians ; i.e., mornings and afternoons. This would also help reduce the risk of passing the deadlines. Table 3.2 shows an example for this kind of scheme for four physicians.

Table 3.2 An Example of a Schedule for 4 Physicians with two tasks per day.

	Monday		Tuesday		Wednesday		Thursday		Friday	
	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.
Phys. 1	A	A	C	B	D	D	A	B	C	D
Phys. 2	D	A	A	B	C	B	D	A	D	C
Phys. 3	B	D	B	A	A	A	C	C	D	B
Phys. 4	C	B	D	C	B	C	B	D	A	A

The only change in model *P2*, is in constraint (3.8) which would become as follows :

$$x_{ti}^{d} = x_{ti}^{d+10}, \qquad \forall i \in I, \forall t \in T, \forall d \in D \tag{3.21}$$

It ensures that for every 10 time slots (5 days), the schedule will be repeated.

CHAPTER 4 METHODOLOGY

Two simple constructive heuristics (H$_{random}$ and H$_{greedy}$) and an improving Tabu Search algorithm are presented in this section to determine a schedule for physicians in a radiotherapy center. The main goal is minimizing the pre-treatment process of cancer patients. In the following, each approach can be found in details.

4.1 Heuristic approaches

In this section, heuristic approaches based on physicians' tasks are being proposed. The problem consists of two parts, (1) assigning tasks to physicians and (2) assigning patients to physicians.

All main characteristics of the problem have been considered for constructing the heuristics.

4.1.1 Heuristic H_{random}

The problem solving procedure was started with a simple iterative heuristic. It starts from a feasible initial solution. The initial solution consists of assigning tasks to physicians and assigning patients to physicians. The former one was constructed completely randomly while the latter one was constructed by a heuristic criterion. Each patient is assigned to a physician who performs the first task on his/her arrival day by considering the cancer type and the capacity of physicians to accept patients. After generating the initial solution, at each iteration, it finds the best possible movement for all physicians by swapping their tasks in a planning horizon. The pseudo-code of this heuristic is presented in algorithm 1.

Algorithm 1 H_{random} algorithm

```
procedure H_random
    Generate a random initial solution ;
    Calculate initial cost ;
    for it < Number of iterations do
        for i < Number of Physicians do
            Find the best possible Movement by swapping the tasks in the horizon ;
        end for
        Apply the best move ;
        Update cost ;
    end for
end procedure
```

The initial solution has a great impact on the quality of solution, thus we tried to find out the performance of other heuristics and used a constructive initial solution which is described in the H_{greedy} section.

4.1.2 Heuristic H_{greedy}

In this heuristic, we constructed the initial schedule based on tasks' duration and order. However, the initial assignment was constructed similar to the heuristic H_{random}. Each patient is assigned to a physician who performs the first task on his/her arrival day. The idea is changing the repeated task at each iteration. In the simple form of the problem, since the planning horizon is five days and we have four main tasks, one task is repeated for each physician. In an iterative procedure, we checked all possible replacements for this repeated task (T) and chose the best one. This procedure presented in algorithm 2.

Algorithm 2 H_{greedy} algorithm

```
procedure H_greedy
    Generate initial solution;
    Calculate initial cost;
    for it < Number of iterations do
        for i < Number of Physicians do
            T ← Find the repeated task;
            Find the best possible replacement for task T;
        end for
        Apply the best move;
        Update cost;
    end for
end procedure
```

However, heuristic approaches usually get stuck in a local optimum and stop improving after some iterations. In order to help it look in to all neighborhoods to find the optimal solution, we applied the Tabu Seach method on the problem. In the following, the complete description of the Tabu Search procedure can be found.

4.2 Tabu Search

Tabu Search method is basically an iterative procedure, which starts from a feasible initial solution and moves step by step in the feasible space to reach a better solution in a neighborhood. Since a risk of cycling in finding a better solution still exists, a procedure should prevent the modifications which brings back the procedure to previously visited solutions. However, sometimes it can be useful to search from an already visited solution in another direction. In order to forbid cycling in solutions, a *Tabu list* is considered; it contains recently visited solutions, and forbids revisiting them for a specific number of modifications. Based on the problem, different strategies can be applied to search through neighborhood solutions. To apply the Tabu Search method to our problem, an initial solution was first generated, which is separated into two parts, assigning tasks to physicians and assigning patients to physicians. Similar to the heuristic algorithms, we generated a complete random schedule for the physicians and assigned patients to physicians who perform the first task on their arrival days. Moreover, three different kinds of modifications were considered to improve the solution and move to the next solution. In movement type 1, we tried to find the best sequence of physicians' tasks by swapping the tasks assigned to them in the initial solution from one day to another in the planning horizon. Figure 4.1 shows this type of movement.

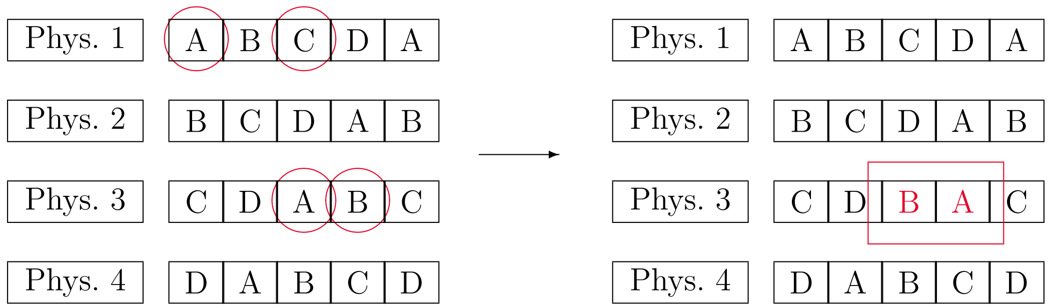

Figure 4.1 Movement "1" - Swapping.

In this example, the schedule of 4 physicians is given and possible sequences of tasks evaluated by swapping the current schedule. For example, after evaluating the swap of all tasks for all physicians, it is concluded that swapping *'A'* and *'B'* for physician 3 gives the best improvement in the cost. Therefore, the swap of *'A'* and *'B'* is applied and the solution is updated.

In movement type 2, for all physicians, we found the repeated task and changed it with tasks visited once in a planning horizon and found the best combination of them. This movement is shown in figure 4.2.

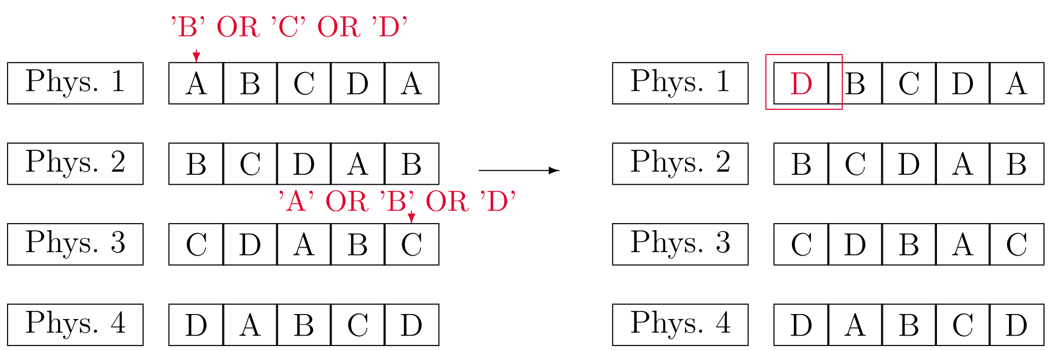

Figure 4.2 Movement "2" - Changing repeated task.

As shown in figure 4.2, for each given schedule to physicians, one task is repeated. The improvement of cost will be evaluated by replacing the repeated task with the remaining ones. In this example, task *'A'* for physician 1 will be replaced with task *'D'*.

These two movements, helped to improve the schedule and found the best scheme for physicians. We still need to improve the assignment of patients to physicians. Thus, our third movement is changing the assignment of patients considering physicians capacity and specialty until finding the best assignments. Figure 4.3 represents movement type 3.

Patient 1.	→	Phys. 2	→	Phys. 1 OR 3 OR 4 OR ... m
Patient 2.	→	Phys. 4	→	Phys. 1 OR 2 OR 3 OR ... m
Patient 3.	→	Phys. 6	→	Phys. 1 OR 2 OR 3 OR ... m
.		.		.
.		.		.
.		.		.
Patient n.	→	Phys. 1	→	Phys. 2 OR 3 OR 4 OR ... m

Figure 4.3 Movement "3" - Changing Assignment.

Figure 4.3 shows that the improvement of cost by changing the current assignment of patients with the rest of physicians would be evaluated through movement 3.

The advantage of proposed movements is that they search into a feasible space and present a new feasible solution. Although each one is effective, the combination of movements would have a greater impact and we need to propose an efficient strategy for that. Preliminary tests show that movements ”1” and ”3” have the greatest impact on the solution and the best results can be derived when the schedule and assignment are improved simultaneously. Therefore, we started with the ”Movement 1” to improve the schedule and we applied ”Movement 3” to improve the assignment, immediately after each iteration with no improvement in the cost.

There might be no improvement in cost after some iterations. Thus, a diversification strategy is required to encourage the method to search into the unvisited regions of the search space. Thus, after ω iterations, which had no improvement in the cost, we applied ”Movement 2” as a diversification strategy. After evaluating each possible move and accepting the best one, the *Tabu List* will be updated and the accepted move will be forbidden for a specific number of iterations. However, sometimes the forbidden move may help to improve the best solution found update to date. Therefore, this move will be accepted through the aspiration criterion.

In the following, one can find a pseudo-code for the complete process.

Algorithm 3 Tabu Search algorithm

```
procedure TABU SEARCH
    Generate initial solution;
    Calculate initial cost;
    neighborhood n ← 1;
    it ← 0;
    while it < Max_it do
        for neighborhood n do
            for i < Number of Physicians do
                Find the best possible movement through Movement "1";
            end for
            Update Tabu List and the aspiration criteria;
            Apply the move;
            Update cost;
            if No improvement in cost for "1" iteration then
                for j < Number of Patients do
                    Find the best possible movement through Movement "3";
                end for
                Update Tabu List and the aspiration criteria;
                Apply the move;
                Update cost;
            end if
            if No improvement in cost for ω iterations then
                for j < Number of Patients do
                    Find the best possible movement through Movement "2";
                end for
                Update Tabu List and the aspiration criteria;
                Apply the move;
                Update cost;
            end if
        end for
    end while
end procedure
```

4.3 Stochastic version of the algorithm

In the deterministic problem patients' *arrival days* and *profiles* are considered fixed. However, in practice, these two factors are not known in advance and they can vary from one patient to another. An efficient strategy is required to consider the uncertainty items in the Tabu Search procedure. A modification on the evaluation function, can easily extend the deterministic problem to the stochastic problem. In this procedure, we considered different patterns for arrival days of patients and their profiles as different scenarios. The uncertain elements can drawn from historical data or probability distributions and then they should be considered in evaluating a move. Thus, at each move we evaluated the expected cost of each scenario and considered the average expected cost of the scenarios in evaluating the moves. Although each move is searching into the feasible space and it is effective itself, we improved the assignments of patients at each move to make the procedure more efficient. This procedure helps to implicitly consider the uncertainty. Figure 4.4 shows a schematic process.

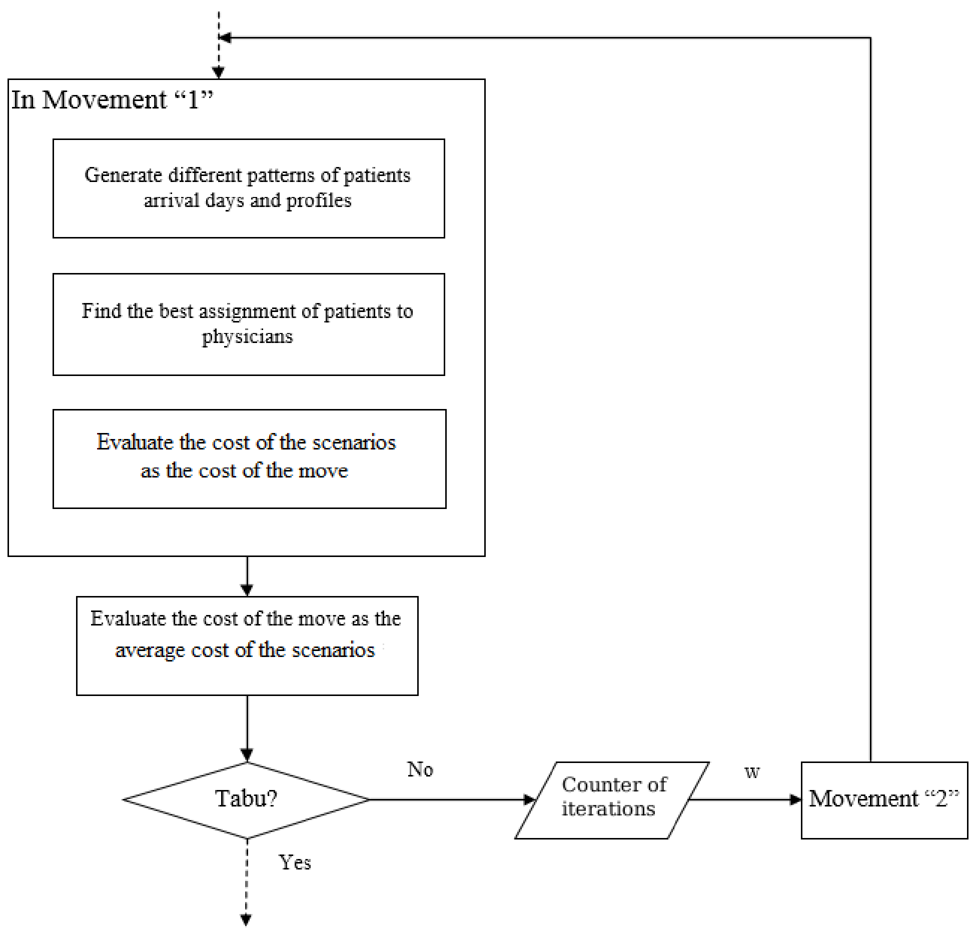

Figure 4.4 Stochastic process at each iteration.

In other words, we started with movement type ”1” and in each movement, we found the best assignment for patients with the current move, evaluated the expected cost of different scenarios in the move and considered the average of them as the cost of the move. After ω iterations with no improvement in the cost, we applied movement type ”2” as a diversification strategy and continued the procedure similar to movement ”1”. You can find the complete procedure in algorithm 4.

Algorithm 4 Stochastic Tabu Search algorithm

```
procedure STOCHASTIC TABU SEARCH
    Scenarios ← Generate S random patterns of arrival days and profiles;
    Generate the initial solution;
    Calculate the initial cost;
    neighborhood n ← 1;
    it ← 0;
    while it < Max_it do
        for neighborhood n do
            for  i < Number of Physicians do
                for  s < Number of Scenarios do
                    Find the best assignments of patients to physicians;
                    Find the best possible movement through Movement "1";
                    Evaluate cost of the move and assignment through scenario s;
                end for
                Evaluate the expected cost of the move as the average of costs of scenarios;
            end for
            Update Tabu List and the aspiration criteria;
            Apply the move;
            Update cost;
            if No improvement in cost for ω iterations then
                for j < Number of Physicians do
                    Find the best possible movement through Movement "2";
                end for
                Update Tabu List and the aspiration criteria;
                Apply the move;
                Update cost;
            end if
        end for
    end while
end procedure
```

CHAPTER 5 EXPERIMENTS

In this chapter, all proposed algorithms, including those based on the mathematical models, the Tabu Search algorithm and heuristics, are evaluated through different instances. The remainder of this chapter organized as follows : section 5.1 presents the generated instances, which will be followed by performance of approaches for deterministic and stochastic cases in sections 5.2 and 5.3. This chapter will be concluded by presenting the results obtained through the application of the method on the real data obtained from CICL.

5.1 Instances

In order to evaluate our method, 18 instances are generated for different numbers of patients and physicians. To take into account the small, medium and large range sizes of data in the proposed method, we tested the generated instances based on the table 5.1.

Table 5.1 Brief description of instances.

Small			Medium			Large		
Tests	physicians	patients	Tests	physicians	patients	Tests	physicians	patients
pr-1	4	7	pr-3	4	11	pr-5	4	20
pr-2	4	9	pr-4	4	12	pr-6	4	40
pr-7	6	7	pr-9	6	11	pr-11	6	20
pr-8	6	9	pr-10	6	12	pr-12	6	40
pr-13	8	7	pr-15	8	11	pr-17	8	20
pr-14	8	9	pr-16	8	12	pr-18	8	40

In which, pr-1, 2, 7, 8, 13 and 14 were generated as small sets of data, pr-3, 4, 9, 10, 15 and 16 were considered as medium size and pr-5, 6, 11, 12, 17 and 18 as large sets of data. The size of instances were determined based on the number of arriving patients in a week.

Some initial parameters were set in the beginning. The preferences of physicians were generated randomly between 1 to 9, which shows their priority for performing each task on different days of a week. The service time of each task were considered as follows : {1, 2, 1, 1} time blocks for tasks A, B, C and D.

The method was meant to evaluate either of deterministic and stochastic situations. For each instance, we generated 50 different patterns for patients' arrival days based on Poisson distribution. 50 different patterns were also generated for patients profiles with Bernoulli distribution for two types of curative and palliative patients. In the deterministic case, one of the 50 scenarios was selected to obtain a typical schedule among all, while, in the stochastic situation, all 50 scenarios were considered.

5.2 Performance of proposed deterministic approaches

We considered both cases of one block per day and two blocks per day. In tables 5.2 and 5.3 all results obtained in four hours are presented.

After some preliminary tests, the parameters used in TS are set as follows : Size of Tabu list was tested between 5 to 21 and different sizes related to the size of the instances (i.e., number of patients, number of physicians and their combinations). The size of Tabu list finally set to 19 in both one-task-per-day problem and two-tasks-per-day problem. The number of non-improved iterations to perform the diversification criterion, ω, was set to "twice of the number of patients + number of physicians + number of blocks in a week" for the one-task-per-day problem.

Table 5.2 Results for generated instances.

Tests	Results					GAP			CPU Time (seconds)		
	H_r	H_{gr}	TS - Ave.	TS - Best	CPLEX	H_r	H_{gr}	TS	TS	P1	P2*
pr-1 (4,7)	99	63	102.3	**105**	**105**	5%	40%	**0%**	1.9	<1	9.4
pr-2 (4,9)	77	55	103.6	**107**	**107**	28%	48%	**0%**	11.2	<1	12
pr-3 (4,11)	73	39	84.2	88	**90**	18%	56%	2%	108.8	<1	142
pr-4 (4,12)	57	32	86.8	93	**94**	39%	65%	1%	32	<1	166
pr-5 (4,20)	13	6	46.6	**50**	**50**	74%	88%	**0%**	364	<1	586
pr-6 (4,40)	-16	-34	15.1	20	**22**	172%	236%	9%	553	<1	945
pr-7 (6,7)	172	132	181.7	**188**	**188**	8%	29%	**0%**	180	<1	84
pr-8 (6,9)	164	124	182.1	190	**191**	14%	35%	0.5%	111	<1	58
pr-9 (6,11)	140	126	159.4	**165**	**165**	15%	23%	**0%**	260	<1	278
pr-10 (6,12)	147	128	172.6	**177**	**177**	17%	27%	**0%**	170	<1	323
pr-11 (6,20)	92	53	126.5	131	**132**	30%	59%	0.7%	567	<1	788
pr-12 (6,40)	24	11	57.2	62	**63**	61%	82%	1.5%	723	1	1096
pr-13 (8,7)	236	178	242.1	**253**	**253**	6%	29%	**0%**	5.6	<1	122
pr-14 (8,9)	228	170	255.6	**262**	**262**	12%	35%	**0%**	260	<1	264
pr-15 (8,11)	205	142	233.7	**241**	**241**	14%	41%	**0%**	133	<1	656
pr-16 (8,12)	211	138	234.6	243	**244**	13%	43%	0.4%	196	<1	804
pr-17 (8,20)	156	99	192.8	**203**	**203**	23%	51%	**0%**	289	<1	1245
pr-18 (8,40)	43	9	134.7	140	**141**	69%	93%	0.7%	1311	<1	2852
Average :						34%	60%	0.87%			

* The CPU time for model P2 (the task-based model) shows the time that CPLEX found the best integer solution and not the computation time.

Table 5.2 shows the best results obtained through ten randomly generated initial solutions for all instances. As shown, the pattern-based model can solve the problem in less than a second while the task-based model is considerably time consuming. Even though it can reach the solution, usually it takes lots of time to prove the optimality. The quality of solution and finding the optimum one is our main purpose, so for large instances, we considered the time that model P2 obtained best integer solution with the Gap of 5%. Heuristics H_r and H_{gr} stopped improving after some iterations, which shows that they got stuck in a local optimum in less than a second. The gap between the results obtained from Tabu search method and the optimal solution obtained from models P1 and P2 is 0.87% in average, which shows that TS performs well on these instances.

Figure 5.1 illustrates the schedule obtained for instance pr-5 (Tabu Search and exact methods).

	Monday	Tuesday	Wednesday	Thursday	Friday
Phys. 1	B	C	C	A	D
Phys. 2	A	B	B	C	D
Phys. 3	B	D	C	D	A
Phys. 4	C	D	A	B	C

Figure 5.1 Schedule obtained through TS Procedure.

In this case, Tabu Search found the optimal solution, same as the models P1 and P2. The presented schedule indicates that tasks *'B'* and *'C'* are repeated more frequently for each physicians. Since these tasks take more time to be processed, having them more frequently in the schedule appears to help decrease the processing time of patients. Besides, at least three of the tasks are performed by different physicians in a day. Hence, the patient would be served at the earliest time from the arrival.

In two-tasks-per-day problem, since the size of the problem is twice the one-task-per-day problem, more diversification is required to check all possible movements. Thus, the number of non-improved iterations, ω, was set equal to the "number of patients" for each instance. The results obtained from the generated instances for a two-tasks-per-days problem is displayed in table 5.3.

Table 5.3 Results for 2 tasks/day.

Tests	Results		GAP	CPU Time (seconds)	
	TS	CPLEX	GAP	TS	CPLEX
pr-1 (4,7)	**258**	**258**	0%	132	18
pr-2 (4,9)	257	**259**	0.7%	222	20
pr-3 (4,11)	239	**241**	0.8%	243	317
pr-4 (4,12)	241	**244**	1.2%	144	194
pr-5 (4,20)	**193**	**193**	0%	526	223
pr-6 (4,40)	108	**110**	1.8%	101	247
pr-7 (6,7)	408	**410**	0.5%	641	86
pr-8 (6,9)	404	**407**	0.7%	718	171
pr-9 (6,11)	383	**388**	1.2%	733	66
pr-10 (6,12)	386	**390**	1%	647	22
pr-11 (6,20)	330	**334**	1%	289	172
pr-12 (6,40)	248	**250**	0.8%	1024	2081
pr-13 (8,7)	**554**	**554**	0%	828	381
pr-14 (8,9)	551	**554**	0.5%	455	2163
pr-15 (8,11)	539	**543**	0.7%	329	147
pr-16 (8,12)	**540**	**540**	0%	1189	430
pr-17 (8,20)	**481**	**481**	0%	1311	276
pr-18 (8,40)	394	**399**	1.2%	1081	3134
Average			0.67%		

Table 5.3 shows that the proposed TS method can again obtain excellent results with a gap of 0.67% from the optimum solution in average. Besides, for small instances, it could present outstanding results with a maximum gap of 0.7% ; on large instances, the gap can reach 1.8%.

As an illustration, a comparison of patients pre-treatment duration in instance pr-5 is given in figure 5.2 for the one-task-per-day and the two-task-per-day problems.

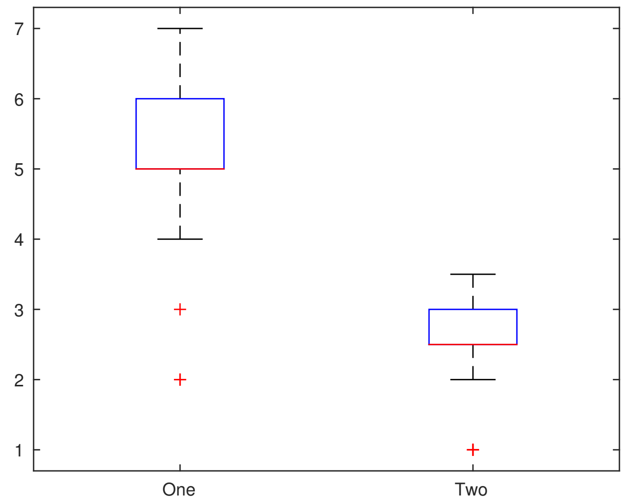

Figure 5.2 Comparison of pre-treatment duration for different blocks per day in instance pr-5.

Figure 5.2 presents the number of days that the process took. It can be derived that when tasks are two blocks per day, a much better performance is obtained and all patients can finish their pre-treatment process in less than four days, while it takes seven days for the one-block-per-day problem.

According to tables 5.2 and 5.3 the CPU time is dependent on the number of patients and for a fixed number of physicians, the CPU time increases with the number of patients. Besides, the objective in the two-task-per-day problem is more than twice of the value observed in the one-task-per-day case, which indicates that increasing time blocks per day not only increases the physicians' satisfaction, but also improved the patient flow and decreased the pre-treatment duration.

After solving the main objective, we tried to understand the effects of physicians' preferences on the patients' waiting time. Table 5.4 represents the results of minimizing the pre-treatment duration for patients regardless of physicians' satisfaction in the one-task-per-day problem.

Table 5.4 Results for minimizing pre-treatment.

Tests	Results		GAP	CPU Time (seconds)	
	TS	CPLEX	GAP	TS	CPLEX
pr-1 (4,7)	**30**	**30**	0%	1.2	<1
pr-2 (4,9)	**33**	**33**	0%	4.2	<1
pr-3 (4,11)	50	**48**	4%	21	<1
pr-4 (4,12)	51	**50**	2%	43	<1
pr-5 (4,20)	97	**95**	2%	73	<1
pr-6 (4,40)	**184**	**184**	0%	105	<1
pr-7 (6,7)	30	**29**	3%	37	<1
pr-8 (6,9)	**32**	**32**	0%	39	<1
pr-9 (6,11)	**47**	**47**	0%	54	<1
pr-10 (6,12)	46	**48**	4%	68	<1
pr-11 (6,20)	91	**90**	1%	93	<1
pr-12 (6,40)	180	**177**	1.6%	121	<1
pr-13 (8,7)	**29**	**29**	0%	1.9	<1
pr-14 (8,9)	**30**	**30**	0%	33	<1
pr-15 (8,11)	47	**46**	2%	86	<1
pr-16 (8,12)	**48**	**48**	0%	57	<1
pr-17 (8,20)	93	**90**	3.3%	176	<1
pr-18 (8,40)	176	**172**	2.3%	243	<1
Average			1.4%		

It can be derived from the results indicated in table 5.4 that the pre-treatment duration is dependent on the number of physicians working in the center. The patient completes this phase earlier when the number of physicians is increased. Table 5.4 also indicates that TS can present outstanding performance on small set of data, in which it could obtain the optimum solution in most of the cases. However, the gap between its results and the optimum one is 1.4% on average.

Figure 5.3 shows a comparison between patients pre-treatment duration with considering physicians' preferences and without physicians' preferences in instance pr-5 for the two-task-per-day problem.

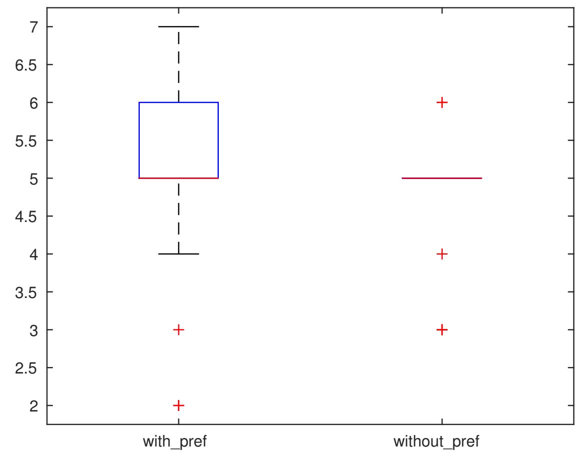

Figure 5.3 Pre-treatment with and without preferences.

It is indicated in figure 5.3 that in both cases patients would finish the pre-treatment phase in five days on average. However, in the case that we considered physicians' preferences in the objective function, we were trying to find a balanced schedule for both physicians and patients. Therefore, there are more diversity in the patients' pre-treatment duration.

Besides to the pre-treatment duration, figure 5.4 represents the average waiting time of patients to start their pre-treatment phase in different instances.

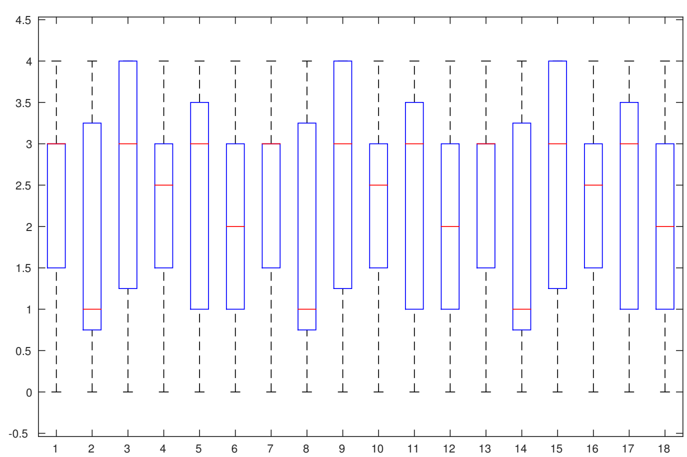

Figure 5.4 Average waiting times to start the pre-treatment process.

It is indicated from figure 5.4 that starting the pre-treatment is not dependant on the number of physicians are working in the center and starting the pre-treatment phase is similar for instances with same number of arriving patients in a week. Although the number of working physicians affects the pre-treatment duration for patients, starting this phase since the arrival, is regardless of how many physicians are working in the center.

5.3 Performance of approaches under uncertainty conditions

In this section, first the stochastic algorithm evaluated and compared with the deterministic case, and then the effects of different scenarios on the objective value is studied. In the following sections, one can find the results obtained for the generated instances.

5.3.1 Algorithm validation

Due to the complexity of the task-based model, solving the current instances based on the scenarios, takes an extremely large time and encounters memory capacity problem. Therefore, the performance of Tabu Search method was validated for a small set of data. A very small instance with 5 scenarios was tested with the task-based model and the TS method. In the exact method, each scenario in arrival days of patients was considered as a new patient which has the same profile, thus, it would be similar to having the same patient arriving on two different days. In this case, both approaches (TS and exact methods) obtained the objective value of 65.

After validating the accuracy of TS, the method was applied to the generated instances. Its performance on different instances is presented in the following section.

5.3.2 Algorithm performance

In order to evaluate the solution obtained from the stochastic tabu search algorithm, we proceed as follows :

— Generate set A of scenarios of patients' arrival and profile. We generate up to 50 different scenarios.

— For each instance (i.e. pr-1 to pr-18), run the algorithm using 1, 10, 20, 30, 40 or 50 scenarios from set A (Note : using only one scenario is equivalent to the deterministic case) for 2000 iterations. We keep the best solution obtained and refer to it as « sol_pr-x_y » where x refers to the instance being solved and y to the number of scenarios used to generate the solution ;

— Generate set B of scenarios of patients' arrival and profile to test the quality of solutions « sol_pr-x_y ». We generate 40 different scenarios for set B ;

— Evaluate the cost of the schedule obtained for each instance on the set B.

Table 5.7 shows the average value of the solutions on set B of scenarios. For each instance, we provide the average value and the standard deviation σ.

Table 5.5 Evaluation of results with different number of scenarios in stochastic situation.

Tests/ # scenarios		sol_pr-x_1	sol_pr-x_10	sol_pr-x_20	sol_pr-x_30	sol_pr-x_40	sol_pr-x_50
pr-1 (4,7)	Ave.	**220**	206	212	211	205	207
	σ	*7.24*	*8.7*	*8.2*	*7.45*	*7.7*	*9.3*
pr-4 (4,12)	Ave.	**161**	156	158	159	**161**	159
	σ	*10.96*	*11.79*	*12.39*	*12.05*	*12.47*	*13.56*
pr-6 (4,40)	Ave.	-72	-55	-46	-51	**-43**	-44
	σ	*21.57*	*24.3*	*17.66*	*17.26*	*16.67*	*16.82*
pr-7 (6,7)	Ave.	371	375	372	375	**377**	371
	σ	*8.72*	*8.21*	*7.19*	*8.41*	*8.2*	*6.96*
pr-10 (6,12)	Ave.	321	323	**334**	325	331	325
	σ	*12.94*	*13.9*	*13.26*	*12.24*	*10.86*	*12.76*
pr-12 (6,40)	Ave.	77	87	105	**107**	97	98
	σ	*25.29*	*26.78*	*23.52*	*19.44*	*23.23*	*18.12*
pr-13 (8,7)	Ave.	519	527	**528**	526	**528**	525
	σ	*8.18*	*9.2*	*8.52*	*8.55*	*8.57*	*8.74*
pr-16 (8,12)	Ave.	488	485	486	487	486	**489**
	σ	*12.9*	*10.79*	*10.75*	*9.39*	*10.83*	*12.1*
pr-18 (8,40)	Ave.	202	239	224	236	**242**	236
	σ	*25.18*	*25.88*	*25.17*	*23.21*	*24.04*	*26.31*
Average	Ave.	254	260	263	263	**264**	262
	σ	*14.85*	*15.51*	*14.07*	*13.1*	*13.62*	*13.86*

We observed that between 20 and 40 scenarios results seem to stabilize. It can be derived from table 5.5 that, depending on the instances, one gives better solution than the other. However, based on the average of standard deviations, 30 number of scenarios gives a better solution.

Figure 5.5 shows a comparison between the pre-treatment duration of patients in deterministic and stochastic cases in instance pr-5.

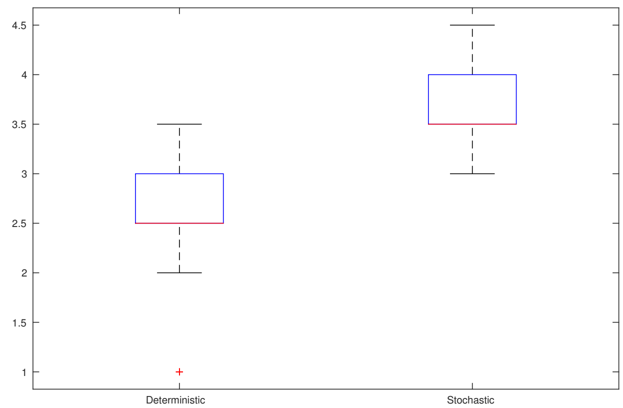

Figure 5.5 Pre-treatment duration for deterministic and stochastic cases in instance pr-5.

It can be derived from the presented figure that, the results obtained through the stochastic version are more realistic. In practice, the arrival of patients and their cancer type are unknown in advance, thus fixing them in the algorithm, may show completely different performance. However, figure 5.5 shows the pre-treatment duration for both deterministic and stochastic algorithms on instance pr-5. It is indicated that in the deterministic case, patients would finish the pre-treatment phase in less than four days, while in the stochastic case, this phase will be completed in less than five days, which meets our main goal perfectly.

5.4 Case study in CICL

In collaboration with the radiation therapy department of the Centre Intégré de Cancérologie de Laval (CICL), we obtained data for a real case in this center. 1740 patients were referred to the center in 2012. The center served 75% of them. In this department, nine physicians serve patients ; they have a capacity of nine patients per week. In addition to tasks that were presented previously, every week they also have a research-time schedule. Each physician can also have some vacation time every six weeks, which means that almost every week only eight physicians serve patients.

Table 5.6 presents the current schedule at CICL.

Table 5.6 Current schedule of CICL.

	Monday		Tuesday		Wednesday		Thursday		Friday	
	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.
Phys. 1	D	D	C	A	F	F	C	E	A	B
Phys. 2	A	C	A	A	D	D	B	C	E	A
Phys. 3	C	B	D	D	C	A	A	A	C	E
Phys. 4	A	A	C	B	A	A	D	D	E	C
Phys. 5	C	A	D	D	C	A	B	E	C	A
Phys. 6	C	A	A	E	C	B	D	D	C	A
Phys. 7	E	C	C	A	A	C	A	B	D	D
Phys. 8	A	C	B	A	D	D	A	C	A	E
Phys. 9	C	A	A	A	C	B	D	D	C	E

It can be derived from this schedule that the main strategy of CICL is, the more consultation (task *'A'*), the better performance. Besides, a physician scheduled to task *'D'* performs the same task the whole day. Research time (task *'E'*) is mainly scheduled on Thursdays and Fridays.

We used their schedule to solve the problem where the preferences were respected 100%. Besides, we also adapted TS to solve the same problem. In order to show the advantage of the new schedule to the previous one, we compared our obtained schedule with their current one in two ways. Figure 5.6 indicates the comparison of pre-treatment durations of patients for both schedules.

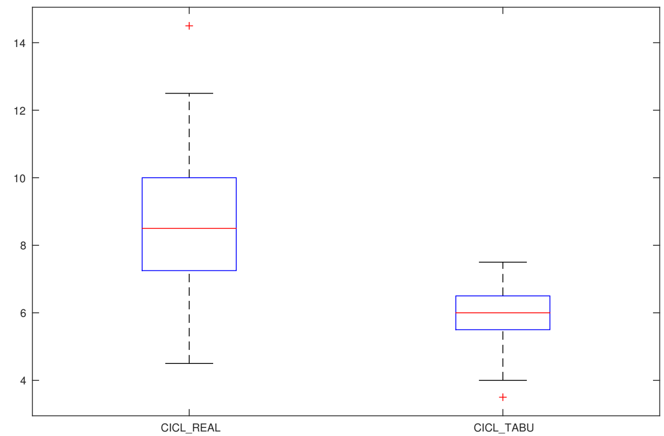

Figure 5.6 Comparison of pre-treatment durations on CICL data.

As shown in figure 5.6, in the current schedule, patients would finish the pre-treatment phase in 14 days while it would be in eight days regarding the proposed one.

Besides, figure 5.7 indicates the comparison of patients' waiting time to start the pre-treatment phase for both schedules. It shows the number of days that a patient waited for a consultation based on some historical data in 2014.

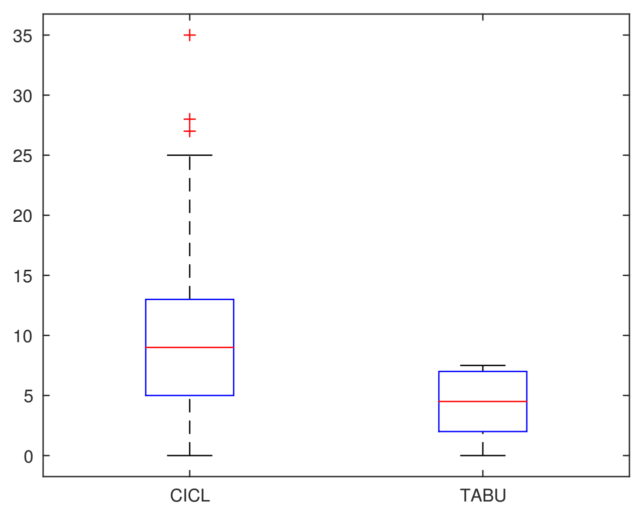

Figure 5.7 Comparison of waiting time to start the pretreatment phase on CICL data.

According to figure 5.7 patients started the pre-treatment phase in 10 days on average with their current schedule while they would start this phase in five days regarding the proposed schedule obtained through TS.

Table 5.7 shows the schedule obtained from our proposed TS method for the CICL data.

Table 5.7 Obtained schedule through the proposed TS method on CICL data.

	Monday		Tuesday		Wednesday		Thursday		Friday	
	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.	A.M.	P.M.
Phys. 1	B	A	B	D	C	D	E	F	B	E
Phys. 2	C	C	D	C	E	B	A	B	A	B
Phys. 3	B	C	C	D	E	C	C	A	D	A
Phys. 4	D	A	E	B	D	A	B	D	C	C
Phys. 5	D	E	C	C	E	B	D	E	A	B
Phys. 6	E	A	B	B	B	A	B	B	C	D
Phys. 7	A	B	A	C	D	B	E	C	D	E
Phys. 8	C	C	D	E	A	B	E	D	A	B
Phys. 9	A	B	D	B	C	D	E	E	D	E

In the proposed schedule, we considered both preferences of physicians and patients in minimizing their process time. It can be derived from the schedule that having tasks *'B'* and *'C'* appear more frequently in a schedule, improves performance for both physicians and patients. Since the processing of dosimetry and its validation take more time, it is better to have these tasks more frequently in a week.

Thus, changing the strategy from performing more consultation in a week to performing more dosimetry validation would satisfy both patients and physicians.

CHAPTER 6 CONCLUSION

In this chapter, a summary of the importance of proposing a scheduling method is presented with corresponding conclusion. In addition, further improvements for the method and possible future research areas are recommended.

6.1 Summary

In order to increase the chance of cure in cancer treatment, time plays a significant role. There is not much time to waste in the pre-treatment phase. Therefore, we proposed a physician scheduling methodology to shorten the wait time in order to start the treatment on the patient within a week of the diagnosis.

To do so, an efficient weekly cyclic schedule for physicians in a radiotherapy center was proposed to help physicians prevent bottlenecks from forming and keep the patient flow moving ; thus, the pretreatment phase would be shortened for patients who are referred to the oncology department. Besides, attempts were made to maximize the satisfaction and preferences of physicians on the performance of tasks.

We considered both deterministic and stochastic cases in which the arrival rate of patients and treatment types, either curative or palliative, were the uncertain parameters of the problem. For this problem, a Tabu Search meta-heuristic was developed and evaluated with two equivalent Integer Programming models, one based on patterns and the other based on physicians' tasks. We could find a way to include the uncertainty factors in the Tabu Search procedure. Moreover, we compared our basic IP model with two alternative heuristics on the possible sequences of physicians' tasks within the planning horizon.

In collaboration with the Centre Intégré de Cancérologie de Laval (CICL), we also evaluated our proposed method based on real data from there.

6.2 Synthesis of the study

Significant results obtained through small, medium, and large instances in various terms. In terms of accuracy, in deterministic cases, the gap between results obtained from TS and exact models is less than 1% on average. Besides, the objective value in two-task-per-day problem increased more than twice of one-task-per-day case, which indicates that increasing time blocks per day, not only increased the physicians satisfaction, but also improved the patient flow and decreased the pre-treatment duration. Moreover, the method is applicable to any size of problem. The advantage of TS over the pattern-based model is that TS can be applied to any size of problem while solving either the pattern-based or task-based models for large-size instances is more complicated and takes more time.

As shown, in both deterministic and stochastic cases, the pre-treatment phase would be completed within a week, which perfectly meets our main goal. Besides, the flexibility in the algorithm helped to determine a preferred schedule for physicians and to keep the pre-treatment time within an acceptable range for patients.

Moreover, to study the application of our proposed method on a real case data, the data obtained from CICL is analyzed and their current schedule was compared to our proposed one. It is indicated that patients would finish the pre-treatment phase within 14 days with their current schedule, while it would be decreased to eight days regarding the proposed one. We also suggested that changing the strategy from performing more consultation in a week to performing more dosimetry validation would satisfy both patients and physicians.

6.3 Future enhancements

This work can be extended in various directions, such as considering different quality measurements, more uncertainty items, more limitations on performing tasks in a week and evaluating the effects of different parts of the objective.

In healthcare, service quality is measured in different terms, i.e., how did the treatment work ? How did I feel during the treatment process ? Sometimes even when a patient is in pain and needs to be seen by the first available physician, he/she may have a strong preference to be seen by a particular physician, which would complicate the efforts to align the healthcare resources with the demand. Therefore, other quality measurements than treatment duration can be modeled and applied to evaluate the satisfaction of patients.

Besides, we considered patients arrival rate and cancer types as two parameters of uncertainty, which can be extended to various ones in different contexts. Processing time of each task is another factor that can be vary in some contexts.

Moreover, the effects of either parts of the objective can be studied, which is considered with the same weights in this thesis.

Finally, the purpose of this study was to propose a Tabu Search algorithm, which was evaluated with mathematical models. However, in proposing MIP models, the attempts were made to keep them linear and simple, while they can be improved by column generation method and stochastic programming.

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