Developing an Efficient Scheduling Template of a Chemotherapy Treatment Unit: Simulation and Optimization Approach

By

Zubair Ahmed

A thesis submitted to the Faculty of Graduate Studies in partial fulfillment of the requirements for the degree of

Master of Science

Department of Mechanical and Manufacturing Engineering

University of Manitoba

Winnipeg, Manitoba, Canada

Abstract

This study is undertaken to improve the performance of a Chemotherapy Treatment Unit by increasing the throughput of the clinic and reducing the average patients' waiting time. In order to achieve this objective, a simulation model of this system is built and several scenarios that target matching the arrival pattern of the patients and resources availability are designed and evaluated. After performing detailed analysis, one scenario proves to provide the best system's performance. The best scenario determines a rational arrival pattern of the patient matching with the nurses' availability and can serve 22.5% more patients daily. Although the simulation study shows the way to serve more patients daily, it does not explain how to sequence them properly to minimize the average patients' waiting time. Therefore, an efficient scheduling algorithm was developed to build a scheduling template that minimizes the total flow time of the system.

Acknowledgement

First and foremost, I would like to express my gratitude to my thesis supervisor, Dr. Tarek ElMekkawy. His support, guidance and confidence gave me enough courage to work though this thesis.

I would like to thank Sue Bates, Director of Patient Navigation Team, Cancercare Manitoba for giving us the opportunity to work as a part of the team. This thesis would not be possible without her recognition. Moreover, many thanks for the research funding received from CancerCare Manitoba, Canada and also from the NSERC Discovery.

I would like to express my sincere gratitude and love to my parents for their continuous support and dedication.

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List of Abbreviation

ALTER	Assigning appointed and new patients in an alternating manner
AS	Appointment Scheduling
APBEG	Appointment of Patient at the Beginning of the clinic
A-FCFS	Adjusted First Come First Serve
A-LPT	Adjusted Least Process Time
A-SPT	Adjusted Shortest Process Time
BA	Backward Algorithm
CCMB	CancerCare Manitoba
CHI	Canadian Health Information
DRC	Dual Resources Constraint
EDD	Earliest Due Date
ERD	Earliest Release Date
LST	Least Slack Time
HAL	A job has the highest priority if it has the SPT among jobs available
HPRTF	A job has a higher priority if it has a smaller priority rule for the total flow time (PRTF) function value
MFHA	Modified Forward Heuristic Algorithm
NP-hard	Non-deterministic Polynomial-time hard
NPBEG	New Patient at the Beginning of the clinic

PICC	Peripherally Inserted Central Catheter
PMSP	Parallel Machine Scheduling Problem
PSEQ	Patient Sequence
SPT	Shortest Process Time
TMO	Two Machine Optimization
RSR	Right Shifting Rule
WAVS	Wavy Assignment, Verified Schedule

Chapter 1

Introduction

1.1 Background

According to the Canadian Institute for Health Information (CIHI), the total spending on health care in Canada is expected to reach $191.6billion in 2010, growing an estimated $9.5 billion, or 5.2%, since 2009. This represents an increase of $216 per Canadian, bringing total health expenditure per capita to an estimated $5,614. Total health care spending continues to vary by province, with spending per person expected to be highest in Alberta and Manitoba at $6,266 and $6,249, respectively. British Columbia and Quebec are forecasted to have the lowest health expenditure per capita at $5,355 and $5,096, respectively (Canadian Institute for Health Information (CIHI).

Despite of spending billions of dollars and highest per capita among the provinces the commitment of providing a quality care within a modest timeframe is still faraway. Every year, more than 6,000 Manitobans are diagnosed with cancer. Like most other jurisdictions, Manitoba is projecting a 50 percent increase in cancer cases over the next 20 years according to CIHI. However, the healthcare system is not yet ready to provide the quality care to this rapidly growing population and this leads to long waiting time, delay and cancelation of appointment. Physicians and nurses are working overtime to maintain the workload although the healthcare managers are experiencing lack of resource utilization. In consequence there is a growing frustration on both care recipients and providers.

In order to ensure the highest quality care for the growing cancer population, the Government of Manitoba is planning a strategy that will streamline cancer services and dramatically reduce the waiting time of the patients.

CancerCare Manitoba is a cancer care agency situated in Winnipeg, Manitoba. It is dedicated to provide quality care to those who has diagnosed and living with cancer. Mc Charles Chemotherapy unit is specially built to provide chemotherapy treatment to the cancer patients. The patients who are diagnosed with cancer and prescribed to take chemotherapy will be scheduled in this chemotherapy unit. Chemotherapy (also called chemo) is a type of cancer treatment that uses drugs to destroy cancer cells. It is usually used when the cancer spread to other areas in the body. It can also be used in combination with surgery and radiation therapy. Sometimes the tumor is surgically removed and then chemotherapy is used to make sure any remaining cancer cells are killed. It is also administered in those cases where the patient is too old to go through surgical treatment or the radiation therapy cannot destroy the whole cancer cell. Therefore, it is the most likely to be common that a cancer patient will take chemotherapy treatment at any stage of his/her cancer treatment journey.

A chemotherapy treatment is a day-to-day visit where a patient comes to the clinic for a treatment that may take from 1 hour to 12 hours. The patient leaves the clinic at the end of the treatment. A patient could continue to take chemotherapy for weeks, months or even for years. In addition, more than 6000 Manitoban are diagnosed with cancer each year. As a result, there is a hasty population growth of chemotherapy patients each year. It is expected that the number of chemotherapy patients will increase by 20% in the next 5 years. In order to maintain the excellence in provided service, the clinic management tries to ensure that patients will get their treatment in a timely manner. But due to rapid increase in the number of patients, it is becoming challenging to maintain that goal. This treatment center has certain boundary of seeing patient on the daily clinic over which it cannot accommodate. Hence, there is a growing pile of patients who are waiting to schedule their treatment. A study from January 2010 to March 2010 showed that, more that 60% of the patients waited more than 4 weeks just to get the first appointment. Moreover, lack of proper roster is responsible for uneven distribution of work load and resource allotment. In this study, it is tried to push this limit a bit further to increase the number of daily patients' visit without bringing any major change in the clinic layout plan and to schedule them so that the patients don't have to wait for long times to get their service. By increasing the number of daily patients' visits, the number of patients waiting to start their treatment may be reduced.

Healthcare system has been using different industrial engineering tools to improve the quality of care by means of reducing the waiting time and earning the satisfaction of the care provider. Industrial engineers gradually realized that many industrial engineering techniques initially applied to manufacturing/production systems is equally applicable in healthcare service system. Healthcare system has been using different industrial engineering tools which are but not limited to:

i) Methods of Improvement and work simplification.

ii) Staffing analysis.

iii) Scheduling.

iv) Queuing and Simulation.

v) Statistical analysis.

vi) Optimization.

vii) Quality improvement.

viii) Information system/decision support system.

In this study, simulation modeling and analysis is used to determine the needed modifications to increase the throughput of the system. Moreover, two scheduling algorithms have been used to minimize the waiting time of the patient.

In order to maintain the satisfaction of the patients and the healthcare providers by serving the maximum number of patients in a timely manner, it is necessary to develop an efficient scheduling template that matches the required demand with the resources availability. This goal can be reached using simulation modeling. Simulation has proven to be an excellent modeling tool. It can be defined as building computer models that represent real world or hypothetical systems, and hence experimenting with these models to study system behavior under different scenarios [Banks et al, 1986, Komashie et al, 2005]. Simulation is the imitation of the operation of the real-world process or system over time. Both existing and conceptual systems can be modeled with simulation. It is an indispensable problem solving methodology for the solution of real-world problems and has been used for modeling healthcare systems for over forty years. Simulation is used to describe and analyze the behavior of the system, evaluate what-if questions without implementation or interrupting the main system.

On the other hand, effective scheduling ensures matching of demand with capacity so that resources are better utilized and patient waiting times are minimized. It streamlines the work flow and reduces crowding in the waiting areas. It has been widely used in healthcare systems to roster the emergency department and the treatment centers to match the availability of care providers with the patients demand.

1.2 Thesis Objectives

The main objectives of this thesis are to increase the throughput of the treatment center to meet the growing demand of the chemotherapy patient and reduce their waiting time by developing an efficient scheduling template. In the first part of this study, a simulation model of the treatment center is built. It depicted the current situation and assisted to appraise the behavior of different scenarios. Throughout the evaluation of the different scenarios, the model distinguished the best state by determining the preeminent arrival pattern of the patients in the treatment center. Finally a scheduling template is developed by applying a simple algorithm. In the second part, a heuristic algorithm is proposed to better schedule the patient so that the waiting time could be reduced. The performance of the proposed heuristic is compared with the best reported heuristics in the literatures.

1.3 Thesis Outline

This thesis includes six chapters. Following this introductory chapter, chapter 2 covers the literature review related to the application of simulation study and scheduling in health care. Simulation modeling and analysis of the current state along with the different scenarios are described in chapter 3. In chapter 4, first the scheduling problem is decomposed as identical parallel machine scheduling problem with release time constraints and then a scheduling template is developed considering the availability of the care providers. Chapter 5 proposes an efficient algorithm to schedule a dual resources constrained scheduling problem. This new heuristic algorithm results in minimizing patients waiting time and maintaining the clinic closing time. Finally, chapter 6 presents the conclusion and suggested future work.

Chapter 2

Literature Review

This chapter covers the literature reviews on simulation modeling and scheduling in healthcare system. Section 2.1 describes the application of simulation study in different hospitals. Section 2.2 first gives an explanation on how a treatment center can be inferred as identical parallel machine environment and the constrain it contains. Later, it discusses the related researches in this area. Section 2.3 gives a comparison between previous researches and the current study.

2.1 Simulation Modeling and Analysis in Healthcare

Simulation has proven to be an excellent modeling tool to analyze a service system and evaluate the as-if scenarios. It can be defined as building computer models that represent real world or hypothetical systems, and hence experimenting with these models to study the system behavior under different scenarios [Banks et al, 1986, Komashie et al, 2005].

A study was undertaken at the Children's hospital of Eastern Ontario to identify the issues behind the long waiting time of a emergency room [Blake et al, 1996]. A twenty day field observation revealed that availability of the staff physicians and interaction among them affects the patient wait time.

Ruohonen et al. (2006) used simulation modeling to analysis different process scenarios, reallocated resources and performed activity based cost analysis in the Emergency Department (ED) at the Central Hospital. The simulation also supported the study of a new operational method, named as “triage-team” method. The proposed triage team method categorizes the patients according to the urgency of “to be seen by the doctor” and allows the patient to complete the necessary test before seen by the doctor for the first time. Simulation study showed that it will decrease the throughput time of the patient, reduce the utilization of the specialist and enable the test reports right after arrival. In consequences it quickens the patient journey.

Santibáñez et al. (2009) developed a discrete event simulation model of British Columbia Cancer Agency’s ambulatory care unit, and it was used to study the scenarios considering different operational factors (delay in start clinic), appointment schedule (appointment order, appointment adjustment, add-ons to the schedule) and resource allocation. It was found that the best outcomes were obtained when not one but multiple changes were implemented simultaneously.

Sepúlveda et al. (1999) studied a cancer treatment facility known as M. D. Anderson Cancer Centre, Orlando. A simulation model was built to analyze the current state and different scenarios were also studied to improve patient flow process and to increase the capacity in the main facility. The scenarios were developed by transferring the laboratory and the pharmacy areas, adding an extra blood draw room and applying different types of patient scheduling techniques. Moreover, this study showed that, the utilization of the chairs could be increased by increasing the number of short-term (4 hours or less) patients in the morning.

Discrete event simulation also assists in depicting the staff's behavior and its effect on the system's performance. Nielsen et al. (2008) used simulation to model such constrains and the lack of accessible data.

Gonzalez et al. (1997) used Total quality management and simulation-animation to improve the quality of emergency room. Study revealed lack of capacity in the emergency room causes the long waiting time, overloads the personnel and increases the amount of appointment withdrawal.

Baesler et al. (2001) developed a methodology to find a global optimum point of the control variables in a cancer treatment facility. At first, a simulation model generated an output using goal programming framework for all the objectives involved in that analysis. Later, a genetic algorithm was used to search an improved solution. The control variables that were considered in this research are the number of treatment chairs, number of drawing blood nurses, laboratory and pharmacy personnel.

Guo et al. (2004) proposed a simulation modeling framework which considered demand for appointment, patient flow logic, distribution of resources and scheduling rules followed by the scheduler. The objective of the study was to develop a scheduling rule which will make sure that 95% of all the appointment requests could be seen within one week after the request is made in order to increase the level of patient satisfaction and to balance the schedule of each doctor in order to maintain a fine harmony between "busy clinic" and "quite clinic".

Huschka et al. (2008) studied a health care system to improve their facility layout. In this case, simulation modeling was used to design a new health care practice by evaluating the changes in layout plan. Historical data like the arriving rate of the patients, number of patients visited each day, patient flow logic was used to build the current system model. Later, different scenarios were designed by changing the current layout and performances were measured to find the best one.

Wijewickrama et al. (2008) developed a simulation model to evaluate appointment schedule (AS)for second time consultations and patient appointment sequence (PSEQ) in a multi facility system. Five different appointment rules (ARULE) were considered: i) Baily, ii) 3Baily, iii) Individual (Ind), iv) 2 patients at a time (2AtaTime), v) Variable Interval (V-I) rule. PSEQ is based on type of patients: Appointment patients (APs) and New patients (NPs). Different PSEQ were studied, and they were: i) first-come first-serve, ii) Appointment of patient at the beginning of the clinic (APBEG), iii) New patient at the beginning of the clinic (NPBEG), iv) Assigning appointed and new patients in an alternating manner (ALTER), v) Assigning a new patient after every five-appointment patients. Furthermore, patients with no show (0% and 5%) and patient's punctuality (PUNCT) (on-time and 10 minute early) were also considered. The study found that ALTER-Ind and ALTER5-Ind performed best on 0% NOSHOW, on-time PUNCT 5% NOSHOW; on-time PUNCT situations reduce WT and IT per patient. As NOSHOW create slack time for waiting patients, their WT tends to decrease while IT increases due to unexpected cancelation. Earliness increases congestions while in turn increases waiting time.

Ramis et al. (2008) conducted a study over Medical Imaging Center (MIC) to build a simulation model. The simulation model was used to improve the patient journey through an imaging center by means of reducing the wait time and making a better utilization of the resources. The simulation model also used Graphic User Interface (GUI) to provide the parameters of the center which are arrival rates, distances, processing times, resources and schedule. Later, different case scenarios were analyzed. Studies found that assigning common function to the resource personnel could improve the waiting time of the patients.

2.2 Scheduling Identical Parallel Machines

In a treatment centre, patient arrives and waits until a treatment bed and a nurse are both available. When both of them are accessible, a nurse takes the patient to a free chair and infuses the chemotherapy drug line into the patient. The patient seizes the treatment chair until the treatment is finished. The treatment length varies from less than an hour to twelve hour based on the infusion. However, the nurse can leave to serve other patients during the treatment duration. At the end of the treatment, the nurse returns and removes the line and the patient leaves the clinic.

Thus the environment of a treatment center can also be inferred as Identical Parallel Machine as the patient stays in the treatment chair until the treatment is finished and the patient seizes only one treatment chair during the whole procedure. An intensive literature review on Identical Parallel Machine is done, and the problem is considered as scheduling identical parallel machine problem with release time constraint to minimize the total completion time. According to the standard machine scheduling classification, this problem is denoted as $Pm|r_i|\sum C_i$, where Pm indicates m number of Parallel machine, r_i is release time of job i and C_i is the processing completion time of job i. Because of potential applications in real life, like in health care service or in parallel multi processors manufacturing system, solving this problem has always been an interest to researchers. Figure 2.1 shows a classification of the previous works on Scheduling Identical Parallel Machines. Following the "Dark Line" of this figure presents the position of our research relative to the literature. Lenstra et al. (1997) showed that, the parallel machine scheduling problem (PMSP) with release date constraints is NP-hard regardless of the considered criterion. Du et al. (1991) proved that with two machines and identical processing times of all jobs the problem is solvable in polynomial time.

Lu et al. (2009) studied bounded single machine parallel batch scheduling problem with release dates and rejections subject to minimizing the sum of the makespan of the accepted jobs and the total penalty of rejected jobs. Based on the jobs release date, several propositions were made such as, when the jobs had identical release dates. A polynomial-time algorithm was followed and when the jobs have a constant number of release dates, a pseudo-polynomial-time algorithm was followed. For the general problem, a 2-approximation algorithm and a polynomial-time approximation scheme were followed.

Ho et al. (2011) presented a two phase non-linear Integer Programming formulation for scheduling n jobs on two identical parallel machines with an objective to minimize weighted total flow time subject to minimum flow time. In the first phase, the integer programming model determined the optimal makespan, whereas the second phase minimized the total weighted flow time, while maintaining the optimal makespan found in the first phase. The non-linearity of the second phase made it difficult to solve this problem. Thus, an optimization algorithm was proposed for small problems, and a heuristic, for large problems, to find optimal or near optimal solutions. The proposed algorithm was known as MOD-TMO algorithm which is a modified version of a TMO algorithm developed by Ho and Wong (1995). Although the proposed procedures showed very good computational performance, the worst-case complexity was still exponential, similar to the TMO algorithm.

Sourd and Kedad-Sidhoum (2008) studied single machine scheduling problem with earliness and tardiness penalties which is closely related to Just-In-Time philosophy. Simple iterated descent algorithm with a generalized pair wise interchange neighborhood heuristic was used to obtain the upper bound of the problem. Results show that the proposed heuristic found the optimum schedule 36% of the time. After n iteration, where n is the number of jobs of the instance, this performance was raised to 84.1%. Lower bound was derived from Lagrangean relaxation of the resource constraints which allows the occurrence of idle time. Finally, this lower bound was efficiently integrated with the branch and bound search algorithm.

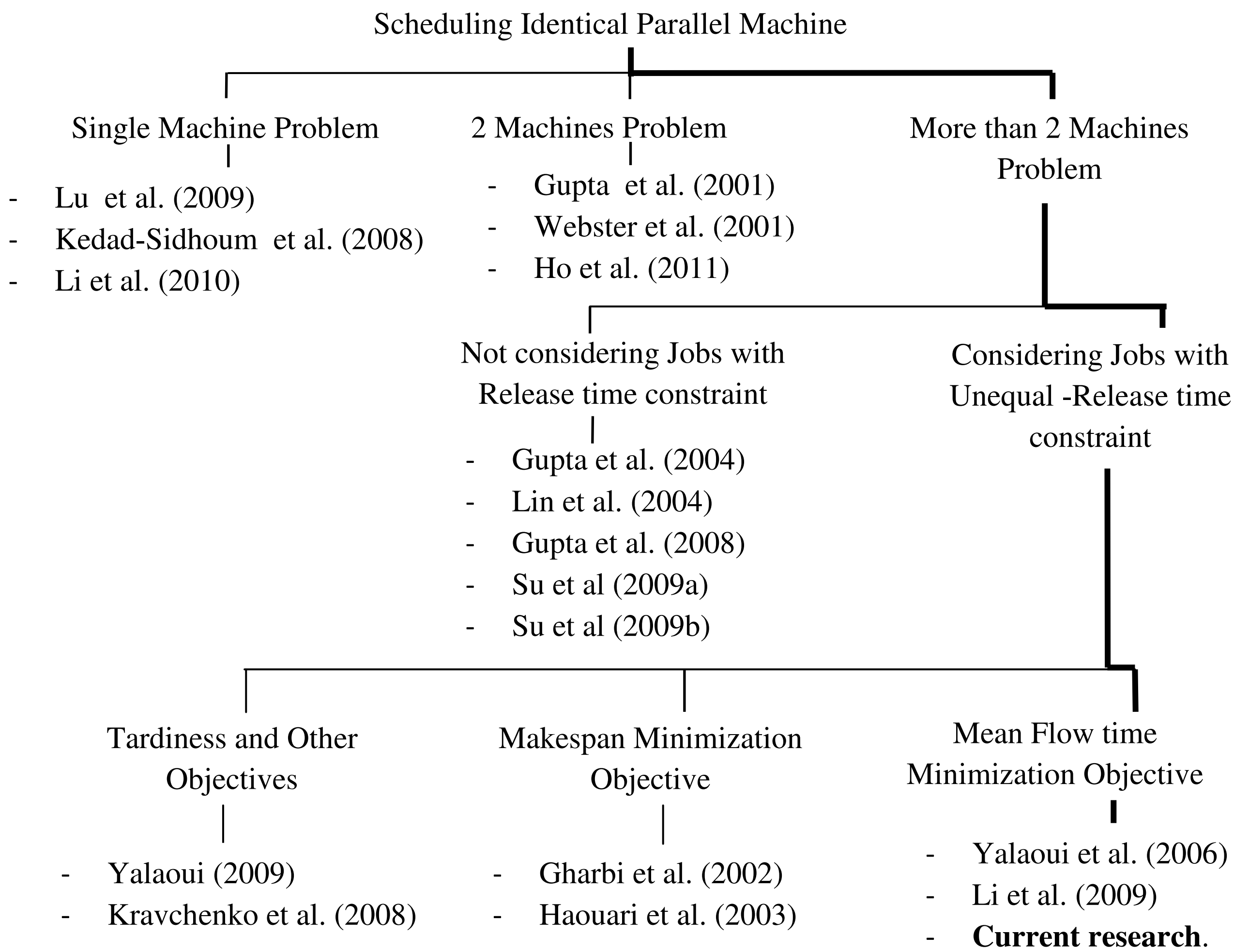


Figure 2.1: Previous works on Identical Parallel Machine Scheduling and Position of the current Research.

Li et al. (2010) studied similar problem with unrestricted idle time (before a machine begins job processing). Several dominance properties of the optimum schedule were proposed and proved, such as: i) m jobs with longest process time should be scheduled on the respective first positions of the m machines, ii) the schedule and mean completion time on each machine is the same and optimum and iii) for the small size problem, the difference between the sums of job processing times plus idle time on two machines is rather small. A heuristic algorithm was developed, named WAVS (Wavy Assignment, Verified Schedule), which generated near optimal schedules for small problem instances and dramatically outperformed existing A-FCFS, A-LPT, A-SPT, DVS algorithms for large problem instances.

Brucker and Kravchenko (2008) applied linear programming approach to solve scheduling problem with release time, due time and equal process time constraints on identical parallel machine problem. A LP formulation was used with relaxing the due time constraints. Due time of all the jobs were set by summing up the maximum release date and the process time times the number of jobs. Polynomial algorithm was developed and used to schedule the problem.

Su (2009a) studied identical parallel machine scheduling problem to minimize total job completion time with job deadlines and machine eligibility problem. A heuristic which combines SPT, LST and algorithm S to schedule jobs and to make sure constrains were maintained was developed to provide the upper bound. A lower bound was proposed, and it is modified version of $R_m || \sum_{j=1}^{n} w_j T_j$ suggested by Liaw (2003). Here, R_m indicates m numbers of unrelated parallel machine and $w_j T_j$ is the weighted tardiness of job *j*. Later, branch and bound algorithm was used to determine the optimum result. Computational results show that the improved lower bound outperforms the lower boundary developed by Liaw et al. by 18% in terms of average CPU time. Computational result also shows that the proposed heuristic generates a good quality schedule and the average deviation with the optimum result is 0.325%.

Yalaoui and Chu (2006) proposed a polynomial lower bound scheme by allowing job splitting or by relaxing release date constraints. Later they used the HPRTF and HAL heuristic to obtain the upper bound or the initial schedule. The best solution found by these two heuristics is used as an initial solution. Finally, the branch and bound method was used over this initial schedule to find the optimum or near optimal solution. Neither the upper bound values nor the optimum values were explicitly reported in their paper. However the deviation of the upper bound versus the average optimal solution was reported as 3%. Nessah et al. (2007) used the same heuristic with set up time constraints. But the methods reported in Yalaoui and Chu (2006) and Nessah et al. (2007) take long time to obtain the optimum solution because of the large gap between the initial solutions obtained by the heuristic and the final optimal solutions. Therefore, these methods can be considered suitable for small size problems.

Li and Zhang (2009) proposed a backward algorithm where instead of using traditional forward scheduling they used backward scheduling and showed the superiority of their algorithm over the forward scheduling. But they did not report any comparison with the optimum solution. Su (2009b) proposed a Binary Integer Programming (BIP) to solve the $P||C_{max}/\sum C_i$ problem. The BIP proved its superiority over the existing optimization algorithm for this problem. Biskup et al. (2008) used Mixed Integer Linear Programming (MILP) to solve the minimization tardiness problem of the Identical Parallel Machine. They provided optimum solutions for small size problems with 10 jobs & 5 machines.

However, in order to schedule a treatment center, it is essential to consider the accessibility of both resources (treatment chair and nurse) as the system is relied on two different types of resources. This sort of scheduling is also known as "Dual Resources

Constraint" (DRC) scheduling problem and the problem can be reformulated as: $P_m, W_n \left| d_j, r_j \right| \sum C_j$

ElMaraghy et al. (2000) developed a genetic algorithm based approach for scheduling a job shop problem under dual resources constrained manufacturing system and found that the dispatching rule which works best for a single-resource constrained shop is not necessarily the best rule for a dual-resources constrained system. Furthermore, it is shown that the most suitable dispatching rule depends on the selected performance criteria and the characteristics of the manufacturing system. Daniels et al. (1999) worked on dual resource constraints to minimize maximum completion time. Hu (2005, 2006) and Chaudhry (2010) worked on minimizing the total flow time for the worker assignment scheduling problem in the identical parallel machine problem. Hu (2005, 2006) applied SPT heuristic to get the order of the jobs and used Largest Marginal Contribution (LPT) heuristic to assign a worker to a machine. However, Chaudhry(2010) developed Genetic Algorithm for this problem and reported that the Genetic Algorithm outperforms Hu's algorithm. But their study was limited to such a scheduling problem where that the number of workers is more than the number of machine and the numbers of constraints were also limited.

2.3 Comparison between Literature and Current Research

Simulation modeling has been used as an extensive tool in healthcare service system to improve the flow of patients in clinics and to reduce the waiting time by analyzing the what-if scenarios. However, reviewers on the previous research works reveal that most of the what-if scenarios were designed by changing the layout plan of the clinic or by changing the schedule of the care provider and the clinic time. But the current study confront the situations where these were not the options. The detail of the Mc Charles Chemotherapy treatment center is given in the following chapter.

Although the environment of a treatment center can be inferred as identical parallel machine, but the literature review on this topic divulges that no research has been done so far that matches with the current scheduling problem.

Chapter 3

Simulation Modeling and Analysis of the Treatment Center

In this chapter, an efficient scheduling template has been developed that maximizes the number of served patients and minimizes the average patients' waiting time at the given resources availability. To accomplish this objective, a simulation model is developed which mimics the working conditions of the clinic. Then we have suggested different scenarios of matching the arrival pattern of the patients with the resources availability. Experiments are performed to evaluate these scenarios. Hence, a simple and practical scheduling template is built based on the identified best scenario. The steps of building a simulation model is given in section 3.1 and the journey of patients in the treatment center is described in section 3.2. Description of the treatment room is given in section 3.3, description on the types of patient and treatment time is in section 3.4 and verification & validation of the simulation model is in section 3.5. In Section 3.6 different Improved Scenario for this system is described and their analysis is described in Section 3.7. Section 3.8 illustrates a scheduling template based on one of the improvement scenario. Finally the achievements and limitations of the simulation model are expressed in section 3.9.

3.1 Steps of Building the Simulation Model

A valid simulation model represents the actual system. This simulation assists in visualizing and evaluating the performance of the system under different scheduling scenarios without interrupting the actual system. Building a proper simulation model of a system consists of the following steps:

i) Observing the system to understand the flow of the entities, key players, resources availability and overall generic frame work.

ii) Collecting the data on the number and type of entities, time consumed by the entities at each step of their journey, and resources availability.

iii) After building the simulation model it is necessary to confirm that the model is valid. It can be done by confirming that the each of the entity flows as it is supposed to be and the statistical data generated by the simulation model is similar to the collected data.

3.2 Flow of Patient in the Treatment Center

Figure 3.1 shows the patient flow process in the treatment room. On the patient's first appointment, the oncologist comes up with the treatment plan. The treatment time varies according to the patient's condition, which may be 1 hour to 10 hours. Based on the type of the treatment, the physician or the clinical clerk books an available treatment chair for that time period.

On the day of the appointment, the patient will wait until the booked chair is free. When the chair is free, a nurse from that station comes to the patient, verifies name and date of birth and takes the patient to a treatment chair. Afterwards, the nurse injects the chemotherapy drug line to the patient's body which takes about 5 minutes. Then the nurse leaves to serve another patient. At the end of the treatment, the nurse comes back, removes the line and notifies the patient about the next appointment date and time which also takes about 5 minutes. Most of the patients visit the clinic to take care of their PICC line. A PICC is a line that is used to inject the patient with the chemical. This PICC line should be regularly cleaned. It takes approximately 10 – 15 minutes to take care of a PICC line by a nurse.

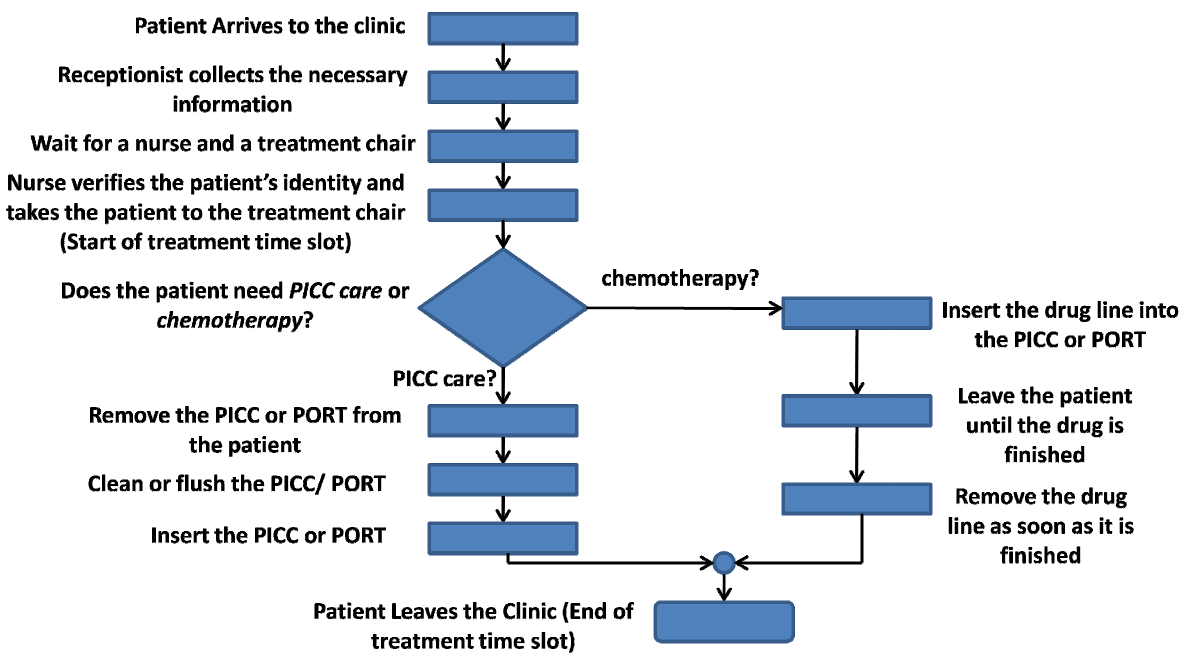


Figure 3.1: Flow of patient through the treatment room

3.3 Description of the Treatment Room

Cancer Care Manitoba gave the access to the electronic scheduling system, also known as "ARIA" which is comprehensive information and image management system that aggregates patient data into a fully-electronic medical chart, provided by VARIAN Medical System. This system is used to find out how many patients are booked in every clinic day. It also provides which chair is used for how many hours. It is necessary to search a patient's history to find how long the patient spent on which chair. Collecting the snap shot of each patient gives the complete picture of a one day clinic schedule.

The treatment room consists of the following two main limited resources:

i) Treatment Chairs: Chairs that are used to seat the patients during the treatment.

ii) Nurses: Nurses are required to inject the treatment line into the patient and remove it at the end of the treatment. They also take care of the patients when they feel uncomfortable.

Mc Charles Chemotherapy unit consists of 11 nurses, and 5 stations with the following description:

i) Station 1: Station 1 has six chairs (numbered 1 to 6) and two nurses. The two nurses work from 8:00 to 16:00.

ii) Station 2: Station 2 has six chairs (7 to 12) and three nurses. Two nurses work from 8:00 to 16:00 and one nurse works from 12:00 to 20:00.

iii) Station 3: Station 4 has six chairs (13 to 18) and two nurses. The two nurses work from 8:00 to 16:00.

iv) Station 4: Station 4 has six chairs (19 to 24) and two nurses. One nurse works from 8:00 to 16:00. Another nurse works from 10:00 to 18:00.

v) Solarium Station: Solarium Station has six chairs (Solarium Stretcher 1, Solarium Stretcher 2, Isolation, Isolation emergency, Fire Place 1, Fire Place 2). There is only one nurse assigned to this station that works from 12:00 to 20:00. The nurses from other stations can help when need arises.

There is one more nurse known as “float nurse” who works from 11:00 to 19:00. This nurse can work at any station. Table 3.1 summarizes the working hours of chairs and nurses. Figure 3.2 exhibits the cumulative number of available nurses over the daily working hours. All treatment station starts at 8:00 and continues until the assigned nurse for that station completes her shift. Figure 3.3 shows the total working hours of each station.

Table 3.1: Allocation of treatment chairs and nurses’ schedule

Station	No of Chairs	Regular Nurses and Working Hour	Float Nurse
Station 1	6	Nurse 1: From 8:00 to 16:00 Nurse 2: From 8:00 to 16:00	Float nurse works from 11:00 to 19:00
Station 2	6	Nurse 1: From 8:00 to 16:00 Nurse 2: From 8:00 to 16:00 Nurse 3: From 12:00 to 20:00	
Station 3	6	Nurse 1: From 8:00 to 16:00 Nurse 2: From 8:00 to 16:00	
Station 4	6	Nurse 1: From 8:00 to 16:00 Nurse 2: From 10:00 to 18:00	
Solarium Station	6	Nurse 1: From 12:00 to 20:00 All the nurses from other station.	

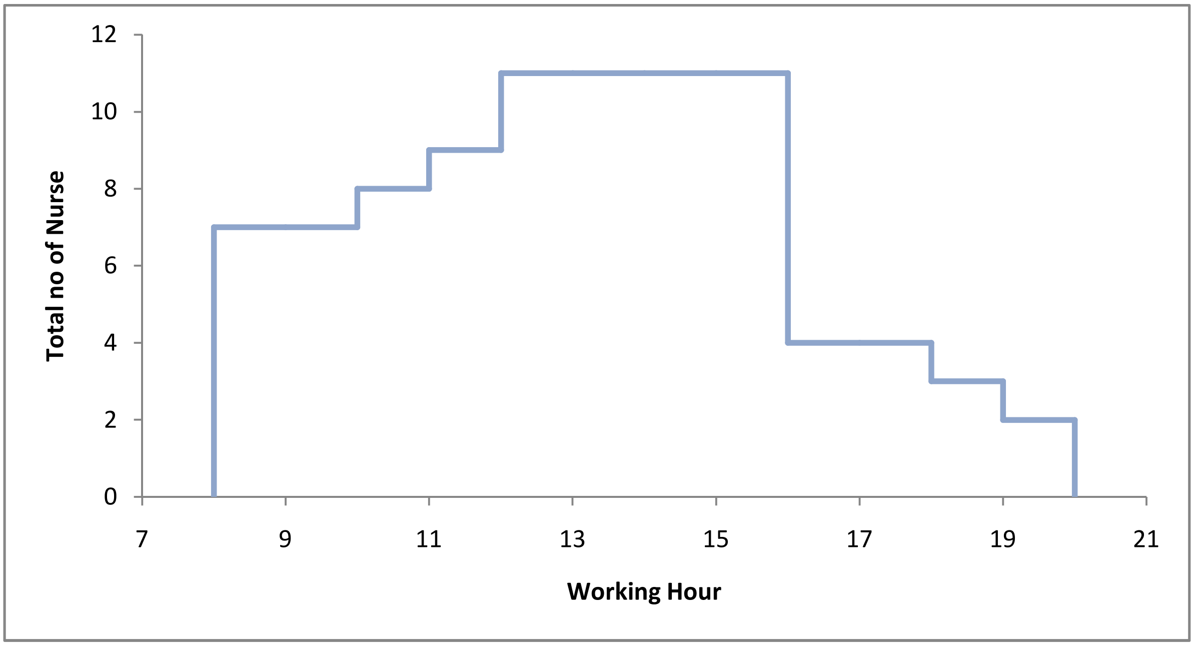


Figure 3.2: Nurses availability at the daily working hours

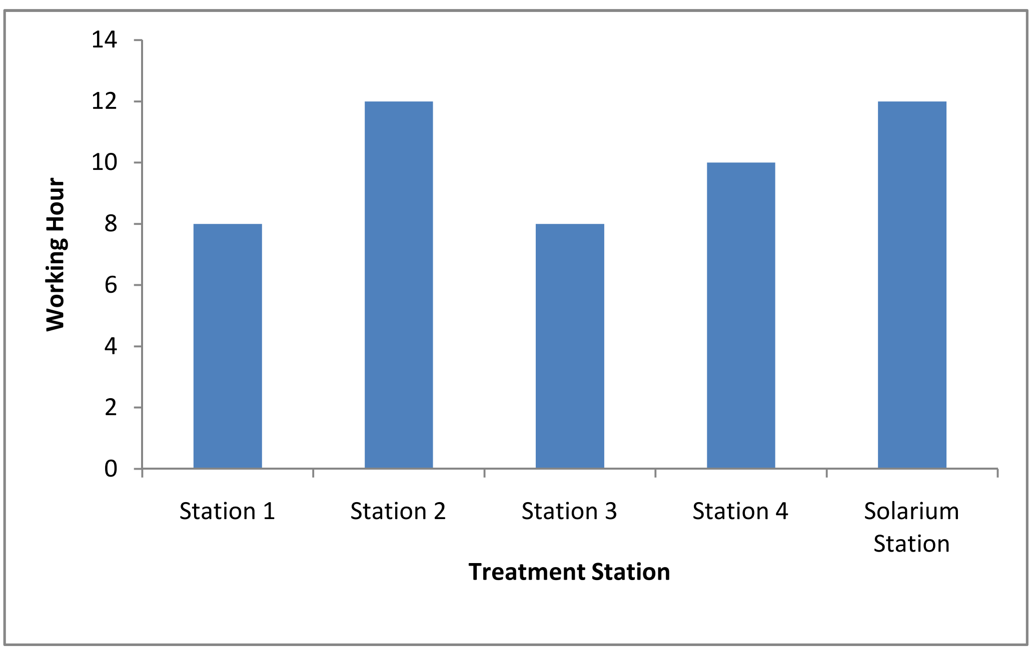


Figure 3.3: Number of working hours of stations

3.4 Types of Patients and Their Treatment Duration

Currently, the clinic is using a scheduling template to assign the patients' appointments. But due to high demand of patient's appointment it is not followed any more. We believe that this template can be improved based on the nurses and chairs availability. Clinic workload is collected from 21 days of field observation. The current scheduling template has 10 types of appointment time slot, like: 15-minute, 1-hour, 1.5-hour, 2-hour, 3-hour, 4-hour, 5-hour, 6-hour, 8-hour and 10-hour and it is designed to serve 95 patients. But when the scheduling template is compared with the 21 days observations, it is found that the clinic is serving more patients than it is designed to be. Therefore, the care providers do not usually follow the scheduling template. Even they break the time slot very often in order to accommodate such slot that does not exist in the template. Hence, we find that some of the stations are very busy (Mostly station 2) and others that are underutilized. If the scheduling template can be improved, it will be possible to bring more patients to the clinic and reduce their waiting time without adding resources.

In order to build or develop a simulation model of the existing system, it is necessary to collect the following data:

i) Types of treatment durations.
ii) Numbers of patients in each treatment type.
iii) Arrival pattern of the patients.
iv) Steps that the patients have to go through in their treatment journey and required time of each step.

Using the observations of 2155 patients over 21 days of historical data, the types of treatment durations and the number of patients in each type were estimated and presented in table 1A of appendix A. This data also assisted in determining the arrival rate and the frequency distribution of the patients. The patients were categorized into 6 types based on their treatment time. The percentage of these types and their associated service times are presented in tables 2A to 7A of appendix A. Table 8A represents the average daily arrival number of patients of the different patient types.

3.5 Model Verification and Validation

ARENA Rockwell Simulation Software v-13© is used to build the simulation model. Entities of the model are tracked to verify if the patients move is as intended. The model is run for 30 replications and statistical data is collected to validate the model. Total number of patients that go through the model have compared with the actual number of served patients during the 21 days of observations. The details of the validation have been described in the appendix A (Tables 9A- 11A).

3.6 Improvement Scenarios

After verifying and validating the simulation model, different scenarios are designed and analyzed to identify the best scenario that can handle more patients and reduces the average patients' waiting time. Based on the clinic observation and discussion with the healthcare providers, the following constraints have been stated:

i) The stations are filled up with treatment chairs. Therefore, it is literally impossible to fit any more chairs in the clinic. Moreover, the stakeholders are not interested in adding extra chairs.

ii) The stakeholders and the care givers are not interested in changing the layout of the treatment room.

Given these constraints the options that can be considered to design alternative scenarios are:

i) Changing the arrival pattern of the patients that will fit over the nurses' availability.

ii) Changing the nurses' schedule.

iii) Adding one full time nurse at different starting times of the day.

Figure 3.4 compares the available number of nurses and the number of patients' arrival during different hours of a day. It can be noticed that there is a rapid growth in arrival of patients (from 13 to 17) between 8:00 to 10:00 even though the clinic has the equal number of nurses during this time period. At 12:00 there is a sudden drop of patient arrival even though there is more number of available nurses. It is obvious that there is an imbalance of the number of available nurses and the number of patient arrivals over different hours of the day. Consequently, balancing the demand (arrival rate of patients) and resources (available number of nurses) will reduce the patients waiting time and increases the number of served patients. The alternative scenarios that satisfy the above three constraints are listed in table 3.2. These scenarios respect the following rules:

i) Long treatments (between 4hr to 11hr) have to be scheduled early in the morning to avoid working overtime.

ii) Patients of type 1 (15 minutes to 1 hr treatment) are the most common. Because they take short treatment time, they can be fitted at any time of the day. Hence, it is recommended to bring these patients at the middle of the day when there are more nurses.

iii) Nurses get tired at the end of the clinic day. Therefore, less numbers of patients should be scheduled at the late hours of the day.

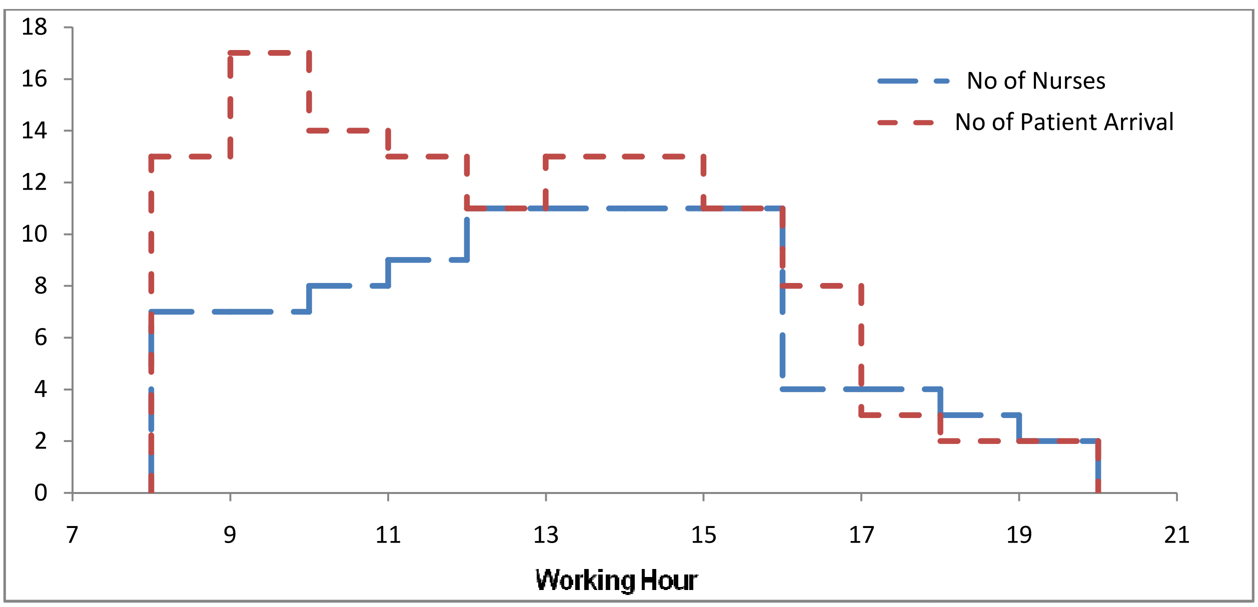


***Figure 3.4: Comparison between number of nurses and number of patient arrivals during different hours of the day*.**

Table 3.2: Suggested improvement scenarios.

Scenarios	Changes
Scenario 1	Change the arrival pattern of the patient to fit the current nurse schedule.
Scenario 2	Reschedule the Float nurse schedule to 10:00-18:00 instead of 11:00 – 19:00
Scenario 2.2	Reschedule the Float nurse schedule to 10:00-18:00 instead of 11:00 – 19:00 and change the arrival pattern of the patient that to fit the change in nurse schedule.
Scenario 3	Add one nurse at different stations from 8:00 to 16:00.
Scenario 4	Add one nurse at different stations from 10:00 to 18:00.
Scenario 4.2	Add one nurse at different stations from 10:00 to 18:00 and change the arrival pattern of the patient to fit the change in nurse schedule.
Scenario 5	Add one nurse at different stations from 11:00 to 19:00.
Scenario 5.2	Add one nurse at different stations from 11:00 to 19:00 and change the arrival pattern of the patient to fit the change in nurse schedule.

In Scenario 1, the arrival pattern of patient is changed so that it can fit over the nurse schedule. This arrival pattern is shown Table 3.3. Figure 3.5 shows the new patients' arrival pattern compared with the current arrival pattern. The detailed description of the remaining scenarios is given in appendix A. The detailed arrival pattern of the different patient types is described in table 12A.

Table 3.3: The patient arrival pattern of Scenario 1

Working Hour	No of Nurses	Current Arrival Rate	Changed Arrival Rate
8:00 - 9:00	7	13	12
9:00 - 10:00	7	17	12
10:00 - 11:00	8	14	15
11:00 - 12:00	9	13	16
12:00 - 13:00	11	11	18
13:00 - 14:00	11	13	18
14:00 - 15:00	11	13	18
15:00 - 16:00	11	11	13
16:00 - 17:00	4	8	7
17:00 - 18:00	4	3	4
18:00 - 19:00	3	2	2
19:00 - 20:00	2	2	0

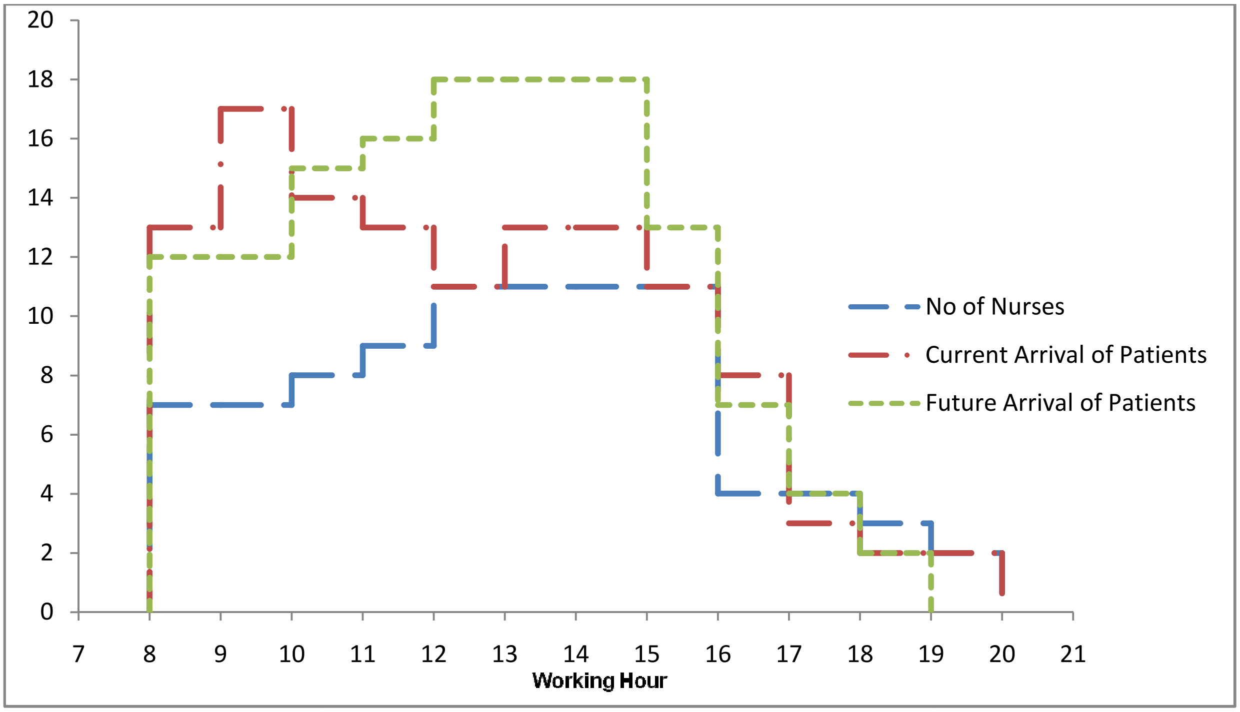


Figure 3.5: Patients' arrival pattern of Scenario 1 compared with the current one.

3.7 Analysis of Results

ARENA Rockwell Simulation software v-13© is used to develop the simulation model. There is no warm up period because the model simulates day-to-day scenarios. The patients of any day are supposed to be served in the same day. The model has run for 30 days (replications) and statistical data are collected to evaluate each scenario. Tables 3.4 and 3.5 show the comparison of the system performance between current scenario and Scenario 1. The results are quite interesting. The average throughput rate of the system has increased from 103 patients to 125 patients per day. The maximum throughput rate can reach 135 patients. Although, the average waiting time has increased, the utilization of the treatment station has increased by 15.6%. Similar analysis has been performed for the rest of the other scenarios. The details of the collected statistical data of all scenarios can be found in appendix A.

Table 3.4: Comparison of the system performance between the current system and Scenario 1

Patient Type	Average Number of Served Patients		Average Patient Waiting Time (minutes)	
	Existing Scenario	Scenario 1	Existing Scenario	Scenario 1
15 minute	33.9	43.7	4.3	16.6
30 minute	15.4	20.9	3.9	14.9
45 minute	1.06	1.2	3.2	12
1 hour	8.4	11.8	4.9	9.02
1.5 hour	7.3	8.3	6.1	17.25
1.25, 1.75, 2.25, 2.75 hr	3	3.5	4.2	5
2 hr	10	10.8	5	14.4
2.5 hr	1.6	2.2	1.4	8.6
3 hr	4.8	5.3	3.8	8.1
3.25, 3.5, 3.75 hr	2.3	1.4	3.6	4.2
4 hr	4.6	4.6	3.2	8.6
4.25, 4.5, 4.75 hr	0.733	0.7	2.5	3.32
5 hr	4.2	3.3	3.1	8.1
5.25, 5.5, 5.75, 6, 6.5, 6.75, 7 hr	2.8	3.32	2.3	2.5
7.25, 7.5, 7.75, 8, 8.25, 8.5 hr	1.96	3.1	3.53	3.5
9.5, 10, 11, 11.5 hr	1	1.3	10	0.71
Average	**103**	**125**	**4.3**	**13.4**
Maximum	**108**	**135**		

Table 3.5: Comparing the stations utilization

	Station 1	Station 2	Station 3	Station 4	Solarium	Average Utilization
Current Scenario	0.73	0.8	0.49	0.49	0.58	0.62
Scenario 1	1.06	0.72	0.76	0.74	0.6	0.776

Table 3.6 exhibits a summary of the results and comparison between the different scenarios. Scenario 1 is able to significantly increase the throughput of the system (by 21%) while it still results in an acceptable low average waiting time (13.4 minutes). In addition, it is worth noting that adding a nurse (Scenarios 3, 4, and 5) does not significantly reduce the average waiting time or increases the system's throughput. The reason behind this is that when all the chairs are busy, the nurses will also have to wait

until some patients finish the treatment. As a consequence, the other patients have to wait for the commencement of their treatment too. Therefore, hiring a nurse, without adding more chairs, will not reduce the waiting time or increase the throughput of the system. In this case, the legitimatize way to increase the throughput of the system is by adjusting the arrival pattern of patients over the nurses' schedule.

Table 3.6: Summary of the results of all scenarios

Scenarios	Main Effect	Average Waiting time (Minute)	Average Throughput	Average Station Utilization
Current Scenario	It represents the current working condition.	4.3	102	61.8%
Scenario 1	It results in minor increase in the waiting time but significantly increases the stations utilization.	13.4	125	77.6%
Scenario 2	It reduces the throughput compared to Scenario 1.	13	119	76.9%
Scenario 2.2	It is similar to Scenario 1 with respect to waiting time and stations utilization but results in lower throughput.	13.21	116	78%
Scenario 3	It obtains best results if the nurse is assigned to station 1. Comparable to Scenario 1.	11.75	125	77.8%
Scenario 4	It obtains best results if the nurse is assigned to station 2. Comparable to Scenario 1	12.45	125	77.8%
Scenario 4.2	It obtains best results if the nurse is assigned to station 2. Compared to Scenario 1, it has lower throughput and waiting time.	10	120	76.2%
Scenario 5	It obtains best results if the nurse is assigned to solarium station. Comparable to Scenario 1.	11.75	125	77.6%
Scenario 5.2	It obtains best results if the nurse is assigned to solarium station. It results in lower throughput and higher stations utilization.	12	122	79.2%

3.8 Developing a Scheduling Template based on Scenario 1

From the analysis of the different scenarios in Section 3.7, it is found that scenario 1 provides the best system performance. In this scenario the arrival pattern of the patients is fitted over the availability of nurses. But a scheduling template is necessary for the care provider to book the patients. A brief description is provided below on how the scheduling template is developed based on this scenario.

Table 3.3 gives the number of patients that arrive hourly, following scenario 1. The distribution of each type of patients is shown in Table 3.7. This distribution is based on the percentage of each type of patients from the collected data. For example, in between 8:00-9:00, 12 patients will come where 6 is of Type 1, 2 is of Type 2, 1 is of Type 3, 1 is of Type 4, 1 is of Type 5 and 1 is of Type 6. It is worth to be noting that, it is assumed that the patients of each type at each hour arrive as a group at the beginning of the hourly time slot. For example, all of the 6 patients of Type 1 from 8:00 to 9:00 time slot arrive at 8:00.

Table 3.7: Arrival pattern (Hourly) of different types of patients based on Scenario 1

TYPE	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Total Patient (by Hour)
8:00-9:00	6	2	1	1	1	1	12
9:00-10:00	6	2	1	1	1	1	12
10:00-11:00	7	4	2	1	1		15
11:00-12:00	8	4	2	1	1		16
12:00-13:00	10	5	2	1			18
13:00-14:00	10	5	2	1			18
14:00-15:00	12	4	2				18
15:00-16:00	10	3					13
16:00-17:00	5	2					7
17:00-18:00	4						4
18:00-19:00	2						2
19:00-20:00							
Total Patient (by Type)	80	31	12	6	4	2	135

The numbers of patient from each of type is distributed in such a way that it honors all the constraints described in Section 1.3. Most of the patients of the clinic are from type 1, 2 and 3 and they take less amount of treatment time compared with the patients of other types. Therefore, they are distributed all over the day. Patients of type 4, 5 and 6 take longer treatment time. Hence, they are scheduled at the beginning of the day to avoid over time. Because patients of type 4, 5 and 6 come at the beginning of the day most of types 1 and 2 patients come at mid day (12:00 to 16:00). Another reason to make the treatment room more crowded in between 12:00 to 16:00 is because the clinic has the maximum number of nurses during this time period. Nurses become tired at the end of the clinic hour which is the reason for not to schedule any patient after 19:00 hour.

Based on the patient arrival schedule and nurse availability a scheduling template is built and shown in figure 3.6.

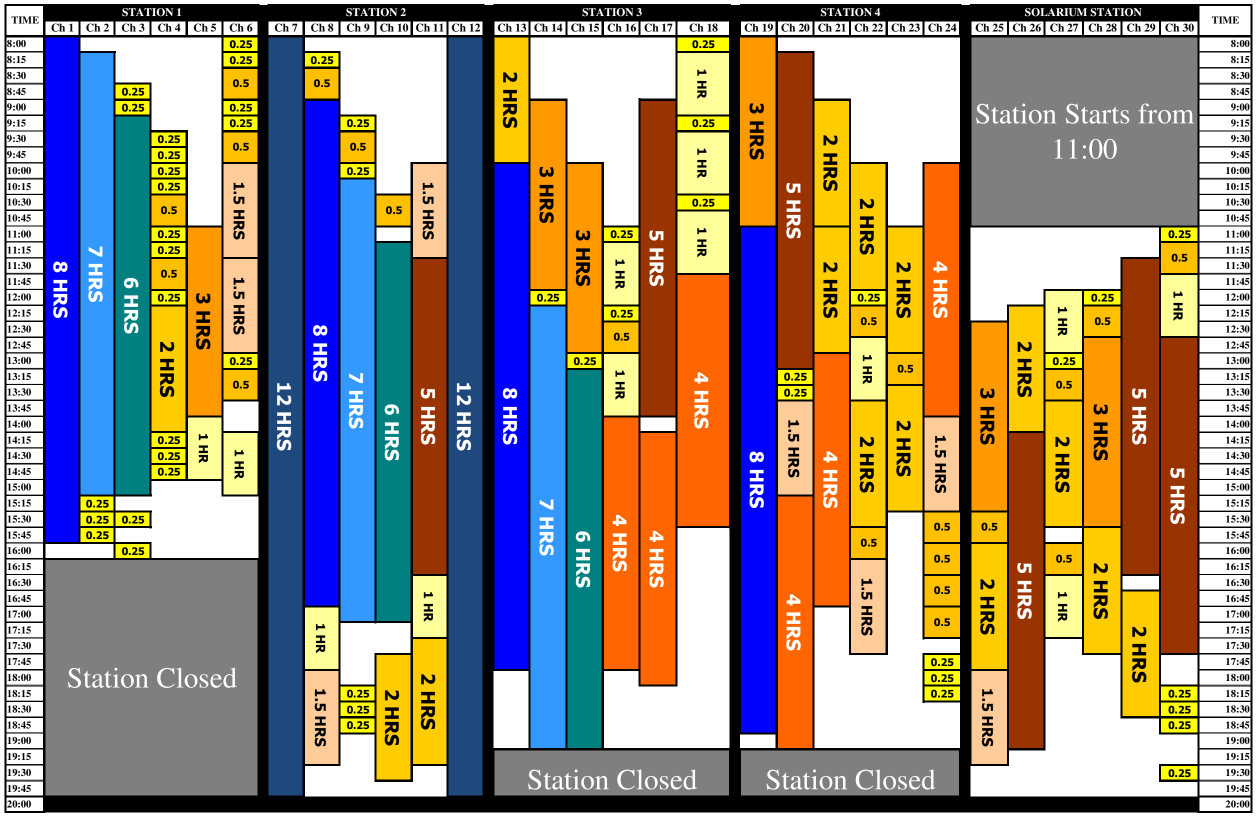


Figure 3.6: Scheduling template based on scenario 1

Figure 3.6 is an illustration of scenario 1. In order to build the template, if a nurse is available and there are waiting patients for service, a priority list of these patients will be developed. They are prioritized in a descending order based on their estimated slack time and secondarily based on the shortest service time. The secondary rule is used to break the tie if two patients have the same slack. The slack time is calculated using the following equation:

Slack time = Due time- (Arrival time + Treatment time)

Due time is the clinic closing time. To explain how the process works, assume at hour 8:00 (in between 8:00 to 8:15) 2 patients in station 1 (one 8-hour and one 15-minute patient), 2 patients in station 2 (two 12-hour patients), 2 patients in station 3 (one 2-hour and one 15-minute patient) and 1patients in station 4 (one 3-hour patient) in total 7 patients are scheduled. Recalling the figure 2 will demonstrate that there are 7 nurses who are scheduled at 8:00 and it takes 15 minutes to preparation a patient. Therefore, it is not possible to schedule more than 7 patients in between 8:00 to 8:15 and the current scheduling is also serving 7 patients by this time. The rest of the hours of the template can be justified similarly.

3.9 Conclusion

This study is undertaken to improve the performance of a Chemotherapy Treatment Unit by increasing the throughput of the clinic and reducing the average patients' waiting time. The main objective is to build an efficient Scheduling Template. A scheduling template gives a vivid picture of when to schedule a patient and it is built based on the arrival pattern of the patient and resources availability. In order to achieve this objective, the treatment center is studied to understand the journey of the patients through different stages of their treatment. Secondly, important data have collected regarding the patient's type, treatment time and resource availability. Finally a simulation model of this system is built. Different scenarios have designed and evaluated in order to find the best schedule of the patients. Comparing all the scenarios, Scenario 1 provides the best performance. This scenario proves to serve 125 patients daily with an average resources utilization of 77.6%. On the other hand, the stakeholders do not have to hire additional nurses compared to scenarios 4 and 5.

A scheduling template has been developed based on scenario 1. In the following chapters, this system is considered as Identical Parallel Machine scheduling problem as the treatment chairs in the clinic can be inferred as Identical Parallel Machine and the patients can to be served by any treatment chair. Hence, our next research goal is to schedule these patients considering the system as identical parallel machine problem with arrival time, due time and the limited availability of nurses as a secondary constrain.

Chapter 4

Scheduling Identical Parallel Machines with Release time constraint to minimize total flow time

In this chapter, a scheduling template has been built following the patients arrival pattern of scenario 1 described in section 3.8 table 3.7. In order to build the template, first the scheduling problem is decomposed as single resource constrain that only considers the availability of treatment chair with the patients release/arrival time restrain. An efficient heuristic algorithm is proposed, known as Modified Forward Heuristic Algorithm (MFHA) to sequence the order of patients of the decomposed problem. The algorithm starts with developing a priority list of all patients. This list is used to develop sub-schedules for each treatment chair based on some propositions related to the patient's treatment and release times with allowing delay schedule. A mathematical model of the problem is developed too. The performance of the algorithm is evaluated by comparing its solutions with the optimal solutions of small test cases obtained from the developed mathematical model. Then, the results of large problems are compared with the results of the best reported heuristic in the literature.

However, it is necessary to consider the availability of treatment chair and nurse to develop a scheduling template for a treatment station. Therefore, another algorithm is used, known as Right Shifting Rule (RSR) which considers the sequence of patients on their assigned chair given by the MFHA and considers the availability of the nurse to develop the template.

In section 4.1 the introduction of the decomposed scheduling problem is given. Section 4.2 describes the traditional Shortest Process Time (SPT), Earliest Release Date (ERD) heuristic and Backward Algorithm (BA). The proposed MFHA is presented in section 4.3 and a mathematical model for solve this problem is described in section 4.4. Section 4.5 presents the computational results and analysis. Section 4.6 concludes the chapter and illustrates the limitation of the proposed algorithm

4.1 Introduction

Healthcare facility is now using different engineering tools to improve their quality of care by means of reducing the waiting time and providing the satisfaction to the care provider. Scheduling is one of the tools that can improve the flow of patients within the system. However, applying scheduling optimization in healthcare systems is a cumbersome process. This is due to the amount of constraints that have to be considered such as availability of the care providers and patients, variability of treatment durations, and preparation and discharge times of patients.

In this chapter, the problem is simplified as Identical Parallel Machine constrain problem with patient's arrival pattern. Accessibility of the nurse, patient preparation and discharge time and clinic closing time are not measured. We have considered to schedule N jobs $J_1, J_2, \ldots, J_N$ with unequal release dates on M identical parallel machines to minimize the total flow time. Each job i has a positive processing time P_i and release time r_i. Preemption or splitting is not allowed. Once a machine starts processing a job, it will not stop until it completes the processing. According to the standard machine scheduling classification, this problem is denoted as $Pm|r_i|\sum C_i$.

4.2 The Traditional Heuristics

Traditional forward heuristics either follow SPT or ERD rule to make a job list and schedule the prior job as early as possible. While in the Backward Heuristic, they follow LPT (Largest Process Time) – LRD (Last Release Date) rule to build the job list and follow backward algorithm to build the schedule.

4.2.1 Theorem 1

SPT: If there are two jobs J_1 and J_2 where processing time $P_1 \leq P_2$, that are available at time T_i and scheduled to a same machine M_i then processing completion time $C_{[i][2\to1]} \geq C_{[i][1\to2]}$. Here $C_{[i][2\to1]}$ means job processing completion time on machine M_i where job 2 is scheduled before job 1. Therefore schedule $C_{[i][1\to2]}$ dominates schedule $C_{[i][2\to1]}$.

4.2.2 Theorem 2

ERD: If there are two jobs J_1 and J_2, where release time $r_1 \leq r_2$ and they are scheduled on same machine M_i, then processing completion time $C_{[i][2\to1]} \geq C_{[i][1\to2]}$. Here $C_{[i][2\to1]}$ means job processing completion time of machine M_i where job 2 is scheduled before job 1. Hence schedule $C_{[i][1\to2]}$ dominates schedule $C_{[i][2\to1]}$.

The proofs of the two theorems are available in Smith (1956) and Reeves (1995) respectively.

In the forward heuristic algorithm, a job list is made where the jobs are arranged following SPT or ERD heuristic. As soon as a machine is available, the head job form the list will be assigned for processing on that machine. Assigned job will be deleted from the list and all the unscheduled jobs on the list will proceed to one step forward position. The process will continue until the job list is null.

Unlike the forward heuristic algorithm, in the Backward Algorithm the jobs are arranged following LPT- LRD rule and the job list is made. Scheduling a job form the job list to an available machine is known as sub-scheduling, when there are still unscheduled jobs on the job list. The head job from the list is pre-inserted with pre-adjusting its start time on each of the sub-schedule of the machines. The influence of that job on each of the machines is calculated by the change of the completion time on the sub-schedule. The higher the change of the completion time of the sub schedule the higher is the influence. Finally the job is assigned to any one of the machine and will start its processing at a certain time for which the influence on the completion time is lowest. The scheduled head job will be deleted from the job list and the process will continue until the job list is empty.

The SPT and ERD heuristic first prioritize the jobs and build a job list. Later, when a machine is available to serve a new job, the heuristic pushes the head job to that available machine. But instead of scheduling the head job first, there could be another job on the list if scheduled before the head job that could lead to reduce the total flow time. For instance, there could be situations when a machine is available to start serving a new job and there is another job J_i in the job list whose processing time is shorter than the head job and the job J_i is available at that time. This type of scenario happens when the job list is created based on ERD heuristic. The ERD heuristic cannot asses the importance of another job other than the head job during creating the machines' sub-schedules, which is considered as an inherent local blindness. Therefore, in this case ERD heuristic could cause a negative impact on the total flow time.

4.3 The Proposed Heuristic Algorithm

In order to overcome this blindness, a heuristic algorithm has been developed, named as Modified Forward Heuristic Algorithm (MFHA) which is a combination of ERD/SPT rules and a new proposed algorithm to build the job list. Later during the sub-scheduling on each of the machine, not only the job list will push a job to a machine but also a machine can pull a job from the job list at certain conditions as it will be explained next. The available machine will look for a suitable job in the job list other than the head job during the sub-scheduling process.

Proposition 1

Assume that there are two jobs i and j such that, release rime $R_i<R_j$, process time $P_i>P_j$, and if $R_i+P_i>R_j$ and $R_j-R_i<P_j$ and $P_i-P_j>2\times(R_j-R_i)$ then job j should be prior to job i on machine M_k.

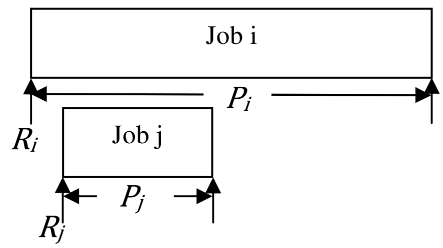
Prove:

From the figure 4.1

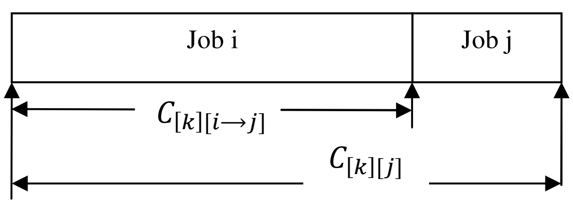
$C_{[k][i\to j]} + C_{[k][j]} > C_{[k][j\to i]} + C_{[k][i]}$

$\Rightarrow (P_i + R_i) + (P_i + R_i + P_j) > (P_j + R_j) + (P_j + R_j + P_i)$

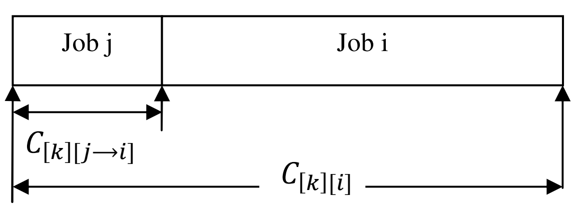
$\Rightarrow (P_i - P_j) > 2 \times (R_j - R_i)$



(a): Job *i* and Job *j* and their release and process time



(b): Job *i* is scheduled before job *j*



(c): Job *j* is scheduled before job *i*.

Figure 4.1: Proposition 1

Therefore, if there are any two jobs that follow the above criteria they should interchange their position to minimize the total flow time (Proved).

4.3.1 Modified Forward Heuristic Algorithm

Consider N jobs with unequal release dates that have to be scheduled on M machines (N>M). Preemption or splitting is not allowed. Once a machine starts processing a job, it will not stop until it completes the processing. In this algorithm, a job list will be built from which jobs will be assigned to the available machine. The following steps show the method of building this list:

Step 1

Sort the jobs based on earliest release date (ERD). Job that comes first will be ranked in the higher position.

Step 2

Jobs that have same release date will be sorted based on shortest process time (SPT).

Step 3

Check the job list and look for any two jobs i and j where Job j is the successor of Job i and the following conditions satisfied:

$R_i<R_j$ and

$P_i>P_j$ and

$R_i+P_i>R_j$ and

$R_j-R_i<P_j$ and

$P_i-P_j>2\times(R_j-R_i)$

Then job j should be prior to job i on machine M_k (Proposition 1).

During building the sub-scheduling of machines, the algorithm will follow the next three steps.

Step 4

Assign the first M jobs from the list to the M machines. Delete these scheduled jobs from the list and all the remaining jobs on the list will proceed forward.

Step 5

As soon as any of the machines is available at time T_i, the head job J_i from the remaining list will be scheduled on that machine unless it is challenged by any of the following conditions:

i) If this head job J_i is not available at T_i, then the machine will wait for the job that will come first, and it could be any job including the head job J_i.

ii) If this head job J_i is not the only available job at T_i, then schedule the job among the unscheduled available jobs at T_i, which has the shortest processing time.

Scheduled jobs will be deleted from the job list and all the jobs on the list will proceed forward.

Step 6

Continue step 5 until the job list is null.

An illustrative example:

Consider an example with 10 jobs and 2 identical machines.

Rank	1	2	3	4	5	6	7	8	9	10
Job no	1	3	6	9	5	4	8	10	2	7
Release	2	3	3	3	5	6	6	7	8	9
Process Time	92	97	4	3	92	93	5	4	92	4

After Step 1 the job list becomes:

Job no	1	2	3	4	5	6	7	8	9	10
Release Time	2	8	3	6	5	3	9	6	3	7
Process Time	92	92	97	93	92	4	4	5	3	4

After Step 2 the job list becomes:

Rank	1	2	3	4	5	6	7	8	9	10
Job no	1	9	6	3	5	8	4	10	2	7
Release	2	3	3	3	5	6	6	7	8	9
Process Time	92	3	4	97	92	5	93	4	92	4

After Step 3 the job list becomes:

Rank	1	2	3	4	5	6	7	8	9	10
Job no	9	6	8	1	10	5	3	7	4	2
Release	3	3	6	2	7	5	3	9	6	8
Process Time	3	4	5	92	4	92	97	4	93	92

During Step 3, Job 9 and 1 interchange their position. Afterwards Job 1 interchanges its position with job no 6 and 8 and so on. In Step 4, Jobs 9 and 6 will be scheduled on Machine 1 and 2 respectively. Machine 1 will be available at time 6. It will chose job 8 as it has the shortest process time compared to job no 1, 5, 3 and 4. Table 4.1 gives the details of the remaining steps to build the full schedule:

Table 4.1: An example of applying MFHA

Job No	Arrival Time	Process Time	Compete with the job no; Step followed	Assigned Machine	Completion Time
9	3	3	Head job; Step 4	1	6
6	3	4	Head job; Step 4	2	7
8	6	5	1,3,4,5; Step 5(ii)	1	11
10	7	4	1,3,4,5; Step 5(ii)	2	11
7	9	4	1,2,3,4,5; Step 5 (ii)	1	15
5	5	92	1,2,3,4; Step 5 (ii)	2	103
1	2	92	2,3,4; Step 5 (ii)	1	107
2	8	92	4,3; Step 5 (ii)	2	195
4	6	93	4; Step 5 (ii)	1	200
3	3	97	Terminate; Step (6)	2	292
Total Completion time$\sum C$= 947.					

4.4 Mathematical Model for $Pm|r_i|\sum C_i$

A mathematical model of this problem is developed in order to determine the optimum solutions of small instances and compare them with the obtained results of the developed heuristic (MFHA). The computational complexity of most scheduling problems limits the application of the mathematical programming to solve only small size problems. The mathematical model is developed based on the following notations:

Parameters:

N	Total number of jobs to be processed.
M	Total number of available machines.
R_j	Release time of job j, where $j = 1, 2, 3..., n$.
P_j	Process time of job j, where $j = 1, 2, 3..., n$.

Decision

Variables:

$C_{[i][k]}$	Processing completion time of any job in position k on machine i.
$X_{[i][j][k]}$	Binary variable that gets the value one if job j is assigned to machine i at position k and zero otherwise.

Objective Function:

Minimize

$$\sum_{i=1}^{M}\sum_{k=1}^{N} C_{[i][k]}$$

Constraints:

$$\sum_{i=1}^{M}\sum_{k=1}^{N} X_{[i][j][k]} = 1 \quad \forall j \quad \ldots\ldots(1)$$

$$\sum_{j=1}^{N} X_{[i][j][k]} \leq 1 \quad \forall i, k \ldots\ldots(2)$$

$$C_{[i][k]} \geq \left(R_j + P_j\right) \times X_{[i][j][k]} \quad for\ k = 1\ \&\ \forall i, j \ldots\ldots(3)$$

$$C_{[i][k]} \geq\ C_{[i][k-1]} +\ (P_j \times X_{[i][j][k]}) \quad for\ k > 1\ \&\ \forall i, j \ldots\ldots(4)$$

$$C_{[i][k]} \geq\ \ (P_j +\ R_j) \times X_{[i][j][k]} \quad \forall i, j, k \ldots\ldots(5)$$

Constraint 1 ensures that each job will be assigned to only one machine and its processing order is k^{th} on that machine while constraint 2 guarantees that each position of each machine can process one job only and there will be no overlapping. Constraint 3 calculates the completion time of a job in the head position (when k=1) of a machine, and it is greater than or equal to sum of the arrival time and process time of the job. However, for the job other than in the head position (when k>1) of the machine Constraint 4 will measure the processing completion time. In this case the processing completion time of that job is greater than or equal to sum of the processing completion time of the previous position job on that machine and the processing time of that job. Constraint 5 makes sure that the processing completion time of any job at any position on any machine is always greater than or equal to the sum of the arrival time and process time of the job.

4.5 Computational Results

In order to evaluate the performance of the developed MFHA, the results obtained by the proposed algorithm has been compared with the optimum solutions found from the mathematical model and also with the best reported methods in the literature. The proposed algorithm is implemented in Microsoft Visual Studio C++. The mathematical model is coded in ILOG and solved using the IBM ILOG CPLEX Studio v-12© and run on PC with 2.40 GHz processor and 3.24 GB RAM. Test cases are generated randomly based on following setting. For each job, the process time P_i is generated from Uniform distribution [1,100], release time R_i is generated from Uniform Distribution [0,100].

Yalaoui et al. (2006) proposed an exact method to solve $\boldsymbol{Pm|r_i|\sum C_i}$. The method was used to solve small problems up to 100 jobs and 10 machines. But neither the upper bound values nor the optimum values were reported in their paper. However, the deviation of the upper bound versus the average optimal solution is reported to be 3%. Therefore, in order to measure the performance of the proposed heuristic algorithm, the results found by our algorithm are compared with the optimum solutions obtained by the developed mathematical model for the small problems with 2,5,10 machines and 10, 20, 50, 100 jobs and is presented in Table 4.2. Five instances are considered for each test case. Hence there are a total of 100 instances. The mathematical model is run for a maximum of two hours to obtain a solution. As it is well known, the mathematical model is limited by the curse of dimensionality. Therefore, only small problems have been solved using the mathematical model. The relative difference of the total flow time between the solutions obtained by the proposed heuristic and mathematical model is given by:

$$GAP1 = \frac{Proposed\ Algorithm - Optimum\ Solution}{Optimum\ Solution} \times 100$$

Table 4.2: Computational results of total flow time for small size problem

Experiment No	N	M	Value Of Total Flow Time		$GAP1$
			MFHA	Mathematical model	
1	10	2	1356.4	1354.4	0.12%
2	20	2	3964.6	3962.8	0.04%
3	50	2	23578.2	23557.2	0.08%
4	100	2	90391.4	90391.4	0%
5	10	5	923	922.4	0.07%
6	20	5	2358	2345.8	0.54%
7	50	5	10347.2	10328.4	0.19%
8	100	5	38590.2	38305	0.71%
9	50	10	6894	6879	0.22%
10	100	10	21465.2	21407.8	0.26%
Average GAP1					0.22%

The scheduling problem up to 100 jobs and 10 machines are solved using mathematical modeling. Computational results show that the efficiency of the MFHA varies with in a short range and the average deviation is 0.22%. It is remarkable that percentage of deviation increases with the increasing number of machines.

Li et al (2009) obtained the values of total flow time using the Backward Algorithm (BA) and compared his value with the SPT and ERD heuristic for large problems with 10, 20, 30, 40, 50 machines and 200, 300, 400, 500 jobs. One hundred instances were considered for each test case. These test cases have been solved and compared with the SPT, ERD and BA algorithm. The results are reported in Table 4.3. The relative difference of the total flow time between the solutions obtained by the proposed heuristic and the best results of SPT, ERD and BA algorithm is given by:

$$GAP2 = \frac{C(MFHA) - Min\{C(ERD), C(SPT), C(BA)\}}{Min\{C(ERD), C(SPT), C(BA)\}} \times 100$$

Table 4.3: Computational results of total flow time for large size problem

Experiment	N	M	Total Flow Time				GAP2
			ERD	SPT	BA (Li et al., 2009)	MFHA	
1	200	10	106191	80262.2	79079.9	74556	-5.7%
2	300	10	234028	170093	168865	159454	-5.6%
3	400	10	412164	294105	292970	278263	-5.4%
4	500	10	641159	451956	450634	429598	-4.7%
5	200	20	55676	46298.8	44833.3	42223	-5.6%
6	300	20	120409	93809.6	92182.6	86510	-6.2%
7	400	20	210321	158502	156707	147556	-5.8%
8	500	20	325636	240081	238052	224812	-5.6%
9	200	30	39252.3	35260.7	33582.2	31787	-5.3%
10	300	30	82935.1	68615.4	66727.3	62738	-6%
11	400	30	143431	113493	111358	104798	-5.9%
12	500	30	220854	169526	167213	157387	-5.9%
13	200	40	31356.3	29806.8	28100.2	26810	-4.6%
14	300	40	64503.4	56213.4	54117.2	51076	-5.6%
15	400	40	110276	91103.4	88787.8	83652	-5.8%
16	500	40	168746	134437	131887	123971	-6%
17	200	50	26891.4	36722	24961.9	24044	-3.7%
18	300	50	53682.2	48937.4	46666.3	44275	-5.1%
19	400	50	90626.1	77917.4	75360.9	71147	-5.6%
20	500	50	137718	113512	110764	104217	-5.6%
Average GAP 2							-5.5%

Scheduling problems, up to 500 jobs and 50 machines, have been compared in this section. Computational result shows that the MFHA outperforms existing SPT, ERD and BA. Comparison with the second best heuristic shows that the average GAP2 is -5.5%.

From table 4.2 and 4.3 it is evident that the proposed heuristic algorithm is efficient and provides a better solution compared to SPT, ERD and BA. It is worth noting that it takes less than a second to solve any problem of table 4.3. The main reason behind the efficiency of the proposed algorithm is that it does not always blindly push the head job to an available machine. A machine chooses a suitable job from the job list other than the head job based on checking some possible conditions as described in section 4.3.2. For example, in case of when a machine is free and no job is available, the job list will push the job which will be released first. But in case of when there is more than one available job, the machine will chose the job that has the shortest processing time.

4.6 Applying MFHA to Develop a Scheduling Template

MFHA can provide a better solution to minimize the total flow time of the scheduled jobs with unequal release date on identical parallel machines. This heuristic can provide the sequence of patients on the treatment chairs, but during assigning the patients to a time slot on the scheduling template it cannot consider the availability of the nurse. Therefore, this heuristic cannot be applied directly to a Dual Resources Constraint (DRC) problem to build a scheduling template. Figure 4.2 shows the scheduling template for station 1 results from the MFHA algorithm.

Figure 4.2 shows the violation of resources constraint as it does not consider the availability of nurses. For example, 6 patients are booked at 8:00 am at station 1. But only 2 patients will get their service at 8:00 am as station one has two nurse and one nurse cannot be in two places at same time. Although this heuristic cannot be applied directly to deal with a DRC scheduling problem, it can be used with some modification:

Step 1

Get the sequences of the patients on the treatment chairs using the MFHA.

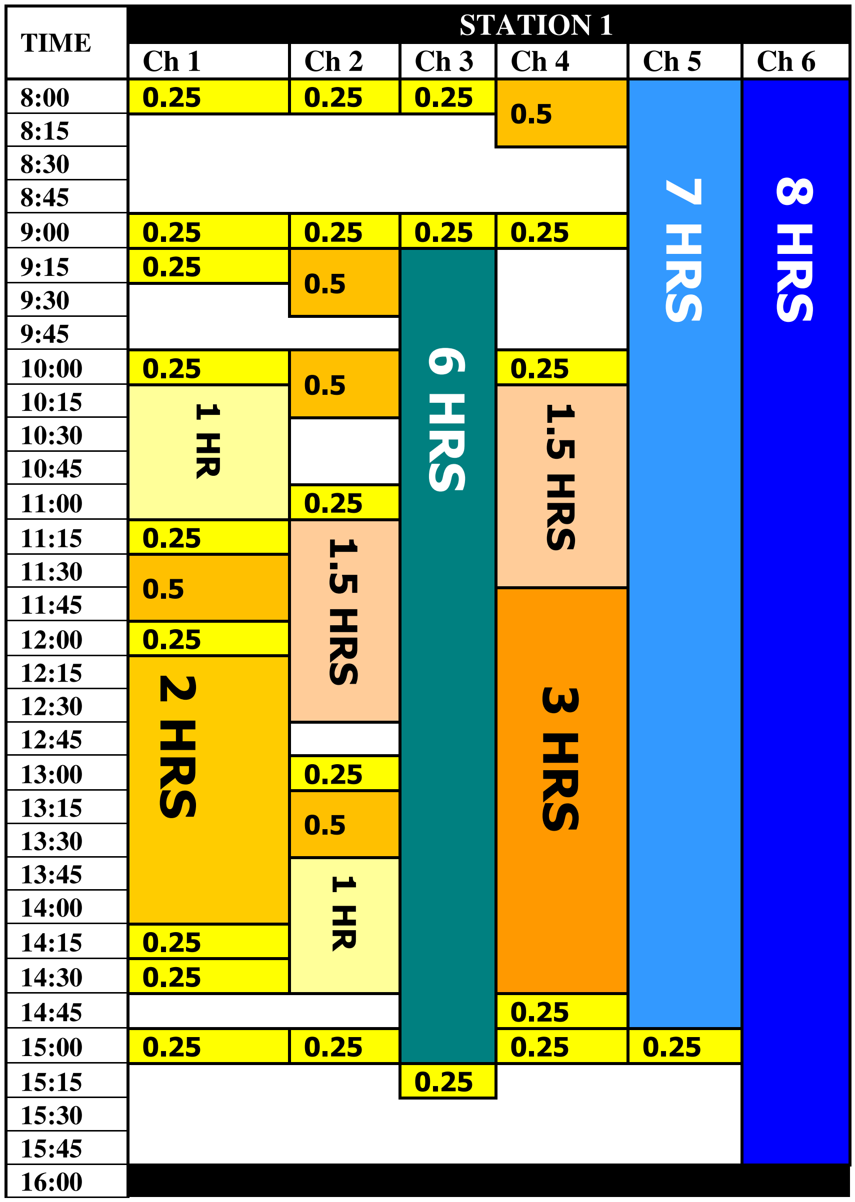


Figure 4.2: Scheduling template for Station 1(Application of MFHA)

<u>Step 2</u>

Later during scheduling on the template, the patient will be booked based on the nurse's availability. This rule is known as Right Shifting Rule (RSR).

According to Step 1, MFHA is used to get the sequence of patients on each chair. For example, in figure 4.2, 12 patients are booked in chair 1 who starts the treatments at particular times. Subsequently in step 1, these patients should be booked on chair 1 following the same sequence but the start time of the treatment could not be the same.

In step 2, during scheduling the patients on a template, nurse's availability will be considered following the RSR. For example 6 patients come at 8:00 am. But only 2 patients are booked at 8:00 am time slot. The preparation time is 15 minutes for each patient. Therefore, the remaining 4 chairs are idle from 8:00 to 8:15 am. The next 2 patients are booked at 8:15 time slot. And the last 2 patients are booked afterwards.

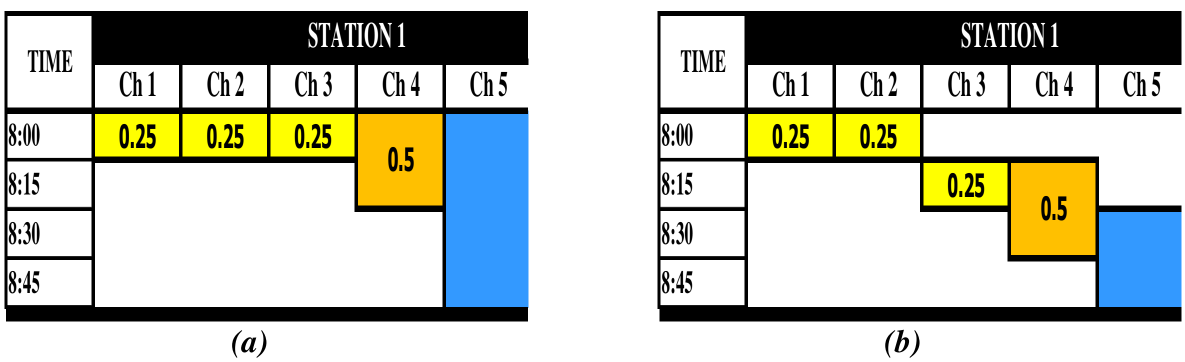


Figure 4.3: Developing a scheduling template, (a) without considering the availability of nurse and (b) considering the availability of nurse.

Figure 4.3 shows the difference between applying only MFHA and applying MFHA with RSR which is more rational. Following MHFA-RSR will result a scheduling template shown in figure 4.4.

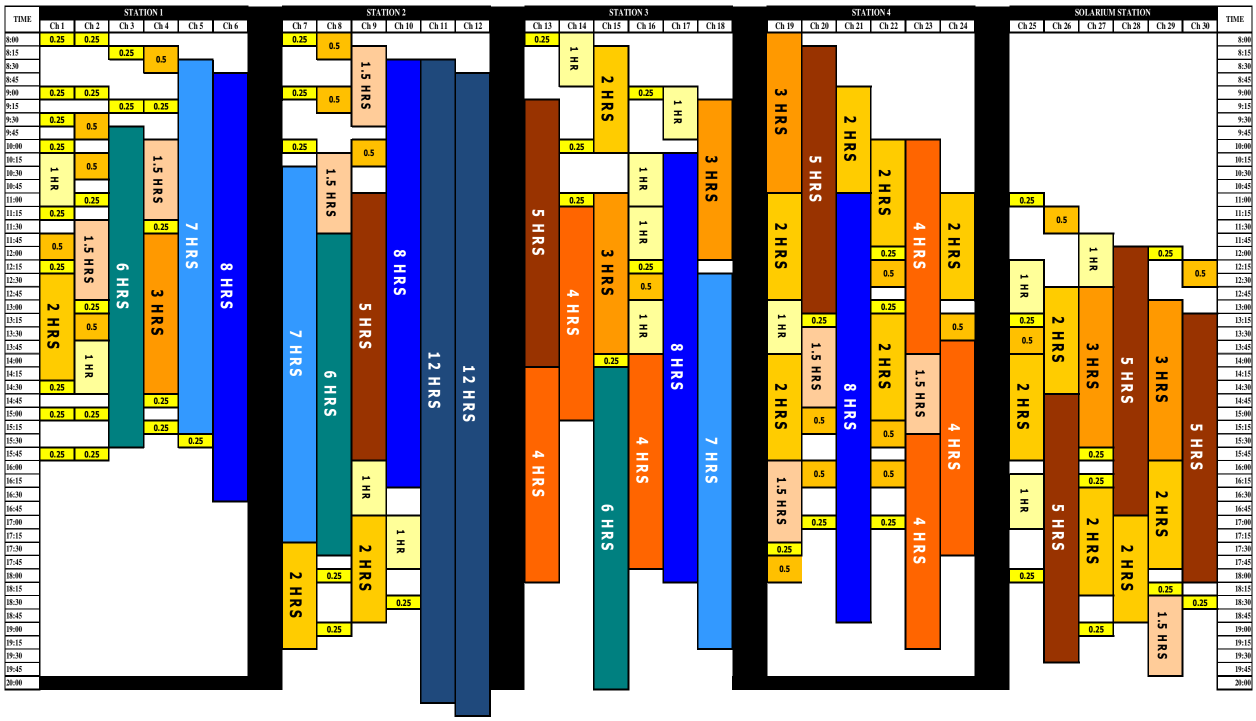


Figure 4.4: Scheduling template for treatment center (Applying MFHA-RSR)

Although MFHA-RSR provides a very reasonable template, it is not quite feasible. Because all the treatment stations need to work overtime and its performance is worse compared with the scheduling template founded using the simulation study (Depicted in section 3 figure 3.6). Table 4.4 gives a comparison of performance for the scheduling template found from simulation study and MFHA-RSR. The comparison shows that the template developed from Simulation Study performs better than MFHA-RSR. It is worth noting that, the performance parameter "Flow Time" of a patient represents the total time spend by a patient in the clinic. It includes the duration between the time a patient arrives in the clinic and the time patient leaves the clinic plus any waiting time in between. Therefore:

Flow Time of a patient = Arrival time + Waiting time + Treatment time.

&, Total Flow time = ∑ Flow time of all patients.

Since, the patient arrival time and treatment time is fixed, from the equation it is evident that reducing the total flow time will proportionally reduce the total waiting time of the treatment center.

Table 4.4: Performance comparison between simulation study template and MFHA-RSR template

	Station 1		**Station 2**		**Station 3**		**Station 4**		**Solarium Station**	
	Simulation Study	**MFHA-RSR**	**Simulation Study**	**MFHA-RSR**	**Simulation Study**	**MFHA-RSR**	**Simulation Study**	**MFHA-RSR**	**Simulation Study**	**MFHA-RSR**
Total Flow time (min)	**9610**	**9705**	**9945**	**8995**	**7350**	**7440**	**12465**	**12300**	**12450**	**12705**
Maximum Clinic time (min)	**480**	**510**	**720**	**750**	**660**	**720**	**660**	**675**	**690**	**715**

4.7 Conclusion

MFHA can provide a better solution when the scheduling problem is stripped down as single resource constraint system and considers only patients arrival time constrain. Therefore, RSR is applied to develop the template. The comparison in table 4.4 shows that the simulation study provides a better solution. The simplification of the main problem during the development of the heuristic algorithm causes the lower performance. Therefore, in the following chapter a new heuristic algorithm is developed which considers the accessibility of the treatment chair and the nurse, patient's treatment and arrival time and the clinic closing time.

Chapter 5

Developing an Efficient Scheduling Template with Dual Resources Constraint

In this chapter, a new heuristic algorithm has been developed to optimize the scheduling of patients following scenario 1 which is described in section 3.7, Table 7. The algorithm considers the accessibility of the treatment chair and nurse, patient preparation and discharge time and clinic closing time. This new heuristic algorithm results in minimizing patients' waiting time and maintaining the clinic closing time. Section 5.1 describes the formulation of the scheduling problem. Section 5.2 presents the proposed algorithm. Section 5.3 depicts the performance comparison among different scheduling procedures. Finally, section 5.4 gives the conclusion and future research direction.

5.1 Introduction

This study is performed to develop a scheduling template for a chemotherapy treatment unit with the objective of reducing the waiting time and preventing the clinic from working over time. From chapter 4, it is found that the simplification of the main problem during the development of the heuristic algorithm causes the lower performance. Therefore, in this chapter a new heuristic algorithm is developed which considers the accessibility of the treatment chair and the nurse, patient's treatment and arrival time and the clinic closing time.

The under study chemotherapy treatment unit has two resources that need to be taken into consideration; namely: treatment chairs and nurses. Therefore, we have to deal with a

"Dual Resources Constrain" (DRC) scheduling problem. In addition, there are other constraints such as release times or the arrival times of the patients and the clinic closing time. The release time is the time when the patient is expected to come to the clinic. The release time constraint is used because of the following reasons:

i) If all the patients come at the same time, a large number of patients will be waiting to get the service. Simulation study in Section 3 reveals that choosing the right arrival pattern can increase the throughput of the resources and reduce the waiting time of the patients. Table 3.6 shows a comparison of different scenarios based on different "patient arrival pattern" and "nurse schedule". Scenario 1 shows a promising outcome where the arrival pattern of patient is fitted over the nurse schedule. It also ensures that patients will get their treatment in a timely manner. This arrival pattern is shown in table 3.3. However, it still requires a dispatching rule to pick a patient among others and to assign the patient to the treatment bed.

ii) Most of the chemotherapy drugs are made at the day of the treatment, as it is not cost effective to preserve those drugs. The pharmacists have to work during the day to prepare those drugs. Very few drugs are being prepared the day before the treatment, mostly for the longer treatments like the twelve-hour treatment. If such drug is not supplied at the beginning of the clinic (9:00 am), the clinic will have to work overtime to finish this treatment. Consequently the chemotherapy preparation time can also be referred as release time constraint.

iii) Sometimes patients need to visit the pathology area or require seeing the Physician prior to visiting the chemotherapy treatment. Therefore, it is reasonable to consider this requirement before booking a patient.

Based on the above discussion, the problem can be formulated as: Scheduling a Dual Resources Constrain system of N workers and M machines where N<M. Each job has individual arrival and processing time. The job needs the worker for setup operation at the beginning of process and for the discharge operation at the end of the process time. It is assumed that the workers availability follows a certain timeline. In other words, each worker is assigned to specific shift-hours of the day. The objective is to find the schedule that minimizes the total flow time. The problem can be formulated as: $P_m, W_n | d_j, r_j | \sum C_j$.

Because of potential applications in the real-life environment such as in the manufacturing industry, a lot of research has been done on dual resources constrain scheduling problems. However, comparability between the current research and previous study is quite far. For example, most of the previous researches have done on job shop or flow shop scheduling where the job goes through several machines following the operations sequence (Cesani et al, 2005, Suresh et al, 2000, Sparling et al, 1998, Aase et al, 2004). But this research is based on identical parallel machine scheduling problem where a patient can receive the treatment from any of the treatment beds. "Number of workers" in the facility is also a key issue. In this study, number of nurses (workers) is less than the number of treatment beds (machines) where most of the studies considered equal or greater number of workers (Hu et al, 2005, 2006, Chaudhry, 2010). Moreover, our study considers release time constraint which is uncommon in most of the studies (McWilliams et al, 2009, ElMaraghy et al, 2000, Daniels et al, 1999). As, no research was found to compare our result with, the performance of the developed algorithm have compared with the traditional SPT and ERD heuristic and later with the MFHA-RSR and the scheduling template found from simulation study.

5.2 Developing New Heuristic

A new heuristic is developed in order to minimize the Total Flow Time and maintaining the clinic closing time. In this case, minimizing the Total Flow Time is equivalent to minimizing the patients' waiting time. Finally the outcomes were compared with the traditional heuristic and later with the developed scheduling template to evaluate the performance of the new heuristic.

The assumptions used in this heuristic are:

i) A facility with dual resources constraints (treatment chairs and nurses).

ii) The available numbers of nurses are less than the available number of chairs.

iii) Nurses follow a certain shift schedule.

iv) Treatment chairs are considered as Identical Parallel Machines.

v) Each patient has his/her own arrival time and treatment duration.

vi) Nurses are required for setting up the patient at the beginning of the treatment and discharging at the end.

vii) Splitting and preemption are not allowed.

The following rules are used to develop priority rule during scheduling the patients.

Rule 1

During assigning a patient for processing on an empty treatment chair at time T_t, choose the patient among the available patients (at time T_t) whose slack time is less than or equal to zero.

Explanation:

Slack time of patient i can be calculated as:

Slack time (i) =Due time (i) – {Arrival time (i) + Process time (i)}

Due time is the time when the treatment center will be closed. In order to avoid working overtime, choose the patient among the available patients whose slack time is less than or equal to zero.

For example, a treatment station with N chairs works from 8:00 to 12:00. At a certain moment, there exist 2 patients as follows:

Table 5.1: Rule 1

Patient	Release time	Process time	Slack time
i	8:30	1.5 hour	0
j	8:30	30 minutes	1 hour

Considering at time 8:30 treatment chair N_k becomes empty and it is ready to take a new patient for treatment. Table 5.1 shows that patients i and j are the only available patients at this time. Because patient i has the shortest slack time, treatment chair N_k will accommodate this patient. Otherwise it will result in working over-time.

Although this rule does not guarantee avoiding working over time, it will prioritize the patient list according to slack time. As a result, patients with minimum slack time will most likely to be assigned to an empty treatment chair and avoid the treatment center from working over time.

This dispatching rule is also known as Shortest Slack time rule and has been widely used for makespan minimization (C_{max}) problem where only due time constraint is considered. But this study also deals with flow time (total completion time/$\sum C_i$) minimization problem. Therefore, this rule will only be applied when slack time is less than or equal to zero.

Rule 2

To assign a free nurse among the two treatment chairs, where one requires the nurse's assistance to discharge a patient who has completed his/her treatment, and the other requires the nurse's assistance to put a new patient, in order to minimize the completion time assign the free nurse to discharge the patient other than serving the new patient.

Explanation:

Consider 2 treatment chairs N_i and N_j that require nurse assistance at the same time T_t. Treatment chair N_i needs the nurse assistance at T_t to discharge patient A who has just finished the treatment. Treatment chair N_j also needs nurse assistance at time T_t, but to serve a new patient B. Figure 1 explains the situation.

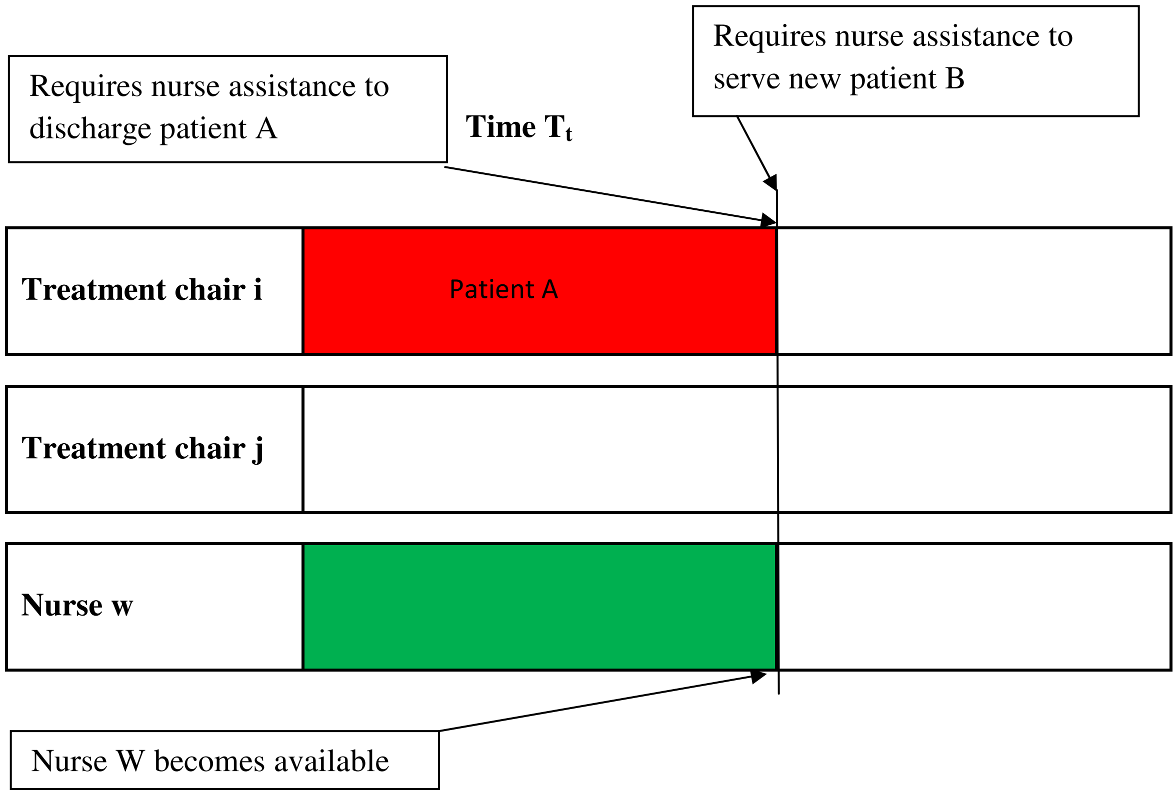


Figure 5.1: Incidences at time T_t (Rule 2)

Case 1:

If the new patient B is served on the chair N_j at time T_t before discharging the patient A from chair N_i.

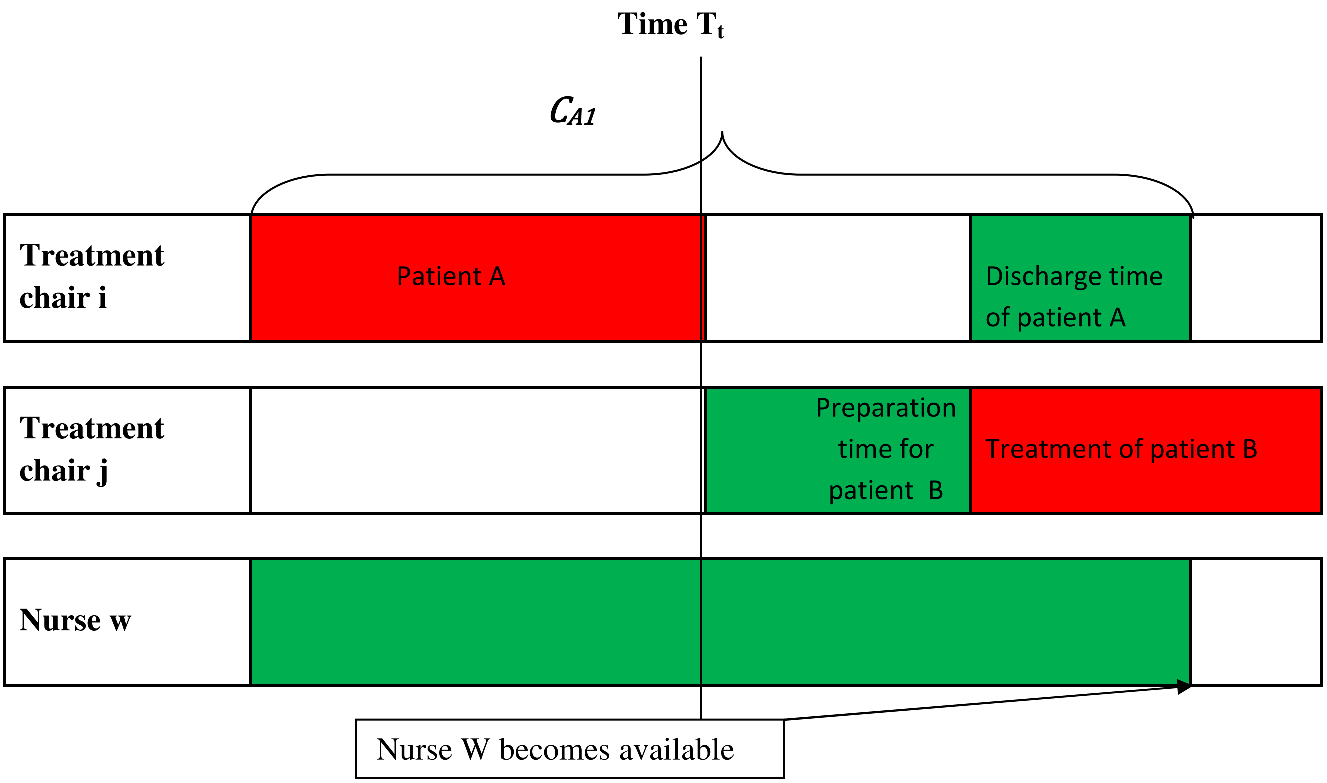


Figure 5.2: Case 1 (Rule 2)

As figure 5.2 shows, in this case the completion time C_{A1} of patient A is:

$C_{A1} = T_t$ + Preparation time of patient B + Discharge time of patient A.

Case 2:

If patient B waits until patient A is discharged.

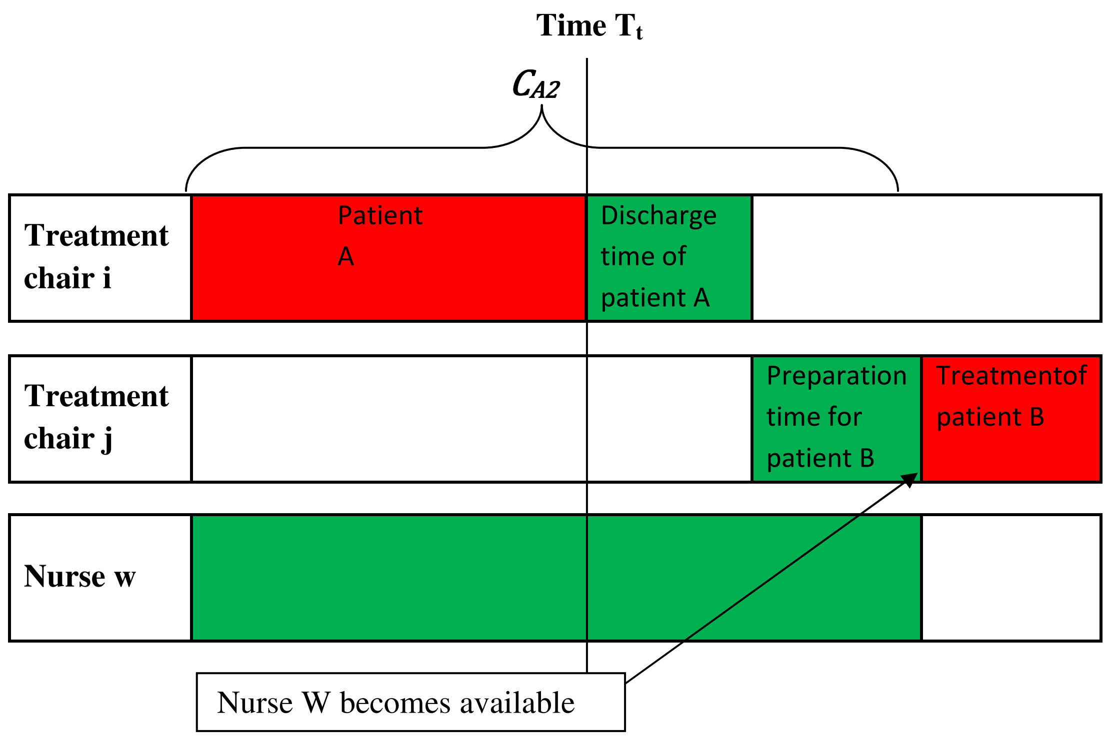


Figure 5.3: Case 2 (Rule 2)

As figure 3 shows, in this case the completion time C_{A2} of patient A is:

$C_{A2} = T_t$ + Discharge time of patient A

Since $C_{A1} > C_{A2}$, therefore between assigning a free nurse among two treatment chairs, where one requires the nurse assistance to discharge a patient and the other to serve a new patient, then in order to minimize the completion time assign the free nurse to discharge the patient other than the serving a new patient.

5.2.1 Steps of the New Heuristic Algorithm

The following steps were followed during scheduling.

Step 1:

Choose a chair (machine) that will require nurse assistance first and suppose the moment when it will be required is at time X. If more than one chair need nurse assistance at time X then choose the chair which requires the nurse to discharge patient other than to intake. Go to step 2.

Step 2:

Choose a nurse (worker) who will be available first and suppose the moment when the nurse becomes available is at time Y. Go to step 3.

Step 3:

If the chair requires the nurse to discharge a patient then go to step 3A, otherwise (to intake) go to step 4.

Step 3A:

If the chair requires the nurse to discharge a patient and if $X<Y$ (when the chair waits for a nurse) then wait until the nurse is free. Afterwards, take the nurse assistant discharge the patient. However, if $X>=Y$ then waiting is not necessary and continue to free the chair. Go to step 5.

Step 4:

Chair needs nurse assistance to accomodate a new patient. If X<Y (when the chair waits for a nurse) then go to step 4A, otherwise go to step 5.

Step 4A:

Chair needs nurse assistance to serve a new patient and the nurse is not available. In this case, wait until the nurse is free and update the value of X to X=Y. Sort and choose a chair that will require nurse assistance at the new time X. If more than one chair need nurse assistance at time X, then choose the chair which requires the nurse to discharge a patient other than to accommodating. If the chair requires the nurse to discharge, then continue discharging and go to step 5. Otherwise just go to step 5.

Step 5:

Choose an unassigned patient from the patient list who is available at time X. If at least one unassigned patient is available at time X then go to step 5A. Otherwise go to step 5B.

Step 5A:

Among all the available unassigned patients at time X if there are some patients whose slack time [Slack time = Due time- (Arrival time + Treatment time)] is less than or equal to zero, then choose the patient who has the shortest slack time (most negative one). If there is no such patient then choose the patient who needs the shortest processing time. Based on the process time of the selected patient choose the preparation time constrains.

Delete the selected patient from the patient list. If there are still unassigned patients on the patient list, go back to step 1, if not go to step 6.

Step 5B:

In this case, both of the chair and nurse are available but unassigned patient is not available at time X. Choose the patient who comes first and updates the value of X with the arrival time of that patient. Review all the chairs and choose the one that will require nurse assistance at the new time X. If more than one chair need nurse assistance at time X, then choose the chair which requires the nurse to discharge a patient other than to loading. If the chair requires the nurse to discharge, then continue discharging and go back to step 1. Otherwise assign the patient to the chair and nurse will do the preparation. Based on the process time of the selected patient, choose the preparation time constrains. Delete the selected patient from the patient list. If there are still unassigned patients on the patient list, go back to step 1, if not go to step 6.

Step 6:

List all the chairs that require nurse assistance to discharge the patient. Among them chose one chair which will require nurse assistance first and suppose the moment is at time A. Choose a nurse (worker) who will be available first and suppose the moment is at time B. Go to step 7 if A<B, if not go to step 8.

Step 7:

If $A<B$ (when the chair waits for a nurse), then wait until the nurse is free. Afterwards use the nurse assistance to discharge the patient. If still there is any chair in the list that will require nurse assistance to discharge a patient, then go back to step 6. If not, go to step 9.

Step 8:

If $A>=B$, then waiting is not necessary and utilize the nurse to discharge the chair. If still there is any chairs in the list that will require a nurse assistance to discharge a patient then go back to step 6. If not, go to step 9.

Step 9:

Stop.

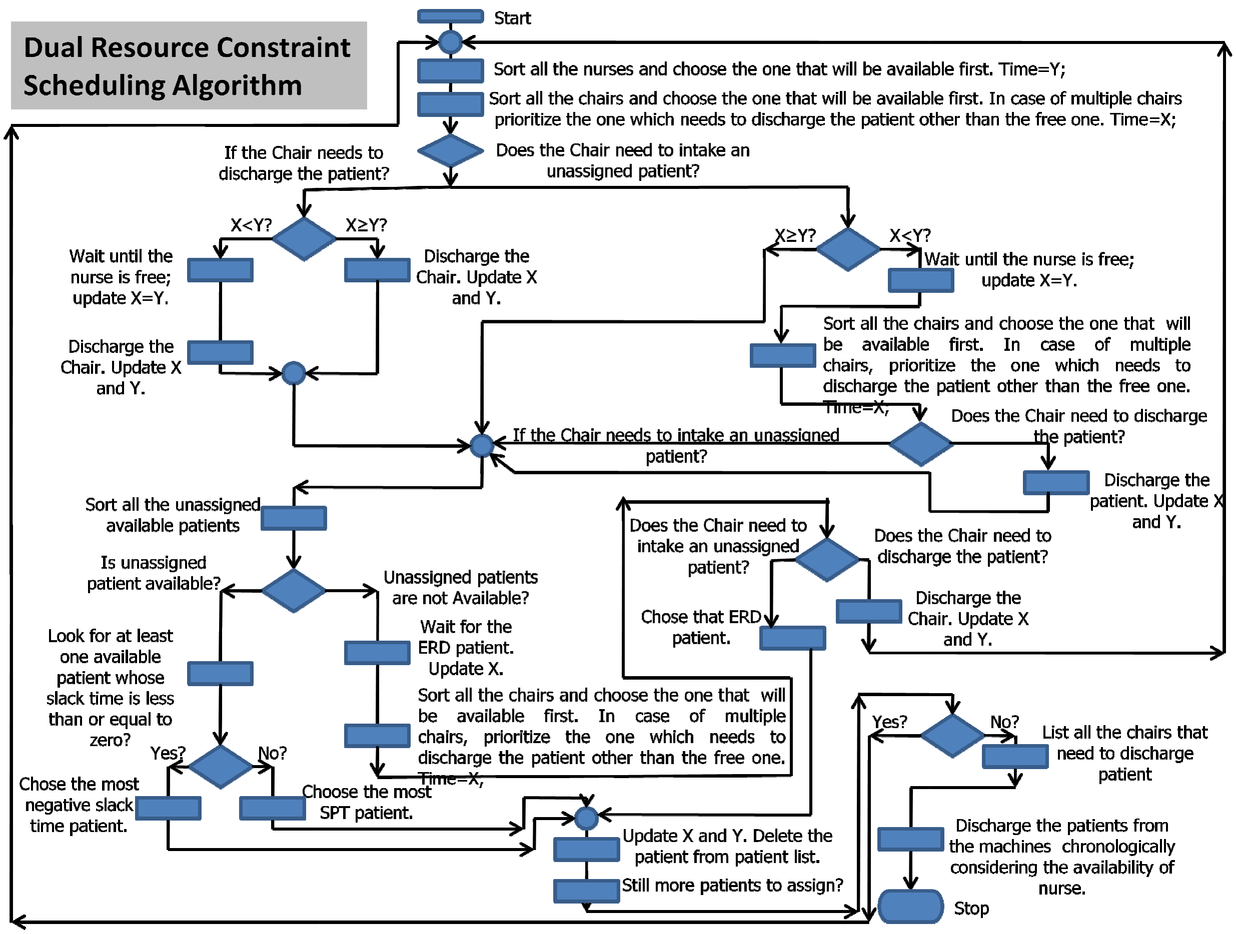


Figure 5.4: Flow chart of the new heuristic algorithm for Dual Resources Constraint Scheduling.

Figure 5.4 shows a schematic diagram of the steps that the new algorithm will follow. The algorithm is implemented in Microsoft Visual Studio C++. Based on the output, a scheduling template is built and is shown in figure 5.5.

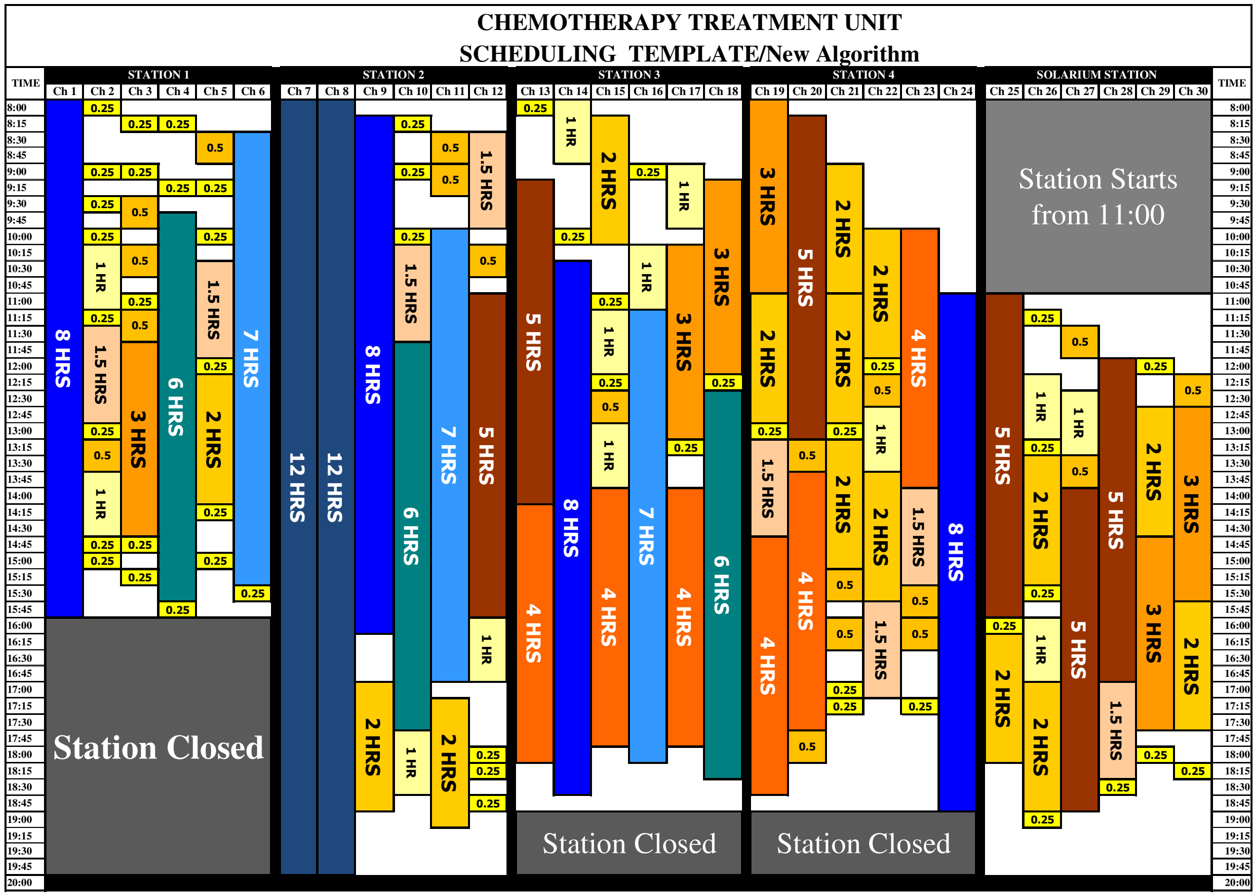


Figure 5.5: Scheduling template developed from new heuristic algorithm

Table 5.2 gives a comparison of performance of different procedure to develop the scheduling template. From the table it is evident that the new algorithm outperforms the other two procedures. SPT and ERD perform quite the same in this study. However, in Station 1 SPT heuristic outperforms ERD heuristic. By comparing with ERD heuristic SPT heuristic results in less total flow time and waiting time. But none of the ERD or SPT heuristics maintain the clinic close time.

Table 5.2: Performance comparison among different scheduling procedures

Stations	Procedures	Total Flow time (min)	Maximum Clinic time (min)
Station 1	ERD	9720	480
	SPT	9495	525
	New Algorithm	**9480**	**465**
Station 2	ERD	8955	765
	SPT	8955	765
	New Algorithm	**8910**	**720**
Station 3	ERD	7395	705
	SPT	7395	705
	New Algorithm	**7365**	**645**
Station 4	ERD	12315	690
	SPT	12315	690
	New Algorithm	**12210**	**660**
Solarium Station	ERD	12600	705
	SPT	12600	705
	New Algorithm	**12465**	**675**

5.3 Discussion

Table 5.3 gives a comparison of performance of the different procedures to develop the scheduling template with. From the table it is evident that the new algorithm outperforms the other two procedures. It can minimize total flow time and waiting time of the system while makes sure that the clinics can be closed at the scheduled time. The reason behind this is that during scheduling it always gives priority to the patient who has the most negative slack time over the shortest treatment time patient. That way it makes sure that the clinics do not need to work over time. Giving the priority to the shortest treatment time patients helps to minimize total flow time or the waiting time of the system.

Table 5.3: Performance comparison among different scheduling procedures

Stations	Procedures	Total Flow time (min)	Maximum Clinic time (min)
Station 1	Simulation Study	9610	495
	MFHA-RSR	9705	510
	New Algorithm	**9480**	**465**
Station 2	Simulation Study	9945	720
	MFHA-RSR	8995	750
	New Algorithm	**8910**	**720**
Station 3	Simulation Study	7350	675
	MFHA-RSR	7440	720
	New Algorithm	**7395**	**675**
Station 4	Simulation Study	12465	675
	MFHA-RSR	12300	675
	New Algorithm	**12225**	**690**
Solarium Station	Simulation Study	12450	690
	MFHA-RSR	12705	715
	New Algorithm	**12465**	**675**

5.4 Conclusion

This study is undertaken to develop a scheduling template that minimizes the total flow time of the system and prevent the clinic from working over time. A treatment center can reduce the total waiting time by reducing the total flow time. A new heuristic algorithm is proposed to build the scheduling template. This algorithm deals with a dual resources constrained system while considering other constrains, such as: unequal release and process time, preparation time, unloading time and closing time of the clinic. However, this heuristic cannot guarantee obtaining an optimal schedule. Therefore, meta-heuristics such as Genetic Algorithm, Simulated Annealing and Tabu Search may be applied in the future to obtain optimal (or near optimal) scheduling templates.

Chapter 6

Conclusions and Future Work

The study is undertaken to increase the throughput of the Chemotherapy Treatment Unit in order to meet the growing demand of the chemotherapy patients and to reduce the waiting time of the patients by means of developing an efficient scheduling template. From the perspective of the clinic staff, a scheduling template assists them by providing a vivid picture of when to schedule a patient. Thus, the scheduling template should be built based on the arrival pattern of the patient and the resources availability. To achieve these objectives, simulation modeling is used to depict the current situation and to determine the needed modification. Moreover, two scheduling algorithms are proposed to minimize the patient waiting time. This chapter summarizes the thesis' research work and results in addition to proposed future research.

6.1 Research Results

- The Chemotherapy Treatment Center is studied to understand the journey of the patients through different stages of their treatment. Important data is collected regarding the patients' types, treatment times and resources availability. Then, a simulation model of this system is built using ARENA v-13© simulation software. The simulation model has depicted the current situation and assisted in detecting the reason for lower throughput. Study shows that the current arrival pattern of the patients does not match the nurses' availability. Consequently, it makes the clinic very busy in the morning and underutilized in the afternoon. Therefore, different scenarios have been developed, considering the constraints given by the care providers and stake holders. Throughout the evaluation of the different scenarios, the model has distinguished the best state by determining the preeminent arrival pattern of the patients in the treatment center. Comparing all the scenarios, one of the scenarios, Scenario 1, provides the best performance. This scenario proves to serve 125 patients daily with an average resources utilization of 77.6%. On the other hand, the stakeholders do not have to hire additional nurses compared to other scenarios such as Scenario 4 and 5. Finally, a scheduling template is developed (Figure 3.6) by applying a simple heuristic algorithm. In addition, it is worth noting that adding a nurse (Scenarios 3, 4, and 5) does not significantly reduce the average waiting time or increases the system's throughput. The reason behind this is that when all the chairs are busy, the nurses will have to wait until some patients finish the treatment. As a consequence, the other patients have to wait for the commencement of their treatment too. Therefore, hiring a nurse, without adding more chairs, will not reduce the waiting time or increase the throughput of the system. In this case, the legitimize way to increase the throughput of the system is by adjusting the arrival pattern of patients over the nurses' schedule. This work has been accepted as journal paper (Ahmed Z., Elmekkawy T. Y. 2011 a), and published in two conference presentations (Ahmed Z., Elmekkawy T. Y. 2011 b, and Ahmed Z., Elmekkawy T. Y., Bates S. 2011 c).

- Although the simulation study shows the way to serve more patients daily, it does not explain how to sequence them properly in order to minimize the total waiting time. Therefore, the scheduling template developed in chapter 3 is certainly not the best arrangement to assign a patient. As a result it is necessary to develop an efficient scheduling algorithm to build the scheduling template that minimizes the total waiting time. Nevertheless, applying scheduling optimization in healthcare systems is a cumbersome process. This is due to the amount of constraints that have to be considered, such as availability of the care providers and patients, variability of treatment durations, and preparation and discharge times of patients. In order to schedule a treatment center, it is essential to consider the accessibility of both resources (treatment chair and nurse) as the system is relied on two different types of resources.

Therefore, in chapter 4, first the problem is simplified as single resource constrain problem with release time constraints. In this case only treatment chair availability was measured. Considering the scheduling formulation, this system can be interpreted as an Identical Parallel Machine scheduling problem. A new heuristic algorithm is developed for scheduling such problem and named as MFHA (Modified Forward Heuristic Algorithm). A mathematical model of the problem is developed too. The performance of the algorithm is evaluated by comparing its solutions with the optimal solutions of small test cases obtained from the developed mathematical model. Then, the results of large problems are compared with the results of the best reported heuristics in the literature. In addition to the simplicity of the proposed algorithm, these comparisons have showed that the proposed algorithm can obtain solutions that are very close to the optimum solutions and better than the other heuristics. For example, for small size problem with less than 100 jobs and 10 machines, it is found that the MFHA obtains solutions that have an average deviation of 0.22% compared to the optimum solutions. In case of large size problem, more than 500 jobs and 50 machines, the MFHA out performs the SPT, ERD and BA with an average improvement of -5.5% compared to the best reported heuristics.

However, the proposed heuristic algorithm cannot be used to develop a scheduling template as it only considers the availability of single resource (treatment chair) while in order to develop a scheduling template, it is necessary to consider the availability of both resources (Treatment chairs and care providers). Therefore, RSR (Right Shifting Rule) is applied to the output of the MFHA to build the scheduling template. Comparison with the scheduling template built by the simulation study of chapter 3 shows that MFHA-RSR does not provide a better template (see table 4.4). It is believed that the simplification of the main problem during the development of the heuristic algorithm is the reason of the worse performance. This work has been accepted as journal paper (Ahmed Z., Elmekkawy T. Y., 2012), and published as a conference presentation (Ahmed Z., Elmekkawy T. Y., 2011 d).

- Finally, a new heuristic algorithm is developed and proposed that deals with a dual resources constrained system to develop an effective scheduling template, considering other restrains such as unequal release and process time, preparation time, discharging time and the closing time of the clinic. Two new propositions are made to build the heuristic algorithm. Finally, the developed algorithm is used to build a new scheduling template (Figure 5.5). As we did not find any related work in the literature to evaluate the performance of the new heuristic algorithm, the new template is compared with the traditional SPT and ERD heuristic (Table 5.2). It is found that the new heuristic algorithm outperforms the SPT and ERD heuristic. Later, the new template is also judged against the MFHA-RSR and the scheduling template that is built based on the simulation study. Assessment shows that the new heuristic algorithm provides a feasible solution against the MFHA-RSR algorithm and provides a better solution compared to the scheduling template built based on the simulation study. The new algorithm can minimize total flow time of the treatment center while makes sure that the clinics do not work overtime. The reason behind this is that during scheduling it always gives priority to the patient who has most negative slack time over the shortest treatment time patient. That's how it makes sure that the clinics don't need to work over time. Although, this rule does not guarantee avoid working over time, it will prioritize the patient list according to slack time. As a result, patients with minimum slack time will most likely to be assigned to an empty treatment chair and resist the treatment center from working over time. Besides, giving the priority to the shortest treatment time patients helps to minimize total flow time or the waiting time of the system. However, this algorithm cannot guarantee obtaining an optimal scheduling. Therefore meta-heuristics, such as Genetic Algorithm, Simulated Annealing, Tabu Search may be applied in the future to obtain optimal (or near optimal) scheduling template.

6.2 Future Research

Current research work opens a wide range of possible future research areas. For example:

- The main motive of using simulation modeling to improve the performance of a facility by exploring a wide range of changes and suggesting the best scenario. Since the care provider restricted the possible changes in the clinic, the scenarios that are built in this study are based on: changing the patients' arrival pattern or by changing the nurses' schedule. Still there are lots of different scenarios that are left to be explored. Therefore, the developed simulation model can be used in future to explore other changes and to design more efficient clinic. Some of the changes in the simulation model that can be evaluated are: by changing the layout of the clinic, increasing or decreasing the number of treatment beds, changing the number of nurses assigned to the different treatment stations. The assessment of these scenarios could propose a better clinic's performance by means of increasing the throughput of the facility and/or by reducing the waiting time.

- In section 4.4, a mathematical model is built to schedule Identical Parallel Machine to minimize total flow time. It only considers release time constraint. However, this model cannot be applied to build a scheduling template as it requires considering other constrains, such as: due date, workers availability and so on. In future, a new mathematical model could be built to schedule a dual resources constraint system. Nonetheless, it will also consider release time, due time and clinic closing time constraint. This model would be more practical to be used in manufacturing systems and healthcare facilities that use two types of resources (man and machine) to provide the service.

- The developed heuristics in section 4 and 5 do not guarantee obtaining an optimal scheduling. Therefore meta-heuristics, such as Genetic Algorithm, Simulated Annealing, Tabu Search could be applied in future to get an optimal or near optimal schedules that may be better than the schedules obtained by the proposed heuristics.

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Appendix A: Simulation Modeling and Analysis

Table 1A: Treatment Type slots and their frequency

Serial No	Treatment Time Slot	No of Patients	Percentage	Serial No	Treatment Time Slot	No of Patients	Percentage
1	15 minute	659	31.4	20	5 hr	115	5.5
2	30 minute	306	14.6	21	5.25 hr	6	0.3
3	45 minute	22	1.05	22	5.5 hr	5	0.24
4	1 hr	163	7.8	23	5.75 hr	1	0.05
5	1.25 hr	19	.9	24	6 hr	30	1.43
6	1.5 hr	139	6.6	25	6.25 hr	1	0.05
7	1.75 hr	23	1.1	26	6.5 hr	3	0.14
8	2 hr	206	9.8	27	6.75 hr	2	0.1
9	2.25 hr	9	0.43	28	7 hr	11	0.53
10	2.5 hr	39	1.9	29	7.25 hr	1	0.05
11	2.75 hr	11	0.52	30	7.5 hr	2	0.1
12	3 hr	108	5.1	31	7.75 hr	7	0.33
13	3.25 hr	9	0.43	32	8 hr	43	2
14	3.5 hr	28	1.33	33	8.25 hr	1	0.05
15	3.75 hr	12	0.57	34	8.5 hr	1	0.05
16	4 hr	134	6.38	35	9.5 hr	1	0.05
17	4.25 hr	3	0.143	36	10 hr	13	0.62
18	4.5 hr	10	0.48	37	11 hr	1	0.05
19	4.75 hr	7	0.33	38	11.5 hr	2	0.1

Table 2A: Patients of Type 1

Time Slot	Percentage	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
15 minute	57.3	TRIA (2,3,5)	7	TRIA (2,3,5)
30 minute	26.08	TRIA (2,3,5)	TRIA (20,25,30)	TRIA (2,3,5)
45 minute	1.91	TRIA (2,3,5)	TRIA (25,30,35)	TRIA (2,3,5)
1 hr	14.71	TRIA (2,3,5)	TRIA (40,45,50)	TRIA (2,3,5)

Table 3A: Patients of Type 2

Time Slot	Percentage	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
1.25hr, 1.75hr, 2.25hr, 2.75hr	11.2	TRIA (2,3,5)	TRIA (64.5, 99, 156); Square Error: 0.001251 P=0.689	TRIA (2,3,5)
1.5hr	25.09	TRIA (2,3,5)	TRIA (70,75,80)	TRIA (2,3,5)
2hr	37.18	TRIA (2,3,5)	TRIA(100,105,110)	TRIA (2,3,5)
2.5hr	7.04	TRIA (2,3,5)	TRIA (130,135,140)	TRIA (2,3,5)
3hr	19.49	TRIA (2,3,5)	TRIA(160,165,170)	TRIA (2,3,5)

Table 4A: Patients of Type 3

Time Slot	Percentage	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
3.25 hr, 3.5hr, 3.75hr	15.4	TRIA (,3,5)	TRIA (185, 203, 216) Square Error: 0.006772 P= 0.373	TRIA (2,3,5)
4 hr	42.15	TRIA (2,3,5)	TRIA (220,225,230)	TRIA (2,3,5)
4.25hr, 4.5hr, 4.75hr	6.29	TRIA (2,3,5)	TRIA (245, 260, 276) Square Error: 0.017 P= 0.5	TRIA (2,3,5)
5hr	36.16	TRIA (2,3,5)	TRIA (280, 285, 290)	TRIA (2,3,5)

Table 5A: Patients of Type 4

Time Slot	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
5.25hr, 5.5hr, 5.5hr, 6hr, 6.25hr, 6.5hr, 6.75hr, 7hr.	TRIA (2,3,5)	TRIA (305, 356, 410) Square Error: 0.004394 P>0.75	TRIA (2,3,5)

Table 6A: Patients of Type 5

Time Slot	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
7.25hr, 7.5hr, 7.75hr, 8hr, 8.25hr, 8.5hr.	TRIA (2,3,5)	TRIA (425, 470, 501) Square Error: 0.0071 P=0.54	TRIA (2,3,5)

Table 7A: Patients of Type 6

Time Slot	Drug Line Install Time (Minute)	Treatment Time Delay (Minute)	Drug Line Removal Time (Minute)
9.5hr, 10hr, 11hr, 11.5hr	TRIA (2,3,5)	TRIA (590, 596, 680) Square Error: 0.150 P>0.15	TRIA (2,3,5)

Table 8A: Average daily number of patient arrival

TYPE	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
8:00-9:00	4	4	2	1	1	1
9:00-10:00	10	3	2	1	1	
10:00-11:00	7	4	2	1		
11:00-12:00	6	4	2	1		
12:00-13:00	5	4	2			
13:00-14:00	7	4	2			
14:00-15:00	7	5	1			
15:00-16:00	8	3				
16:00-17:00	5	3				
17:00-18:00	2	1				
18:00-19:00	2					
19:00-20:00	2					

A1: Model Validation:

Total number of patients during 21 days observation was:

90, 90, 94, 95, 96, 96, 96, 98, 98, 99, 100, 102, 103, 103, 105, 109, 111, 115, 117, 119, 119

Mean: 102
Standard Deviation: 9.11
Variance: 82.95

Total number of patient during 30 replication time was:
93, 96, 98, 99, 100, 100, 102, 102, 102, 102, 102, 103, 103, 103, 103, 103, 104, 104, 104, 105, 105, 106, 106, 106, 106, 106, 107, 107, 108, 108

Mean: 103.1
Standard Deviation: 3.5
Variance: 12.1

A 1.1: Normality test:

From system data:

Table 9A: Normality test of the system data

Data Range	90-95	95-101	102-108	109-102
Observed Value	4	7	4	6
Expected Value	5	5	5	5
$\frac{(O-E)^2}{E}$	0.2	0.8	0.2	0.2

Square error = 1.4.
Degrees of freedom=4-2-1=1
Chi – square critical value for 1 degree of freedom and α of 0.05 is 3.84.
So, the system data follows normal distribution.

From model data:

Table 10A: Normality test of the simulation data

Data Range	93-98	99-100	101-102	103-104	105-106	107-112
Observed Value	3	3	5	8	7	4
Expected Value	5	5	5	5	5	5
$\frac{(O-E)^2}{E}$	.8	0.8	0	1.8	0.8	0.2

Square error = 4.4
Degrees of freedom=6-2-1=3
Chi – square critical value for 3 degree of freedom an α of 0.05 is 7.82.
So, the model data also follows the normal distribution.

A 1.2: F – Test:

The F test compares the variance of the system validation data set and that of the model validation data set.

$$F = \frac{S_M{}^2}{S_m{}^2}$$

$S_M{}^2$ = Variance of the data set with larger variance.
$S_m{}^2$ = Variance of the data set with smaller variance.

$$F = \frac{82.95}{12.1}$$

=6.9

Degrees of freedom for numerator= 21-1=20
Degrees of freedom for denominator= 30-1=29
Critical value at α/2 (0.05) with 20 degrees of freedom in numerator and 29 degrees of freedom in denominator is 1.94.
The test statistics 6.9 is greater than the critical value 1.79, so both data sets do not have similar variance.

As because the variance is not similar now we have to run Smith-Satterthwaite test.

A 1.3: Smith-Satterthwaite t- Test:

The independent t-test is utilized when the data are normal and the data sets do not have the similar variance. This test accounts for the differences in variance by adjusting the degree of freedom for the t critical value. The formula for calculating the degree of freedom is:

$$d.f = \frac{\left[\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right]^2}{\frac{\left[\frac{s_1^2}{n_1}\right]^2}{(n_1 - 1)} + \frac{\left[\frac{s_1^2}{n_1}\right]^2}{(n_1 - 1)}}$$

Where

d.f= calculated test statistics.
s_1^2 = variance of the first alternative
s_2^2 = variance of the second alternative
n_1 = number of data point in first alternative.
n_2 = number of data point in second alternative.

$$d.f = \frac{\left[\frac{82.95}{21} + \frac{12.1}{30}\right]^2}{\frac{\left[\frac{82.95}{21}\right]^2}{(21 - 1)} + \frac{\left[\frac{12.1}{30}\right]^2}{(30 - 1)}}$$

$$= 24$$

The Formula to calculate Smith Satterthwaite test is:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where

T = t-test statistic for the Smith-Scatterthwaite.
$\bar{x}_1$ =Mean of the first alternative replication.
$\bar{x}_2$ =Mean of the second alternative replication.
s_1^2 = variance of the first alternative.
s_2^2 = variance of the second alternative.
n_1 = number of data point in first alternative.

n_2 = number of data point in second alternative.

$$t = \frac{101.42 - 103.1}{\sqrt{\frac{82.95}{21} + \frac{12.1}{30}}}$$

$$= -0.8$$

Level of significance α = 0.05
Critical value for t at α/2, 24 degree of freedom is 2.06.
Test statistics t of -0.8 is in between -2.06 and 2.06.

Comparing the outputs of each type of Patient:

Table 11A: Comparing the outputs of each type of patient

Types of Patients	Current System	Simulation Model
15 minute Patient	31.4	32.8
30 minute Patient	14.6	14.9
45 minute Patient	1.04	1.02
1 hr Patient	7.8	8.1
1.5hr Patient	6.6	7.08
1.25h 1.75h 2.25h 2.75h Patient	2.9	2.9
2hr Patient	9.8	9.7
2.5hr Patient	1.9	1.55
3hr Patient	5.1	4.65
3.25h 3.5h 3.75h Patient	2.32	2.2
4 hr Patient	6.3	4.4
4.25h 4.5h 4.75h Patient	0.94	0.711
5hr Patient	5.4	4.07
5.25h 5.5h 5.75h 6h 6.5h 6.75h 7h Patient	2.76	2.72
7.25h 7.5h 7.75h 8h 8.25h 8.5h Patient	2.57	2
9.5h 10h 11h 11.5h Patient	0.81	0.97
Average	102	103.1

This means that the current model follows the real situation and there is no statistically significant difference between the actual system and the simulation model. So we can conclude that our model is valid.

A 2: Scenario 1:

Table 12A: Changed arrival pattern of different types of patients (Scenario 1).

TYPE	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
8:00-9:00	6	2	1	1	1	1
9:00-10:00	6	2	1	1	1	1
10:00-11:00	7	4	2	1	1	
11:00-12:00	8	4	2	1	1	
12:00-13:00	10	5	2	1		
13:00-14:00	10	5	2	1		
14:00-15:00	12	4	2			
15:00-16:00	10	3				
16:00-17:00	5	2				
17:00-18:00	4					
18:00-19:00	2					
19:00-20:00						

Table 13A: Comparing the output of the system (Current system and Scenario 1)

	Average Patient No	
	Current System	Scenario 1
15 minute Patient	33.9	43.7
30 minute Patient	15.4	20.9
45 minute Patient	1.06	1.2
1 hr Patient	8.4	11.8
1.5hr Patient	7.3	8.3
1.25h 1.75h 2.25h 2.75h Patient	3	3.5
2hr Patient	10	10.8
2.5hr Patient	1.6	2.2
3hr Patient	4.8	5.3
3.25h 3.5h 3.75h Patient	2.3	1.4
4 hr Patient	4.6	4.6
4.25h 4.5h 4.75h Patient	0.733	0.7
5hr Patient	4.2	3.3
5.25h 5.5h 5.75h 6h 6.5h 6.75h 7h Patient	2.8	3.32
7.25h 7.5h 7.75h 8h 8.25h 8.5h Patient	1.96	3.1
9.5h 10h 11h 11.5h Patient	1	1.3
Average	103.053	125.42
Maximum	108	135

Table 14A: Comparing average waiting time (Current system and Scenario 1)

Average Waiting Time		
	Current System	Scenario 1
15 minute Patient	4.3	16.6
30 minute Patient	3.9	14.9
45 minute Patient	3.2	12
1 hr Patient	4.9	9.02
1.5hr Patient	6.1	17.25
1.25h 1.75h 2.25h 2.75h Patient	4.2	5
2hr Patient	5	14.4
2.5hr Patient	1.4	8.6
3hr Patient	3.8	8.1
3.25h 3.5h 3.75h Patient	3.6	4.2
4 hr Patient	3.2	8.6
4.25h 4.5h 4.75h Patient	2.5	3.32
5hr Patient	3.1	8.1
5.25h 5.5h 5.75h 6h 6.5h 6.75h 7h Patient	2.3	2.5
7.25h 7.5h 7.75h 8h 8.25h 8.5h Patient	3.53	3.5
9.5h 10h 11h 11.5h Patient	10	0.71
Grand Waiting Time	4.3	13.04

Table 15A: Comparing the utilization of the facility (Current system and Scenario 1)

	Station 1 Chair	Station 2 Chair	Station 3 Chair	Station 4 Chair	Solarium Station Chair	Average Utilization
Current System	0.73	0.8	0.49	0.49	0.58	0.62
Scenario 1	1.06	0.72	0.76	0.74	0.6	0.776

A 3: Scenario 2 and 2.2:

In Scenario 2 float nurse is rescheduled at 10:00-18:00 instead of 11:00 – 19:00 and it is shown in Table 16A.

Table 16A: Rescheduling the float nurse (Scenario 2)

Scenario 2	
Working Hr	No of Nurses
8:00 - 9:00	7
9:00 - 10:00	7
10:00 - 11:00	9
11:00 - 12:00	9
12:00 - 13:00	11
13:00 - 14:00	11
14:00 - 15:00	11
15:00 - 16:00	11
16:00 - 17:00	4
17:00 - 18:00	4
18:00 - 19:00	2
19:00 - 20:00	2

There is another scenario 2.2 where the arrival pattern has changed to fit over scenario 2 nurse schedules.

Table 17A: Scenario 2.2

Scenario 2.2		
Working Hr	No of Nurses (Scenario 2)	Changed Arrival rate
8:00 - 9:00	7	13
9:00 - 10:00	7	13
10:00 - 11:00	9	15
11:00 - 12:00	9	15
12:00 - 13:00	11	17
13:00 - 14:00	11	17
14:00 - 15:00	11	17
15:00 - 16:00	11	10
16:00 - 17:00	4	6
17:00 - 18:00	4	4
18:00 - 19:00	2	2
19:00 - 20:00	2	

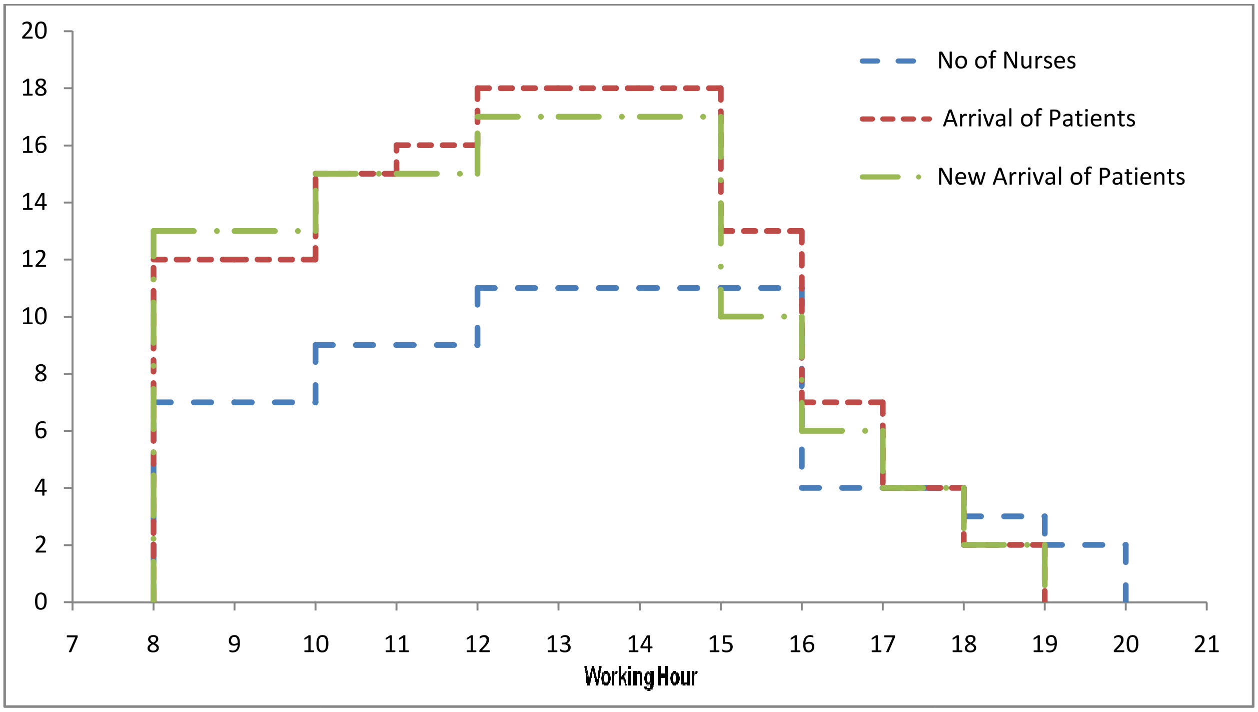

Figure 1A: Scenario 2.2 nurse schedule and patient arrival pattern

Table 18A and 19A represents the details of the scenarios. It is found that in scenario 2 and scenario 2.2 the resource utilization has increased up to 77% but compared to Scenario 1 the average throughput has decreased and compared with the current system the waiting time has increased.

Table 18A: Average waiting time and throughput of the system in Scenario 2 and Scenario 2.2

	Scenario 2		Scenario 2.2	
	Waitin	Throughp	Waitin	Throughp
15 minute Patient	15.2	43.3	15.4	40.7
30 minute Patient	16.04	21.2	15.4	18.5
45 minute Patient	6.9	1.2	7.5	0.9
1 hr Patient	11.6	10.4	11.5	11.3
1.5hr Patient	16.1	7.8	15.8	8.2
2hr Patient	15.23	11.23	18.7	10.8
2.5hr Patient	3.52	1.63	9.3	2.7
3hr Patient	6.8	4.4	10.5	4.5
3.5h Patient	3.4	0.6	12.1	1
4 hr Patient	8.5	4	7.4	4.3
4.5 h Patient	1	0.33	3.7	0.3
5hr Patient	8.92	3	5.4	3
5.5h Patient	2.25	0.23	0	0.1
6h Patient	10.2	1.6	5.8	1.6
6.5h Patient	0	0.13	0	0.3
7h Patient	0.1571	0.5	0.2	0.47
8h Patient	3.83	3	3.1	3
10h Patient	0	0.133	0.04	0.2
Average	13	119	13.21	116

Table 19A: Scheduled chair utilization in Scenario 2 and Scenario 2.2

	Station 1 Chair	Station 2 Chair	Station 3 Chair	Station 4 Chair	Solarium Station Chair	Average Utilization
Scenario 2	1.07	0.71	0.76	0.75	0.55	0.769
Scenario 2.2	1.09	0.71	0.76	0.78	0.56	0.78

A4: Scenario 3:

In scenario 3 one nurse has added at 8:00-16:00 time slot at different station and its effect has measured. The nurse schedule and arrival of patient is shown in Table 20A and figure 2A.

Table 20A: Scenario 3 Nurse Schedule and Arrival of patient

Working Hr	No of Nurses	Arrival Rate
8:00 - 9:00	8	12
9:00 - 10:00	8	12
10:00 - 11:00	9	15
11:00 - 12:00	10	16
12:00 - 13:00	12	18
13:00 - 14:00	12	18
14:00 - 15:00	12	18
15:00 - 16:00	12	13
16:00 - 17:00	4	7
17:00 - 18:00	4	4
18:00 - 19:00	3	2
19:00 - 20:00	2	

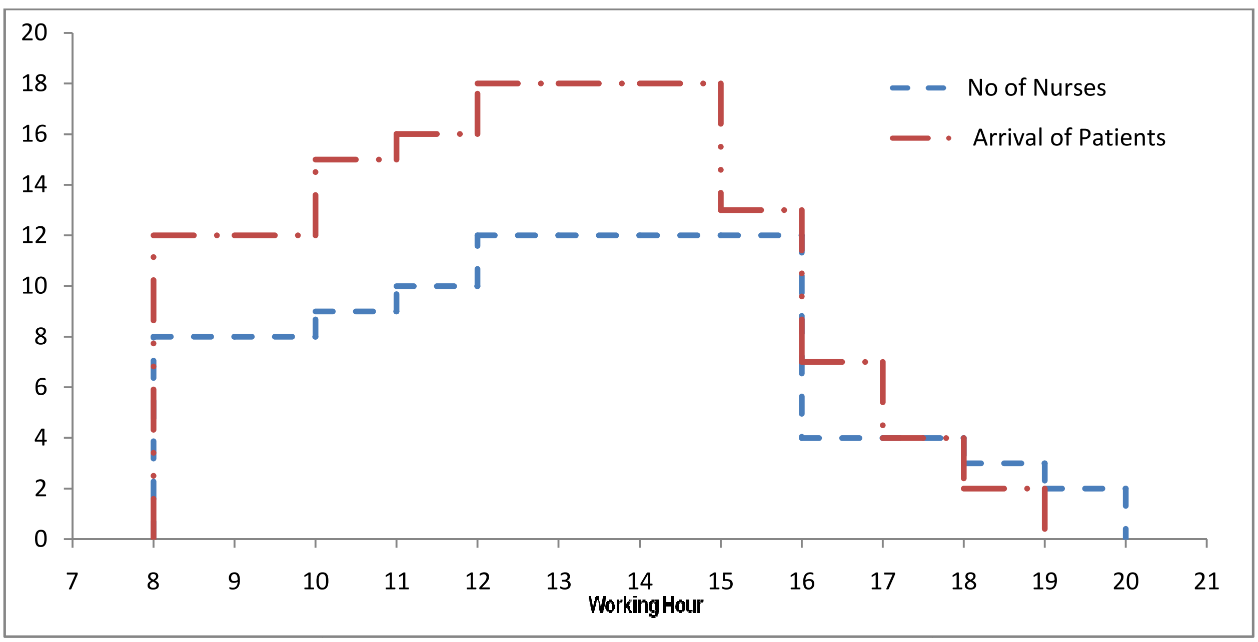

Figure 2A: Scenario 3 nurse schedule and arrival of patient.

This nurse can be added at any one of the station (Station 1-4) or even work as a float nurse for all the stations. The detail of the Scenario 3 is presented in appendix (Table 21A, 22A).

From table 21A and 22A it can be concluded that, it will be best to add the 8:00 -16:00 time slot nurse at Station no 3 where the average waiting time is 6.8 minute, average throughput is 125 and average utilization of the chair is 77%.

Table 21A: Scenario 3

	Scenario 3 -Add 1 more nurse 8:00- 16:00 at									
	Station 1		Station 2		Station 3		Station 4		All Stations	
	Waiting Time	Output	Waiting Time	Output	Waiting Time	Output	Waiting Time	Output	Waiting Time	Output
15 minute Patient	15.2	44.2	6.17	4.6	4.8	3.7	6.3	44	4.1	4.6
30 minute Patient	13.3	20.2	3.22	20.4	11.8	20.2	14	21	11.38	20.3
45 minute Patient	13.5	1.2	14.2	1.1	8.6	1.13	9.5	1	7.5	1.1
1 hr Patient	9.7	11.7	8.3	11.6	9	11.2	8.7	11.9	7.6	10.8
1.5hr Patient	17.16	7.5	16.7	8	15.8	8.33	17.1	8.2	15.1	7.5
2hr Patient	12.7	10.4	13.7	11.3	13.5	11.5	15.5	11.1	14.2	11.7
2.5hr Patient	8.2	2.7	5.5	2	10.2	2	7.5	1.9	13.3	2.2
3hr Patient	6.6	5.7	9.4	5.5	8.2	5.6	8.9	5.5	10.79	5.2
3.5h Patient	4.2	0.9	5.6	0.8	2.9	0.7	8.2	0.73	5.6	0.9
4 hr Patient	7.1	4.1	7.3	4.6	7	4.7	10.7	4.6	7.4	4.6
4.5 h Patient	1.7	0.3	0.48	0.3	0.84	0.4	2	0.4	1.02	0.3
5hr Patient	5.8	3.1	8.2	3,4	7.2	3.33	7.7	3.5	5.2	3.3
5.5h Patient	1.7	0.3	1.5	0.23	1.5	\0.2	1.5	0.23	1.4	0.3
6h Patient	5.8	1.8	7.6	1.7	6.8	1.8	7.9	1.8	3.6	1.63
6.5h Patient	0.1	0.2	0.25	0.13	0.15	0.13	0.27	0.13	2.8	0.2
7h Patient	1.5	\0.6	0.94	0.43	0	0.43	0.5	0.5	1.38	0.6
8h Patient	3.7	3.1	3.5	3.1	3.7	3.2	3.5	3.1	3.8	3.1
10h Patient	1.3	1.3	0.88	1.3	1	1.23	0.5	1.3	1.98	1.3
Average	**11.75**	**125**	**12.36**	**125**	**11.46**	**125**	**12.76**	**126**	**11.14**	**125**

Table 22A: Comparing the utilization of the facility (Scenario 3)

	Scenario 3				
Scheduled Chair Utilization	Station 1	Station 2	Station 3	Station 4	All Station
Station 1 Chair	1.06	1.06	1.05	1.06	1.06
Station 2 Chair	0.73	0.72	0.73	0.74	0.71
Station 3 Chair	0.75	0.72	0.73	0.75	0.77
Station 4 Chair	0.76	0.75	0.75	0.75	0.74
Solarium Station Chair	0.59	0.59	0.6	0.6	0.59
Average Utilization	0.778	0.768	0.772	0.78	0.774

A 5: Scenario 4:

In Scenario 4, one nurse has been added to the simulation model who will work from 10:00 to 18:00.

Table 23A: Scenario 4

Scenario 4		
Working Hr	No of Nurses	Arrival Rate
8:00 - 9:00	7	12
9:00 - 10:00	7	12
10:00 - 11:00	9	15
11:00 - 12:00	10	16
12:00 - 13:00	12	18
13:00 - 14:00	12	18
14:00 - 15:00	12	18
15:00 - 16:00	12	13
16:00 - 17:00	5	7
17:00 - 18:00	5	4
18:00 - 19:00	3	2
19:00 - 20:00	2	

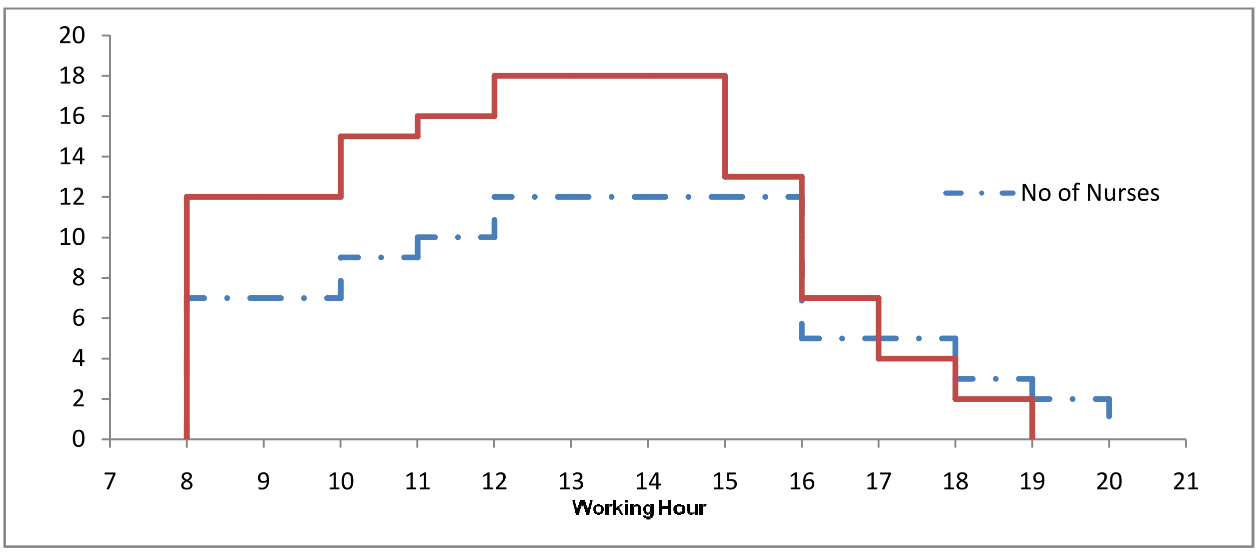

Figure 3A: Scenario 4

This new nurse can also be added at any of the stations. From the figure 2 it is found that Station 1 and station 3 closes at 16:00. Therefore if this nurse is assigned to station 1 or 3, she will be idle for the last two hrs. But Station 2, 4 and Solarium Station work until 18:00 or 20:00 hr. In order to get the best utilization of this nurse it is best to assign this nurse at these stations.

A detail of the scenario is presented in Table 24A, 25A. From the tables it is evident that it is best to assign the 10:00 to 18:00 hr at station 2.

Table 24A: Scenario 4 (Comparison among Station 2, 4 and Solarium Station)

	Scenario 4 (Add 1 more nurse 10:00- 18:00)					
	Station 2		Station 4		Solarium Station	
	Waiting Time	Output	Waiting Time	Output	Waiting Time	Output
15 minute Patient	16.3	44.6	16.02	43.7	16.5	44.1
30 minute Patient	12.7	20.1	16.5	20.9	13.8	20.4
45 minute Patient	12.1	1.3	8.9	1.3	11.2	1.2
1 hr Patient	10.9	11.8	8.3	12.03	9.4	11.7
1.5hr Patient	16.6	8.1	19.5	8.6	18.1	8.5
2hr Patient	13.6	11.3	14.6	10.6	14	10.7
2.5hr Patient	5.5	1.9	8.4	2	8.6	2.3
3hr Patient	8.3	5.3	6.1	5.2	7.7	5.6
3.5h Patient	5.5	0.83	6.8	0.7	4.8	0.7
4 hr Patient	6.1	4.7	8.8	4.5	9.4	4.5
4.5 h Patient	0.5	0.3	4.3	0.4	2	0.3
5hr Patient	8.2	3.4	6.1	3.3	11.6	3.2
5.5h Patient	1.5	0.23	1.7	0.3	1.5	0.2
6h Patient	7.6	1.7	9.2	1.8	9.3	1.9
6.5h Patient	0.25	0.13	0.3	0.2	0.3	0.13
7h Patient	0.94	0.43	0.5	0.5	0.5	0.5
8h Patient	3.6	3.1	3.8	3.1	3.5	3.1
10h Patient	0.8	1.3	0.93	1.3	0.6	1.3
Average	12.45	125	13	125	12.9	125

Table 25A: Scenario 4 throughput analysis

	Scenario 4		
Scheduled Chair Utilization	Station 2	Station 4	Solarium Station
Station 1 Chair	1.06	1.05	1.06
Station 2 Chair	0.73	0.72	0.73
Station 3 Chair	0.75	0.73	0.73
Station 4 Chair	0.76	0.76	0.76
Solarium Station Chair	0.59	0.61	0.58
Average Utilization	0.778	0.774	0.772

There is a another scenario named Scenario 4.2 where the arrival pattern of the patient has changed to fit over scenario 4 nurse schedule. So the scenario becomes:

Table 26A: Arrival pattern of the patients at Scenario 4.2

Working Hr	No of Nurses	Arrival Rate	Changed Arrival Rate Scenario 4.2
8:00 - 9:00	7	12	12
9:00 - 10:00	7	12	12
10:00 - 11:00	9	15	14
11:00 - 12:00	10	16	15
12:00 - 13:00	12	18	17
13:00 - 14:00	12	18	17
14:00 - 15:00	12	18	17
15:00 - 16:00	12	13	10
16:00 - 17:00	5	7	8
17:00 - 18:00	5	4	6
18:00 - 19:00	3	2	4
19:00 - 20:00	2		2

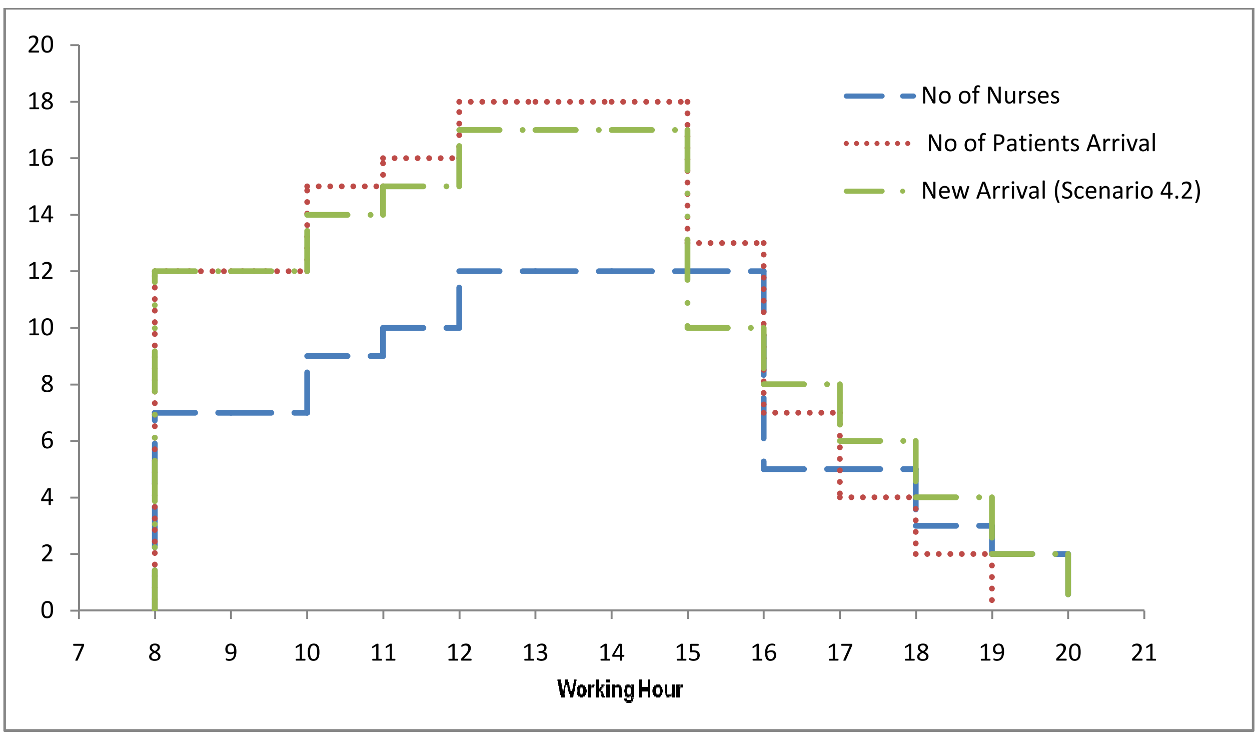

Figure 4A: Scenario 4.2 nurse schedule and patient arrival rate

Studying table 27A and 28A we found that the average waiting time will be minimum (6.1 minute) if the nurse is assigned to station 2 but compared with scenario 4 it is found that the throughput has decreased from 125 to 121.

Table 27A: Waiting time and output comparison (Scenario 4.2)

	Scenario 4.2 (Add 1 more nurse 10:00- 18:00)(Arrival Changed)					
	Station 2		Station 4		Solarium Station	
	Waiting Time	Output	Waiting Time	Output	Waiting Time	Output
15 minute Patient	12.9	41	12.6	40.9	12.7	40.7
30 minute Patient	11.5	20	13.1	19.4	12.5	19.4
45 minute Patient	7.6	1.2	12.3	1.3	5.5	1.2
1 hr Patient	6.9	9.9	7.8	10.8	6.5	10.9
1.5hr Patient	14.5	7.7	14.8	7.7	15	7.7
2hr Patient	9.2	11.9	9.3	12	10	11.9
2.5hr Patient	7.9	1.9	7.1	1.9	9.1	2
3hr Patient	6.8	5.7	8.3	5.8	7.8	6
3.5h Patient	2.7	1.03	6.7	0.8	6.2	0.87
4 hr Patient	7.9	3.8	9.1	3.8	9.7	3.8
4.5 h Patient	1.8	3	2	0.4	1.9	0.4
5hr Patient	7.5	3.3	7.4	3.5	7.2	3.4
5.5h Patient	1.4	0.2	1.4	0.2	1.4	0.2
6h Patient	6	1.9	6.2	1.8	6	1.83
6.5h Patient	0	0.1	0	0.1	0	0.13
7h Patient	0.9	0.5	3.2	0.6	3.2	0.53
8h Patient	3.5	3.1	3.8	3.1	3.6	3.1
10h Patient	1.1	1.3	1.1	1.3	1.3	1.3
Average	10	120	10.3	121	10.2	121

Table 28A: Comparison of scheduled chair utilization (Scenario 4.2)

	Scenario 4.2		
Scheduled Chair Utilization	Station 2	Station 4	Solarium Station
Station 1 Chair	1.06	1.06	1.06
Station 2 Chair	0.72	0.71	0.71
Station 3 Chair	0.72	0.75	0.75
Station 4 Chair	0.74	0.75	0.75
Solarium Station Chair	0.57	0.58	0.58
Average Utilization	0.762	0.77	0.77

A 6: Scenario 5:

In scenario 5 one nurse has been added to the simulation model whose clinic time will start at 11:00 and finish at 19:00.

Table 29A: Scenario 5 Nurse schedule and patient arrival rate

Scenario 5		
Working Hr	No of Nurses	Arrival Rate
8:00 - 9:00	7	12
9:00 - 10:00	7	12
10:00 - 11:00	8	15
11:00 - 12:00	10	16
12:00 - 13:00	12	18
13:00 - 14:00	12	18
14:00 - 15:00	12	18
15:00 - 16:00	12	13
16:00 - 17:00	5	7
17:00 - 18:00	5	4
18:00 - 19:00	4	2
19:00 - 20:00	2	

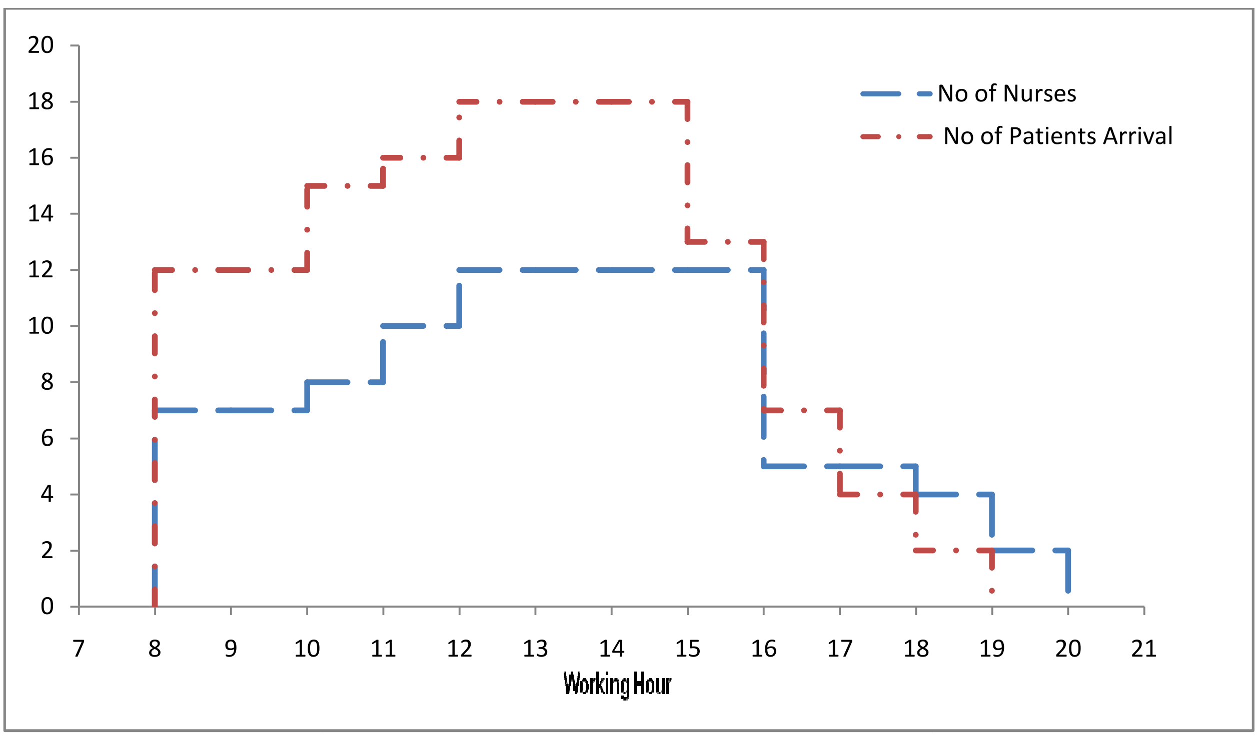

Figure 5A: Scenario 5 nurse schedule and patient arrival rate

This nurse should be assigned either at station 2 or solarium station because these are the stations that fit around this nurse schedule. Comparing table 30A and 31A it is best to place this nurse at Solarium station where the average waiting time is reasonable (6.7 minute) and throughput of patient is 125.

Table 30A: Average waiting time and throughput comparison of Scenario 5

	Scenario 5 (Add 1 more nurse 11:00- 19:00)			
	Station 2		Solarium Station	
	Waiting Time	Throughput	Waiting Time	Throughput
15 minute Patient	15	43.8	15.9	43.8
30 minute Patient	13.5	20.9	13.8	20.9
45 minute Patient	7.5	0.87	8.7	0.83
1 hr Patient	9	11.8	8.3	12.1
1.5hr Patient	14.7	8.5	11.8	8.2
2hr Patient	13.9	10.8	11	10.8
2.5hr Patient	7.2	2	10.3	2.1
3hr Patient	6.7	5.4	5.3	5.1
3.5h Patient	6.8	0.73	4	0.63
4 hr Patient	7.8	4.4	8.4	4.6
4.5 h Patient	3.3	0.33	1.9	0.4
5hr Patient	7.9	3.3	6.7	3.5
5.5h Patient	1.4	0.2	3.6	0.23
6h Patient	6.9	1.9	7.4	0
6.5h Patient	0.22	0.13	0	0.13
7h Patient	0.5	0.5	0.6	0.5
8h Patient	3.7	3.1	3.3	3.1
10h Patient	0.13	1.3	0.8	1.3
Average	11.75	125	11.5	125

Table 31A: Comparison of scheduled chair utilization of scenario 5

Scenario 5		
Scheduled Chair Utilization	Station 2	Solarium Station
Station 1 Chair	1.05	1.07
Station 2 Chair	0.73	0.73
Station 3 Chair	0.74	0.75
Station 4 Chair	0.77	0.76
Solarium Station Chair	0.58	0.57
Average Utilization	0.774	0.776

There is another scenario named Scenario 5.2 where the arrival pattern of the patient has changed to fit over Scenario 5 nurse schedule. So the scenario becomes:

Table 32A: Scenario 5.2 nurse schedule and patient arrival rate

Scenario 5.2			
Working Hr	No of Nurses	Patient Arrival Rate	Changed Arrival Rate in Scenario 5.2
8:00 - 9:00	7	12	11
9:00 - 10:00	7	12	11
10:00 - 11:00	8	15	12
11:00 - 12:00	10	16	15
12:00 - 13:00	12	18	17
13:00 - 14:00	12	18	17
14:00 - 15:00	12	18	17
15:00 - 16:00	12	13	15
16:00 - 17:00	5	7	6
17:00 - 18:00	5	4	6
18:00 - 19:00	4	2	4
19:00 - 20:00	2		

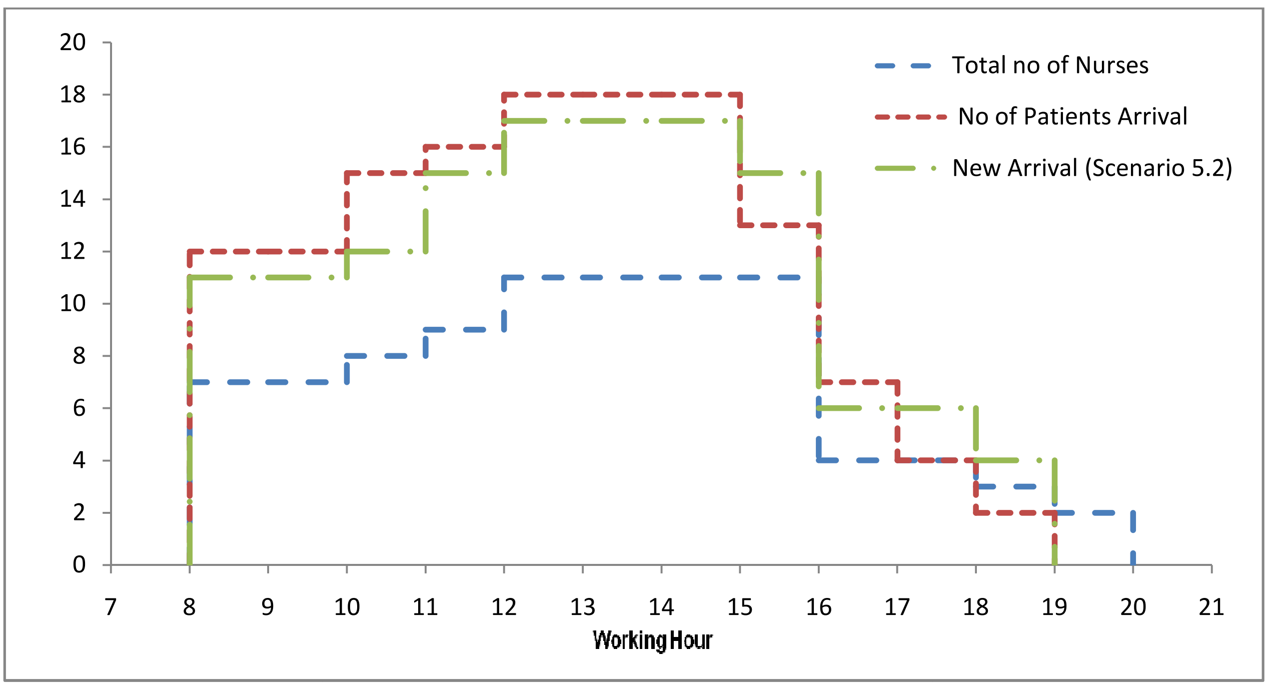

Figure 6A: Scenario 5.2 nurse schedule and patient arrival rate

In scenario 5.2 it will be best if this nurse is scheduled at solarium station, studying the table 33A and 34A.

Table 33A: Average waiting time and throughput comparison (Scenario 5.2)

	Scenario 5.2 (Add 1 more nurse 11:00- 19:00)(Arrival Changed)			
	Station 2		Solarium Station	
	Waiting Time	Throughput	Waiting Time	Throughput
15 minute Patient	16.4	40.6	16.3	41
30 minute Patient	15.3	18.3	14.2	19.2
45 minute Patient	13.5	1	14.1	1.4
1 hr Patient	11.7	11.5	9.2	11.4
1.5hr Patient	15.2	8.6	14.4	7.5
2hr Patient	13.3	11.6	13.6	11.8
2.5hr Patient	4.7	2.2	5.1	2.1
3hr Patient	8.3	5.6	8.9	5.6
3.5h Patient	1.5	0.93	3.7	1.1
4 hr Patient	7.8	4.4	7.2	4.5
4.5 h Patient	0.43	0.4	0.42	0.43
5hr Patient	5.5	3.4	6.4	3.4
5.5h Patient	0.2	0.27	0.2	0.3
6h Patient	3.2	1.9	2.6	1.8
6.5h Patient	0	0.17	0	0.17
7h Patient	1.6	0.6	1.6	0.6
8h Patient	2.7	3.3	3	3.3
10h Patient	0.5	1.3	0.6	1.3
Average	12.5	121	12	122

Table 34A: Comparison of scheduled chair utilization (Scenario 5.2)

Scenario 5.2		
Scheduled Chair Utilization	Station 2	Solarium Station
Station 1 Chair	1.08	1.07
Station 2 Chair	0.74	0.73
Station 3 Chair	0.74	0.74
Station 4 Chair	0.79	0.79
Solarium Station Chair	0.62	0.63
Average Utilization	0.794	0.792

Appendix B: Mathematical Modeling Using LINGO & CPLEX

B 1: Mathematical Modeling Using LINGO

The LINGO coding for the $Pm|\, r_i \,|\sum C_i$ problem is shown below.

```
MODEL:

SETS:

JOB/1.. /:ARV,PRCT;

MACHINE/1.. /;

POSSITION/1.. /;

ASSIGN(MACHINE,JOB,POSSITION):X;

MCHNPST(MACHINE,POSSITION):MAP;

ENDSETS

DATA:

ARV =……..;

PRCT =…….;

ENDDATA

MIN = @SUM(MACHINE(I):@SUM(POSSITION(K) :MAP(I,K)));

@FOR(JOB(J):@SUM( MACHINE(I):@SUM( POSSITION(K):X(I,J,K)))=1);

@FOR(MACHINE(I):@FOR(POSSITION(K):@SUM( JOB(J):X(I,J,K))<=1));

@FOR(ASSIGN:@BIN( X));

@FOR(JOB(J):@FOR(MACHINE(I):@FOR(POSSITION(K)|K#EQ#1:MAP(I,K)>=(ARV(J)+
PRCT(J))*X(I,J,K))));

@FOR(JOB(J):@FOR(MACHINE(I):@FOR(POSSITION(K)|K#GT#1:MAP(I,K)>=(MAP(I,K
-1)+(PRCT(J)*X(I,J,K))))));

@FOR(JOB(J):@FOR(MACHINE(I):@FOR(POSSITION(K):MAP(I,K)>=(ARV(J) +
PRCT(J))*X(I,J,K))));

END
```

B 2: Mathematical Modeling Using ILOG CPLEX

The ILOG coding for the $Pm| \, r_i \, | \sum C_i$ problem is shown below.

```
int nbJobs = ...;
int nbMchs = ...;

range Jobs = 1..nbJobs;
range Mchs = 1..nbMchs;

int duration[Jobs] = ...;
int release [Jobs] = ...;

dvar interval task[j in Jobs] size duration[j];
dvar interval opttask[j in Jobs][m in Mchs] optional size duration[j];
dvar sequence tool[m in Mchs] in all(j in Jobs) opttask[j][m];

dexpr int cmpt [j in Jobs][m in Mchs]=endOf(task[j][m]);

execute {
  //cp.param.FailLimit = 1000000;
  cp.param.TimeLimit= 7200;
}

// Minimize the total processingtime
 minimize sum(j in Jobs, m in Mchs)cmpt[j][m];


subject to {

  // Each job needs one unary resource of the alternative set
    forall(j in Jobs)
    alternative(task[j], all(m in Mchs) opttask[j][m]);

  // A job cannot start its processing before the release time
    forall(j in Jobs)
    startOf(task[j])>=release[j];

  // No overlap on machines
    forall (m in Mchs)
    noOverlap(tool[m]);

                };
```