

OPERATING ROOMS SCHEDULING AT SAMSO

BY

JUMAAN ALI ALZAHIRANI

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

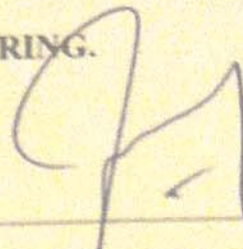
MASTER OF SCIENCE

In

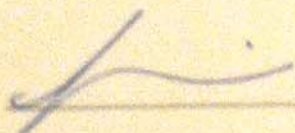
SYSTEMS ENGINEERING

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN- 31261, SAUDI ARABIA
DEANSHIP OF GRADUATE STUDIES

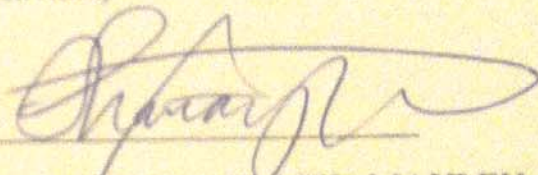
This thesis, written by **JUMAAN ALI ALZAHIRANI** under the direction his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN SYSTEMS ENGINEERING.**



Dr. MALICK NDIAYE
(Advisor)



Dr. FOUAD AL-SUNNI
Department Chairman



Dr. ABDULRAHIM SHAMAYLEH
(Co-Advisor)



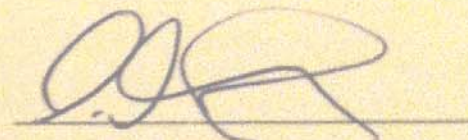
Dr. SALAM A. ZUMMO
Dean of Graduate Studies



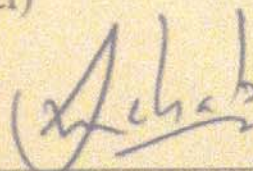
Dr. UMAR AL-TURKI
(Member)

15/6/13

Date



Dr. ABDULBASIT ANDIJANI
(Member)



Dr. WAHAB MOHAMED ISMAIL
(Member)

©Jumaan Ali Alzahrani

2013

My parents... I owe you this.

My wife and son... I would not make it without you.

ACKNOWLEDGMENTS

I would like to express my appreciation to SAMSO teams for their support and cooperation, especially Dr. Saffar, Geale, Hubaishi, and Asiri. I would like to thank Doctor Malick Ndiaye for the many evening sessions he volunteered from his own family's time. My appreciation is extended to every single member at my thesis committee for their guidance and advice. Finally I would like to salute my Saudi Aramco supervisor, Khalid Alshamekh, for his motivation and support throughout my thesis work.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS	VI
LIST OF TABLES.....	VIII
LIST OF FIGURES.....	IX
ABSTRACTS.....	X
CHAPTER 1 INTRODUCTION.....	1
1.1 SAMSO Overview.....	2
1.2 Thesis Organization.....	8
CHAPTER 2 LITERATURE REVIEW	9
2.1 OR Scheduling: Major Work	9
2.2 Simulation Based Solutions	13
2.3 Heuristics Based Solutions.....	15
2.4 Mathematical Programming Based Solutions	18
2.5 Non-technical & Other Solutions	22
CHAPTER 3 PROBLEM DESCRIPTION & SOLUTION APPROACH	25
3.1 PROBLEM DESCRIPTION.....	25
3.2 SAMSO ORs Mathematical Program.....	32
3.2.1 Variables and Sets:.....	34
3.2.2 Mathematical Model	35
3.2.3 Numerical Example.....	38
3.3 SAMSO Case Study	41

3.3.1	Case Study Data	41
3.3.2	Case Study Solution	43
3.3.3	Case Study Observations & Findings	46
3.4	Defining SAMSO’s Optimum Master Surgical Schedule “MSS”	49
3.4.1	Generating a New SAMSO MSS.....	49
3.4.2	Total Duration Verification to the Proposed SAMSO MSS	55
3.4.3	Bin Packing Approach to Verify the Proposed SAMSO MSS.....	57
CHAPTER 4 CONCLUSION AND FUTURE RESEARCH.....		68
4.1	Thesis Conclusion	68
4.2	Future Research Opportunities.....	69
4.3	SAMSO Recommendations	70
APPENDIX		73
Appendix A:		73
Appendix B		75
Appendix C		91
Appendix D		101
Appendix E		105
VITAE.....		109
REFERENCES		111

LIST OF TABLES

Table 1: SAMSO 2012 Master Surgical Schedule.	27
Table 2: SAMSO 2012 Surgical Block Schedule.	28
Table 3: Mathematical Model Numerical Example Data	39
Table 4: Mathematical Model Numerical Example Solution	39
Table 5: SAMSO Case Study- (April 15 2013) Data	42
Table 6: SAMSO Proposed MSS- EYE Specialty	51
Table 7: SAMSO ORs capacity requirements during 2012 and proposed block assignments	52
Table 8: SAMSO Proposed Master Surgical Schedule	53
Table 9: Number of OR Blocks comparison between the proposed MSS and SAMSO current MSS	54
Table 10: Total Duration Verification to the Proposed SAMSO MSS for ENT and General Specialties	56
Table 11: General Specialty Data used to determine the items and multiplicity for HMBP	58
Table 12: HMBP Validation to SAMSO Proposed and Modified MSS	61
Table 13: SAMSO Modified (Improved) Master Surgical Schedule (MSS).....	62
Table 14: Number of OR Blocks comparison between the Modified (improved) MSS and SAMSO current MSS	63
Table 15: Selecting the Average Weekly Number of Cases and Duration for SAMSO MSS HMBP	65
Table 16: Average Week Data Selected for the HMBP for Each Specialty	66

LIST OF FIGURES

Figure 1: SAMSO 2011 Cases Distribution by Specialty.....	4
Figure 2: 2011 SAMSO Cases Distribution by Case Type.....	4
Figure 3: 2011 SAMSO Cases Distribution by Patient Type	6
Figure 4: SAMSO 2011 Operating Rooms Monthly Utilization	6
Figure 5: SAMSO ORs Scheduling Process (Orthopedic Cases), source: SAMSO	31
Figure 6: Mathematical Model Numerical Example Expansion.....	40
Figure 7: SAMSO Case Study- a comparison between proposed Mathematical Model (MD) and current SAMSO scheduling system	44
Figure 8: SAMSO Case Study- ORs Utilization under the proposed Mathematical Model (MD) and current SAMSO scheduling system	45
Figure 9: SAMSO Case Study- ORs Remaining Capacity (% of OR Time) under the proposed Mathematical Model (MD) and current SAMSO scheduling system	45
Figure 10: SAMSO 2012 cases and utilization contribution for each specialty	48
Figure 11: SAMSO 2012 Surgeries Distribution By Work Day and Admission Type.....	48
Figure 12: SAMSO future 2013 surgery requests as appeared on February 27th, 2013 ...	48
Figure 13: HMBP solution to the Eye Specialty under the modified (improved) MSS.....	67

ABSTRACTS

Full Name : Jumaan Ali Alzahrani
Thesis Title : Operating Rooms Scheduling at SAMSO
Major Field : Industrial & Systems Engineering
Date of Degree : May 2013

The work presented in this thesis addresses the Operating Rooms (ORs) Scheduling Problem in the context of Saudi Aramco Medical Services Organization (SAMSO). A literature review about the problems and its variant frameworks is classified and discussed. In addition, SAMSO ORs scheduling process and guidelines are presented along with SAMSO adapted Master Surgical Schedule “MSS” and Surgical Block Schedule “SBS”.

The problem is then defined to be determining the optimum ORs schedule that considers ORs utilization rate, patients waiting time, cases criticality, and sequencing preferences of SAMSO while maintaining the current Master Surgical Schedule. To accomplish this, a mathematical model is introduced to select the cases based on their duration fit in the OR time constraints and based on their priority values (i.e. patient’s waiting time and cases criticality). The same model develops the optimum sequencing based on SAMSO rules. To test the model, a real data of one random day is chosen from SAMSO.

The current SAMSO’s MSS has been evaluated for its efficiency with deep analysis at many aspects. Based on a full year’s workload of each specialty, a new MSS is proposed with significant potential resources savings to SAMSO. This introduced MSS is then tested using two approaches: total duration approach and bin-packing approach, both proving its practicality to SAMSO.

ملخص الرسالة

الاسم الكامل: جمعان علي معيض العدوانى الزهراني

عنوان الرسالة:جدولة غرف العمليات في دائرة الخدمات الطبية بأرامكو السعودية

التخصص: الهندسة الصناعية والنظم

تاريخ الدرجة العلمية: مايو، 2013 م

العمل المقدم في أطروحة الماجستير هذه يتناول جدولة غرف العمليات في دائرة الخدمات الطبية بأرامكو السعودية. قمنا أولاً بتصنيف المراجع التي تناولت الموضوع ومناقشة مختلف أطرها بالإضافة إلى ذلك، قمنا بتوثيق وتقديم إطار العمل الحالي في الدائرة للقيام بجدولة غرف العمليات مع شرح "الجدول العام لجراحات التخصصات" و "جدول التوزيع الزمني لغرف العمليات" المستخدم في الدائرة.

نعرف مشكلة جدولة غرف العمليات في دائرة الخدمات الطبية بأرامكو السعودية بتحديد الجدول الأمثل لغرف العمليات آخذين في الاعتبار معدل استخدام غرف العمليات، وقت انتظار المرضى، مدى حرج الحالة الطبية، وقوانين الجدولة المتبعة في الدائرة. ولتحقيق ذلك، يتم تقديم نموذج رياضي لتحديد الحالات الواجب جدولتها بناء على مدى أولويتها (أي وقت انتظار المريض و مدى حرج حالته) ومدى توفر المدة الملائمة في غرفة العملية. يقوم نفس النموذج الرياضي بتطوير التسلسل الأمثل للحالات الجراحية على أساس قوانين الدائرة. و لاختبار هذا النموذج، يتم اختيار بيانات حقيقية من يوم عشوائي واحد من الدائرة.

تم تقييم الوضع الحالي لـ "الجدول العام لجراحات التخصصات" المتبع في الدائرة مع تحليل عميق لمختلف جوانبه على أساس بيانات سنة كاملة من دائرة الخدمات الطبية بأرامكو السعودية. بناء على ذلك، يتم اقتراح "جدول عام لجراحات التخصصات" جديد مع تحقيق وفورات محتملة كبيرة للدائرة. أخيراً، تم اختبار الجدول المقترح باستخدام طريقتين: طريقة المدة الإجمالية، وطريقة التعبئة، وكلتا الطريقتين أثبتتا إمكانية تطبيق الجدول المقترح في دائرة الخدمات الطبية بأرامكو السعودية.

CHAPTER 1

INTRODUCTION

Health care sectors are increasingly attracting more governments spending around the globe to cope with the pressing populations' demands for higher quality and agile medical services [6]. However, under the constraints of scarce medical resources and rising operating costs, administrators strive to create all possible opportunities to reduce financial expenditures and improve service quality at Health Care Facilities while meeting the needs of both patients and caregivers. The Operating Rooms (ORs) are considered the highest revenue stream for profit-oriented hospitals [35]. In light of this, ORs scheduling plays an important role in maximizing that profit. The literature review indicates that this is a rich field of research with many introduced mathematical models, heuristics, and simulation models.

This chapter of the thesis includes two sections. Since ORs scheduling is being evaluated at the environment of SAMSO (Saudi Aramco Medical Services Organization), we will dedicate the first section of this chapter to provide the reader an overview of SAMSO. In the second section, we will address the organization of this thesis and the contents of its three others.

1.1 SAMSO Overview

Saudi Aramco is the largest Oil and Gas Company globally. It is a fully integrated petroleum and chemicals enterprise and a world leader in exploration, production, refining, distribution, shipping and marketing with 259.9 billion barrels of proven conventional crude oil and condensate reserves. Saudi Aramco's headquarter is located in Dhahran, Saudi Arabia. In order to support its employees in Dhahran and throughout the company operation sites, Saudi Aramco Medical Services Organization (SAMSO) was established [50].

SAMSO has one major inpatient health center and oversees 4 primary care/emergency facilities located in the company major operational districts. In addition, it supports contracted remote area clinics and designated health care facilities across the Kingdom of Saudi Arabia. SAMSO's Dhahran Health Center is the largest facility for SAMSO. It include a number of primary care clinics, an urgent care clinic, outpatient specialized clinics, inpatients wards with a capacity of about 350 beds, round the clock emergency services and a ten room operating theatre that is described below. This facility is referred to as SAMSO from here onward, in this thesis.

SAMSO has ten ORs, each working from 7:15 am – 3:15 pm. There are an additional two rooms that can be opened for emergency cases if required. These ORs can be accessed by thirteen specialties (as recognized by the scheduling team). The specialties are mentioned below while Figure 1 summarizes the number of surgeries for each of the thirteen specialties during 2011 calendar year.

- | | |
|--------------------------------|----------------------------|
| 1. ENT (Ear, Nose, and Throat) | 2. Orthopedic |
| 3. Ophthalmology (Eye) | 4. Plastic |
| 5. Gynecology | 6. General |
| 7. Neurology/ Neurospinal | 8. Thoracic (Chest/ Lungs) |
| 9. Dental (OMF&PEDD) | 10. Vascular |
| 11. Urology | 12. Anesthesia |
| 13. Bariatric | |

Any surgery can be performed at any of the ten ORs, except for the ENT and Ophthalmology which can only be performed at OR1 or OR2. During the surgery, the surgeon, his assistant “ward physician” (except for ENT and EYE), charged nurse, and at least one more nurse need to attend the surgery. SAMSO’s ORs scheduling team classifies the cases into three types, based on their scheduling request time:

- *Elective cases*: any surgery requested up to 24 hours from the surgery start day, this accounts for the majority of SAMSO cases.
- *Add-on cases*: represents surgeries requested within 24 hours of their start day, this is less frequent, as seen in Figure 2, and has less scheduling priority than elective cases.
- *Emergency cases*: can be requested any time but usually scheduled after 4 pm, if deemed absolutely necessary; ORs scheduling team fits emergency cases within the daily ORs schedule, even if that yields to cancelling scheduled case.

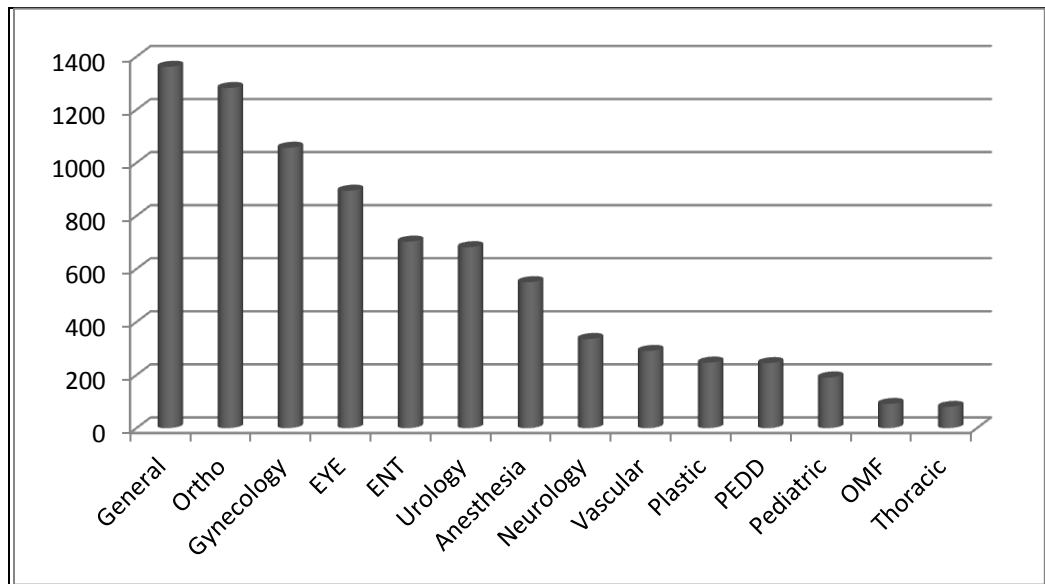


Figure 1: SAMSO 2011 Cases Distribution by Specialty

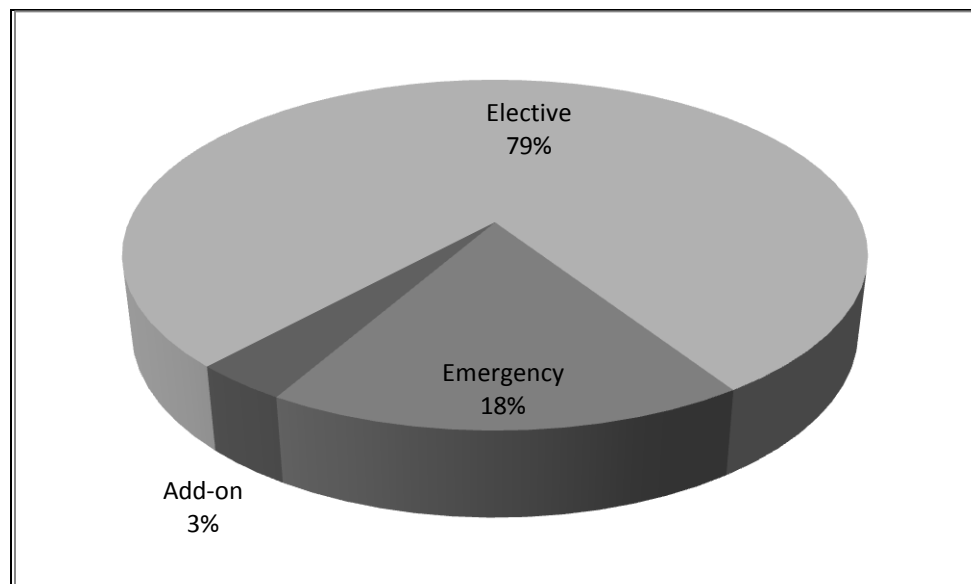


Figure 2: 2011 SAMSO Cases Distribution by Case Type

SAMSO has another classification based on the type of admission process; there are three types of patients' admissions, see Figure 3:

- *Day Surgery*: for patients who show-up few hours before the surgery start-time. Once arrived, a day-surgery patient uses the (day-surgery suit) for cloth changing, preparation... etc, and then goes to the assigned OR. After the surgery, the day-surgery patient stays for couple of hours at the recovery room then is discharged home.
- *Same-day admission*: similar to day-surgery patients except that patients need to spend around 6-48 hours at the inpatients wards.
- *Inpatient*: those already at inpatients wards. They are marked and prepared at their wards, then go immediately to the assigned OR. After the surgery, they spend minimum time at the recovery room then back to their wards.

SAMSO performs an average of 8,000 surgeries on annual basis giving their ORs monthly utilization that varies between 41% to 68% as seen in Figure 4. This utilization percentage does not include the turnover time between surgeries.

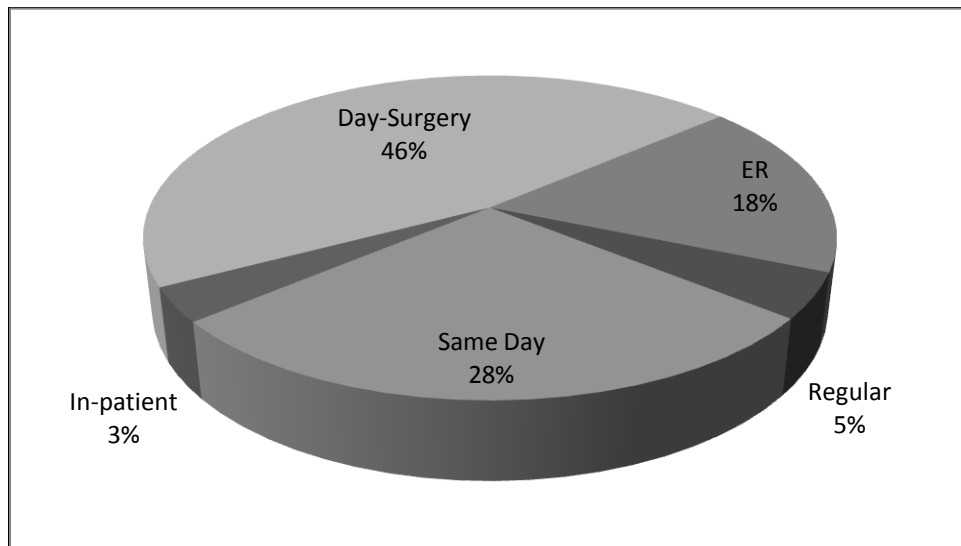


Figure 3: 2011 SAMSO Cases Distribution by Patient Type

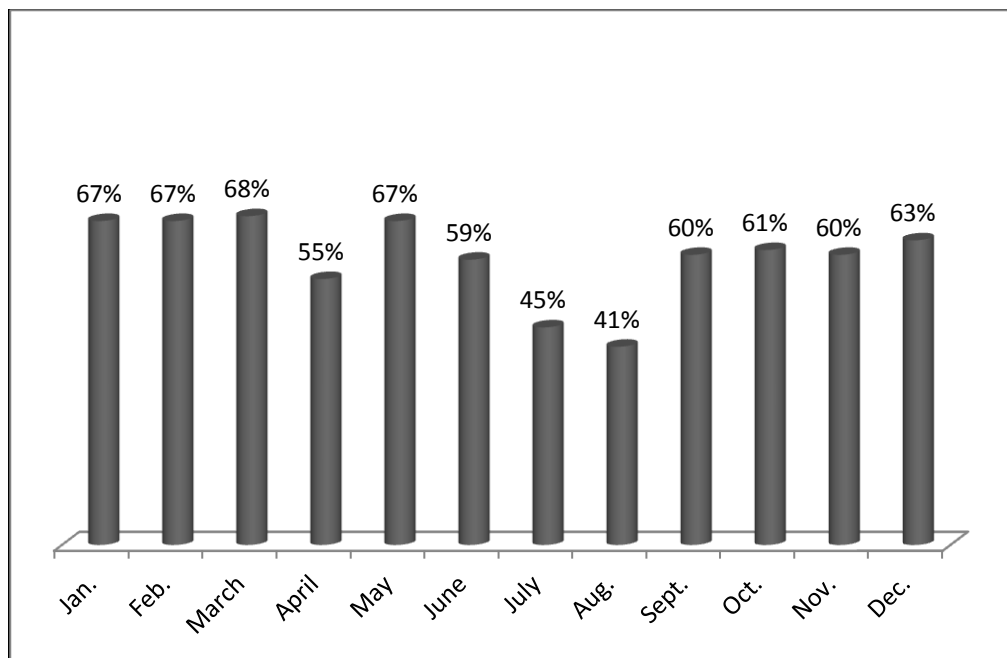


Figure 4: SAMSO 2011 Operating Rooms Monthly Utilization

SAMSO management has been trying to reduce the patients waiting time to perform surgery, reduce the patients' no-show rates, and optimize the turnover times between surgeries. Over the past three years, SAMSO worked to:

- Reduce no-show rate by increasing follow-ups, reminders, and inform employee's management of any no-shows. (daily percentage of no-shows dropped from 17% to around 4%)
- Improve the scheduling process by creating a scheduling team who has control over the OR schedule rather than surgeons themselves. Thus, reducing the patients waiting times and improving the ORs utilization rates.
- Reducing "un-cleared" cases by creating a "pre-admission" stage with assigned resources. Many surgeries used to be cancelled because the surgeon discover the patient is not "ready" during the day of surgery, but should have taken certain lab tests, x-rays.. etc. A "pre-admission" clinic was created to reduce the rate of "un-ready" cases and schedule only the "ready" cases for surgeries.

SAMSO recognizes the importance of OR scheduling, thus, dedicated a scheduling team to look after contacting surgeons, patients, pre-admission clinic, and the material and equipment supply. Under the current practice, the team generates a daily ORs schedule 24 hours ahead. The daily schedule sequences a number of surgeries in each OR, utilizing the knowledge and experience of available SAMSO scheduling team. However, low ORs utilization, long patients waiting times, unbalanced surgeries assignments, and idle medical staff time are all observations that have been noticed. SAMSO management seeks the improvement of the current scheduling process to be more efficient by

maximizing the ORs utilization as well as the medical resources utilization with the least possible patients waiting time.

1.2 Thesis Organization

The thesis comprises of four chapters. The first chapter is an introduction to the thesis. It includes an overview about SAMSO and then describes the thesis organization.

The second chapter represents the Operating Rooms Scheduling relevant literature review. Since the literature before 2010 is well documented through several efforts, this thesis considers mostly the papers found after 2010. The literature is classified based on the approach used to model and solve the Operating Rooms Scheduling problems to include five sections. Each section describes a family of solutions such as simulation, heuristic, mathematical programming, and the non-technical and other solutions.

The third chapter is the core of this thesis and includes four sections. It starts by the problem description, complications, and current SAMSO scheduling process. Then, describes a mathematical model developed to schedule SAMSO ORs along with a numerical example. The third section represents a case study based on actual data from SAMSO to apply the introduced mathematical model. The last section aims to develop a new Master Surgical Schedule which is validated using two approaches: total duration approach and a bin-packing based approach.

The thesis concludes with the fourth chapter, which presents the thesis conclusion and some recommendations to SAMSO management. In addition, suggestions and opportunities for future research in the Operating Rooms Scheduling are provided.

CHAPTER 2

LITERATURE REVIEW

This chapter of the thesis documents relevant literature in the area of Operating Rooms (ORs) scheduling. The topic is extensively studied in the literature, with many efforts to model, optimize, and enhance the scheduling process of the ORs. This chapter will start in its first section by reviewing the major works done in the area of ORs scheduling, based on this section, we conclude that only the literature post the year 2010 will be looked at, except some few papers. The following sections in this chapter will discuss the ORs scheduling literature classified by the solution method of the presented papers: the simulation based solutions are discussed in the second section, the heuristic based in the third, the mathematical programming will be covered in the fourth section, while the non-technical and other solutions will be looked at in the fifth section of this chapter.

2.1 OR Scheduling: Major Work

The major work related to the ORs scheduling which will be discussed in this section include two Ph. D. Dissertations [35, 6], one Master of Science Thesis [20], and three comprehensive literature review papers. To start with, Shamayleh [35], built his Philosophy of Doctorate Dissertation around three elements of ORs: capacity planning, time assignment, and cases sequences. He introduced an integer program based on cost factors to determine amount of time to allocate for each specialty, which helps

determining the required number of ORs. In addition, another integer program was developed to assign ORs time to specialties based on OR utilization, per-hour contribution margin, surgeons availability, and surgeons' preference. Finally, the sequencing of surgical cases of a given day of each OR was determined using simulation based tools; the same model was extended to study the impact of changing Post-Anesthesia Care Unit capacity and the model performance when a different start-time is changed. The three introduced model act like a chain, where the result of each model depends on the outcomes of the preceding model.

Another Philosophy of Doctorate Dissertation of Cardoen [6], Ph. D. Dissertation studied the sequencing of surgeries in each operating room of a medical center so that an overall qualitative schedule is obtained without violating a specific set of constraints. Six different objectives to measure the quality of a surgery schedule are introduced; those include minimization of the peak bed use in the post-anesthesia care units and the minimization of recovery overtime. On the other hand, a set of constraints that incorporates the limited availability of medical instruments, equipment sterilization requirements or the cleaning obligations that result from scheduling MRSA-infected patients are considered. Cardoen proved that the introduced problem, under the mentioned constraints, is NP hard problem. Therefore, customized algorithms were developed in exact or heuristic based. For example, branch-and-bound procedures, including fathoming and dominance rules, were presented along with linear programming based solution techniques.

Cardoen reviewed the literature extensively at Cardoen et al. [5], where the authors reviewed recent research and incorporated some planning & scheduling considerations.

They categorize the 247 manuscripts, which were published before 2009; according to patient characteristics, performance measures, decision delineation, research methodology, uncertainty, and applicability of research. The contributions were evaluated according to multiple perspectives, such as the explicit incorporation of uncertainty, the type of analysis, the kind of decision that is handled in the manuscript, the application of solution techniques or the use of performance measures. Part of the same work, a survey of 52 hospitals to understand if hospitals tend to adopt the developed algorithms and decision rules concluded low implementation rate of satisfying planning and evaluation systems.

The Master of Science Thesis of Knoeff [20] focused on the evaluation of alternative scheduling approaches to improve OR efficiency and minimize peak demands for ward beds at SKB Winterswijk Hospital. The different approaches performance was evaluated using event-based simulation for two sets of real data. Knoeff showed that the best results were generated when applying a straightforward (Random Fit) constructive heuristic. However, to meet the current referenced hospital information systems capabilities, the author recommended using the Master Surgical Schedule with cycle length of 4 weeks for planned surgeries, and the use of straightforward Random Fit for the remaining surgeries.

Another extensive literature review exists at May et al. [26] that provides a review of the general problem of surgical scheduling literature published before 2011. The authors organized the literature based on the time frame or planning horizon of the schedule into six categories: capacity planning, process reengineering/redesign, the surgical services portfolio, procedure duration estimation, schedule construction, and schedule execution,

monitoring, and control. They surveyed past work and suggest topics for potential future research in each of those areas.

On a wider range, Rais and Viana [1] studied the literature found using Operations Research in the Healthcare sector. The authors considered the decreasing birth rates in the developed countries and increasing average longevity globally to be the reasons for the need of optimization in the healthcare. They studied a variety of optimization problems and solution techniques used for solving those problems. The paper related to Operations Research in the Healthcare sector prior to the year 2011, where Simulation and related non-deterministic research in OR cover only 15% of the literature found. Four areas were summarized to reflect the literature. The first section includes Healthcare Planning, where demand forecasting, healthcare centers and emergency vehicles location selection, and capacity planning relevant literature was discussed. In the second section, Healthcare Management and Logistics related work that includes patient scheduling, resource scheduling (nurses, operating room, and physicians), and logistics literature is presented. Moreover, Operations Research on Healthcare Practices, disease diagnosis and treatment planning in particular, was discussed in the third section of the paper. Finally, Specialized and Preventive Care applications of Operations Research such as organ donation and transplant and prevention of diseases were summarized in the last section of the paper.

We can see from the discussion above that the literature is very well developed and documented prior 2010, while this work focuses on the literature found after that.

2.2 Simulation Based Solutions

From the literature review it seems that simulation results stand a much stronger chance of being implemented if a specific model is developed for a particular hospital ORs [37]. Even though researchers try to uncover general facts regarding OR management, it can be concluded that great care needs to be taken when applying them in practice, since local circumstances can be very different and vary from country to country and hospital to hospital [13].

Simulation tools have been used at ORs for multiple reasons. Sabah and Samir [2] used simulation to determine the required number of medical staff (physicians and nurses) at the OR rooms dedicated for emergency used. Their model used real data of patients arrival rate at two large public hospitals at Baghdad, the data were approximated using empirical distributions, and the staffing requirements were develop to ensure 24 hours coverage to the OR rooms of emergency services. Another work considered the minimization of total maximum bed occupancy across all hospital wards, where Chow et. al [7] used a Monte Carlo simulation to evaluate the impact of Surgical Block Scheduling on the remaining hospital wards bed occupancies. The patients' arrival rate was assumed to follow a Poisson or empirical distribution with specific arrival rate for each day of the week.

Yang and Xueping [40] used a simulation-based response surface method to determine each surgery start time where surgery durations are stochastic in an environment where ORs are already assigned to surgeons and each day surgeries are already sequenced. They proved that this problem is a special case of the periodic review inventory problem where

the lead time is zero and inventory items (time units) perish in a single period. Excess inventory cannot be carried to the next period (i.e., used by the next surgery); however, backorders are carried throughout the entire planning horizon. Sangbok and Yuehwern [21], extended the same problem to include the sequencing of surgeries in multiple ORs where limited post-anesthesia resources bind the problem. They used simulation model based on a genetic algorithm to minimize the total cost shared by patients waiting time, OR under-utilization or over-utilization.

Steins et. al [37] used discrete-event simulation combined with a priority logic to increase the utilization of the whole “Operations Center (OPC)”. OPC is the part of the hospital that includes ORs, pre and post-operative care. The authors considered the volume and specific characteristics of surgery cases, number of ORs and their operating hours, and the number of beds for pre- and post-operative care. Their simulation model measures the utilization of allocated OR times, waiting time for patients, queue dynamics, number of cancellations, and variation of finishing times, in addition to occupancy statistics in the post-operative care unit.

On a similar context, White et. al [44] introduced an empirically based discrete-event simulation to study the resources utilization and patients waiting at limited number of Examination Rooms. Based on this simulation model, they proposed that shorter appointments to be scheduled earlier in the clinic where as cases that exhibit high-variance or longer duration to be scheduled later.

Shylo et. al [36] presented a simulation model for OR scheduling where they assumed surgery duration to follow a Gaussian distribution. They proposed using dynamic

scheduling policy which they proved to reduce the variance in patient waiting times and backlogs.

Arnaout [3] modeled the OR scheduling as jobs scheduling in an identical parallel machine environment with sequence-dependent setup times. He introduced a heuristic algorithm called “Longest Expected Processing with Setup Time (LEPST)” and applied that in a simulation model with the objective of minimizing each OR’s makespan.

To conclude this section, we would like to highlight the work of Gunal and Pidd [13] that summarizes the literature related to the use of Discrete Event Simulation (DES) in health-care systems. The literature prior to 2010 was classified according to their specific health-care application. Apparently, DES use in accidents & emergencies is the most common, followed by DES at inpatient facilities, outpatient facilities, and whole hospital simulations. According to the authors, only two papers were issued on DES for Operating Rooms. As a main conclusion, the authors believe that simulation is mostly unit specific, which means that what fits one surgery suit in a hospital may not necessarily work in another.

2.3 Heuristics Based Solutions

ORs scheduling problem complexity and size make heuristic based search methods and algorithms an appealing option, especially for medical schedulers and planners. This is mainly due to the ease and efficiency of heuristics solutions, mostly. For example, Ya et. al [22] studied Operating Rooms scheduling problem with open scheduling strategy (no Surgical Block Schedule or Master Surgery Schedule exists). They developed a heuristic

algorithm based on dynamic programming by aggregating available time slots. The resulted OR schedule based on this heuristic aims to maximize the OR utilization and minimizing the overtime costs. In addition, Vijayakumar and Parikh [43] modeled the multi-period, multi-resource, and priority-based OR surgeries scheduling problem as a classical bin-packing problem where surgeries are considered to be the items and resources are considered to be the bins. Then a First Fit Decreasing Algorithm is introduced considering resource availability, case priorities, and surgeon performance. The authors prioritize more “fit” surgeries based on their priorities and case duration. Therefore, during the schedule generation, cases with high priority are considered before the low priority cases, shorter cases are given more weight, and the assignment to OR rooms are based on the surgeon (and other medical staff and equipment) availability. A comprehensive review of various heuristic algorithms of Bin-packing problem is summarized at Coffman et al. [8].

In an older paper, Vargas et al. [42] discussed the advantages and disadvantage for using first-come-first-served (FCFS) heuristic and the Block Surgery Schedule. They concluded that Block scheduling yield better results with surgeons who serve patients for elective surgeries, where it is of less attractive for surgeons who serve patients for urgent and emergent surgeries. This is mainly due to surgeons’ lack of flexible available time.

Herring and Herrmann [15] limited the surgery studied type to single-day surgeries and introduced a stochastic dynamic programming formulation of the OR scheduling problem considering equal duration of surgeries. In the case where surgeries durations are not equal, a threshold-based heuristic is introduced with priority ratio parameters such as deferral cost-to-duration ratio and blocking cost-to-duration ratio.

Riise and Burke [32] built a meta-heuristic algorithm to assign ORs and dates to a set of elective surgeries (Creating a SBS), as well as scheduling the surgeries of each day and room. Simple Relocate and Two-Exchange neighborhoods heuristic techniques are used along with iterated local search framework to minimize the patient waiting time, surgeon overtime, and waiting time for children in the morning on the day of surgery.

Marques et al. [25] created an integer linear programming (ILP) model to schedule elective surgeries on a weekly time horizon with the objective of maximizing ORs utilization. Where the introduced ILP model results in sub-optimal solution; the authors recommended the use of a simple custom-made improvement heuristic.

Tanfani and Testi [41] modeled the Master Surgical Schedule “MSS” (determining the ORs assignment among hospital wards during a given planning horizon) using an integer linear program. This is an NP-hard combinatorial optimization problem. The authors presented a heuristic algorithm to solve this problem while minimizing a cost function based upon a priority score that takes into proper account both the waiting time and the urgency status of each patient.

Nouaouriet al. [29] proposed a heuristic approach to be used during disasters and hospitals over-flow situations. The heuristic deals with the ORs rescheduling to insert the unexpected new emergency in a pre-established operating schedule with the objective of maximizing the number of surgical cases to save most human lives.

2.4 Mathematical Programming Based Solutions

Mathematical programming is by far the most applied tool found at ORs scheduling literature. However, it is more used in the modeling rather than solving these problems. Jeang and Chiang [17] aimed to minimize the deviation between the total OR scheduled time and the total available time in ORs over a planned period using a Nonlinear Integer Program. Surgeons availability, outpatient consulting hours (clinic appointments), and unfavorable surgery hours were considered in the introduced model. However, the same model did not consider surgeries turnaround times, which was assumed to be zero.

Min and Yih [28] formulated the problem for scheduling elective patients under Surgical Intensive Care Units (SICU) bed constraints. The formulation adapted a mixed integer program where surgery durations are stochastic, and patients' length of stay in SICU and new demand are assumed to be random with known distributions. The sample Average Approximation Algorithm (SAA) is used, with modification, to obtain the optimal surgery schedule with an objective function of minimizing the total of patient costs and overtime costs. Special consideration was paid to the patients cost which was modeled by A. Testi in 2007. The concept stands on multiplying a patient priority score with his/ her waiting time. The priority score of each patient depends on three clinical criteria: disease progression, pain, and dysfunction & disability.

Marques et al. [25] created an integer linear program to schedule elective surgeries from the waiting list on a weekly time horizon with the objective of maximizing the use of the surgical suite. The authors considered having four types of patients priority, namely “deferred urgency” for surgeries must be completed in 72 hours, “high priority” for

surgeries must be completed within 14 days, “priority” for surgeries must be completed within 2 months, and “normal” for surgery must be completed within 1 year. No out-patient admission is allowed under this model, no change in OR assignments to specialties (obtained through MSS), all ORs were assumed to have the same equipment, and given the constraints of resources availability (including patients) and some logic constraints, the mathematical model was tested using real data. Where non-optimal solutions are found, simple and custom-made improvement heuristic are applied by the authors. The introduced improvement heuristics include: re-scheduling surgeries as early as possible in the day, scheduling unscheduled surgeries in the time available at the end of each day, and exchanging consecutive scheduled surgeries, with priority or normal level of priority.

Erdemet al. [9] proposed a mixed integer linear programming (MILP) model for scheduling elective cases at ORs, considering the OR, surgical teams and downstream post-anesthesia care units (PACUs) availability and capacity requirements. The model focused on emergency surgery admissions impact on the designed schedule. The objective of the introduced model is to reduce the cost of rejecting emergency surgery request, minimize the costs associated with changing the current elective surgery schedule, and the overutilization costs of the ORs and the PACUs when an emergency patient is accepted. Due to the problem complex structure, obtaining an optimal solution was difficult to attain at reasonable time for realistic cases.

Keller and Bayraksan [19] considered the OR scheduling problem in the context of multiple resources constrained scheduling problem (MRCSP). In this context, surgeries are analogues to operations to be performed, and the constrained resources correspond to

surgeons, nurses, anesthesiologists, special equipment, and the ORs. A two-stage stochastic Integer Program is developed. With an objective function of minimizing expected cost for starting operation (j) at time (t), the first stage of the program ends with determining jobs start times. The second stage aims to minimize the overtime by measuring how much of temporary resource expansion should be used. The Benders decomposition (frequently referred to as the L-shaped method) is used to solve the introduced stochastic integer program.

Jebali et al. [18] is an older paper that included a two-step approach for Operating Rooms scheduling. The first step assigns surgeries at ORs in daily basis using a Mixed Integer Program with the objective of minimizing overtime, under-utilization, patients waiting time, and bed requirements. The recovery room capacity and beds availability were treated as the bottlenecks in this modeling. The second step deals with the sequencing of assigned surgeries within each OR. Another MIP is created with the objective of maximizing ORs utilization considering resource-related constraints and the specifications of the operations processes. The later step was approached using two strategies: sequence operations with no consideration to the (operations/ ORs) schedule obtained at the first step (pure sequencing strategy) or sequencing operations within ORs by redefining the order obtained at the first step (a sequencing strategy with a possible re-assignment). The second strategy was proven to yield better results in sequencing surgeries of OR.

Essen et al. [10] designed an Integer Linear Program for the OR re-scheduling problem. The objective of their model is to obtain the OR schedule with the minimum deviation

from the preferences of stakeholders. When the introduced model was applied, scheduled surgeries were either shifted or new breaks were slotted between two surgeries.

Mannino et al. [23] tackled the optimization of two performance measures of the Master Surgical Schedule “MSS” (determining the of ORs assignment among hospital wards during a given planning horizon). Those two aspects are balancing patient queue lengths among different specialties and minimizing overtime need. A mix integer linear program is introduced and OR stochastic demand fluctuation was smoothed by a deterministic one. Tanfani and Testi [41] modeled the MSS as an integer linear program and proved it to be an NP-hard combinatorial optimization problem. The authors presented a heuristic algorithm to solve this problem while minimizing a cost function based on the waiting time and urgency status of each patient.

Chow et. al [7] modeled a Mixed Integer Program for determining both surgeon blocks and patient mix within each block to help planners create surgical schedules with minimal bed requirements. This model comes after the full design of SBS using the simulation model mentioned above. However, since the application of this model was found not to be easy, the authors developed a set of scheduling guidelines to best determine the ORs schedules. First, group surgical blocks with similar ward requirements together, then within each group, schedule surgeon blocks with high patient volumes and long length of stay requirements at the beginning and the end of the week, finally, for wards that close on weekends, schedule surgeons with high demand for short length of stay cases (2 days) on Mondays and Wednesdays. Scheduling primarily on Mondays and Wednesdays maximizes ward utilization and minimizes patient off-servicing to inpatient

wards on the weekend. The main principle behind these guidelines is that surgical blocks should be scheduled based on both surgical ward requirements and patient mix.

Zhang et al. [45] worked on developing a Mixed Integer Program to the Block Time Scheduling problem, by developing the weekly OR allocations to each specialty. They assumed that all model input parameters are deterministic and proportional to OR time demand. The objective function of the introduced model is to maximize the time allocated to each specialty per week. In addition, the authors used some simulation-based analysis to evaluate the performance of MIP model.

2.5 Non-technical & Other Solutions

Other methods found in the literature to formulate and solve OR scheduling problem are few. At once, OR scheduling problem was modeled as a single machine scheduling problem with sequence dependent processing time and due dates, where patients are the jobs to be assigned to ORs (machines) with limited capacity [38]. Limiting the scope of surgeries to “day-surgeries” only (patients discharged on the same day of surgery), the authors formulated an NP-Hard problem to maximize the number of surgeries completed on-time. Then a branch-and-bound algorithm is proposed to solve the problem based on the Horowitz-Sahni algorithm. The surgeries preparation time was assumed to depend on the surgery type, therefore, sequence-dependent processing time that follows lognormal distribution is also assumed in the paper.

Min and Yih [27] considered the scheduling of patients with elective surgeries having different priorities for a single surgery type in one OR scenario. The problem was

modeled using stochastic dynamic programming to decide between the cost of overtime and the cost of surgery postponement. The value iteration method was used as a solution approach after deep investigation of the method structural analysis to improve its computational efficiency. Each patient's priority is generated from the weighted sum of the numerical values of three clinical criteria considered here to be disease progression, pain or dysfunction, and disability.

Holte and Mannino [16] studied the optimization of the Master Surgery Scheduling by using row and column generation algorithm adapting the implementer/ adversary algorithm for robust optimization introduced by Bienstock for portfolio selection.

Su et al. [39] introduced a self-organizing map optimization algorithm for the OR scheduling problem. They modeled the problem as flexible job-shop scheduling problem (FJSP) where N jobs are to be scheduled on M machines and each job consists of an ordered sequence of operations and each operation is performed on a single machine.

Zonderland et al. [47] investigated the impact of semi-urgent surgeries that represents an uncertain demand for hospital resources, in their evaluation. Therefore, the queuing theory models are used to evaluate the OR capacity needed to accommodate every incoming semi-urgent surgery and building a trade-off model between the cancellation rate of elective surgeries and unused OR time. Finally, a decision support tool based on Markov decision theory is developed to assist the scheduling process of elective and semi-urgent surgeries.

On the other hand, there exist some of the non-technical solutions used to improve ORs utilization or revues. Those include process re-engineering, lean, Six Sigma, and other

process improvement techniques. For example, Peters [31] was able to save \$2.5 million, generate additional hospital revenues and accommodate 14% more cases by redesigning surgery booking slots, using historical data when assigning new cases, introducing OR KPIs (first-case on-time rate, surgical infection rates, overall surgical/ patient satisfaction) and classifying ORs based on FCFS, open heart OR, and same-day OR.

Ferreira et. al [11] illustrated the benefits of a re-engineering project for a public Portuguese hospital with major enhancement resulted due to the introduction of a commercial simulation software used for the OR scheduling.

Schmalzried and Liszak [34] documented various approaches to lower the no-show rates, including changing behavior through education, sanctions, incentives, overbooking, and reminders. The authors highlighted that the most popular approaches have been reminder calls or mailings, which consume around 20 hours per week of staff time, in an average hospital size.

Zhu et al. [46] studied the factors yielding to long patient waiting time, and indirectly: clinic overtime. The reasons identified were overloaded session, late start of a session, unevenly distributed slots, irregular calling sequence, and unused session time. Recommendations have been developed to mitigate those causes and reduce patients waiting times. On the other hand, Gupta et al. [14] identified the common reasons for start-time delays to be lack of proper planning, deficiencies in team work, communication gap, and limited availability of trained supporting staff.

This concludes the literature review chapter and we will start detailing the problem discretion and solution approach in the next chapter.

CHAPTER 3

PROBLEM DESCRIPTION & SOLUTION APPROACH

In the previous chapters of this thesis, a SAMSO overview is presented and then the literature of Operating Rooms (ORs) Scheduling is discussed. This is the core chapter of the thesis where the ORs scheduling problem on hand will be described and solutions are discussed. This chapter comprises of four sections.

The first section documents SAMSO current ORs scheduling process and describes the problem to be researched. Based on the first section, the mathematical model to the current SAMSO OR scheduling problem is introduced and illustrated with a numerical example in the second section. This is followed by a case study that utilized real data obtained from SAMSO. The case study findings suggest looking at the current SAMSO Master Surgical Schedule (MSS). Therefore, a proposed MSS is introduced at the fourth section using two approaches to verify its practicality to SAMSO.

3.1 PROBLEM DESCRIPTION

In the context of Saudi Aramco Medical Services Organization (SAMSO), there are thirteen specialties that can request scheduling a surgical case at SAMSO ten ORs. Each specialty has a number of surgeons. Each OR is assigned to certain specialty, for a particular day at the week, this assignment is made by the OR scheduling team while trying to maintain balance between specialties. Where each specialty is reserved an OR

The surgeons are not full-time assigned to the ORs surgeries, but rather have their own clinic appointments. To enable them do both duties a schedule is developed. On annual basis; SAMSO management decide the assignment of OR time (blocks) between specialties, depending on each specialty demand. At SAMSO, each time block is found to be a full-day of one OR. This is known in the literature as the “Master Surgical Schedule (MSS)”. On the other hand, each specialty determines how to distribute their available OR time blocks to the specialty’s surgeons while maintaining clinical appointments load. This is often referred to as “Surgical Block Schedule (SBS)” in the literature. After such schedule is available, the OR scheduling team is informed and this schedule represents the “surgeon available time”, and the “surgeon assigned OR”. Currently, there is no coordination efforts exerted to prepare these schedules neither by the specialties nor by OR scheduling team. As a result, some days experience empty blocks while other experience over-booking. Table 1 represents SAMSO 2012 Master Surgical Schedule and Table 2 represents their Surgical Block Schedule.

When surgeons want to request a surgery, they access the OR schedule of a particular day, determine the available day, and add a request on that day. Once the surgeon request scheduling a surgical case, the request goes into a “working list”, more like a queue of surgeries for the requested date. Unfortunately, SAMSO scheduling system does not allow the surgeons to see their older requests through the “OR schedule”, rather, another transaction need to be executed in order for the surgeons to know their requested surgeries. This results in overbooking some days and under-booking others. The only way surgeon can see their surgeries requests is if the OR scheduling team has moved the surgery requests from the “working list” into the “OR schedule”.

Table 1: SAMSO 2012 Master Surgical Schedule.

OR Day	1	2	3	4	5	6	7	8	9	10
Saturday	ENT	Opthal.	Gyne	Dental	Urology	General	General		Thoracic	Ortho
Sunday	ENT	Opthal.	Gyne	Ortho	Urology	Plastic	Bariatric	General	Nurospinal	Nurospinal
Monday	ENT	Opthal.		Ortho	Urology	Plastic	General	Vascular	Nurospinal	Ortho
Tuesday	ENT	Opthal.	ENT	General	Urology	General		Vascular	Ortho	Ortho
Wednesday	ENT	Opthal.	Gyne	Dental	Dental	Plastic	General	Anesth.	Nurospinal	

Table 2: SAMSO 2012 Surgical Block Schedule.

OR Day	1	2	3	4	5	6	7	8	9	10
Saturday	ENT S1	Opthal. S1 S2	Gyne	Dental	Urology S1	General S3	General S4		Thoracic S1 S2	Ortho S3
Sunday	ENT S2	Opthal. S3 S4	Gyne	Ortho S5	Urology S2	Plastic S3	Bariatric S1	General	Nurospinal	Nurospinal
Monday	ENT S3	Opthal. S5		Ortho S6	Urology S3	Plastic S2	General S5	Vascular S1	Nurospinal	Ortho S1
Tuesday	ENT	Opthal. S6	ENT	General S1	Urology S4	General S2		Vascular S2	Ortho S4	Ortho S2
Wednesday	ENT	Opthal. S7	Gyne	Dental	Dental S1	Plastic S1	General	Anesth.	Nurospinal	

S: donate a surgeon from the same assigned specialty

Every working day, the scheduling team develops the OR schedule for the next day. The ORs available time is eight hours a day, for five days a week (Saturday through Wednesday). The eight hours of each room can be distributed into as many surgeries as needed; i.e., no fixed slot duration exists. When opening the work list screen, the ten ORs appear, each with the requested surgeries. Each surgery request includes the surgeon name and specialty, patient name and medical file number, decision from the pre-admission clinic (patient ready for surgery or not), name of special medical equipment needed, and surgery duration based on the average of the last three performed surgeries of the same type (system calculations, yet adjustable by surgeon or OR scheduling team “if needed”). The scheduling team then moves the surgery requests from the “working list” into the “OR schedule” for each OR separately. There are no rules for sequencing the surgeries of each OR, however, based on the experience of the team, some cases that require certain medical examinations to be made on the day of surgery should not be scheduled as the first surgery. Currently, the team is usually successful in accommodating all the cases of each OR with no overtime and while meeting the surgeons’ availability. If an extra capacity is found, the team tries to pull some surgeries from next days to the current day, providing that it is for the same surgeon and that the surgeon himself approve such action. In addition, if another surgeon requested a surgery in a day that he is not assigned an OR at, then, he would “follow” the originally assigned surgeon. At the same time, the team does not allow a surgeon to operate in multiple rooms during the day; mainly to avoid scheduling complexity and for convenience factors of the surgeons.

Figure 5 summarizes the patient journey from the time they see the primary care physician until they are discharged from the surgery back to home.

It was observed that the current system generated durations include the surgery turnover time. Which is the time needed to clean the OR, bring necessary surgery tools/ equipment, and bring the next patient. However, most of the turnaround time is spent on cleaning the OR since tools required are readily available and the patient should pass through his/ her preparation outside the OR i.e., Day Surgery Suite or In Patient room. Therefore, the OR scheduling team assumes that OR cases follow each other with no gaps, since the turnover durations are already imbedded in. Currently, the average turnaround time is around 25 minutes. Yet, this duration varies significantly between surgery types and specialties. SAMSO management aims to reduce the turnover time to an average of 15 minutes through an ongoing Lean Six Sigma project.

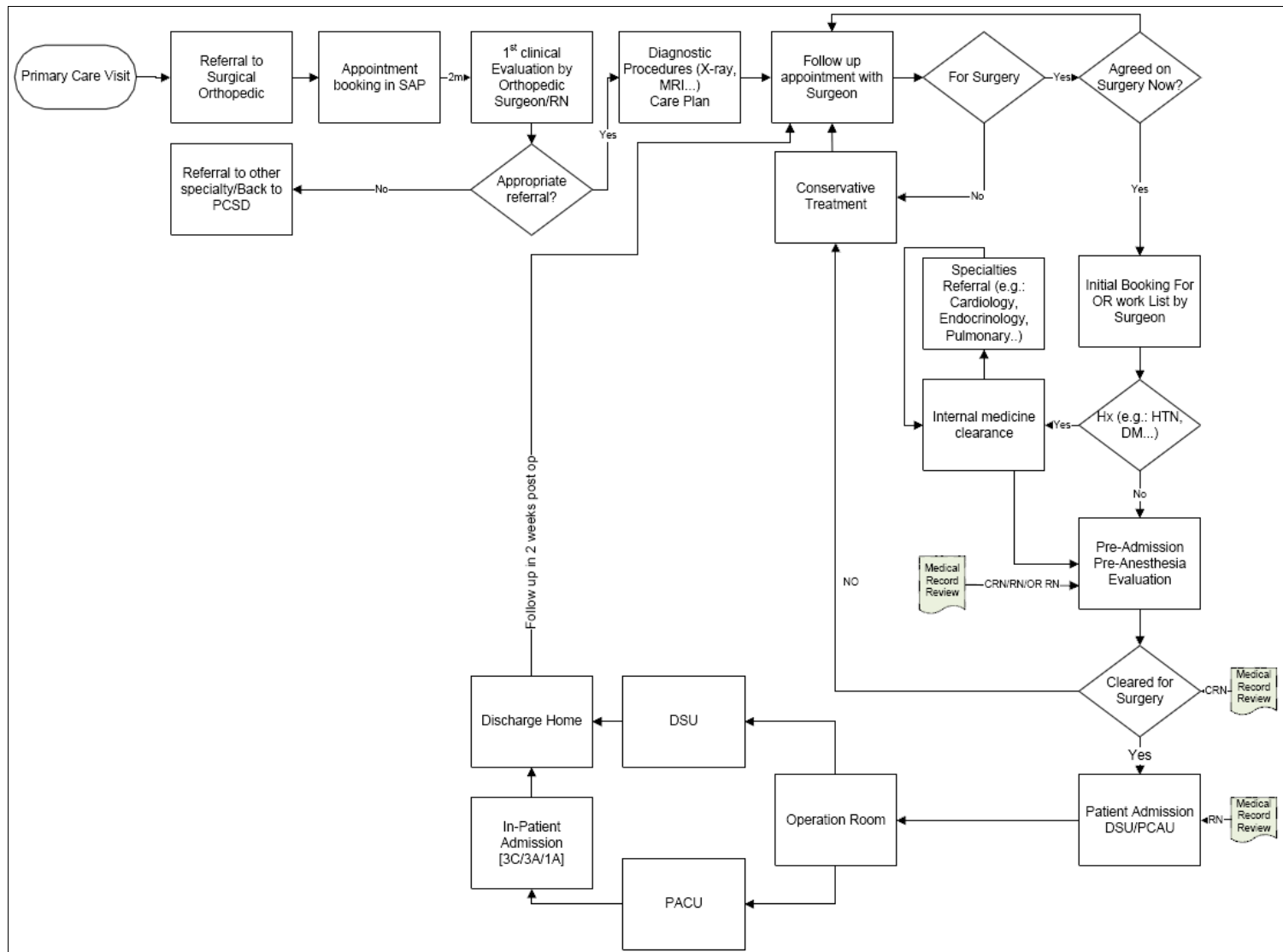


Figure 5: SAMSO ORs Scheduling Process (Orthopedic Cases), source: SAMSO

In this thesis, the ORs scheduling will be looked at in the context of SAMSO ORs. A mathematical model is developed to provide SAMSO ORs scheduling team the optimum ORs schedule that considers ORs utilization rate, patients waiting time, cases criticality, and sequencing preferences. The introduced mathematical model maintains the current Surgical Block Schedule (SBS) of SAMSO since it is tightly linked with the surgeons' clinic appointments.

This work excludes the admission of emergency cases; those can be scheduled after working hours or fitted in the generated ORs schedule after running the model. In addition, we assume that all patients show for their surgery on the requested time, the same applies for the surgeons and ORs medical staff.

3.2 SAMSO ORs Mathematical Program

In this section, we present a mathematical model developed to optimally schedule SAMSO ORs while maintaining its current Surgical Block Schedule (SBS). The SBS describes the ORs assignments to each specialist for each working day. Therefore, on a given day, each OR is expecting a queue generated from its assigned specialist. Since the SBS is maintained, the ORs scheduling problem will be solved for each OR independently for each day. Hence, the problem is to:

- Select what cases to be scheduled from the requested surgeries.
- Sequencing the selected surgeries following SAMSO internal guidelines.

SAMSO is not a profit oriented organization; therefore, our objective function may not include direct cost elements; unlike many of the literature work. In this work, we try to maximize the ORs utilization by occupying as much time as possible. At the same time, we would like to choose the patients who have the highest priority for scheduling. Patient's priority is represented by a numerical value that results from the multiplication of the patient waiting time and the case criticality, where the higher the priority value, the more important is the case associated with this priority value [28].

In this work, we assume that the duration of surgeries is deterministic. However, each specialty has its own turnaround deterministic time. In addition, we assume that the pre-surgery and post care units are capable of handling all of the ORs scheduled cases. As we mentioned earlier, emergency cases are excluded from this scheduling problem and that both patients and surgeons are expected to show on time for their surgeries. To avoid surgery cancellation, all requested surgeries are assumed to meet the medical requirements and tests, and have been "cleared" from the pre-admission clinic of SAMSO. Furthermore, if the demand of a particular OR is more than its available capacity, then patients can be deferred to later date. Finally, we assume the availability of medical tools and equipment prior to the start time of each surgery.

SAMSO has certain procedures and guidelines regarding the sequencing of surgeries within each OR. First, day surgeries are preferred to start early in the morning. This is to discharge patients before evening time, as possible, therefore, enhancing the safety of those patients during their commute from/ to Dhahran and utilize the company provided transportation available before the evening time. Second, since add-on cases are only requested within 24 hours from the surgery day, these have second priority after the

elective cases. Third, SAMSO management tries their best to avoid overtime, hence, trying to accommodate all surgeries within the ORs eight hours operating time. Finally, a surgeon cases are preferred to be continuous i.e. no gaps between surgeries.

3.2.1 Variables and Sets:

Before we write down the mathematical model, let us define the following:

- $k \in (1, 2)$, where 1 represents a day-surgery patient type and 2 represents same-day or inpatient type
- $l \in (1, 2)$, where 1 represents an add-on case type and 2 represents elective case type
- J_{kl} represents the set of surgeries requested at each OR for one particular day. Therefore, we will have four potential sets in each OR: J_{11} , J_{12} , J_{21} , and J_{22} .
- $\theta \in [0,1]$ To be a flexible weight value to decide how important is it to have the day surgeries early in the morning. The value of θ is chosen to be small so that the first part remains the main contributor to the objective function's value.
- u be a location index that indicates the position of case within the resulting sequence where the u can have a maximum value of $\sum_{l=1}^2 \sum_{k=1}^2 |J_{kl}|$, which is the total number of cases to be scheduled on a given day.
- c_{klj} to be the numerical value that represents the criticality of case number j of surgery type k , and patient type l , determined by the surgeon when requesting the surgery on a scale of 1-10.
- w_{klj} represents the patient's waiting time, system calculated number (in days) for each case number j of surgery type k , and patient type l .

- p_{klj} represents the priority of case number j of surgery type k , and patient type l defined by the multiplication of that case's criticality and its patient's waiting time;
 $p_{klj} = c_{klj} * w_{klj}$
- d_{klj} to be the duration of case number j of surgery type k , and patient type l .
- TA to be the turnaround time between surgeries, this includes the OR cleaning time and equipment checks time between cases, each specialty has its own turnaround time depending on the performed procedures inside the OR, since all the cases assigned to one OR are within the same specialty; this value is fixed for all cases of that studied OR. In this model, we assume that each OR starts the day cleaned and ready to start the surgery.
- $x_{klj} \in (1, 0)$, where it equals 1 if the case number j of surgery type k , and patient type l is selected for assignment in this OR and 0 if not.
- $y_{klju} \in (1, 0)$, 1 if the surgical case (x_{klj}) is assigned to the position (u) and 0 otherwise.

3.2.2 Mathematical Model

This section introduces the mathematical program developed to select the surgical cases to be scheduled and determine the optimum sequence of selected cases for each OR.

$$Max \sum_{l=1}^2 \sum_{k=1}^2 \sum_j^{|J_{kl}|} p_{klj} d_{klj} x_{klj} + \theta \left[\sum_{u=1}^{|U_{J_{12}}|} \sum_j^{|J_{12}|} y_{12ju} + \sum_{u=1}^{|U_{J_{11}}|} \sum_j^{|J_{11}|} y_{11ju} \right] \quad (1)$$

Subject to

$$\sum_{l=1}^2 \sum_{k=1}^2 \sum_j^{|J_{kl}|} d_{klj} x_{klj} + TA \left[\sum_j^{|J_{kl}|} x_{klj} - 1 \right] \leq 8 \quad (2)$$

$$\sum_j^{|J_{12}|} (d_{12j} + TA) x_{12j} + \sum_j^{|J_{11}|} (d_{11j} + TA) x_{11j} \leq 5 - TA \quad (3)$$

$$\begin{aligned} & \sum_j^{|J_{12}|} (d_{12j} + TA) x_{12j} + \sum_j^{|J_{11}|} (d_{11j} + TA) x_{11j} + \sum_j^{|J_{22}|} (d_{22j} + TA) x_{22j} \\ & + \sum_j^{|J_{21}|} (d_{21j} + TA) x_{21j} \leq 8 - TA \end{aligned} \quad (4)$$

$$\sum_{u=1}^{\sum_{k=1}^2 \sum_{l=1}^2 |J_{kl}|} y_{klju} = x_{klj} \quad \forall k, l, j \quad (5)$$

$$\sum_{l=1}^2 \sum_{k=1}^2 \sum_j^{|J_{kl}|} y_{klju} \leq 1 \quad \forall u \quad (6)$$

$$\sum_{u=1}^{|J_{12}|} \sum_j^{|J_{12}|} y_{12ju} + \sum_{u=1}^{|J_{11}|} \sum_j^{|J_{11}|} y_{11ju} \leq \sum_j^{|J_{12}|} x_{12j} + \sum_j^{|J_{11}|} x_{11j} \quad (7)$$

$$p_{klj} = c_{klj} w_{klj} \quad (8)$$

$$p_{klj}, c_{klj}, w_{klj}, d_{klj} > 0 \quad (9)$$

$$y_{klju} = \{0,1\} \forall k, l, j, u \quad (10)$$

$$x_{klj} = \{0,1\} \forall k, l, j \quad (11)$$

The model considers all the cases requested to be scheduled in a particular OR. The output of the model is in terms of x 's and y 's. Where the x 's variables present the cases to be scheduled and y 's represents their ranks (sequencing order) in the OR schedule. The start time of each case can be easily calculated after stacking the cases in the proper (y) given order. The below is a description of each part of the model:

(1) is the objective function which consists of two parts. The first part maximizes the priority and duration of assigned cases to each OR. This works on maximizing the utilization of the OR as well as selecting the highest priority cases to be scheduled. The second part introduces a weight (θ) that increases the objective function value upon scheduling cases from the sets J_{I2} and J_{I1} during early morning slots. Therefore, pushing the model toward assigning cases from the sets J_{I2} and J_{I1} before cases from other sets.

Constraint (2) limits the selected cases to be accommodated within normal operating hours of eight hours per OR per day, thus disallowing overtime, while constraint (3) is concerned with assigning all day surgeries to finish before 12 pm. Since those day surgeries can be “electives” or “add-ons”, both sets are chosen in the constraint.

We introduce constraint (4) to ensure that no gaps between assigned surgeries exist and that all cases are completed before 3:00 pm.

- (5) This constraint links the cases assignments “ x ’s” with the rank of each assigned cases “ y ” by ensuring that a rank is awarded to each selected cases and only them.
- (6) This is a logical constraint that limits the number of assigned cases in each rank to one case only.
- (7) This constraint is introduced to enforce assigning the first ranks to the cases from sets J_{12} and J_{11} (Day Surgeries).
- (8) The case priority equals the multiplication of its criticality and the patient’s waiting time before placed on the schedule, both values are deterministic and determined by from the patient’s medical records.
- (9) Non-negativity constraints, while (10) and (11) are binary constraints for the x ’s and y ’s defined earlier.

3.2.3 Numerical Example

In this section we present a numerical example of four cases where the values of k , l , d , p , and TA are randomly generated. Table 3 shows the details of each of the four cases. Figure 6 shows the mathematical model used to solve the example. The value of θ used here is 0.6.

The model is solved using LINGO13.0 (input and output can be found at Appendix A), to obtain the solution at Table 4. Under this solution, cases 2, 3, and 4 are selected to be scheduled based on their priority value and the duration limitation of each set. The selected cases are then ordered based on the preference given to Day Surgeries over

Inpatient/ Same Day, and for Elective cases over Add-in. The cases are ordered 1, 3, 2 respectively, where the total Operating Room utilization is calculated to be 92.5% with only 7.5% of remaining OR capacity.

Table 3: Mathematical Model Numerical Example Data

Case	Priority (p_{klj})	Duration(d_{klj})	Patient Type (k)	Admission Type (l)	TA
1	3	2	Day Surgery (1)	Add-on (1)	0.20
2	5	2	Day Surgery (1)	Elective (2)	0.20
3	6	1	Same-Day (2)	Add-on (1)	0.20
4	10	4	Inpatient (2)	Add-on (1)	0.20

Table 4: Mathematical Model Numerical Example Solution

Case	Assigned	Order
1	No	-
2	Yes	1
3	Yes	3
4	Yes	2

Maximise $6x_{111}+10x_{121}+6x_{211}+40x_{212}+0.6(y_{1211}+y_{1111}+y_{1212}+y_{1112})$

$$2x_{111}+2x_{121}+x_{211}+4x_{212}+0.2(x_{111}+x_{121}+x_{211}+x_{212} -1)\leq 8$$

$$2.2*x_{121}+2.2*x_{111}\leq 5 - 0.2$$

$$2.2x_{121}+2.2x_{111}+1.2x_{211}+4.2x_{212}\leq 8 - 0.2$$

$$y_{1111}+y_{1112}+y_{1113}+y_{1114}= x_{111}$$

$$y_{1211}+y_{1212}+y_{1213}+y_{1214}=x_{121}$$

$$y_{2111}+y_{2112}+y_{2113}+y_{2114}=x_{211}$$

$$y_{2121}+y_{2122}+y_{2123}+y_{2124}=x_{212}$$

$$y_{1111}+y_{1211}+y_{2111}+y_{2121}\leq 1$$

$$y_{1112}+y_{1212}+y_{2112}+y_{2122}\leq 1$$

$$y_{1113}+y_{1213}+y_{2113}+y_{2123}\leq 1$$

$$y_{1114}+y_{1214}+y_{2114}+y_{2124}\leq 1$$

$$y_{1211}+y_{1111}+y_{1212}+y_{1112}\leq x_{121}+x_{111}$$

$$x_{111}, x_{121}, x_{211}, x_{212}= \{0,1\}$$

$$y_{1111}, y_{1211}, y_{2111}, y_{2121}, y_{1112}, y_{1212}, y_{2112}, y_{2122}, y_{1113}, y_{1213}, y_{2113}, y_{2123}, y_{1114}, y_{1214}, y_{2114},$$

$$y_{2124}= \{0,1\}$$

Figure 6: Mathematical Model Numerical Example Expansion

3.3 SAMSO Case Study

In this section of the chapter, we address applying the mathematical model developed in section 3.2 to the surgeries requested on a random day at SAMSO. This section includes three parts; the first discusses and presents the data used. The second part illustrates the solution obtained. While the last part documents the major observations and findings on both the data used and the resulted solution.

3.3.1 Case Study Data

The surgery requests of a random day (April 15th 2013) were used to feed section 3.2 mathematical model in order to determine what the cases to be scheduled are, and what sequence should they have. Table 5 shows all the cases durations, patient and admission types, and the turnaround time under each of the ten Operating Rooms. It should be noted that some difficulties were faced to determine the priority value of each case; therefore, the average of ten randomly generated values (each between one and ten) was used to represent p_{klj} . Finally, the value of θ used here is 0.6, although it can be any value between zero and one.

Table 5: SAMSO Case Study- (April 15 2013) Data

OR no.	Case	Priority (p_{klj})	Duration (d_{klj})	Patient Type (k)	Admission Type (l)	TA
1	1	7	0.50	2	2	0.16
1	2	5.8	0.50	1	2	0.16
1	3	3	0.50	1	2	0.16
1	4	6.6	0.42	1	2	0.16
1	5	7.2	0.42	1	2	0.16
2	1	4.6	0.67	1	2	0.16
2	2	6.6	0.58	1	2	0.16
2	3	4.4	0.58	1	2	0.16
2	4	5.6	0.67	1	2	0.16
3	1	4.6	0.17	1	1	0.16
3	2	5.8	0.50	1	1	0.16
4	1	6.2	0.83	1	2	0.33
4	2	3.4	1.33	2	2	0.33
4	3	6.2	0.50	2	2	0.33
4	4	3.4	0.50	2	1	0.33
5	1	5.4	0.08	2	2	0.16
5	2	3.8	0.75	2	2	0.16
6	1	6	0.67	1	2	0.33
6	2	4.6	0.67	1	2	0.33
6	3	5.8	1.67	1	2	0.33
6	4	4	1.75	2	2	0.33
7	1	5.4	1.33	2	2	0.33
7	2	4.8	2.92	2	2	0.33
8	1	6	1.25	1	2	0.50
8	2	4	3.58	2	2	0.50
8	3	6.6	1.50	2	2	0.50
8	4	4.2	3.58	2	2	0.50
9	1	7.8	0.08	1	2	0.25
9	2	5.8	2.50	2	2	0.25
9	3	5.2	1.42	1	2	0.25
9	4	5	0.92	1	2	0.25
9	5	4	6.75	2	2	0.25
10	1	5.2	2.08	2	2	0.50

3.3.2 Case Study Solution

The mathematical model is designed to work for each Operating Room independently. Therefore, each OR's data were inputted in LINGO software to determine the optimum cases to be scheduled along with their sequence. All the LINGO inputs/ outputs can be found at Appendix B.

Out of 33 cases, 31 (94%) were selected to be scheduled by the mathematical model compared to 29 (88%) cases selected by SAMSO scheduling team. Figure 7 illustrates the schedule obtained for the selected cases and compares that to the ORs schedule developed by SAMSO scheduling team.

In addition, two measures are introduced to reflect the performance of both schedules. The first measure is the OR utilization, which is defined by the amount of scheduled OR time and turnaround time compared to the OR available time (8 hours per day). The second measure is the OR remaining capacity after the last scheduled case.

Under the first measure, we can see in Figure 7 that the introduced mathematical model achieved higher percentage of OR utilization in 6 out of the 10 ORs. The average overall percentage of ORs time utilization for this date is 47% which is 26% higher than the utilization rate obtained by SAMSO scheduling team as illustrated at Figure 8. Although this percentage represents moderate utilization, the mathematical model ability to stack the cases introduces significant capacity that is quantified by the second measure. We can see that up to 92% of the ORs time can be still utilized to fit in more cases; see Figure 9. Overall, 54% of all the ORs time is identified as additional capacity; this is 252% more than that obtained using SAMSO scheduling team.

OR no	Solution Method	Time (Hr.)																OR Utilization	Remain. Capacity After Last Case
		0700	0730	0800	0830	0900	0930	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430		
1	MD	2	5	3	4	1												37%	63%
	SAMSO		1			2		3		4								30%	33%
2	MD	3	2	4	1													38%	63%
	SAMSO		1		2		3	4										38%	44%
3	MD	1	2															8%	92%
	SAMSO												1	2				8%	8%
4	MD	1		2		3		4										52%	48%
	SAMSO			1		2						3						42%	21%
5	MD	1	2															12%	88%
	SAMSO								1				2					12%	17%
6	MD		4			3		2		1								72%	28%
	SAMSO		1			2				3							4 ...	58%	0%
7	MD			2				1										57%	43%
	SAMSO		1					2										57%	27%
8	MD			4						3			1					92%	8%
	SAMSO					1				4**			3					66%	2%
9	MD		3		1		4		2									71%	29%
	SAMSO	2**		3				4								1		43%	0%
10	MD		1															26%	74%
	SAMSO														1	...		16%	0%
* OR Utilization does not include time spent/ scheduled after 1500													MD Average Utilization			47%	54%		
** Those cases were completed in less than the scheduled duration													SAMSO Average Utilization			37%	15%		
													Improvement % from SAMSO to MD			26%	252%		

Figure 7: SAMSO Case Study- a comparison between proposed Mathematical Model (MD) and current SAMSO scheduling system

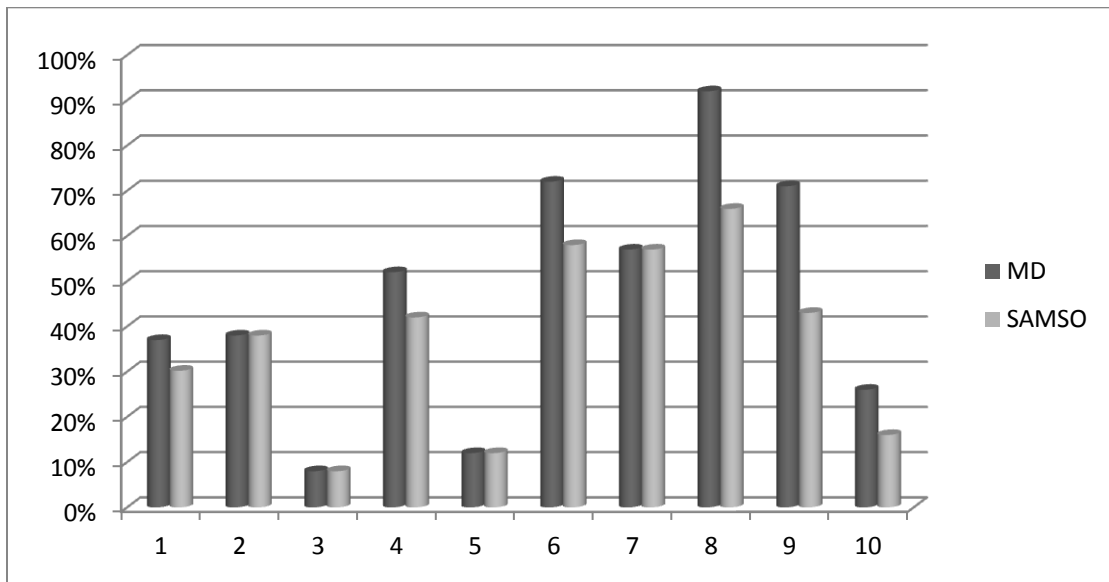


Figure 8: SAMSO Case Study- ORs Utilization under the proposed Mathematical Model (MD) and current SAMSO scheduling system

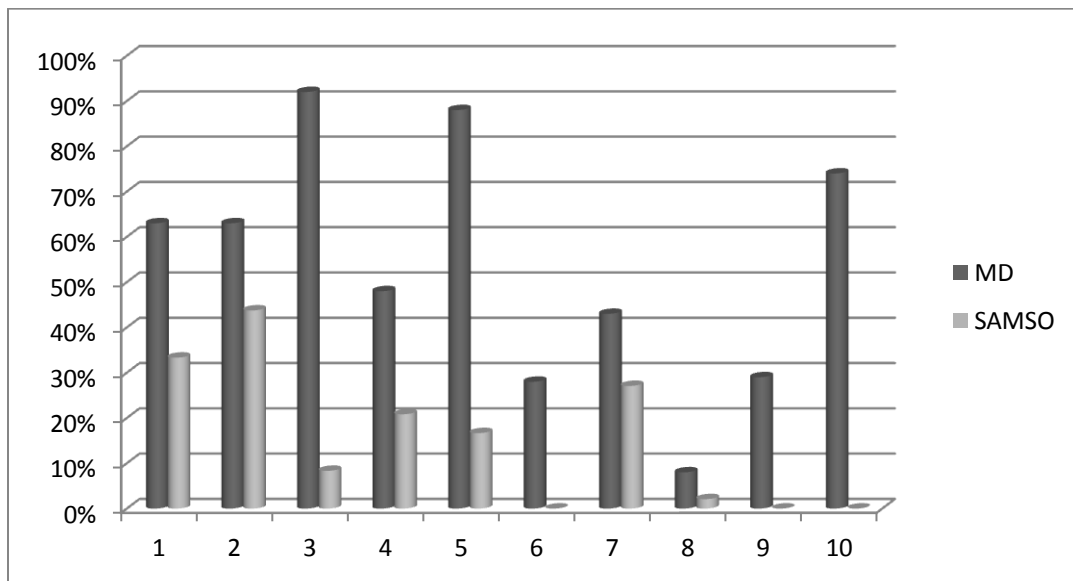


Figure 9: SAMSO Case Study- ORs Remaining Capacity (% of OR Time) under the proposed Mathematical Model (MD) and current SAMSO scheduling system

3.3.3 Case Study Observations & Findings

In the previous two sub-sections, we presented and discussed SAMSO case study data and solution. However, there are some major findings that can be observed from the solution generated and from the extensive analysis performed on SAMSO surgery requests for the year 2012.

From the solution illustrated at Figure 7, we can conclude that although SAMSO scheduling team have certain preferences and scheduling procedures, they were not seen to put in place. For example, OR#9 started the day with an inpatient before the scheduling of other available Day-surgeries. This contradicts with the preference in day-surgeries over other types of cases. The same conclusion can be made at OR#1.

Another notable observation is the amount of time wasted as gaps between surgeries. According to the assumptions made, each surgeon is assigned on full-time basis for the day having surgeries at his/ her OR. These gaps are mostly attributed to surgeons' preference or difficulties in finishing the scheduled cases on time.

Furthermore, despite the available capacity at OR#6 and OR#10, over time costs were recorded due to the last case scheduling in each of the two ORs.

The historical workload of 2012 and future surgery requests for the year 2013 are examined to have a bigger picture. Looking at 2012 OR time distribution per specialty (Figure 10), we see that four specialties (ENT, EYE, General, and Ortho) account for 57% of all SAMSO surgical requests that were scheduled within the ORs working hours for all days at 2012. On the other hand, 57% of the OR time is being consumed on surgical cases that belong to four specialties (Gyne, Neurology, General, and Ortho). This

indicates that higher number of surgeries assigned to an OR does not mean that is more utilized since there exists a significant fluctuation in the duration of a surgical case between specialty and another.

It looks like SAMSO surgeons prefer to start their week fresh with few cases performed on Saturdays. Figure 11 summarizes the number of surgical cases performed in each day of the week during 2012 year. Each day cases are classified based on the patient admission type. We can see the high number of Day-surgeries performed on Wednesdays mainly to avoid patient visits for follow-ups during the weekends.

It worth to highlight that more than 72% of SAMSO surgical requests for the year 2013, as extracted on February 27th, 2013, belong to the Plastic and Ortho specialties. Figure 12 includes the full list. This can be a sign that SAMSO does not really have a scheduling problem more than shortage of staffing in those highly demanded specialties or lack of proper distribution to their OR time blocks.

In light of the above observations, it was evident that the question need to be asked is: does SAMSO ORs experience underutilization due to scheduling problem, or were they just over-capacitated? If SAMSO can run with less number of ORs, what would that number be and how does the optimum Master Surgical Schedule look like? Those are the questions addressed at the next section of this chapter.

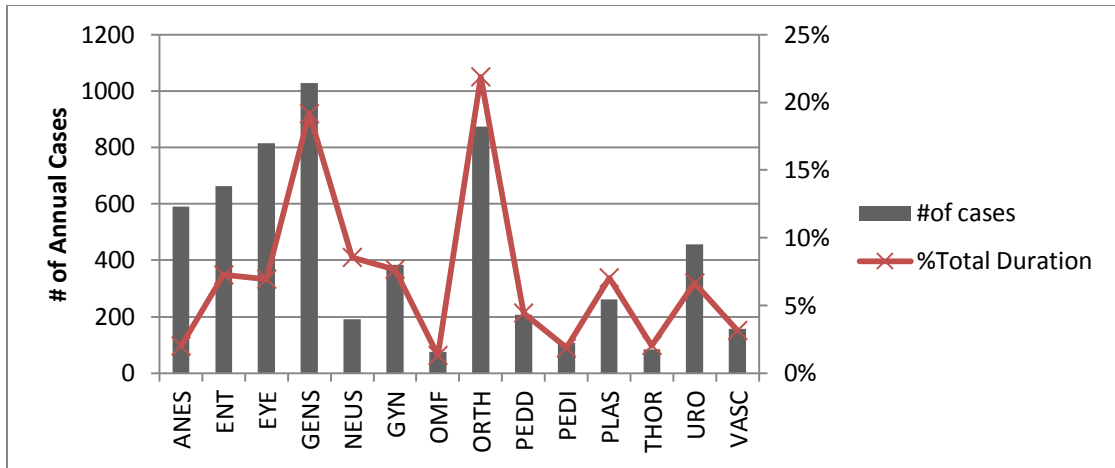


Figure 10: SAMSO 2012 cases and utilization contribution for each specialty

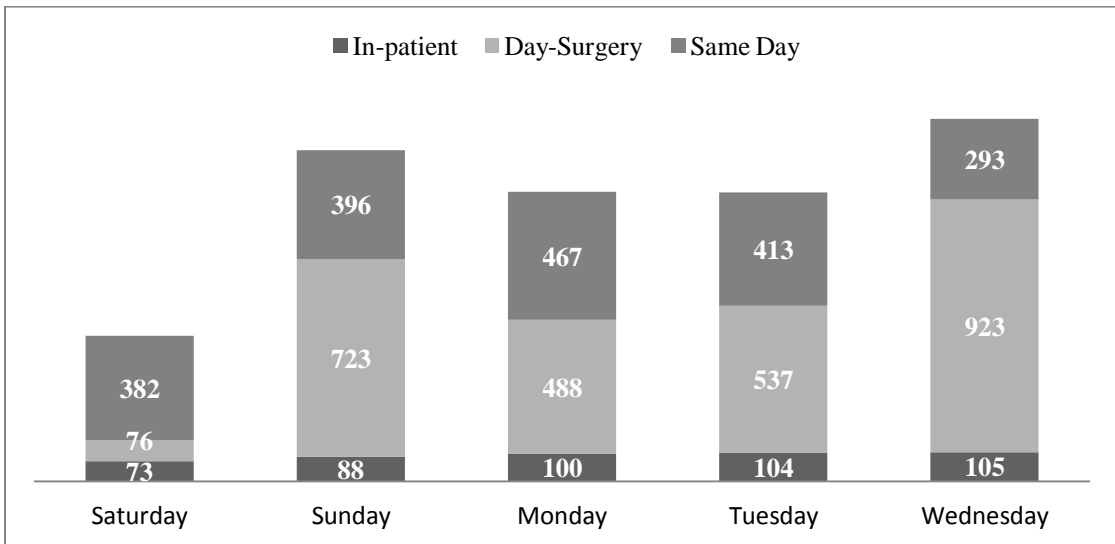


Figure 11: SAMSO 2012 Surgeries Distribution By Work Day and Admission Type

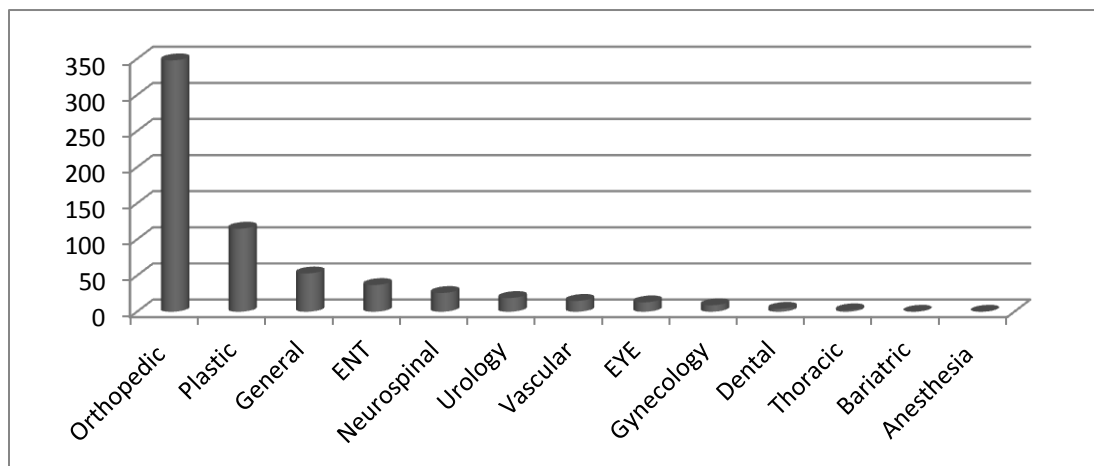


Figure 12: SAMSO future 2013 surgery requests as appeared on February 27th, 2013

3.4 Defining SAMSO’s Optimum Master Surgical Schedule “MSS”

In this section, we define the optimum OR time assignment to the thirteen SAMSO specialties based on their workload for one complete year (2012). The section consists of three parts. The first part describes the analysis done to generate the new Master Surgical Schedule “MSS”. The second part of the section aims to verify the proposed MSS using the total duration for each OR per day. Finally, the last part ensures the applicability of the proposed MSS by utilizing a bin-packing problem approach.

3.4.1 Generating a New SAMSO MSS

The ORs schedule of 2012 is obtained through SAMSO scheduling team; this includes the actual durations of all performed surgeries. Then, each specialty is studied separately to determine the amount of OR time required for each particular day of the week. Therefore, the total time scheduled is obtained throughout the year. Table 6 presents the complete analysis done for one specialty (EYE) to illustrate the approach. We need to highlight that the “Needed Capacity” is inclusive of the turnaround time between surgeries. Moreover, the “Full OR Capacity” takes into consideration the number of off-days and surgeons vacations. It is assumed to have 50 working “schedulable” day in the year.

The above approach is applied for each specialty; Table 7 summarized the (Needed) and (Assigned) Capacities of each Specialty by Day. As a final step, each specialty is added to the MSS manually, at this stage, new grouping of specialties per day is developed in

trying to minimize the number of OR time blocks. Table 8 represents the proposed SAMSO new MSS while Table 9 compares the current MSS blocks assignments to the proposed MSS. Under the proposed MSS, SAMSO can save up to 33% of its OR time blocks; thus building additional capacity and avoiding unnecessary costs.

Table 6: SAMSO Proposed MSS- EYE Specialty

Day	2012 Cases	Total Consumed Duration (min.)	Needed Capacity (Hr/ Yr)	Full Day OR Capacity (Hr/ Yr)	#of ORs Needed	Currently Assigned OR Blocks	Proposed Assigned OR Blocks
Saturday	192	9742	185	400	0.46	1	0.5
Sunday	170	9146	171	400	0.43	1	0.5
Monday	148	7963	148	400	0.37	1	0.5
Tuesday	127	8751	158	400	0.40	1	0.5
Wednesday	178	7990	153	400	0.38	1	0.5

Table 7: SAMSO ORs capacity requirements during 2012 and proposed block assignments

Day	Capacity	ENT	EYE	Gynecology	Neurology	Dental	Urology	Bariatric	Orthopedic	Plastic	General	Thoracic	Vascular	Anesthesia
Saturday	Required	0.42	0.46	0.41	0	0.31	0.49	0.27	1.29	0	1.74	0.18	0	0.12
	Assigned	0.5	0.5	0.5	0	0.5	1	0.5	2	0	2	0	0	0
Sunday	Required	0.54	0.43	0.74	0.93	0.40	0.70	0.01	0.81	0.23	1.00	0	0.01	0.03
	Assigned	0.5	0.5	1	1	0.50	1	0	1	0	1	0	0	0
Monday	Required	0.46	0.37	0.12	0.57	0	0.27	0.09	1.87	0.82	1.08	0.16	0.41	0.02
	Assigned	0.5	0.5	0	0.5	0	0	0	2	1	1	0.5	0.5	0
Tuesday	Required	0.27	0.40	0.10	0.03	0	0.15	0	1.91	0.12	1.73	0.07	0.36	0.01
	Assigned	0.5	0.5	0	0	0	0	0	2	0	2	0	0.5	0
Wednesday	Required	0.38	0.38	0.75	0.68	0.88	0.27	0.02	0.64	0.70	0.1	0	0.01	0.49
	Assigned	0.5	0.5	1	1	1	0	0	0	1	0	0	0.01	0.5

Table 8: SAMSO Proposed Master Surgical Schedule

OR Day	1	2	3	4	5	6	7	8	9	10
Saturday	ENT	General	General	Ortho	Ortho	Dental				
	Opthal.									
Sunday	Opthal.	General	Gyne	Ortho	Nurospinal	Urology				
	ENT									
Monday	ENT	General	Plastic	Ortho	Urology	Vascular	Ortho			
	Opthal.					Thoracic				
Tuesday	Opthal.	General	General	Ortho	Ortho	Vascular				
	ENT					Bariatric				
Wednesday	ENT	Nurospinal	Gyne	Plastic	Gyne	Dental				
	Opthal.				Anesth.					

Table 9: Number of OR Blocks comparison between the proposed MSS and SAMSO current MSS

Specialty	Old # of Blocks*	Proposed # of Blocks Assigned	Change
ENT	6	2.5	-3.5
Ophthalmology (Eye)	5	2.5	-2.5
Gynecology	3	2.5	-0.5
Neurology/ Neurospinal	4	2	-2
Dental (OMF&PEDD)	3	2	-1
Urology	4	2	-2
Bariatric	1	0.5	-0.5
Orthopedic	6	7	+1
Plastic	3	2	-1
General	7	6	-1
Thoracic (Chest/ Lungs)	1	0.5	-0.5
Vascular	2	1	-1
Anesthesia	1	0.5	-0.5
TOTAL	46	31	-15

* Each Block is represented by one full day of one OR

3.4.2 Total Duration Verification to the Proposed SAMSO MSS

In this section, we would like to verify the feasibility of SAMSO proposed MSS in section 3.4.1. To accomplish this, we compare the total duration for all the scheduled cases of each specialty and for each day, however, under the current MSS available OR time. Then, three questions are answered:

1. How many days, out of the current number of days with scheduled cases, where the assigned OR block is not enough to cover the OR workload?
2. If we fully utilize the assigned OR block time for all the days with scheduled cases; would it be enough to cover that OR's workload?
3. If we fully utilize the assigned OR block time for all the days in the year (excluding holidays and vacations); would it be enough to cover that OR's workload?

Answering the above three questions requires extensive analysis, therefore, two specialties (ENT and General) are selected and performed the analysis on. Table 10 summarizes the findings. We can see that under the current unbalanced distribution of cases between the weeks, it is only possible almost 50% of the time to accommodate all scheduled cases within the assigned OR block time. As we stretch the system to full utilization during days with scheduled cases and then during all days, we see better results. Actually, it is proved that the proposed SAMSO MSS is practical to work with if we utilize the full OR assigned time all the days possible in the year.

Table 10: Total Duration Verification to the Proposed SAMSO MSS for ENT and General Specialties

Specialty	# of Days with Scheduled Cases	Target # of Days with Scheduled Cases	# of Days where assigned OR block is <u>not</u> enough	Is assigned OR block time enough under (1)	Is assigned OR block time enough under (2)
ENT- Saturday	37	48	20	No	Yes
ENT- Sunday	36	48	30	No	Yes
ENT- Monday	31	48	19	No	Yes
ENT- Tuesday	38	48	4	Yes	Yes
ENT- Wednesday	37	48	17	Yes	Yes
General- Saturday	43	48	15	Yes	Yes
General - Sunday	43	48	23	No	Yes
General - Monday	47	48	24	No	Yes*
General - Tuesday	49	48	11	Yes	Yes
General - Wednesday	17	48	17	Yes	Yes

(1) Balance within currently scheduled Days

(2) Balance within currently scheduled Days and schedule up to the Target number of Days

* only if 20 Surgery-Hours are deferred to other days

3.4.3 Bin Packing Approach to Verify the Proposed SAMSO MSS

In this section, we would like to verify the feasibility of SAMSO proposed MSS in section 3.4.1 using a Bin Packing Approach. Through our literature review, we found this type of Bin Packing to be known as “High Multiplicity Bin Packing Problem (HMBP)”. It typically defined as “*Given a set of objects with different sizes (or weights) and multiplicities, is there a feasible assignment of all items to (n) bins of capacity (C) each?*” [48]. The problem’s definition is:

Let $v \in N^m$, $w \in R^m$, and $C \in R^m$. A general High Multiplicity Bin Packing Instance $B = (v, w, C)$ consists of m classes of items. Each class i contains v_i items of size w_i each. Furthermore, n bins of capacity C_j , $j \in \{1 \dots n\}$ are given. The decision variant of the general High Multiplicity Bin Packing Problem consists in determining if there is a distribution of items to the bins, such that no bin capacity is exceeded, and no item is left unpacked.

To test the practicality of SAMSO proposed MSS, we deal with each week data in an isolation of another. Therefore, each specialty would have would have (n) available bins each week and each bin has a capacity “length” of (C_j). We would like to determine if we can fit all the weekly cases of that specialty under the given bins’ available capacity. Of course, the capacity of bins is calculated adapting the proposed MSS. Moreover, the number of specialty weekly cases is determined using SAMSO’s historical data of 2012. Then, the obtained number of cases per week is classified based on each case length (in minutes); i.e., 30, 60, 90... etc. Hence, we generate the number of items (m) and the multiplicity of each item (v_i). Table 11 illustrates an example of the General specialty data.

Table 11: General Specialty Data used to determine the items and multiplicity for HMBP

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v_i)
0-30	30	7	1%	0.14	0
31-60	60	175	17%	3.57	4
61-90	90	282	27%	5.76	6
91-120	120	194	19%	3.96	4
121-150	150	138	13%	2.82	3
151-180	180	90	9%	1.84	2
181-210	210	44	4%	0.90	1
211-240	240	32	3%	0.65	1
241+	270	67	7%	1.37	0
Average Number of Cases per Week =21.00				Specialty: General	

A table similar to Table 11 is generated for each of the thirteen SAMSO specialties; those can be found at Appendix C.

HMBP mathematical model below is applied to all specialties. Where y_j is a binary variable that decides the need to utilize the bin or not, and x_{ij} is an integer variable that determine the number of assigned items to each of the bins [48].

$$\text{Min } \sum_{j=1}^K y_j$$

Subject to

$$\sum_{i=1}^m w_i x_{ij} \leq C y_j \quad \forall j \in \{1, \dots, K\}$$

$$\sum_{j=1}^m x_{ij} = v_i \quad \forall i \in \{1, \dots, m\}$$

$$x_{ij} = \mathbb{Z} \quad \forall i \in \{1, \dots, m\}, \forall j \in \{1, \dots, K\}$$

$$y_j \in \{0, 1\} \quad \forall j \in \{1, \dots, K\}$$

Since the average number of cases performed per year is a critical factor in determining the “multiplicity factor” of each item (case), two scenarios were developed:

First, HMBP under the proposed MSS using SAMSO current average number of weekly cases (current capacity).

Second, HMBP under the proposed MSS using SAMSO target average number of weekly cases when all specialties work 48 weeks/ year (target capacity).

The two scenarios were applied on the thirteen specialties, the resulted Bin Packs can be found at Appendix D. In addition, Table 12 summarizes the conclusion of each scenario application by specialties. As can be seen, the proposed MSS did not yield a practical Bin Packing solution for most of the specialties when using the current capacity. However, target capacity significantly improved the solutions obtained, but not to the extent of 100%. Actually, 5 of the 13 specialties will not have feasible Bin Packing solutions even when their surgeons work 48 weeks per year.

To resolve this, we present a modified MSS which represent the Final SAMSO MSS at Table 13. As expected, the number of Blocks increased from 31 in seven ORs to 33.5 also in seven ORs. Table 14 summarizes the difference between the Modified (Improved) MSS and SAMSO current MSS block assignments to each specialty. An overall 27% optimization in the number of surgical blocks resulted with seven ORs still proposed to be opened compared to ten currently used by SAMSO. Using 2005 ORs costs of \$62/ min [49], this can save SAMSO \$21.4 million annually.

Table 12: HMBP Validation to SAMSO Proposed and Modified MSS

Specialty	Current Average # of Cases/ Week	#of MSS weekly Blocks	MSS Practical Under <u>Current</u> Capacity	MSS Practical Under <u>Target</u> Capacity	<u>Modified</u> MSS Practical Under <u>Target</u> Capacity
ENT	38	2.5	No	Yes	Yes
EYE	41	2.5	No	Yes	Yes
Gynecology	40	2.5	No	Yes	Yes
Neurology	46	2	No	No	Yes
Dental	42	2	No	Yes	Yes
Urology	42	2	Yes	No	Yes
Bariatric	33	0.5	No	No	Yes
Orthopedic	48	7	Yes	Yes	Yes
Plastic	43	2	Yes	Yes	Yes
General	49	6	Yes	Yes	Yes
Thoracic	24	0.5	No	No	Yes
Vascular	34	1	Yes	Yes	Yes
Anesthesia	46	0.5	No	No	Yes

Table 13: SAMSO Modified (Improved) Master Surgical Schedule (MSS)

OR Day	1	2	3	4	5	6	7	8	9	10
Saturday	ENT	General	General	Ortho	Ortho	Dental				
	Opthal.									
Sunday	Opthal.	General	Gyne	Ortho	Nurospinal	Urology	Thoracic			
	ENT									
Monday	ENT	General	Plastic	Ortho	Urology	Vascular	Ortho			
	Opthal.									
Tuesday	Opthal.	General	General	Ortho	Ortho	Bariatric	Nurospinal			
	ENT						Urology			
Wednesday	ENT	Nurospinal	Gyne	Plastic	Anesth.	Dental	Gyne.			
	Opthal.									

Table 14: Number of OR Blocks comparison between the Modified (improved) MSS and SAMSO current MSS

Specialty	Old # of Blocks*	Proposed # of Blocks Assigned	Change
ENT	6	2.5	-3.5
Ophthalmology (Eye)	5	2.5	-2.5
Gynecology	3	2.5	-0.5
Neurology/ Neurospinal	4	2.5	-1.5
Dental (OMF&PEDD)	3	2	-1
Urology	4	2.5	-1.5
Bariatric	1	1	0
Orthopedic	6	7	+1
Plastic	3	2	-1
General	7	6	-1
Thoracic (Chest/ Lungs)	1	1	0
Vascular	2	1	-1
Anesthesia	1	1	0
TOTAL	46	33.5	-12.5 (-27%)

* Each Block is represented by one full day of one OR

Finally, to test SAMSO modified (improved) MSS, one week actual data is used for each specialty under the MSS blocks. Since the specialties workload varies significantly between the weeks, there is no single week that can be chosen to represent the average of each specialty. While a single week can be the average week of one specialty, it may be the peak of another. Therefore, a separate representative week is selected for each specialty based on the analysis shown at Table 15. Selected weeks should be the closest to the average week in both the number of cases and the total duration of the requested cases, those are mentioned at the last column of Table 15. Table 16 illustrates the number of surgery requests and their duration for each specialty.

The modified (improved) MSS successfully accommodated all SAMSO surgical requests for all specialties, based on the average week of each, when solved the HMBP problem for each specialty using LINGO. Figure 13 shows an example solution for the Eye specialty, whereas Appendix E documents the Bin Packs schedules for each specialty combined with the distribution of cases at Table 16 to surgical bins. It should be noted that the extra capacity allocated at each bin provided great flexibility to stretch some time blocks beyond their design limits (i.e., a 1 hour block can be used to schedule a 1.5 hour case utilizing the extra capacity of the assigned bin). Therefore, the MSS introduced in this work is practical and can be implemented by SAMSO management..

Table 15: Selecting the Average Weekly Number of Cases and Duration for SAMSO MSS HMBP

Specialty	#of weekly cases/ Total Duration “minutes per week”			
	Minimum	Average	Maximum	Selected Week
ENT	2/ 169	13.79/ 949.5	27/ 2159	16/ 968
EYE	5/ 311	16.98/ 908.2	29/ 1452	16/ 889
Gynecology	1/ 67	8/ 1003.5	18/ 2573	8/ 1054
Neurology	1/ 127	4.06/ 1142.2	10/ 2429	4/ 1127
Dental	1/ 102	5.88/ 753.4	10/ 1438	6/ 770
Urology	1/ 63	9.5/ 870.9	19/ 1931	9/ 918
Bariatric	1/ 48	2.77/ 299.6	9/ 1650	3/ 298
Orthopedic	9/ 1253	17.8/ 2803.9	35/ 4894	17/ 2870
Plastic	1/ 133	5.35/ 903.2	11/ 1605	5/ 905
General	2/ 139	21/ 2454.8	31/ 3649	20/ 2495
Thoracic	1/ 40	2.3/ 347.6	5/ 1620	3/ 350
Vascular	1/ 85	3.76/ 472	7/ 953	4/ 471
Anesthesia	2/ 36	12.3/ 262.5	24/ 456	14/ 260

Table 16: Average Week Data Selected for the HMBP for Each Specialty

Specialty	0-20	20-40	0-30	31-60	61-90	91-120	121-150	151-180	181-210	211-240	241-270	270-300	301-330	331-360	361-390	451+	Total
Anesthesia	6	2															8
ENT			3	9	1		2	1									16
EYE				12	3	1											16
General				2	5	3	6	2		1			1				20
Neurology					1				1			1				1	4
Gynecology				3		1	1	1	1			1					8
Orthopedic				2	1	5	2	1	1	1			2	1	1		17
Dental					1	2	1	1		1							6
Bariatric				1	1			1									3
Plastic				1*			1			2		1					4
Thoracic						1	2										3
Urology				1	3	4				1							9
Vascular						1	1		1								3
Total	6	2	3	30	16	18	16	7	4	6	0	3	3	1	1	1	117

EYE	1	2	3	4	5
7:00	1	1	1	0.5	1.5
7:30				1.5	
8:00	1	1	1		1.5
8:30					
9:00	1	1	1	2	
9:30					
10:00	1	1	1		
10:30					

Figure 13: HMBP solution to the Eye Specialty under the modified (improved) MSS

CHAPTER 4

CONCLUSION AND FUTURE RESEARCH

This is the last chapter in the thesis and consists of three sections. In the first section, we summarize the thesis work and highlight its contribution. The second section presents some possible ideas for future research in the Operating Rooms Scheduling area. The chapter concludes with some recommendations for the custodian of the ORs studied in this work, SAMSO.

4.1 Thesis Conclusion

The work presented in this thesis addressed the Operating Rooms (ORs) Scheduling Problem in the context of Saudi Aramco Medical Services Organization (SAMSO). A literature review about the problems and its variant frameworks is discussed. The literature was classified based on the solution methods used to solve the ORs scheduling problem. We concluded the literature review chapter with a focus to study SAMSO ORs scheduling.

SAMSO ORs scheduling process and guidelines were thoroughly discussed along with SAMSO adapted Master Surgical Schedule “MSS” and Surgical Block Schedule “SBS”. We defined the problem on hand to choose the optimum surgical cases to be scheduled at each of the SAMSO ORs and deliver the most favorable sequence of the selected cases.

We select the cases based on their duration fit in the OR time constraints and based on their priority values (i.e. patient's waiting time and cases criticality). The sequencing of surgeries is developed based on some preference rules set by SAMSO. To accomplish this, a mathematical model is introduced and illustrated using a numerical example. To test the model, a real data of one random day is chosen from SAMSO.

The current SAMSO's MSS has been evaluated for its efficiency with deep analysis at many aspects. Based on a full year's workload of each specialty, a new MSS is proposed with significant potential resources savings to SAMSO. This introduced MSS is then tested using two approaches: total duration approach and bin-packing approach, both proving its practicality to SAMSO.

In conclusion, SAMSO can adapt a new Master Surgical Schedule with less number of ORs to carry all the surgical cases requested. The new MSS is valid unless a significant OR demand change is introduced. In addition, the introduced mathematical model shall be utilized as the engine of user-friendly software to select the optimum cases that fit each OR and the way those are sequenced.

4.2 Future Research Opportunities

The literature of Operating Rooms Scheduling is very rich with so many directions and scenarios. However, the work presented in this thesis can be further extended to address many areas. For example, what is the impact of the designed OR schedules on the patients' receiving area (i.e., Day –surgery suits or inpatient wards) and recovery rooms

utilization and beds requirements? What if we relax the assumption that each specialist operates only using the assigned OR. Having floating ORs would reveal additional capacity to the ORs by getting around unnecessary surgeon waiting time during the turnaround period.

Another area that can be considered is the timeframe of developed ORs schedule. As extending the OR schedule beyond one day introduces more sequencing and selection options which may eventually improves the overall ORs utilization. Finally, what would the ORs schedule look like when the durations of surgeries and turnarounds are stochastic? And what changes need to be made to the designed ORs schedule to accommodate emergency admissions?

4.3 SAMSO Recommendations

The work presented in this thesis came to light with the cooperation of SAMSO scheduling team and management. This section includes some general recommendations that are believed to enhance SAMSO ORs performance as identified from the literature and observed through the difference meetings and interviews with SAMSO personnel. This includes three parts: scheduling policies, performance measurement, and technology.

We recommend that SAMSO adapts different ORs scheduling policies where surgeons and specialties do not directly control the ORs time, rather the scheduling team does. For example, SAMSO can keep the surgeons' preference of OR time to "day" only. Hence,

the scheduling team will assign/ group different surgeons into a particular OR and determine the proper start time of each surgery. This would allow higher OR utilization rates and make the scheduling process more effective by implementing parallel surgeries. Another suggestion is to have the scheduling process cycle for each week, rather than for each day. This would call for a change in the definition of elective and add-on case, as electives need to be requested at least one week before the surgery week. Adapting weekly ORs schedule provides the scheduling team with greater flexibility in assigning the OR time blocks. Finally on this family of suggestions, is to assign each patient (surgery request) a priority value, which is mentioned on the work at Chapter 3. This would be a great help for the schedulers to decide which cases to defer to next days when the current ORs capacity is not sufficient. Those would also help SAMSO management in case an overtime decision needs to be taken. As an ultimate objective, SAMSO can use the bin-packing results documented in this work, therefore, surgeons request a surgery and then assigned only one item of the block (bin) instead of a full OR day. It should be noted that the bin packing proposed in this work is adjustable to shuffle between the days, as long as the total number of days is not exceeded.

SAMSO ORs performance measurement can be improved by introducing cost elements for idle time, and cost of opening an OR. Admitting surgical cases from outside of Saudi Aramco employees and dependents may encourage the current SAMSO scheduling process and ORs utilization to be more efficient. In an interim step toward higher performance, the work presented at this thesis (both the mathematical model and the proposed MSS) shall be tested.

Furthermore, we present some recommendations regarding automation and the use of technology at SAMSO. One recommendation is to rely on actual duration (from the patient check-in to the check-out at the OR), i.e., without Turnaround time. To account for the turnaround time, it can be calculated for each specialty, as assumed earlier in this work. Moreover, SAMSO can work with the IT entity of the company to provide “first available slot” feature upon implementing the proposed MSS part of the thesis. Finally, it is recommended to include more data points to the schedulers at the “work list” such as whether the patient is cleared or not, as well as patient’s contact information. This would allow SAMSO’s scheduling team to better make right decisions before confirming the patients to surgery dates.

Appendix

Appendix A:

Numerical Example

```
max = 6*x111+10*x121+6*x211+40*x212+0.6*(y1211+y1111+y1212+y1112);

2*x111+2*x121+x211+4*x212+0.2*(x111+x121+x211+x212 -1)<=8;

2.2*x121+2.2*x111+t1<=12-0.2 ;

2.2*x121+2.2*x111+1.2*x211+4.2*x212+t1<=15-0.2;

y1111+y1112+y1113+y1114<=x111;
y1211+y1212+y1213+y1214<=x121;
y2111+y2112+y2113+y2114<=x211;
y2121+y2122+y2123+y2124<=x212;

y1111+y1211+y2111+y2121<=1;
y1112+y1212+y2112+y2122<=1;
y1113+y1213+y2113+y2123<=1;
y1114+y1214+y2114+y2124<=1;

y1111+y1211+y2111+y2121+y1112+y1212+y2112+y2122+y1113+y1213+y2113+y2123+y1114+y1214+y2114+y2124=x111+x121+x211+x212 ;

y1211+y1111+y1212+y1112<=x121+x111;

t1=7 ;

@BIN(x111); @BIN(x121); @BIN(x211); @BIN(x212);

@GIN(t1);

@BIN(y1111); @BIN(y1112); @BIN(y1113); @BIN(y1114);
@BIN(y1211); @BIN(y1212); @BIN(y1213); @BIN(y1214);
@BIN(y2111); @BIN(y2112); @BIN(y2113); @BIN(y2114);
@BIN(y2121); @BIN(y2122); @BIN(y2123); @BIN(y2124);
```

Solution

Global optimal solution found.	
Objective value:	56.60000
Objective bound:	56.60000
Infeasibilities:	0.000000
Extended solver steps:	0

Total solver iterations:		0		
Model Class:		PILP		
Total variables:	20			
Nonlinear variables:	0			
Integer variables:	20			
Total constraints:	14			
Nonlinear constraints:	0			
Total nonzeros:	80			
Nonlinear nonzeros:	0			
Cost	Variable	Value	Reduced	
	X111	0.000000	-6.000000	
	X121	1.000000	-10.00000	
	X211	1.000000	-6.000000	
	X212	1.000000	-40.00000	
	Y1211	0.000000	-0.6000000	
	Y1111	0.000000	-0.6000000	
	Y1212	1.000000	-0.6000000	
	Y1112	0.000000	-0.6000000	
	T1	7.000000	0.000000	
	Y1113	0.000000	0.000000	
	Y1114	0.000000	0.000000	
	Y1213	0.000000	0.000000	
	Y1214	0.000000	0.000000	
	Y2111	0.000000	0.000000	
	Y2112	0.000000	0.000000	
	Y2113	1.000000	0.000000	
	Y2114	0.000000	0.000000	
	Y2121	1.000000	0.000000	
	Y2122	0.000000	0.000000	
	Y2123	0.000000	0.000000	
	Y2124	0.000000	0.000000	
	Price	Row	Slack or Surplus	Dual
		1	56.60000	1.000000
		2	0.6000000	0.000000
		3	2.600000	0.000000
4		0.2000000	0.000000	
5		0.000000	0.000000	
6		0.000000	0.000000	
7		0.000000	0.000000	
8		0.000000	0.000000	
9		0.000000	0.000000	
10		0.000000	0.000000	
11		0.000000	0.000000	
12		1.000000	0.000000	
13		0.000000	0.000000	
14		0.000000	0.000000	
15		0.000000	0.000000	

Appendix B

Case Study : OR1

```
max
7*0.5*x221+5.8*0.5*x121+3*0.5*x122+6.6*0.42*x123+7.2*0.42*x124+0.6*(y1211+y1212+y1213+y1214
+y1221+y1222+y1223+y1224+y1231+y1232+y1233+y1234+y1241+y1242+y1243+y1244);

0.5*x221+0.5*x121+0.5*x122+0.42*x123+0.42*x124+0.16*(x221+x121+x122+x123+x124-1)<=8;

0.67*x121+0.67*x122+0.58*x123+0.58*x124+t1<=12-0.16 ;

0.67*x221+0.67*x121+0.67*x122+0.58*x123+0.58*x124+t1<=15-0.16 ;

y1211+y1212+y1213+y1214+y1215=x121;
y1221+y1222+y1223+y1224+y1225=x122;
y1231+y1232+y1233+y1234+y1235=x123;
y1241+y1242+y1243+y1244+y1245=x124;
y2211+y2212+y2213+y2214+y2215=x221;

y1211+y1221+y1231+y1241+y2211<=1;
y1212+y1222+y1232+y1242+y2212<=1;
y1213+y1223+y1233+y1243+y2213<=1;
y1214+y1224+y1234+y1244+y2214<=1;
y1215+y1225+y1235+y1245+y2215<=1;

@BIN(x121); @BIN(x122); @BIN(x123); @BIN(x124);@BIN(x221);

@GIN(t1);

@BIN(y1211);@BIN(y1212);@BIN(y1213);@BIN(y1214);@BIN(y1215);
@BIN(y1221);@BIN(y1222);@BIN(y1223);@BIN(y1224);@BIN(y1225);
@BIN(y1231);@BIN(y1232);@BIN(y1233);@BIN(y1234);@BIN(y1235);
@BIN(y1241);@BIN(y1242);@BIN(y1243);@BIN(y1244);@BIN(y1245);
@BIN(y2211);@BIN(y2212);@BIN(y2213);@BIN(y2214);@BIN(y2215);
```

Solution :

```
Global optimal solution found.
Objective value:                16.09600
Objective bound:                16.09600
Infeasibilities:                0.000000
Extended solver steps:          0
Total solver iterations:        0

Model Class:                    PILP

Total variables:                31
Nonlinear variables:            0
Integer variables:              31

Total constraints:              14
Nonlinear constraints:          0
```

Total nonzeros:		92		
Nonlinear nonzeros:		0		
		Variable	Value	Reduced
Cost				
	X221	1.000000	-3.500000	
	X121	1.000000	-2.900000	
	X122	1.000000	-1.500000	
	X123	1.000000	-2.772000	
	X124	1.000000	-3.024000	
	Y1211	1.000000	-0.600000	
	Y1212	0.000000	-0.600000	
	Y1213	0.000000	-0.600000	
	Y1214	0.000000	-0.600000	
	Y1221	0.000000	-0.600000	
	Y1222	0.000000	-0.600000	
	Y1223	1.000000	-0.600000	
	Y1224	0.000000	-0.600000	
	Y1231	0.000000	-0.600000	
	Y1232	0.000000	-0.600000	
	Y1233	0.000000	-0.600000	
	Y1234	1.000000	-0.600000	
	Y1241	0.000000	-0.600000	
	Y1242	1.000000	-0.600000	
	Y1243	0.000000	-0.600000	
	Y1244	0.000000	-0.600000	
	T1	0.000000	0.000000	
	Y1215	0.000000	0.000000	
	Y1225	0.000000	0.000000	
	Y1235	0.000000	0.000000	
	Y1245	0.000000	0.000000	
	Y2211	0.000000	0.000000	
	Y2212	0.000000	0.000000	
	Y2213	0.000000	0.000000	
	Y2214	0.000000	0.000000	
	Y2215	1.000000	0.000000	
		Row	Slack or Surplus	Dual
Price				
	1	16.09600	1.000000	
	2	5.020000	0.000000	
	3	9.340000	0.000000	
	4	11.67000	0.000000	
	5	0.000000	0.000000	
	6	0.000000	0.000000	
	7	0.000000	0.000000	
	8	0.000000	0.000000	
	9	0.000000	0.000000	
	10	0.000000	0.000000	
	11	0.000000	0.000000	
	12	0.000000	0.000000	
	13	0.000000	0.000000	
	14	0.000000	0.000000	

Case Study : OR#2 :

```
max
4.6*0.67*x1212+6.6*0.58*x1222+4.4*0.58*x1232+5.6*0.67*x1242+0.6*(y12121+y12122+y12123+y12124+y12221+y12222+y12223+y12224+y12321+y12322+y12323+y12324+y12421+y12422+y12423+y12424);

0.67*x1212+0.58*x1222+0.58*x1232+0.67*x1242+0.16*(x1212+x1222+x1232+x1242-1)<=8;

0.83*x1212+0.74*x1222+0.74*x1232+0.83*x1242+t1<=12-0.16 ;

y12121+y12122+y12123+y12124=x1212;
y12221+y12222+y12223+y12224=x1222;
y12321+y12322+y12323+y12324=x1232;
y12421+y12422+y12423+y12424=x1242;

y12121+y12221+y12321+y12421<=1;
y12122+y12222+y12322+y12422<=1;
y12123+y12223+y12323+y12423<=1;
y12124+y12224+y12324+y12424<=1;

t1=7 ;

@BIN(x1212); @BIN(x1222); @BIN(x1232); @BIN(x1242);

@GIN(t1); @GIN(t2); @GIN(t3);

@BIN(y12121);@BIN(y12122);@BIN(y12123);@BIN(y12124);
@BIN(y12221);@BIN(y12222);@BIN(y12223);@BIN(y12224);
@BIN(y12321);@BIN(y12322);@BIN(y12323);@BIN(y12324);
@BIN(y12421);@BIN(y12422);@BIN(y12423);@BIN(y12424);
```

Solution :

```
Global optimal solution found.
Objective value:                15.61400
Objective bound:                15.61400
Infeasibilities:                0.000000
Extended solver steps:          0
Total solver iterations:        0

Model Class:                    PILP

Total variables:                22
Nonlinear variables:            0
Integer variables:              22

Total constraints:              11
Nonlinear constraints:          0

Total nonzeros:                64
Nonlinear nonzeros:            0
```

	Variable	Value	Reduced
Cost	X1212	1.000000	-3.082000
	X1222	1.000000	-3.828000
	X1232	1.000000	-2.552000
	X1242	1.000000	-3.752000
	Y12121	0.000000	-0.600000
	Y12122	0.000000	-0.600000
	Y12123	0.000000	-0.600000
	Y12124	1.000000	-0.600000
	Y12221	0.000000	-0.600000
	Y12222	1.000000	-0.600000
	Y12223	0.000000	-0.600000
	Y12224	0.000000	-0.600000
	Y12321	1.000000	-0.600000
	Y12322	0.000000	-0.600000
	Y12323	0.000000	-0.600000
	Y12324	0.000000	-0.600000
	Y12421	0.000000	-0.600000
	Y12422	0.000000	-0.600000
	Y12423	1.000000	-0.600000
	Y12424	0.000000	-0.600000
	T1	7.000000	0.000000
	T2	0.000000	0.000000
	T3	0.000000	0.000000
	Row	Slack or Surplus	Dual
Price	1	15.61400	1.000000
	2	5.020000	0.000000
	3	1.700000	0.000000
	4	0.000000	0.000000
	5	0.000000	0.000000
	6	0.000000	0.000000
	7	0.000000	0.000000
	8	0.000000	0.000000
	9	0.000000	0.000000
	10	0.000000	0.000000
	11	0.000000	0.000000
	12	0.000000	0.000000

Case Study : OR#3 :

$\max = 4.6*0.17*x_{111} + 5.8*0.50*x_{112} + 0.6*(y_{1111} + y_{1112} + y_{1121} + y_{1122});$

$0.17*x_{111} + 0.58*x_{112} + 0.16*(x_{111} + x_{112} - 1) \leq 8;$

$0.33*x_{111} + 0.66*x_{112} + t_1 \leq 12 - 0.16;$

$y_{1111} + y_{1112} \leq x_{111};$

$y_{1121} + y_{1122} \leq x_{112};$

$y_{1111} + y_{1121} \leq 1;$

$y_{1112} + y_{1122} \leq 1;$

```

y1111+y1121+y1112+y1122<=x111+x112;

t1=7;

@BIN(x111); @BIN(x112);

@GIN(t1);

@BIN(y1111);@BIN(y1112);@BIN(y1121);@BIN(y1122);

```

Solution

Global optimal solution found.			
Objective value:		4.882000	
Objective bound:		4.882000	
Infeasibilities:		0.000000	
Extended solver steps:		0	
Total solver iterations:		0	
Model Class:		PILP	
Total variables:	6		
Nonlinear variables:	0		
Integer variables:	6		
Total constraints:	8		
Nonlinear constraints:	0		
Total nonzeros:	26		
Nonlinear nonzeros:	0		
Cost	Variable	Value	Reduced
	X111	1.000000	-0.782000
	X112	1.000000	-2.900000
	Y1111	1.000000	-0.600000
	Y1112	0.000000	-0.600000
	Y1121	0.000000	-0.600000
	Y1122	1.000000	-0.600000
	T1	7.000000	0.000000
Price	Row	Slack or Surplus	Dual
	1	4.882000	1.000000
	2	7.090000	0.000000
	3	3.850000	0.000000
	4	0.000000	0.000000
	5	0.000000	0.000000
	6	0.000000	0.000000
	7	0.000000	0.000000
	8	0.000000	0.000000
	9	0.000000	0.000000

Case Study : OR#4

```
max = 6.2*0.83*x121+3.4*1.33*x221+6.2*0.5*x222+3.4*0.5*x211+0.6*(y1211+y1212+y1213+y1214);  
  
0.83*x121+1.33*x221+0.5*x222+0.5*x211+0.33*(x121+x221+x222+x211-1)<=8;  
  
1.16*x121+t1<=12-0.33 ;  
  
1.16*x121+1.66*x221+0.83*x222+0.83*x211+t1<=15-0.33 ;  
  
y1211+y1212+y1213+y1214=x121;  
y2211+y2212+y2213+y2214=x221;  
y2221+y2222+y2223+y2224=x222;  
y2111+y2112+y2113+y2114=x211;  
  
y1211+y2211+y2221+y2111<=1;  
y1212+y2212+y2222+y2112<=1;  
y1213+y2213+y2223+y2113<=1;  
y1214+y2214+y2224+y2114<=1;  
  
t1=7;  
  
y1211+y1212+y1213+y1214<=x121;  
  
@BIN(x121); @BIN(x221); @BIN(x222); @BIN(x211);  
  
@GIN(t1);  
  
@BIN(y1211);@BIN(y1212);@BIN(y1213);@BIN(y1214);  
@BIN(y2211);@BIN(y2212);@BIN(y2213);@BIN(y2214);  
@BIN(y2221);@BIN(y2222);@BIN(y2223);@BIN(y2224);  
@BIN(y2111);@BIN(y2112);@BIN(y2113);@BIN(y2114);
```

Solution :

```
Global optimal solution found.  
Objective value:                15.06800  
Objective bound:                15.06800  
Infeasibilities:                0.000000  
Extended solver steps:         0  
Total solver iterations:        0  
  
Model Class:                    PILP  
  
Total variables:                20  
Nonlinear variables:            0  
Integer variables:              20  
  
Total constraints:              13  
Nonlinear constraints:          0  
  
Total nonzeros:                58
```

Nonlinear nonzeros:		0	
		Variable	Value
Cost			Reduced
	X121	1.000000	-5.146000
	X221	1.000000	-4.522000
	X222	1.000000	-3.100000
	X211	1.000000	-1.700000
	Y1211	0.000000	-0.600000
	Y1212	1.000000	-0.600000
	Y1213	0.000000	-0.600000
	Y1214	0.000000	-0.600000
	T1	7.000000	0.000000
	Y2211	0.000000	0.000000
	Y2212	0.000000	0.000000
	Y2213	1.000000	0.000000
	Y2214	0.000000	0.000000
	Y2221	1.000000	0.000000
	Y2222	0.000000	0.000000
	Y2223	0.000000	0.000000
	Y2224	0.000000	0.000000
	Y2111	0.000000	0.000000
	Y2112	0.000000	0.000000
	Y2113	0.000000	0.000000
	Y2114	1.000000	0.000000
		Row	Slack or Surplus
Price			Dual
	1	15.06800	1.000000
	2	3.850000	0.000000
	3	3.510000	0.000000
	4	3.190000	0.000000
	5	0.000000	0.000000
	6	0.000000	0.000000
	7	0.000000	0.000000
	8	0.000000	0.000000
	9	0.000000	0.000000
	10	0.000000	0.000000
	11	0.000000	0.000000
	12	0.000000	0.000000
	13	0.000000	0.000000
	14	0.000000	0.000000

Case Study : OR#5

$\max = 5.4 * 0.08 * x_{221} + 3.8 * 0.75 * x_{222};$
 $0.08 * x_{221} + 0.75 * x_{222} + 0.16 * (x_{221} + x_{222} - 1) \leq 8;$
 $0.24 * x_{221} + 0.91 * x_{222} + t_1 \leq 12 - 0.16 ;$
 $y_{2211} + y_{2212} = x_{221};$
 $y_{2221} + y_{2222} = x_{222};$

```

y2211+y2221<=1;
y2212+y2222<=1;

t1=7;

@BIN(x221); @BIN(x222);

@GIN(t1);

@BIN(y2211);@BIN(y2212);@BIN(y2221);@BIN(y2222);

```

Solution :

Global optimal solution found.			
Objective value:		3.282000	
Objective bound:		3.282000	
Infeasibilities:		0.000000	
Extended solver steps:		0	
Total solver iterations:		0	
Model Class:		PILP	
Total variables:	6		
Nonlinear variables:	0		
Integer variables:	6		
Total constraints:	7		
Nonlinear constraints:	0		
Total nonzeros:	16		
Nonlinear nonzeros:	0		
Cost	Variable	Value	Reduced
	X221	1.000000	-0.432000
	X222	1.000000	-2.850000
	T1	7.000000	0.000000
	Y2211	0.000000	0.000000
	Y2212	1.000000	0.000000
	Y2221	1.000000	0.000000
	Y2222	0.000000	0.000000
Price	Row	Slack or Surplus	Dual
	1	3.282000	1.000000
	2	7.010000	0.000000
	3	3.690000	0.000000
	4	0.000000	0.000000
	5	0.000000	0.000000
	6	0.000000	0.000000
	7	0.000000	0.000000
	8	0.000000	0.000000

Case Study : OR#6

```
max =
6*0.67*x121+4.6*0.67*x122+5.8*1.67*x123+4*1.75*x221+0.6*(y1211+y1212+y1213+y1214+y1221+y1222+y1223+y1224+y1231+y1232+y1233+y1234);

0.67*x121+0.67*x122+1.67*x123+1.75*x221+0.33*(x121+x122+x123+x221-1)<=8;

x121+x122+2*x123+t1<=12-0.33 ;

x121+x122+2*x123+2.08*x221+t1<=15-0.33 ;

y1211+y1212+y1213+y1214=x121;
y1221+y1222+y1223+y1224=x122;
y1231+y1232+y1233+y1234=x123;
y2211+y2212+y2213+y2214=x221;

y1211+y1221+y1231+y2211<=1;
y1212+y1222+y1232+y2212<=1;
y1213+y1223+y1233+y2213<=1;
y1214+y1224+y1234+y2214<=1;

t1=7;

y1211+y1212+y1213+y1214+y1221+y1222+y1223+y1224+y1231+y1232+y1233+y1234<=x121+x122+x123
;

@BIN(x121); @BIN(x122); @BIN(x123); @BIN(x221);

@GIN(t1);

@BIN(y1211);@BIN(y1212);@BIN(y1213);@BIN(y1214);
@BIN(y1221);@BIN(y1222);@BIN(y1223);@BIN(y1224);
@BIN(y1231);@BIN(y1232);@BIN(y1233);@BIN(y1234);
@BIN(y2211);@BIN(y2212);@BIN(y2213);@BIN(y2214);
```

Solution

```
Global optimal solution found.
Objective value:                25.58800
Objective bound:                25.58800
Infeasibilities:                0.000000
Extended solver steps:          0
Total solver iterations:         0

Model Class:                    PILP

Total variables:                20
Nonlinear variables:             0
Integer variables:              20
```

Total constraints:		13		
Nonlinear constraints:		0		
Total nonzeros:		78		
Nonlinear nonzeros:		0		
		Variable	Value	Reduced
Cost				
	X121	1.000000	-4.020000	
	X122	1.000000	-3.082000	
	X123	1.000000	-9.686000	
	X221	1.000000	-7.000000	
	Y1211	0.000000	-0.600000	
	Y1212	0.000000	-0.600000	
	Y1213	0.000000	-0.600000	
	Y1214	1.000000	-0.600000	
	Y1221	0.000000	-0.600000	
	Y1222	0.000000	-0.600000	
	Y1223	1.000000	-0.600000	
	Y1224	0.000000	-0.600000	
	Y1231	0.000000	-0.600000	
	Y1232	1.000000	-0.600000	
	Y1233	0.000000	-0.600000	
	Y1234	0.000000	-0.600000	
	T1	7.000000	0.000000	
	Y2211	1.000000	0.000000	
	Y2212	0.000000	0.000000	
	Y2213	0.000000	0.000000	
	Y2214	0.000000	0.000000	
		Row	Slack or Surplus	Dual
Price				
	1	25.58800	1.000000	
	2	2.250000	0.000000	
	3	0.6700000	0.000000	
	4	1.590000	0.000000	
	5	0.000000	0.000000	
	6	0.000000	0.000000	
	7	0.000000	0.000000	
	8	0.000000	0.000000	
	9	0.000000	0.000000	
	10	0.000000	0.000000	
	11	0.000000	0.000000	
	12	0.000000	0.000000	
	13	0.000000	0.000000	
	14	0.000000	0.000000	

Case Study : OR#7

$\max = 5.4*1.33*x_{221} + 4.8*2.92*x_{222};$

$1.33*x_{221} + 2.92*x_{222} + 0.33*(x_{221} + x_{222} - 1) \leq 8;$

$1.66*x_{221} + 3.25*x_{222} + t_1 \leq 15 - 0.33;$

```

y2211+y2212=x221;
y2221+y2222=x222;

y2211+y2221<=1;
y2212+y2222<=1;

t1=7;

@BIN(x221); @BIN(x222);

@GIN(t1);

@BIN(y2211);@BIN(y2212);@BIN(y2221);@BIN(y2222);

```

Solution

Global optimal solution found.			
Objective value:		21.19800	
Objective bound:		21.19800	
Infeasibilities:		0.000000	
Extended solver steps:		0	
Total solver iterations:		0	
Model Class:		PILP	
Total variables:	6		
Nonlinear variables:	0		
Integer variables:	6		
Total constraints:	7		
Nonlinear constraints:	0		
Total nonzeros:	16		
Nonlinear nonzeros:	0		
Cost	Variable		Value
			Reduced
	X221	1.000000	-7.182000
	X222	1.000000	-14.01600
	T1	7.000000	0.000000
	Y2211	0.000000	0.000000
	Y2212	1.000000	0.000000
	Y2221	1.000000	0.000000
	Y2222	0.000000	0.000000
Price	Row	Slack or Surplus	Dual
	1	21.19800	1.000000
	2	3.420000	0.000000
	3	2.760000	0.000000
	4	0.000000	0.000000

5	0.000000	0.000000
6	0.000000	0.000000
7	0.000000	0.000000
8	0.000000	0.000000

Case Study : OR#8

```

max = 6*1.25*x121+4*3.58*x221+6.6*1.5*x222+4.2*3.58*x223+0.6*(y1211+y1212+y1213+y1214);

1.25*x121+3.58*x221+1.5*x222+3.58*x223+0.50*(x121+x221+x222+x223-1)<=8;

1.75*x121+t1<=12-0.50 ;

1.75*x121+4.08*x221+2*x222+4.08*x223+t1<=15-0.5 ;

y1211+y1212+y1213+y1214=x121;
y2211+y2212+y2213+y2214=x221;
y2221+y2222+y2223+y2224=x222;
y2231+y2232+y2233+y2234=x223;

y1211+y2211+y2221+y2231<=1;
y1212+y2212+y2222+y2232<=1;
y1213+y2213+y2223+y2233<=1;
y1214+y2214+y2224+y2234<=1;

t1=7;

y1211+y1212+y1213+y1214=x121;

@BIN(x121); @BIN(x221); @BIN(x222); @BIN(x223);

@GIN(t1);

@BIN(y1211);@BIN(y1212);@BIN(y1213);@BIN(y1214);
@BIN(y2211);@BIN(y2212);@BIN(y2213);@BIN(y2214);
@BIN(y2221);@BIN(y2222);@BIN(y2223);@BIN(y2224);
@BIN(y2231);@BIN(y2232);@BIN(y2233);@BIN(y2234);

```

Solution

Global optimal solution found.		
Objective value:		24.93600
Objective bound:		24.93600
Infeasibilities:		0.000000
Extended solver steps:		0
Total solver iterations:		0
Model Class:		PILP
Total variables:	20	
Nonlinear variables:	0	

Integer variables:		20	
Total constraints:		13	
Nonlinear constraints:		0	
Total nonzeros:		58	
Nonlinear nonzeros:		0	
		Variable	Value
Cost			Reduced
	X121	0.000000	-7.500000
	X221	0.000000	-14.32000
	X222	1.000000	-9.900000
	X223	1.000000	-15.03600
	Y1211	0.000000	-0.6000000
	Y1212	0.000000	-0.6000000
	Y1213	0.000000	-0.6000000
	Y1214	0.000000	-0.6000000
	T1	7.000000	0.000000
	Y2211	0.000000	0.000000
	Y2212	0.000000	0.000000
	Y2213	0.000000	0.000000
	Y2214	0.000000	0.000000
	Y2221	0.000000	0.000000
	Y2222	1.000000	0.000000
	Y2223	0.000000	0.000000
	Y2224	0.000000	0.000000
	Y2231	1.000000	0.000000
	Y2232	0.000000	0.000000
	Y2233	0.000000	0.000000
	Y2234	0.000000	0.000000
		Row	Slack or Surplus
Price			Dual
	1	24.93600	1.000000
	2	2.420000	0.000000
	3	4.500000	0.000000
	4	1.420000	0.000000
	5	0.000000	0.000000
	6	0.000000	0.000000
	7	0.000000	0.000000
	8	0.000000	0.000000
	9	0.000000	0.000000
	10	0.000000	0.000000
	11	1.000000	0.000000
	12	1.000000	0.000000
	13	0.000000	0.000000
	14	0.000000	0.000000

Case Study : OR#9

$\max =$
 $7.8*0.08*x_{121}+5.8*2.5*x_{221}+5.2*1.42*x_{122}+5*0.92*x_{123}+4*6.75*x_{222}+0.6*(y_{1211}+y_{1212}+y_{1213}+y_{1214}+y_{1215}+y_{1221}+y_{1222}+y_{1223}+y_{1224}+y_{1225}+y_{1231}+y_{1232}+y_{1233}+y_{1234}+y_{1235});$

```

0.08*x121+2.5*x221+1.42*x122+0.92*x123+6.75*x222+0.25*(x121+x221+x122+x123+x222-1)<=8;

0.33*x121+1.67*x122+1.17*x123+t1<=12-0.25 ;

0.33*x121+1.67*x122+1.17*x123+2.75*x221+7*x222+t1<=15-0.25 ;

y1211+y1212+y1213+y1214+y1215=x121;
y1221+y1222+y1223+y1224+y1225=x122;
y1231+y1232+y1233+y1234+y1235=x123;
y2211+y2212+y2213+y2214+y2215=x221;
y2221+y2222+y2223+y2224+y2225=x222;

y1211+y2211+y2221+y1221+y1231<=1;
y1212+y2212+y2222+y1222+y1232<=1;
y1213+y2213+y2223+y1223+y1233<=1;
y1214+y2214+y2224+y1224+y1234<=1;
y1215+y2215+y2225+y1225+y1235<=1;

t1=7;

y1211+y1212+y1213+y1214+y1215+y1221+y1222+y1223+y1224+y1225+y1231+y1232+y1233+y1234+y1235<=x121+x122+x123;

@BIN(x121); @BIN(x221); @BIN(x222); @BIN(x122);@BIN(x123);

@GIN(t1);

@BIN(y1211);@BIN(y1212);@BIN(y1213);@BIN(y1214);@BIN(y1215);
@BIN(y2211);@BIN(y2212);@BIN(y2213);@BIN(y2214);@BIN(y2215);
@BIN(y2221);@BIN(y2222);@BIN(y2223);@BIN(y2224);@BIN(y2225);
@BIN(y1221);@BIN(y1222);@BIN(y1223);@BIN(y1224);@BIN(y1225);
@BIN(y1231);@BIN(y1232);@BIN(y1233);@BIN(y1234);@BIN(y1235);

```

Solution

```

Global optimal solution found.
Objective value:                28.90800
Objective bound:                28.90800
Infeasibilities:                0.000000
Extended solver steps:          0
Total solver iterations:        0

Model Class:                    PILP

Total variables:                30
Nonlinear variables:            0
Integer variables:              30

Total constraints:              15
Nonlinear constraints:          0

Total nonzeros:                106

```

Nonlinear nonzeros:		0		
		Variable	Value	Reduced
Cost	X121	1.000000	-0.6240000	
	X221	1.000000	-14.50000	
	X122	1.000000	-7.384000	
	X123	1.000000	-4.600000	
	X222	0.000000	-27.00000	
	Y1211	0.000000	-0.6000000	
	Y1212	1.000000	-0.6000000	
	Y1213	0.000000	-0.6000000	
	Y1214	0.000000	-0.6000000	
	Y1215	0.000000	-0.6000000	
	Y1221	1.000000	-0.6000000	
	Y1222	0.000000	-0.6000000	
	Y1223	0.000000	-0.6000000	
	Y1224	0.000000	-0.6000000	
	Y1225	0.000000	-0.6000000	
	Y1231	0.000000	-0.6000000	
	Y1232	0.000000	-0.6000000	
	Y1233	1.000000	-0.6000000	
	Y1234	0.000000	-0.6000000	
	Y1235	0.000000	-0.6000000	
	T1	7.000000	0.000000	
	Y2211	0.000000	0.000000	
	Y2212	0.000000	0.000000	
	Y2213	0.000000	0.000000	
	Y2214	1.000000	0.000000	
	Y2215	0.000000	0.000000	
	Y2221	0.000000	0.000000	
	Y2222	0.000000	0.000000	
	Y2223	0.000000	0.000000	
	Y2224	0.000000	0.000000	
	Y2225	0.000000	0.000000	
		Row	Slack or Surplus	Dual
Price	1	28.90800	1.000000	
	2	2.330000	0.000000	
	3	1.580000	0.000000	
	4	1.830000	0.000000	
	5	0.000000	0.000000	
	6	0.000000	0.000000	
	7	0.000000	0.000000	
	8	0.000000	0.000000	
	9	0.000000	0.000000	
	10	0.000000	0.000000	
	11	0.000000	0.000000	
	12	0.000000	0.000000	
	13	0.000000	0.000000	
	14	1.000000	0.000000	
	15	0.000000	0.000000	
	16	0.000000	0.000000	

Case Study : OR#10

```

max = 5.2*2.08*x221;

2.08*x221+0.5*(x221-1)<=8;

2.58*x221+t1<=15-0.50 ;

y2211=x221;

y2211<=1;

t1=7;

@BIN(x221); @BIN(y2211);

@GIN(t1);

```

Solution

Global optimal solution found.				
Objective value:			10.81600	
Objective bound:			10.81600	
Infeasibilities:			0.000000	
Extended solver steps:			0	
Total solver iterations:			0	
Model Class:			PILP	
Total variables:		2		
Nonlinear variables:		0		
Integer variables:		2		
Total constraints:		5		
Nonlinear constraints:		0		
Total nonzeros:		6		
Nonlinear nonzeros:		0		
Cost	Variable		Value	Reduced
	X221	1.000000	-10.81600	
	T1	7.000000	0.000000	
	Y2211	1.000000	0.000000	
Price	Row		Slack or Surplus	Dual
	1	10.81600	1.000000	
	2	5.920000	0.000000	
	3	4.920000	0.000000	
	4	0.000000	0.000000	
	5	0.000000	0.000000	
	6	0.000000	0.000000	

Appendix C

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v_i)
0-30	30	11	2%	0.26	0
31-60	60	127	28%	3.02	3
61-90	90	155	34%	3.69	4
91-120	120	78	17%	1.86	2
121-150	150	35	8%	0.83	1
151+	180	50	11%	0.88	0
Average Number of Cases per Week =10.85				Specialty: Urology	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v_i)
0-30	30	1	1%	0.03	0
31-60	60	6	4%	0.18	0
61-90	90	28	18%	0.82	1

91-120	120	51	32%	1.50	2
121-150	150	41	26%	1.21	1
151+	180	31	20%	0.91	0
Average Number of Cases per Week =4.65				Specialty: Vascular	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	3	3%	0.09	0
31-60	60	32	30%	0.97	1
61-90	90	27	25%	0.82	1
91-120	120	22	20%	0.67	1
121+	150	24	22%	0.73	0
Average Number of Cases per Week =3.27				Specialty: Bariatric	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v_i)
0-30	30	2	1%	0.05	0
31-60	60	40	15%	0.93	1
61-90	90	37	14%	0.86	1
91-120	120	27	10%	0.63	1
121-150	150	22	8%	0.51	1
151-180	180	25	10%	0.58	1
181-210	210	19	7%	0.44	0
211-240	240	33	13%	0.77	1
241+	270	57	22%	1.33	0
Average Number of Cases per Week =6.09				Specialty: Plastic	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	2	2%	0.05	0
31-60	60	9	11%	0.93	1
61-90	90	14	16%	0.86	1
91-120	120	15	18%	0.63	1
121-150	150	21	25%	0.51	1
151-180	180	10	12%	0.58	1
181+	210	14	16%	0.44	0
Average Number of Cases per Week =3.54				Specialty: Thoracic	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	5	1%	0.10	0
31-60	60	155	18%	3.23	3
61-90	90	135	15%	2.81	3
91-120	120	99	11%	2.06	2
121-150	150	81	9%	1.69	2
151-180	180	119	14%	2.48	3
181-210	210	109	12%	2.27	2
211-240	240	70	8%	1.46	2
241-270	270	31	4%	0.65	1
271-300	300	22	3%	0.46	1
301+	330	47	5%	0.98	0
Average Number of Cases per Week =18.79				Specialty: Orthopedic	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v_i)
0-30	30	0	0%	0.00	0
31-60	60	15	8%	0.33	1
61-90	90	13	7%	0.28	0
91-120	120	12	6%	0.26	0
121-150	150	10	5%	0.22	0
151-180	180	10	5%	0.22	0
181-210	210	25	13%	0.54	1
211-240	240	17	9%	0.37	1
241-270	270	15	8%	0.33	0
271-300	300	12	6%	0.26	0
301-330	330	5	3%	0.11	0
331-360	360	2	1%	0.04	0
361-390	390	8	4%	0.17	0

391-420	420	6	3%	0.13	0
421-450	450	5	3%	0.11	0
450+	480	36	19%	0.78	1
Average Number of Cases per Week =4.15				Specialty: Neurology	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	30	4%	0.73	1
31-60	60	593	73%	14.46	14
61-90	90	143	18%	3.49	4
91-120	120	40	5%	0.98	1
121+	150	9	1%	0.22	0
Average Number of Cases per Week =19.88				Specialty: EYE	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	49	7%	1.29	1
31-60	60	319	48%	8.39	8
61-90	90	136	21%	3.58	4
91-120	120	82	12%	2.16	2
121-150	150	44	7%	1.16	1
151-180	180	25	4%	0.66	1
181+	210	7	1%	0.18	0
Average Number of Cases per Week =17.42				Specialty: ENT	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	3	1%	0.08	0
31-60	60	53	14%	1.33	1
61-90	90	70	18%	1.75	2

91-120	120	77	20%	1.93	2
121-150	150	75	20%	1.88	2
151-180	180	43	11%	1.08	1
181-210	210	24	6%	0.60	1
211-240	240	19	5%	0.48	1
241+	270	20	5%	0.5	0
Average Number of Cases per Week =9.6				Specialty: Gynecology	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-20	30	275	47%	5.98	6
21-40	60	297	50%	6.46	7
41-60	90	16	3%	0.35	0
61-90	120	3	1%	0.07	0
91-120	150	0	0%	5.98	6
Average Number of Cases per Week =12.85				Specialty: Anesthesia	

Range (min.)	Assigned Block Duration (min.)	# of Cases Per Year	Percentage From Annual Total	#of Cases Per Week	Item Multiplicity (v _i)
0-30	30	0	0%	0.00	0
31-60	60	13	5%	0.31	1
61-90	90	44	16%	1.05	2
91-120	120	75	27%	1.79	2
121-150	150	68	24%	1.62	1
151-180	180	51	18%	1.21	1
181-210	210	18	6%	0.43	0
211+	240	9	5%	0.31	0
Average Number of Cases per Week =6.71				Specialty: Dental	

Appendix D

D.1 Current Capacity:

Plastic	1	2
7:00	1	2.5
7:30		
8:00	1.5	
8:30		
9:00	2	4
9:30		
10:00		
10:30		
11:00	3	
11:30		
12:00		
12:30		
13:00		
13:30		
14:00		
14:30		

Vascular	1
7:00	1.5
7:30	
8:00	2
8:30	
9:00	
9:30	
10:00	2.5
10:30	
11:00	
11:30	
12:00	2
12:30	
13:00	
13:30	
14:00	
14:30	

Urology	1	2
7:00	1	1
7:30		
8:00	1	2
8:30		
9:00		
9:30	1.5	
10:00		2
10:30		
11:00	1.5	
11:30		
12:00		2.5
12:30	1.5	
13:00		
13:30		
14:00	1.5	
14:30		

General	1	2	3	4	5	6	
7:00	1	1	2.5	1.5	3	1.5	
7:30							
8:00	2	1					
8:30							
9:00		1		2.5		1.5	
9:30							
10:00	2	1.5		3			4
10:30							
11:00							
11:30		2.5		3.5		1.5	
12:00							
12:30	2						
13:00							
13:30						2	
14:00							
14:30							

Orthopedic	1	2	3	4	5	6	7
7:00	1	2	1.5	1	3	4.5	1.5
7:30							
8:00	1						
8:30							
9:00	2	2.5	1.5	2.5	3		
9:30							
10:00							
10:30	4		3	3.5		4	5
11:00							
11:30							
12:00							
12:30	4	3	3.5	4	5	3.5	
13:00							
13:30							
14:00							
14:30							

D2. Target Capacity

Plastic	1	2	Vascular	1	Dental	1	2
7:00	1	2.5	7:00	1.5	7:00	1.5	2
7:30			7:30		7:30		
8:00	1.5		8:00		8:00		
8:30		4	8:30	2	8:30	2.5	2
9:00			9:00		9:00		
9:30			9:30		9:30		
10:00	2		10:00	2.5	10:00	3	2.5
10:30			10:30		10:30		
11:00			11:00		11:00		
11:30			11:30		11:30		
12:00	3		12:00		12:00		
12:30			12:30		12:30		
13:00			13:00		13:00		
13:30			13:30		13:30		
14:00			14:00		14:00		
14:30			14:30		14:30		

Orthopedic	1	2	3	4	5	6	7
7:00	1	2	1.5	1	3	4.5	1.5
7:30							
8:00	1	2.5	1.5	2.5	5	3.5	3
8:30							
9:00	2						
9:30		3	3.5	4	5		
10:00							
10:30							
11:00							
11:30	4						
12:00							
12:30							
13:00		3					
13:30							
14:00							
14:30							

General	1	2	3	4	5	6			
7:00	1	1	2.5	1.5	3	1.5			
7:30									
8:00	2	1							
8:30									
9:00		1	2.5	2.5	4	1.5			
9:30									
10:00	2	1.5				3	3.5	2	1.5
10:30									
11:00									
11:30									
12:00	2	2.5		3.5	4	1.5			
12:30									
13:00									
13:30									
14:00						2			
14:30									

EYE	1	2	3	4	5
7:00	1	1	1	0.5	1.5
7:30				1.5	
8:00	1	1	1		
8:30					
9:00	1	1	1	2	1.5
9:30					
10:00	1	1	1		
10:30					

ENT	1	2	3	4	5
7:00	1	0.5	1	1.5	1
7:30		1.5			2
8:00	1		2.5		
8:30		1		2	
9:00	1.5				2
9:30		1	2		
10:00	1			2	
10:30		1			2

Gynecology	1	2	3	
7:00	3	1.5	1	
7:30				
8:00		2	2.5	
8:30				
9:00				
9:30				
10:00	3.5	2		
10:30				
11:00		2		
11:30				
12:00				
12:30				
13:00		2.5		
13:30				
14:00				
14:30				

Appendix E

Dental	1	2
7:00	1.5	2
7:30		
8:00	2.5	2
8:30		
9:00		
9:30		
10:00	3	2.5
10:30		
11:00		
11:30		
12:00		2.5
12:30		
13:00		
13:30		
14:00		
14:30		

Vascular	1
7:00	1.5
7:30	
8:00	2
8:30	
9:00	
9:30	
10:00	2.5
10:30	
11:00	
11:30	
12:00	
12:30	
13:00	
13:30	
14:00	
14:30	

Thoracic	1
7:00	2
7:30	
8:00	2.5
8:30	
9:00	
9:30	
10:00	2.5
10:30	
11:00	
11:30	
12:00	
12:30	
13:00	
13:30	
14:00	
14:30	

Plastic	1	2
7:00	1	
7:30		
8:00		2.5
8:30	1.5	
9:00		
9:30		
10:00	2	
10:30		
11:00		4
11:30		
12:00		
12:30	3	
13:00		
13:30		
14:00		
14:30		

Bariatric	1
7:00	1
7:30	
8:00	
8:30	1.5
9:00	
9:30	
10:00	2
10:30	
11:00	
11:30	
12:00	
12:30	
13:00	
13:30	
14:00	
14:30	

Anesthesia	1
7:00	0.33
7:20	0.33
7:40	0.33
8:00	0.33
8:20	0.33
8:40	0.33
9:00	0.67
9:20	
9:40	0.67
10:00	
10:20	0.67
10:40	
11:00	0.67
11:20	
11:40	0.67
12:00	
12:20	0.67
12:40	
13:00	
13:20	
13:40	
14:00	
14:20	
14:40	

Orthopedic	1	2	3	4	5	6	7
7:00	1			1			
7:30		2	1.5				1.5
8:00	1				3		
8:30						4.5	
9:00			1.5	2.5			
9:30	2	2.5					3
10:00							
10:30							
11:00							
11:30			3.5				
12:00				4	5		
12:30							
13:00	4	3					3.5
13:30							
14:00							
14:30							

Nurology	1	2	3
7:00	1		
7:30			
8:00			
8:30			4
9:00			
9:30	3.5		
10:00			
10:30		8	
11:00			
11:30			
12:00			
12:30			
13:00			
13:30			
14:00			
14:30			

Gynecology	1	2	3
7:00			1
7:30		1.5	
8:00	3		
8:30			
9:00		2	2.5
9:30			
10:00			
10:30			
11:00		2	
11:30	3.5		
12:00			
12:30			
13:00		2.5	
13:30			
14:00			
14:30			

General	1	2	3	4	5	6
7:00	1	1		1.5		1.5
7:30						
8:00		1	2.5		3	
8:30	2					1.5
9:00		1		2.5		
9:30						
10:00		1.5	3			1.5
10:30	2					
11:00					4	
11:30						1.5
12:00		2.5		3.5		
12:30	2					
13:00						
13:30						
14:00						2
14:30						

EYE	1	2	3	4	5
7:00	1	1	1	0.5	1.5
7:30					
8:00	1	1	1	1.5	1.5
8:30					
9:00	1	1	1	2	
9:30					
10:00	1	1	1		
10:30					

ENT	1	2	3	4	5
7:00	1	0.5	1	1.5	1
7:30					
8:00	1	1.5	2	2.5	1
8:30					
9:00	1	1.5			2
9:30					
10:00	1				
10:30					

Urology	1	2	3
7:00	1	2	1
7:30			
8:00	1.5	2.5	1
8:30			
9:00	1.5		
9:30			
10:00	1.5		
10:30			
11:00	1.5	3.5	
11:30			
12:00			
12:30			
13:00			
13:30			
14:00			
14:30			

Vitae

JUMAAN ALI ALZAHIRANI

P.O.BOX 13051, DHAHRAN 31311, KINGDOM OF SAUDI ARABIA,
(+966)504761022 ALZAHIRANI.2@HOTMAIL.COM

EDUCATION

May 2015 **The George Washington University, Washington D.C., United States**

Master of Business Administration.

May 2013 **King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia**

Master of Science (part time) in Industrial and Systems Engineering; (GPA: 3.75/4.0). Thesis title "Operating Rooms Scheduling at SAMSO". A seminar and a conference paper presented. Three Journal papers under editing.

July 2009 **King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia**

Bachelor of Science in Industrial and Systems Engineering with first honors; (GPA: 3.83/4.0). Saudi Aramco sponsored degree (2% acceptance rate). Best Academic Award- Systems Engineering Department (2008). Name in Dean's List of Honor Students (2005–2006). Participant of KFUPM International Advisory Board.

EXPERIENCE

Saudi Arabian Oil Company (Saudi Aramco), Dhahran, Saudi Arabia

Government owned; fully integrated, global petroleum and chemicals enterprise and a world leader in exploration, production, refining, distribution, shipping and marketing with 259.9 billion barrels of proven conventional crude oil and condensate reserves.

Organization Performance Advisor, Management Consulting Resources Analysis Division (MCRAD)

August 2009- July 2013

MCRAD acts as an internal consulting house for resources optimization with a main focus on manpower

- Conducted resources optimization studies for fifteen different company functions. Such studies include detailed analysis and evaluation of current business processes and work procedures through activity analysis, work measurement, benchmarking, and workload analysis. Functions include inspection services, public relations, environmental protection, utilities, medical, government affairs, security, pipelines, land affairs, training, and personnel. Identified potential annual savings to the company.
- Created two work instruction manuals for resources analysis studies detailing the different approaches and techniques, currently used as the sole reference for such studies within the Division.
- Mentored seven Division new hires on resources optimization studies.

*Summer Trainee, Computer Operations Department
July-August, 2008*

- Developed work standardization approach, presented and approved by Department management.
- Created and updated 8 procedures and processes within “SAP Change Management Group”.

ADDITIONAL

High school: ranked 10th kingdom-wide (99.75% cumulative percentage). *KFUPM:* action day organizing committee, Systems Engineering & Industrial Management clubs, level 5 at AP Physics & AP Calculus, instructor assistant for 3 courses (Math, Statistics, Production Systems). *Saudi Aramco:* CDPNE graduation ceremony organizing committee, frequent blood donor, volley ball league golden medal, Qudwa Group (aid gender balance at the workplace).

References

- [1] AbdurRais and Ana Viana, “Operations Research in Healthcare: a Survey”, *International Transactions in Operational Research*, vol. 18, pp. 1-31, 2010
- [2] Al-Najjar, Sabah M. and Samir Hussain Ali, “Staffing and Scheduling Emergency Rooms in Two Public Hospitals: A Case Study”, *International Journal of Business Administration*, vol.2- 2, pp. 137-148,May 2011
- [3] Arnaout, Jean-Paul, “Heuristics for the Maximization of Operating Rooms Utilization Using Simulation”, *Simulation*, vol. 86-9, pp. 573-83,2009
- [4] Begen, Mehmet A. and Maurice Queyranne, “Appointment Scheduling with Discrete Random Durations”, *Mathematics of Operations Research*, vol. 36- 2, pp. 240–257, May 2011
- [5] Cardoen, Brecht; Erik Demeulemeester; and Jeroen Belien. “Operating Room Planning and Scheduling: a Literature Review”. *European Journal of Operations Research*, vol. 201-3, pp. 921–32, 2010
- [6] Cardoen, Brecht, “Operating Room Planning and Scheduling: Solving a Surgical Case Sequencing Problem”. Ph. D. Dissertation, Katholieke Universiteit Leuven, January 2009.
- [7] Chow, Vincent S; Martin L Puterman; Neda Salehirad; Wenhai Huang; and Derek Atkins, “Reducing Surgical Ward Congestion Through Improved Surgical Scheduling and Uncapacitated Simulation”. *Production and Operations Management*, vol. 20- 3, pp. 418-430, May/Jun 2011

- [8] Coffman, E.; Garey, M. ; and Johnson D. “Approximation Algorithms for Bin Packing: A Survey”. *Approximation Algorithms for NP-Hard Problems* (Book). PWS Publishing, Boston, pp. 46 – 93, 1997
- [9] Erdem, Ergin; XiuliQu; Jing Shi; and Sudhi Upadhyaya, “a Mathematical Modeling Approach for Rescheduling Elective Admissions Upon Arrival of Emergency Patients”, *Proceedings of the 2011 Industrial Engineering Research Conference*.
- [10] Essen, J. Theresia van; Johann L. Hurink; Woutske Hartholt; and Bernd J. van den Akker, “Decision Support System for the Operating Room Rescheduling Problem”, *Health Care Management Science*, vol. 15-4, pp. 355–72, December 2012
- [11] Ferreira, Jose; Carlos Gomes; and Mahmoud Yasin, “Improving Patients’ Satisfaction Through More Effective Utilization of Operating Rooms Resources: an Informational-Based Perspective”, *Clinical Governance: An International Journal*, vol. 16- 4, pp. 291-307, 2011
- [12] Foster, Tina, “Data for Benchmarking Your OR’s Performance”, *OR Manager*, vol. 28-1, pp. 13-6, January 2012
- [13] Gunal, MM and M Pidd, “Discrete Event Simulation for Performance Modelling in Health Care: a Review of The Literature”, *Journal of Simulation*, vol. 4, pp. 42–51, 2010
- [14] Gupta Babita; Pramendra Agrawal; Nita D’souza; and Kapil Dev Soni, “Start Time Delays in Operating Room: Different Perspectives”, *Saudi Journal of Anesthesia*, vol. 5-3, pp. 286-8, July-September 2011

- [15] Herring, William L. and Jeffrey W. Herrmann, “The Single-Day Surgery Scheduling Problem: Sequential Decision-Making and Threshold-Based Heuristics”, *OR Spectrum*, vol. 34, pp. 429–59, 2012
- [16] Holte, Matias and Carlo Mannino, “Innovative Applications of OR: The implementor/ Adversary Algorithm for the Cyclic and Robust Scheduling Problem in Health-Care”, *European Journal of Operational Research*, vol. 226, pp. 551–9, 2013
- [17] Jeang, Angus and An-Jen Chiang. “Economic and Quality Scheduling for Effective Utilization of Operating Rooms”. *Journal of Medical Systems*, vol. 36, pp. 1205–22, 2012
- [18] Jebali, Aida; Atidel B. Hadj Alouane; and Pierre Ladet, “Operating Rooms Scheduling”, *International Journal of Production Economics*, vol. 99, pp. 52–62, 2006
- [19] Keller, Brian and Guzin Bayraksan, “Scheduling Jobs Sharing Multiple Resources Under Uncertainty: a Stochastic Programming Approach”, *IIE Transactions*, vol. 42-1, pp. 16-30, January 2010
- [20] Knoeff, Thijs, “Operating Room Scheduling: an Evaluation of Alternative Scheduling Approaches to Improve OR Efficiency and Minimize Peak Demands for Ward Beds at SKB Winterswijk”, M. Sc. Thesis, University of Twente, September 2010.
- [21] Lee, Sangbok, and Yuehwern Yih, “Surgery Scheduling of Multiple Operating Rooms under Uncertainty and Resource Constraints of Post-Anesthesia Care

Units”, *Proceedings of the 2012 Industrial and Systems Engineering Research Conference*.

- [22] Liu, Ya; Chengbin Chu; and Kanliang Wang, “A New Heuristic Algorithm for the Operating Room Scheduling Problem”, *Computers & Industrial Engineering*, vol. 61, pp. 865–71, 2011
- [23] Mannino, Carlo; Eivind J. Nilssen; and Tomas Eric Nordlander. “A Pattern Based Robust Approach to Cyclic Master Surgery Scheduling”, *Journal of Scheduling*, vol. 15, pp. 553–63, 2012
- [24] Marques, Ines; M. Eugenia Captivo; and Margarida Vaz Pato, “Exact and Heuristic Approaches for Elective Surgery Scheduling”, *CLAIO-SBPO Conference*, Rio de Janeiro, Brazil, September 24-28, 2012
- [25] Marques, Ines; M. Eugenia Captivo; and Margarida Vaz Pato, “An Integer Programming Approach to Elective Surgery Scheduling: Analysis and Comparison Based on a Real Case”, *OR Spectrum*, vol. 34, pp. 407–27, 2012
- [26] May, Jerrold H.; William E. Spangler; David P. Strum; and Luis G. Vargas. “The Surgical Scheduling Problem: Current Research and Future Opportunities”, *Production and Operations Management*, vol. 20- 3, , pp. 392–405, May–June 2011
- [27] Min, Daiki and Yuehwern Yih, “An Elective Surgery Scheduling Problem Considering Patient Priority”, *Computers & Operations Research*, vol. 37, pp. 1091–99, 2010

- [28] Min, Daiki and Yuehwern Yih, “Innovative Applications of OR: Scheduling Elective Surgery Under Uncertainty and Downstream Capacity Constraints”, *European Journal of Operational Research*, vol. 206, pp. 642–52, 2010
- [29] Nouaouri, Issam; Jean Christophe Nicolas; and Daniel Jolly, “Chapter 45: Operating Schedule: Take into Account Unexpected Events in Case of a Disaster”, *Electrical Engineering and Applied Computing (Book)*, pp. 567-580, 2011
- [30] Pandit, J. J.; T. Abbott; M. Pandit; A. Kapila; and R. Abraham, “Is ‘Starting on Time’ Useful (or Useless) as a Surrogate Measure for ‘Surgical Theatre Efficiency’?”, *Anesthesia*, vol. 67, pp. 823–32, 2012
- [31] Peters, Jeffry A and Harrison M Dean, “Enhancing OR Capacity and Utilization”, *Healthcare Financial Management*, vol. 65- 1, pp. 66-71, Jan 2011
- [32] Riise, Atle, and Edmund K. Burke, “Local Search for the Surgery Admission Planning Problem”, *Journal of Heuristics*, vol. 17, pp. 389–414, 2011
- [33] Schimmelpfeng, Katja; Stefan Helber; and Steffen Kasper, “Decision Support for Rehabilitation Hospital Scheduling”, *OR Spectrum*, vol. 34, pp. 461–489, 2012
- [34] Schmalzried, Hans D. and Joseph Liszak, “A Model Program to Reduce Patient Failure to Keep Scheduled Medical Appointments”, *Journal of Community Health*, vol. 37, pp. 715-8, 2012

- [35] Shamayleh, Abdulrahim Okleh. “Operating Room Planning and Scheduling: Mathematical Models and Simulation Modeling”. Ph. D. Dissertation, Arizona State University, August 2010.
- [36] Shylo, Oleg V.; Louis Luangkesorn; Oleg A. Prokopyev; Jayant Rajgopal; and Andrew Schaefer, “Managing Patient Backlog in a Surgical Suite That Uses a Block-Booking Scheduling System”, *Proceedings of the 2011 Winter Simulation Conference*.
- [37] Steins, Krisjanis; Fredrik Persson; and Martin Holmer, “Increasing Utilization in a Hospital Operating Department Using Simulation Modeling”, *Simulation*, vol. 86-8, pp. 463-80, 2010
- [38] Stuart, Kari and Erhan Kozan, “Reactive Scheduling Model for the Operating Theatre”. *Flexible Services and Manufacturing Journal*, vol. 24, pp. 400–21, 2012
- [39] Su, Mu-Chun; Shih-Chang La; Pa-Chun Wang; Yi-Zeng Hsieh; and Shih-Chieh Lin, “A SOMO-Based Approach to the Operating Room Scheduling Problem”, *Expert Systems with Applications*, vol. 38, 15447–54, 2011
- [40] Sun, Yang and Xueping Li, “Optimizing Surgery Start Times for a Single Operating Room via Simulation”, *Proceedings of the 2011 Winter Simulation Conference*
- [41] Tanfani, Elena and Angela Testi, “A Pre-assignment Heuristic Algorithm for the Master Surgical Schedule Problem (MSSP)”, *Annals of Operations Research*, vol. 178-1, pp. 105–19, 2010

- [42] Vargas, Luis G.; Jerrold H. May; William Spangler; Alia Stanciu; and David P. Strum, "Chapter 19: Operating Room Scheduling and Capacity Planning", *Anesthesia Informatics (Book)*, pp. 361-92, 2008
- [43] Vijayakumar, Bharathwaj and Pratik J. Parikh, "Surgical Case Scheduling as a Dual Bin-Packing Problem", *Proceedings of the 2011 Industrial Engineering Research Conference*
- [44] White, Denise L; Craig M. Froehle; and Kenneth J. Klassen, "The Effect of Integrated Scheduling and Capacity Policies on Clinical Efficiency", *Production and Operations Management*, vol. 20-3, pp. 442-56, May/ June 2011
- [45] Zhang, Bo; Pavankumar Murali; Maged Dessouky; and David Belson, "Mixed Integer Programming Approach for Allocating Operating Room Capacity", *Journal of the Operational Research Society*, vol. 60, pp. 663 -73, 2009
- [46] Zhu, Zhecheng; Bee Hoon Heng; and Kiok Liang Teow, "Analysis of Factors Causing Long Patient Waiting Time and Clinic Overtime in Outpatient Clinics". *Journal of Medical Systems*, vol. 36, pp.707-13, 2012
- [47] Zonderland, Maartje E.; Richard J. Boucherie; Nelly Litvak; and Carmen L. A. M. Vleggeert-Lankamp, "Planning and Scheduling of Semi-urgent Surgeries", *Health Care Management Science*, vol. 13, pp. 256–67, 2010
- [48] Stille, Wolfgang Michael, "Solution Techniques for Specific Bin Packing Problems with Applications to Assembly Line Optimization", Ph. D Dissertation, Technische Universität Darmstadt, June 2008.

- [49] Macario, Alex, “What does one minute of operating room time cost?”, *Journal of Clinical Anesthesia*, vol. 22, pp. 233–6, 2010.
- [50] [Http://www.saudiaramco.com](http://www.saudiaramco.com). Retrieved: 15th January, 2013.