A Mathematical Model for Patient Scheduling in Radiotherapy Treatment

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Abstract

Scheduling radiotherapy treatments for cancer patients is a major concern for hospitals and patients. The delay in radiotherapy has a negative effect on the patient and flow of patients in hospitals. This research proposes a mathematical model for multi-period radiotherapy planning and scheduling problems with capacity constraints over a particular time horizon. The goal is to schedule a list of 3D curative patients who must undergo radiotherapy. The problem is formulated with a multi-objective model with two objectives and two stages: minimize the makespan and priority score in the first stage and minimize and the sum of the finish time and the sum of different balance workloads in the second stage. Computational experiments are executed using the simulated data according to real treatments of 3D curative patients. The results show that the model satisfies all constraints with the right assignment and operation sequence. Thus, the proposed mathematical model can assist in the decision-making process for cancer patient scheduling for radiotherapy treatment. This helps reduce the time for planning and scheduling in the radiotherapy department.

Keywords
Patient Scheduling; Mathematical Model; Waiting Time; Radiotherapy Treatment.

1. Introduction

“Healthcare management is becoming a significant issue in the world scale due to the increasing demands in the healthcare section. Many countries endeavor to improve and develop their healthcare system to support those demands. Thailand is a country that also aims to develop the healthcare system to the world-class” (Boonmee & Kasemset, 2019). Noncommunicable diseases (NCDs) are now responsible for most global deaths. Cancer is one of the NCDs that is predicted to rate as the cause of death and the single most important threat to rising life expectancy in every country in the world in the 21st century. The International Agency for Research on Cancer (IARC) is the specialized cancer agency of the World Health Organization (WHO), and according to the 2018 Global Cancer report, the estimated number of new cancer cases will increase by more than 18 million people, and the deaths from cancer will increase to 9.6 million. Nearly half of all new cancer cases and more than half of all deaths are in Asia. It is estimated that by 2040 there will be as many as 29.3 million cancer cases and the death rate will increase to 16.3 million. Cancer is the first or second major cause of death in 91 out of 172 countries around the world(Bray et al., 2018).

Cancer is one of the major public health problems in Thailand. It is the leading cause of death among Thai people followed by accidents and heart disease, respectively. Statistical data from the Department of Medical Services in 2018 show an average of 336 new patients per day, an average of 215 deaths per day, 78,540 people per year, and an average of 8 deaths per hour, with an increasing trend. The director of Lampang Cancer Hospital said that the cancer situation in northern Thailand is still a major problem. According to the Northern Cancer Registration report statistics of cancer registration at Lampang Cancer Hospital, the incidence of cancer in the northern region is higher than the average for Thailand. The highest mortality rates in Phayao, Phrae, and Lampang cost a total loss to the Thai economy of nearly 80,000 million baht per year (hfocus, 2015).

Small hospitals are not capable of treating cancer because radiotherapy services require expensive equipment and specialized personnel in many departments, and the coordination and planning systems for small hospitals are not enough. Treating cancer requires a university hospital, a medical school, or a college of medicine because it is a hospital that is used for teaching and learning to produce medical personnel for the various research. In northern Thailand, two hospitals are ready to treat cancer where they are located in Lampang and Chiang Mai provinces. Therefore, many people queue for treatment.

The radiology department of Maharaj Nakorn Chiang Mai Hospital, with the progress of modern technology and tools, can provide treatment with special techniques. The radiotherapy department is responsible for providing radiotherapy to patients receiving treatment at Maharat Nakorn Chiang Mai Hospital which covers patients in the eight northern provinces of Chiang Mai, Chiang Rai, Lamphun, Lampang, Phayao, Nan, Phrae, and Mae Hong Son. The average number of patients who come to the radiotherapy Maharaj Nakorn Chiang Mai hospital is approximately 3,400 people per year, and this number tends to rise each year. In real world problems, it is not just patients on appointment but including uncertain parameters such as emergency patient this makes a complexity of problems that make blocked healthcare access results and patients having a longer waiting time, which leads to crowded emergency departments and other departments. Blocked access is associated with increased dissatisfaction among patients and increased mortality.

Radiotherapy is divided into levels that are separated according to the treatment technique (2D and 3D) and classified into three categories according to the objective including emergency by radiotherapy (to cure cancer), (to alleviate pain, such as for cancer that cannot be cured), and emergency (to relieve intense pain, for example, internal wounds). The difference between the treatment techniques 2D and 3D is the lead time in planning. Technique 2D is not scheduled in advance. It is a simple scheduler based on walk-in patients who cannot be cured for the purpose of relieving intense pain with 2-3 days lead time. In 3D, the purpose to cure cancer is pre-arranged with no priority, and every case lead time is equal to 21 days (3 weeks). We are interested in developing a model that will improve the makespan of the whole system because some cases do not need to wait up to 3 weeks. “In any cancer treatment, waiting times are critical, the faster the patient is treated the more effective the treatment is”(Yoan et al., 2011). “Many studies have shown that a delay in starting radiotherapy has a negative effect on the patient’s clinical condition”(Legrain et al., 2015).

This study focuses on the radiology department of Maharaj Nakorn Chiang Mai Hospital. The department faces wide variation in demands from various specialties or patients while having limited resources and using manual scheduling. Therefore, in this research, the researcher applies the principles of industrial engineering to analyze the scheduling system of the radiotherapy department of Maharaj Nakorn Chiang Mai Hospital. Improved radiotherapy patient schedules using mathematical modeling will optimize patient schedules and reduce patient’s waiting time, and they can be implemented in a hospital case study and be suitable for further application in other areas.

1.1 Objectives

The research objectives are to develop a mathematical model for the patient scheduling problem in radiotherapy treatment and to propose an efficient algorithm for the patient scheduling problem in radiotherapy treatment.

2. Literature Review

It is clear that the number of patients and deaths from cancer increases every year in many countries (Conforti et al., 2007; Kapamara, 2014; Legrain et al., 2015), thereby increasing the waiting time for treatment (Petrovic et al., 2011). A first approach can be found in 1993. Improper timing of procedures may negatively affect the success of treatment and the survival rate of patients. For example, patients who have received radiation may miss or not will be tracking follow to appointments, in this case, the process may be repeated. Resulting in managing the dose that the patient received no medical benefit. The Arden Cancer Center classifies patients underoing radiotherapy into three categories according to the illness: emergency by radiotherapy (to cure cancer), (to alleviate pain, such as for case cancer that cannot be cured), and emergency (to relieve intense pain, for example, internal wounds). Radiotherapy patient schedules can be categorized as static or dynamic. Static problems will have the number of jobs and times that had been known and fixed. Dynamic problems can involve many types and factors, such as the random arrival of patients, emergency patients, and patients who miss appointments. Dynamic problems involve the complexity of scheduling problems. Researchers have concluded that rescheduling approaches for better schedule results after each unexpected event are not always beneficial (Kapamara, 2014).
The literature review is therefore focused on the problem of patient scheduling in healthcare. Operation research on healthcare began before the 2000s and has mostly addressed the challenges of healthcare systems, such as pressures to contain costs, patient flow, timely treatment, and utilization of resources. In 2000, Marinagia et al. (2000) proposed a dynamic model for a approach for planning and scheduling program to patients test requests in hospital laboratories. to minimize patient waiting time and maximize the utilization of equipment. The authors use a heuristic model due to the continual nature and complexity of the problem. Conforti et al. (2007) proposed meta-heuristic algorithms for healthcare systems in which patient scheduling is crucial for the efficiency of the patient flow and waiting lists increase the overall performance of healthcare systems and considerably improve the schedule. Petrovic et al. (2011) proposed compare and analyze meta-heuristic scheduling techniques to reduce delays and patient waiting times for cancer treatments at Arden Cancer Center. The authors also conclude that exact methods cannot be applied to generic radiotherapy treatment scheduling problems due to the complexity of constraints and the size of the problems. STAM (2011) argued that every minute waiting is a waste of time. The authors used simulation and genetic algorithms to find an optimal appointment system for one general practitioner for one day, but in this model, the authors assume about uncertain parameters, such that no one fails to show up on time and there are no walk-in patients. Yoan et al. (2011) proposed the specific radiotherapy problem has a few studies and a steadily increasing of number radiotherapy patients. Radiotherapy treatment is a complex process involving several steps, where decreasing waiting times is directly related to the effectiveness of the treatment. Legrain et al. (2015) proposed a hybrid method combining stochastic optimization and online optimization to offer patients a reasonable waiting time while maximizing utilization of resources at Center Int´egr´e de Canc´erologie and providing a good metaheuristic review for the radiotherapy scheduling problem. Xiang et al. (2015) claimed that with the increase of the ageing population, social demands for surgical services will lead to limited resources. The authors provide flexible job shop scheduling problems with ant colony optimization or solving an operating room surgery scheduling problem. The problem is the multi-stages like radiotherapy problem and need to be providing timely treatments for the patients while balance utilization of the resource. Riff et al. (2016) proposed a new heuristic-based scheduling algorithm for radiotherapy treatments and compared the algorithm with As Soon As Possible (ASAP) and Just In Time (JIT) strategies. The authors consider that including the patient waiting time during the planning is crucial to improve the effectiveness of the treatments. Lee et al. (2018) explained that the healthcare industry should not only cure the patient but also consider customer satisfaction. Researchers proposed applying an exact algorithm to the appointment scheduling problem to maximize profit in one day while minimizing the patient waiting time and doctor idle time. Characteristics of appointment scheduling optimization techniques can solve different problems like manufacturing problems. Moosavi and Ebrahimnejad (2018) compared about 50 studies to propose a multi-objective mathematical model for advanced and allocation model to proposed considering upstream and downstream units referred to the Alborz Hospital. In real-world problems, some parameters are uncertain, such as length of stay in upstream and downstream units and

emergency demand. The authors point out that many studies have not considered emergency demand. Ala and Chen (2019) proposed a two-stage mathematical model and algorithmic frameworks to minimize the waiting time of patients referred to the emergency department of a government hospital. Patients' waiting time management requires reasonable decisions and tools. Simulation and optimization techniques can support decisions and reduce the risk of the decision process. The problem in healthcare is heavily influenced by random factors, increasing the complexity and the difficulty of solving. Shi et al. (2019) proposed optimization for a home healthcare routing and scheduling. One of the most important objectives is meeting the demands of patients in a timely fashion. The difficulty of the problem is uncertain travel and service times. This paper ignores the uncertainty of travel time, which causes delayed services and inefficient scheduling. Wisittipanich et al. (2019) proposed a mathematical model by using an exact method for multi-period surgical scheduling problems to support decision-makers. The author said one of the most important roles is providing prompt health services to patients. The model makes operations of patients can be planned and orderly. The mathematical model can be further used as a smart decision tool in hospitals.
To compare recently published papers with this study, the researcher compares an objective function, constraint, method, and algorithms of a mathematical model for healthcare scheduling that most objectives of each paper are to minimize patient waiting time, but the constraint of each paper has different which determined by the author or their problem but most model has common constraint are patient assigned and capacity constraint. The number of methods that the mathematical model uses for healthcare scheduling, many papers refer to a complex, uncertain parameters and the large size of the problem is therefore recommended to use a heuristic to reduce problem resolution time, but there are still some papers that use the exact method to solve problems. The number of algorithms that use to solve problem in 13 papers from 2000 to 2019 no refer to which algorithms special. Also, some papers tried to find which algorithms are best and to compare suitable algorithms, but they did not conclude on which one is the best. The long time waiting affect many parties such as patient's satisfaction, patient flow. Delay of process is a negative effect on the patient's condition but using a mathematical model helps decision makers to schedule more efficiently.

3. Problem formulations

The model is divided into two parts to simplify the problem and reduce the time it takes to solve problems. The process in the first step depends on doctors and medical technicians, but the process in the second step depends on the radiotherapy room. Uncertainty parameters will not be considered such as no-show patients and emergency patients. The first step of the model is the simulation and the planning and design step. The second step is the treatment step. The process of radiation therapy is divided into five processes: CT simulation, contouring, planning, plan approval, and starting radiotherapy. The first four processes are solved in the first step of the model, and the last process is solved in the second step. Model will be able to assist the decision-making process and reduce patient's waiting time and planning time.
Assumptions are made as follows:
-All patients do not have equal priority.
-Time for operations treatment is a deterministic variable.
-Uncertainty parameters will not be considered.
To formulate a metaheuristic model, the following notations are defined for sets, parameters and the decision variables.

3.1 First stage

Indices

P	set of patients
O	number of operations
D	set of doctors
T	time period (days)

Decision variables

Z_{podt}	$\begin{cases} 1 \text{ if patients } p \text{ is assigned to operation } o \text{ by doctor } d \text{ in time period } t \\ 0 \text{ otherwise} \end{cases}$
X_{po}	treatment completion time of patients p operation o
Y_{pod}	treatment completion time of patients p operation o on doctor d
R_{po}	ready time for starting operation o of each patient p
DD_p	expected date of completing operation of patient p

Cmax	maximum completion time of all patients
Tsc	total priority score

Parameters

aa_p	arrival day of patient *p*
p_{po}	processing time for treatment patient *p* in operation *o*
e	expected date
pr_p	priority score of patient *p*
a_{po}	operation requirement $\begin{cases} 1 \text{ if patient } p \text{ needs operation } o \\ 0 \text{ otherwise} \end{cases}$

The mathematical model is described as follows:

$$Minimize\ (0.5 * Cmax) + (0.5 * tsc) \quad (1)$$

s.t.

$$C_{max} = Max\{Y_{pod}\} \quad ; \forall i, j, k, j; a_{ij} = 1 \quad (2)$$

$$\sum_{p=1}^{n} \sum_{o=1}^{m} Z_{podt} \leq 1 \quad ; \forall d, t \quad (3)$$

$$\sum_{t=1}^{p} \sum_{d=1}^{e} Z_{podt} = a_{po} \quad ; \forall p, o \quad (4)$$

$$DD_p = aa_p + e \quad ; \forall p \quad (5)$$

$$Y_{pod} - Y_{p,o-1,d} \geq \sum_{d=1}^{e} (Z_{podt} * P_{po}) \quad ; \forall p, o, d, t ; o \neq 1 \quad (6)$$

$$R_{po} = aa_p \quad ; \forall p, o ; o = 1 \quad (7)$$

$$Y_{pod} \geq r_{po} + P_{po} \quad ; \forall p, o, d \quad (8)$$

$$Y_{pod} \leq DD_p \quad ; \forall p, o = 4, d \quad (9)$$

$$Max(Y_{pod}) = X_{po} \quad ; \forall p, o, d \quad (10)$$

$$Y_{pod} * a_{po} = \sum_{t=1}^{p} \sum_{d=1}^{e} Z_{podt} * T \quad ; \forall p, o, d \quad (11)$$

$$tsc = \sum_{p=1}^{n} \sum_{o=1}^{m} \sum_{d=1}^{p} \sum_{t=1}^{e} Z_{podt} * pr_p * T \quad (12)$$

$$Z_{podt} \in (0,1) \quad (13)$$

The objective function (1) is to be minimize the makespan and priority score. Constraint (2) specifies the makespan, Cmax (maximum completion time of all patients). Constraint (3) constraint of doctor that can treat operation in a time period less than or equal to capacity. Constraint (4) ensures that a patient must be treated for each operation by only one doctor for one period. Constraint (5) is the expected date constraint of the last operation n^{th}. Constraint (6) is a precedence constraint to ensure that the completion time of any operation must be greater than or equal to its ready time plus its processing time. Constraint (7) is the first ready time, such as arrival time of the patient. Constraint (8) and (9) states that the completion time of a patient who treats which operation at which doctor must be between the patient's ready time plus processing time of that operation and maximum specified age of a patient to perform that operation. Constraints (10) and (11) explain the completion time of a patient who treats which operation at which doctor. Constraint (12) calculates the total priority score for assigned priority patients. Constraint (13) specifies that decision variables are binary.

3.2 Second stage

To integrate the proposed metrics within the mathematical model, equations (14)-(21) should be considered as the second stage of the proposed problem which was added by equations (1)-(13).

Indices

P	set of patients
E	number of examination rooms (machiners)
T	time period (days)

Decision variables

Z_{etp}	$\begin{cases} 1 \text{ if patients } p \text{ is f to examination room } e \text{ starting during time slot } t \\ 0 \text{ otherwise} \end{cases}$
I_{et}	$\begin{cases} 1 \text{ if examination room } e \text{ is idle during period } t \\ 0 \text{ otherwise} \end{cases}$
P_t	compute balance of examination room processing times at time slot t
S	sum of finish times

Parameters:

a_p	arrival or available time of patient p, the first period in which p can be processed
d_p	number of doses for patients p
pt_{ep}	number periods (time slot) needed in examination room e of patients p
dd_p	due date for patient p
ts_t	time slot of day t

$$Min \ = S + \sum_{t=1}^{m} P_t \tag{14}$$

s.t.

$$S = \sum_{e=1}^{n}\sum_{t=1}^{m}\sum_{p=1}^{o}(T + pt_{ep}) * Z_{etp} \tag{15}$$

$$P_t = \sum_{p=1}^{o} Z_{1tp} - \sum_{p=1}^{o} Z_{2tp} \qquad ; \forall e, \forall t \tag{16}$$

$$\sum_{e=1}^{n}\sum_{t=1}^{m}\sum_{p=1}^{o} Z_{etp} \leq 1 \qquad ; \forall p, \forall t \tag{17}$$

$$\sum_{e=1}^{n}\sum_{t=1}^{m}\sum_{p=1}^{o} Z_{etp} = d_p \qquad ; \forall p \tag{18}$$

$$I_{e,1} + \sum_{e=1}^{n}\sum_{t=1}^{m}\sum_{p=1}^{o} Z_{etp\,(t=1)} \ = ts_t ; \forall e \tag{19}$$

$$I_{e,t-1} + \sum_{p\in a_p \leq t - pt_{ep} \text{ and } t \leq DD_d} Z_{e,t-PT_{e,p}} = I_{e,t} + \sum_{p\in a_p \leq t \text{ and } t + pt_{ep} \leq DD_p} Z_{etp}$$

$$\forall e; e = \{A, C\} \ \forall t; t \geq 1 \ and \ T \leq timeend \tag{20}$$

$$Z_{etp} \epsilon \ (0,1) \tag{21}$$

The objective function (14) is to minimize the sum of finish times and the sum of different balance process times. Constraint (15) computes the sum of finish times. Constraint (16) compute the balance of examination room processing times. In constraint (17), each patient must be assigned to one examination room at most. In constraint (18) each patient must be assigned to at examination room according to the dose. In constraint (19), each patient can be active in the examination room at a time period equal to the time slot per day. Every examination room is idle before the first period and remains idle or gets some work. Constraint (20) for subsequent periods, in period t-1 (the left-hand side), if the examination room is either a) idle or b) not idle but some patients finish, then in period t (the right-hand side) the examination room will be either a) idle or b) starts a new task. Constraint (21) specifies that decision variables are binary.

4. Results

In this study, a numerical example is given to illustrate the solution methods of the proposed multi-period radiotherapy planning and scheduling model. To make the problem practical, the computational experiments are executed using simulated data according to real treatments of 3D curative patients. Three main parameters the number of patients, list of operations, and priority score are generated along with other parameters, such as doctor capacity and operation requirement in the first stage. Each schedule is on a weekly basis over a planning horizon. An example of a radiotherapy planning and scheduling problem with 10 patients and 4 doctors is used for model analysis. Each doctor's capacity is set to 1 in the first stage. First-stage decision variables should be considered as the second-stage parameters. Example parameters are shown in Table 1.
The patient scheduling mathematical model is solved by the LINGO program version 14.0. Fig.1 shows the optimal schedule of operations for all patients with the assigned doctor. The maximum completion time of all patients is 12 days, and the least preference score is 2703. After that, each decision variable should be a parameter in the second **step.** The main parameters are the arrival of patients and the number of doses needed for patients. In this example, radiotherapy scheduling is performed with two radiotherapy rooms. The sum of the finish time is 1744. The above description is illustrated in Fig. 1, which shows the optimal schedule of the two stages for all patients.

Table 1: Example of input data in the first stage

	Priority score	Arrival time	Process time and operation requirement							
			CT-sim	required	contour	required	planning	required	plan approve	required
P1	1	0	1	1	3	1	3	1	3	1
P2	1	2	1	1	3	1	3	1	3	1
P3	1	1	1	1	3	1	3	1	3	1
P4	1	0	1	1	3	1	3	1	3	1
P5	1	0	1	1	3	1	3	1	3	1
P6	1	0	1	1	3	1	3	1	3	1
P7	1	0	0	0	0	0	3	1	3	1
P8	30	0	0	0	3	1	3	1	3	1
P9	1	0	1	1	3	1	3	1	3	1
P10	90	0	1	1	3	1	3	1	3	1

	Process / Patient	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Stage 1	CT Sim	1	3	2	1	1	2	-	-	2	1
	Contourng	4	6	5	4	4	5	-	3	5	4
	Planning	7	9	8	7	7	8	3	6	8	7
	Planapprove	10	12	11	10	10	11	6	9	11	10

Stage 2	P7	P8	P1	P4	P5	P10	P3	P6	P9	P2
Parameter	6	9	10	10	10	10	11	11	11	12

Room	Time slots / Days	6	7	8	9	10	11	12	13	14	15
A	1	P7	P7	P7	P8	P7	P3	P2	P4	P2	P3
	2	x	x	x	x	P8	P7	P3	P5	P6	P6
	3	x	x	x	x	P10	P8	P6	P7	P7	P9
	4	x	x	x	x	x	P9	P7	P9	P9	P10
	5	x	x	x	x	x	P10	P9	P10	P10	x
	6	x	x	x	x	x	x	x	x	x	x
	7	x	x	x	x	x	x	x	x	x	x
	8	x	x	x	x	x	x	x	x	x	x
	9	x	x	x	x	x	x	x	x	x	x
	10	x	x	x	x	x	x	x	x	x	x
C	1	x	x	x	P7	P1	P1	P1	P1	P1	P2
	2	x	x	x	x	P4	P4	P4	P2	P3	P7
	3	x	x	x	x	P5	P5	P5	P3	P4	P8
	4	x	x	x	x	x	P6	P8	P6	P5	x
	5	x	x	x	x	x	x	P10	P8	P8	x
	6	x	x	x	x	x	x	x	x	x	x
	7	x	x	x	x	x	x	x	x	x	x
	8	x	x	x	x	x	x	x	x	x	x
	9	x	x	x	x	x	x	x	x	x	x
	10	x	x	x	x	x	x	x	x	x	x

Fig.1 The optimal schedule of the two stages

5. Conclusion

The multi-period radiotherapy planning and scheduling problem with capacity constraint over a particular time horizon. increase scheduling performance such as patient waiting time, scheduling time during the procedures. The problem is formulated with a multi-objective model with two objectives, and two stages are considered in the proposed model: minimization of makespan and priority score in first and minimize the sum of the finish time and sum of difference balance workload. Then, an instance inspired by the real process of 3D curative patients planning. The results show that the model satisfies all constraints with the right assignment and operation sequence. The proposed mathematical model is able to assist in the decision-making process for cancer patient scheduling for radiotherapy treatment. This helps reduce the time for planning and scheduling in the radiotherapy department. Thus, the average patient waiting time is decreased.

Nevertheless, the radiotherapy planning and scheduling problem is usually discussed under the assumption that the parameter and capacity are deterministic variables. In practice, some of these assumptions are unrealistic. In the future, research should focus on a dynamic model for handling uncertainty in real-world practice.

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