MULTI-STAGE MULTI-OBJECTIVE OPTIMIZATION FOR OPERATING ROOM RESOURCES PLANNING AND SCHEDULING PROBLEM CONSIDER DEMAND REQUIREMENT UNCERTAINTY: A POST-PANDEMIC RECOVERY PERSPECTIVE

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การวางแผนและจัดตารางการใช้ทรัพยากรห้องผ่าตัดแบบหลายขั้นตอน เชิงพหุวัตถุประสงค์ ภายใต้ความไม่แน่นอนของความต้องการ จากมุมมองของการฟื้นฟูหลังโรคระบาด

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต
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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's degree.

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โซวัน ตั๊ก : การวางแผนและจัดตารางการใช้ทรัพยากรห้องผ่าตัดแบบหลายขั้นตอนเชิงพหุวัตถุประสงค์ ภายใต้ความไม่แน่นอนของความต้องการจากมุมมองของการฟื้นฟูหลังโรคระบาด (MULTI-STAGE MULTI-OBJECTIVE OPTIMIZATION FOR OPERATING ROOM RESOURCES PLANNING AND SCHEDULING PROBLEM CONSIDER DEMAND REQUIREMENT UNCERTAINTY: A POST-PANDEMIC RECOVERY PERSPECTIVE) อาจารย์ที่ปรึกษา: รองศาสตราจารย์ ดร.พงษ์ชัย จิตตะมัย, 163 หน้า.

คำสำคัญ: การจัดสรรทรัพยากรด้านสุขภาพ/การบริหารจัดการทรัพยากรห้องผ่าตัด/การจัดการรายชื่อผู้ป่วยรอผ่าตัด/ปัญหาความล่าช้าในการผ่าตัด/การปรับเหมาะเชิงหลายวัตถุประสงค์/ระยะเวลารอคอยของผู้ป่วย

การระบาดใหญ่ของโรคติดเชื้อไวรัสโคโรนา 2019 (COVID-19) ได้สร้างผลกระทบอย่างรุนแรงต่อระบบโรงพยาบาลและสาธารณสุขทั่วโลก โดยเฉพาะอย่างยิ่งในโรงพยาบาลที่การผ่าตัดแบบทั่วไปที่ไม่มีความเร่งด่วน (elective surgery) ต้องถูกเลื่อนการผ่าตัดออกไปหรือยกเลิกการผ่าตัดอย่างหลีกเลี่ยงไม่ได้ เพื่อให้โรงพยาบาลสามารถรองรับผู้ป่วยโรคติดเชื้อได้มากยิ่งขึ้นและจำกัดการแพร่กระจายของเชื้อโรค ซึ่งจากเหตุผลดังกล่าวส่งผลให้เกิดผลกระทบที่ตามมาก อันได้แก่ เกิดปัญหาการตกค้างของผู้ป่วยที่รอรับการผ่าตัดในระยะยาว ส่งผลให้ระยะเวลารอผ่าตัดเพิ่มสูงขึ้น ความต้องการใช้ทรัพยากรภายในโรงพยาบาล เช่น ห้องผ่าตัด (Operating Room: OR) หน่วยดูแลผู้ป่วยหนัก (Intensive Care Unit: ICU) และหอผู้ป่วยใน มีความแออัดมากขึ้น และเกิดความยากลำบากในการบริหารจัดการทรัพยากรอย่างมีประสิทธิภาพในโรงพยาบาล

เมื่อสถานการณ์เริ่มคลี่คลายและเข้าสู่ช่วงการฟื้นตัวหลังการระบาด โรงพยาบาลต่าง ๆ ต้องเผชิญกับจำนวนผู้ป่วยที่สูงขึ้นเนื่องจากมีผู้ป่วยที่ตกค้างจากการเลื่อนผ่าตัด ขณะเดียวกันก็ต้องบริหารจัดการทรัพยากรภายใต้ข้อจำกัดที่ยังคงอยู่ เช่น ขีดความสามารถที่ไม่เพียงพอ ความไม่แน่นอนของระยะเวลาการผ่าตัด และระยะเวลาพักรักษาในโรงพยาบาล (Length of Stay: LOS) สถานการณ์เช่นนี้สะท้อนถึงความจำเป็นในการพัฒนากรอบแนวคิดใหม่ในการวางแผนและจัดสรรทรัพยากรอย่างรอบคอบ เพื่อให้เกิดความสมดุลระหว่างประสิทธิภาพและความเป็นธรรมในการให้บริการ

วิทยานิพนธ์ฉบับนี้มีจึงมีวัตถุประสงค์เพื่อเสนอแนวทางการวางแผนและจัดตารางการใช้ทรัพยากรในห้องผ่าตัดแบบหลายขั้นตอน ภายใต้เป้าหมายหลายมิติ และความไม่แน่นอนของปัจจัยด้านความต้องการ โดยมุ่งเน้นการแก้ไขปัญหา Block Master Surgery Scheduling Problem (BMSSP) ซึ่งเป็นปัญหาหลักในการจัดสรรบล็อกเวลาการผ่าตัดให้กับแผนกศัลยกรรมต่าง ๆ อย่างเหมาะสมและมีประสิทธิภาพ ภายใต้ข้อจำกัดด้านทรัพยากรและความไม่แน่นอนของจำนวนคนไข้ จำนวนห้องผ่าตัด และอื่นๆ และเพื่อดำเนินการศึกษาวิจัยภายใต้หัวข้อดังกล่าว งานวิจัยนี้ได้เสนอกรอบการตัดสินใจที่ขับเคลื่อนด้วยข้อมูล (Data-Driven Decision Framework) ซึ่งแบ่งออกเป็น 2 ระยะหลัก ได้แก่

ระยะที่ 1 มุ่งเน้นการวางแผนในระดับกลยุทธ์ โดยพัฒนาแบบจำลองการเพิ่มประสิทธิภาพเชิงสุ่ม (Stochastic Optimization Model) ที่เรียกว่า DORA Model เพื่อใช้ในการจัดสรรบล็อกเวลาของห้องผ่าตัดให้กับแต่ละแผนก แบบจำลองดังกล่าวพิจารณาเกณฑ์ด้านประสิทธิภาพ เช่น ระยะเวลาเฉลี่ยในการลดจำนวนผู้ป่วยที่รอผ่าตัด และต้นทุนรวมในการดำเนินงาน ผลการทดลองซึ่งใช้ข้อมูลจริงจากโรงพยาบาลขนาดใหญ่แห่งหนึ่งในประเทศไทย แสดงให้เห็นว่า แบบจำลองสามารถลดระยะเวลารอผ่าตัดเฉลี่ยลงได้ร้อยละ 7 (จาก 40.5 สัปดาห์ เหลือ 37.67 สัปดาห์) และลดต้นทุนรวมลงได้ร้อยละ 5 (จาก 4.27 ล้านดอลลาร์ เหลือ 4.08 ล้านดอลลาร์) พร้อมทั้งช่วยเพิ่มประสิทธิภาพในการใช้ทรัพยากรของห้องผ่าตัด ICU และหอผู้ป่วย

ระยะที่ 2 มุ่งเน้นการตัดสินใจในระดับยุทธวิธี โดยใช้วิธีการตัดสินใจแบบหลายเกณฑ์ (Multi-Criteria Decision Making: MCDM) ด้วยเทคนิค TOPSIS เพื่อจัดลำดับความสำคัญของผู้ป่วยรายบุคคลในแต่ละแผนก โดยพิจารณาปัจจัยหลัก ได้แก่ ความเร่งด่วนในการผ่าตัด ระยะเวลารอคอย และปริมาณทรัพยากรที่คาดว่าจะใช้ วิธีการนี้ช่วยเพิ่มความเหมาะสมและเพื่อประสิทธิภาพของการจัดตารางผ่าตัดได้ เมื่อเปรียบเทียบกับวิธีแบบดั้งเดิมที่ใช้ลำดับตามลำดับการมาถึง (First-Come, First-Served: FCFS)

กรอบแนวทางที่นำเสนอในวิทยานิพนธ์นี้จึงเป็นการนำการวางแผนเชิงกลยุทธ์กับการตัดสินใจเชิงยุทธวิธีอย่างเป็นระบบมาใช้ร่วมกัน ซึ่งสามารถนำไปประยุกต์ใช้ได้จริงในสถานพยาบาลที่ต้องเผชิญกับข้อจำกัดด้านทรัพยากร ทั้งในช่วงฟื้นตัวหลังภาวะวิกฤตและในสถานการณ์ปกติ ช่วยให้การตัดสินใจของโรงพยาบาลในการจัดสรรทรัพยากรอย่างเหมาะสม ลดความเหลื่อมล้ำในการเข้าถึงบริการ และเพิ่มความยืดหยุ่นของระบบในการรองรับสถานการณ์ฉุกเฉินในอนาคต เช่น การระบาดใหญ่ ภัยพิบัติ หรือการหยุดชะงักของกระบวนการให้บริการ ทั้งนี้ เพื่อเพิ่มประสิทธิภาพและความสามารถในการใช้งานของแบบจำลองในระดับปฏิบัติการ งานวิจัยในอนาคตควรพิจารณาประเด็นอื่นๆ เพิ่มเติม อาทิเช่น การจัดลำดับรายชื่อผู้ป่วยรอผ่าตัดที่สามารถปรับเปลี่ยนได้อย่างยืดหยุ่น ความแตกต่างของขีดความสามารถในแต่ละห้องผ่าตัด และการพัฒนาระบบสนับสนุนการตัดสินใจแบบเรียลไทม์ ซึ่งจะช่วยให้แบบจำลองมีความยืดหยุ่นและครอบคลุมมากยิ่งขึ้น

สาขาวิชาวิศวกรรมอุตสาหการ ลายมือชื่อนักศึกษา..........

ปีการศึกษา 2567 ลายมือชื่ออาจารย์ที่ปรึกษา..........

SOVANN TOEK : MULTI-STAGE MULTI-OBJECTIVE OPTIMIZATION FOR OPERATING ROOM RESOURCES PLANNING AND SCHEDULING PROBLEM CONSIDER DEMAND REQUIREMENT UNCERTAINTY: A POST-PANDEMIC RECOVERY PERSPECTIVE. THESIS ADVISOR : ASSOC. PROF. PHONGCHAI JITTAMAI, Ph.D., 163 PP.

KEYWORDS: Healthcare Resource Allocation/Operating Room Resource Management/ Waiting List Management/Surgical Backlogs/Multi-Objective Optimization/Patient Waiting Time

The COVID-19 pandemic has intensified long-standing challenges in elective surgical care, leading to widespread cancellations, prolonged waiting times, and increased strain on hospital resources. As healthcare systems transition into the post-pandemic era, hospitals must address growing surgical backlogs while managing persistent uncertainty and capacity constraints. This thesis tackles the Block Master Surgery Scheduling Problem (BMSSP), which involves the equitable and efficient allocation of limited operating room (OR) resources among competing surgical departments under uncertainty in surgery duration and patient length of stay (LOS).

To address this problem, a two-phase, data-driven decision-making framework is proposed. In Phase 1, a stochastic optimization model—referred to as the DORA model—is developed to allocate OR blocks based on performance criteria including waiting list clearance time and total incurred costs. The model was validated using real-world data from a major hospital in Thailand, demonstrating a 7% reduction in average patient waiting time (from 40.5 to 37.67 weeks) and a 5% decrease in total costs (from 4.27 million to 4.08 million dollar), along with improved utilization across ORs, ICUs, and wards. In Phase 2, a Multi-Criteria Decision-Making (MCDM) approach using the TOPSIS method is employed to prioritize patients within each department based on clinical urgency, waiting time, and expected resource needs. This approach enhances fairness and efficiency compared to traditional first-come, first-served (FCFS) scheduling.

The proposed framework integrates strategic-level resource planning with tactical-level patient prioritization, offering a robust and adaptable tool for elective surgery scheduling in resource-constrained environments. It supports hospital

administrators in optimizing resource allocation, minimizing disparities in access to care, and enhancing system resilience during future crises such as pandemics, disasters, or operational disruptions. Future work should explore dynamic waiting lists, heterogeneous OR capacities, and real-time decision support to further increase the model's practical relevance and scalability.

School of Industrial Engineering　　Student's Signature ....Sovanny..........

Academic Year 2024　　Advisor's Signature ....

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Sovann Toek

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MINLP: MIX INTEGER NON-LINEAR PROGRAMMING.

OR: OPERATING ROOM.

ICU: INTENSIVE CARE UNIT.

MCU: MEDIUM CARE UNIT.

LOS: LENGTH OF STAY.

MOOP: MUTI-OBJECTIVE OPTIMIZATION PROBLEM.

DORA: DETERMINISTIC OPERATING ROOM ALLOCATION.

MOMC: MULTI OBJECTIVE MULTI CONSTRAINT.

CHAPTER I

INTRODUCTION

1.1 Background

Over the past two decades, the healthcare industry has faced significant transformation. One of the most pressing global challenges of the 21st century is the aging population. The increasing proportion of individuals aged 65 and above has contributed to a worldwide surge in healthcare expenditure, driven by higher demand for both medical and long-term care services. This trend poses substantial threats to the sustainability of public health financing across countries (Lopreite & Zhu, 2020).

The COVID-19 pandemic has further disrupted global healthcare systems. Hospitals became overwhelmed with patients, while public health authorities focused on mitigating the virus's spread. As a result, non-urgent medical services, including elective surgeries, were postponed or canceled. Restrictions such as curfews, transportation limitations, and stay-at-home mandates prevented patients from accessing care, while many avoided healthcare facilities out of fear of infection. These disruptions severely affected elective surgical services, leading to extensive waiting lists and delays in nearly every country. Although concerns about surgical wait times are not new, the combination of limited operating room (OR) resources and growing demand has exacerbated the issue (Angelis et al., 2016).

The pandemic has worsened this already strained system. According to the COVIDSurg Collaborative, it would take a median of 45 weeks to clear the backlog of surgeries caused by just 12 weeks of peak pandemic disruption, assuming a 20% increase in normal surgical volume post-pandemic. However, with the pandemic persisting for over two years, this estimate likely underrepresents the true extent of the problem (Mehta et al., 2022). These delays increase both operational costs and the complexity of scheduling, as urgent and delayed procedures must be managed simultaneously.

Extended waiting times can lead to severe consequences. Prolonged delays in diagnosis and treatment may worsen patients' conditions, reduce recovery prospects, and even impact survival rates. The long-term effects include irreversible loss of function or poorer health outcomes, while short-term consequences range from worsened symptoms to decreased ability to work (Mehta et al., 2022). For example, patients awaiting elective procedures like joint replacements face prolonged pain and reduced quality of life. Delays in cancer surgeries or missed chemotherapy sessions can have life-threatening implications. Additionally, deferring appointments increases the likelihood of missed diagnoses and necessitates more expensive, resource-intensive interventions later. These delays impose not only a burden on the healthcare system but also broader societal and economic costs.

As COVID-19 transitions to an endemic phase, it is imperative that healthcare institutions address the backlog of elective surgeries and resume routine operations. Effective allocation of OR resources is now more critical than ever to ensure timely access to surgical care and restore normal system functionality.

1.2 Motivations and Significances

Resource allocation is a constant challenge for healthcare decision-makers. Whether prioritizing between services (priority setting) or among patients (rationing), the pandemic has highlighted the necessity for systematic, transparent, and equitable allocation decisions (Angelis et al., 2016). COVID-19 created a stark mismatch between demand and available resources. Hospitals and governments were forced to make urgent decisions regarding who would receive care, often without clear guidelines for admissions, discharges, or the use of limited resources such as ICU beds and protective equipment (Frank et al., 2020). Allocation protocols were rapidly developed to reduce bias and improve decision-making under uncertainty (Badalov et al., 2022).

Now, with the acute phase of the pandemic largely behind us, hospital administrators are under increasing pressure to reduce surgical backlogs and meet rising demand for elective procedures. The competition for limited OR blocks across departments has intensified, necessitating better planning and scheduling strategies. However, the challenges remain: hospitals continue to face resource shortages, including limited surgical staff, operating theatre slots, beds, and ICU capacity. Uncertainties about future surgical demand and resource availability further complicate planning efforts.

In this context, effective OR block allocation is crucial. The number of blocks assigned to each surgical department directly affects hospital performance by influencing patient throughput, operating costs, and overall revenue. Different surgical specialties generate varying revenues, incur different costs, and require different postoperative recovery times and ICU stays. Moreover, the cost of waiting varies across specialties—some patients experience more severe health declines from delays than others.

Given these complexities, a strategic approach is required to optimize the allocation of OR resources and prioritize patients within each department in a fair and clinically informed manner. This research aims to address these challenges through a two-phase approach:

1.1 **Phase 1**: focuses on allocating OR blocks among surgical departments based on multiple performance and capacity considerations.

2.1 **Phase 2**: applies a multi-criteria decision-making (MCDM) framework to prioritize patients within each department, ensuring that limited surgical slots are used for those with the most urgent needs or the highest potential benefit. By improving planning and scheduling processes, hospitals can better manage surgical backlogs, enhance resource utilization, and ensure timely and equitable access to elective surgical care in the post-pandemic era.

1.3 Problem Definition

The Operating Theatre (OT) is a critical and resource-intensive component of the hospital system, where the coordination of various resources—operating rooms (ORs), surgical teams, intensive care units (ICUs), and inpatient wards—is essential to delivering timely and efficient elective surgical care. As demand for elective surgeries continues to rise across multiple surgical departments, hospitals face growing challenges in optimizing the use of constrained OR capacity while minimizing patient waiting times and operational costs.

Hospitals typically adopt a Block Scheduling Strategy—allocating fixed time blocks within ORs to specific surgical departments over a planning horizon (e.g., a week). However, if these blocks are not optimally assigned, it can result in unfair access among departments, under-utilized ORs, prolonged patient waiting lists, and inflated hospital costs. Furthermore, uncertainty in surgery durations and patient length of stay (LOS) complicates planning, making traditional deterministic models inadequate for real-world applications.

The Block Master Surgery Scheduling Problem (BMSSP) arises from the need to allocate surgical specialties to OR blocks under such uncertainty, while balancing multiple, often conflicting, performance objectives. Despite its practical relevance, existing approaches often overlook the stochastic nature of surgical services or treat uncertainty in a simplified manner. To address these issues, this study proposes a two-phase decision framework:

Phase 1: OR Block Allocation – A mathematical optimization model is developed to allocate OR blocks to surgical departments while incorporating uncertainty in both surgery durations and patient LOS. The model aims to ensure fairness in access—by minimizing disparities in waiting list clearance time—and to reduce total incurred costs associated with surgery overtime, delays, and capacity overflow.

Phase 2: Patient Prioritization – After block allocation, an MCDM-based approach is applied within each department to prioritize patients for surgery based on multiple criteria, including clinical urgency, waiting time, and expected resource utilization, under limited OR time and stochastic conditions.

By integrating strategic-level OR block planning with tactical-level patient scheduling, the proposed framework contributes a comprehensive, uncertainty-aware solution to improving surgical service delivery. It aims to enhance OR utilization, reduce patient wait disparities, and contain hospital operational costs in a resource-constrained environment.

1.4 Problem features

1.4.1 Block Master Surgery Scheduling Problem (BMSSP)

Master Surgery Scheduling Problem (MSSP) is to schedule the surgical specialties (SSs) to the different operating rooms available, such that surgeries may be performed efficiently. MSSP determines the workload distribution, and the revision of the MSS is restricted by the capacity and demand constraint. The availability of the operating room is based on block scheduling strategies adopted. As a large body of literature is based on the block scheduling strategy, while relatively fewer studies follow the open scheduling strategy. In practice, the block scheduling strategy is applied more often than the open scheduling strategy in hospitals. Once a block time of an OR is allocated to one surgeon or surgical specialty, others cannot occupy the block even if that surgeon doesn't arrange any surgical cases in the block time.

In this study, we focus on BMSSP, the problem of allocating surgical specialties (SSs) to operating rooms over a given time horizon (one week). OR capacity is divided into blocks or slots with each OR for a specified duration of 8 hours.

1.4.2 Uncertainty

Uncertainty is an impacting issue due to the highly variable nature of surgical cases (Vancroonenburg et al. 2015). The literature on OR scheduling shows that the uncertainty of surgery duration is inherent to surgical services. Surgery duration refers to the processing time of the surgery. Duration uncertainty refers to the deviations between the actual and the planned durations of relevant activities during the surgical process. The uncertainty of surgery duration is mainly caused by the patient condition, the skill of the surgeon and any other factors that can make the surgery smooth or not (Molina-Pariente et al., 2015). Furthermore, the duration depends on the surgical specialty such as orthopedic, cardiac, or neurological. Uncertain actual surgery duration is a significant factor in surgery planning and scheduling problems, which makes the problems much more challenging. The consideration of uncertainty in surgery durations and emergency interventions can make the OR scheduling problems quite different from the deterministic ones. Such uncertainty or variability is commonly ignored in many OR planning and scheduling problems which assuming deterministic surgery durations, while stochastic approaches try to incorporate it. In addition to duration uncertainty, the inherent uncertainty in surgeries such as the unforeseen arrival of an emergency patient also has an impact on the surgery schedule.

Although plenty of studies show that the uncertainty factors such as emergency requirements in OR planning are extremely important, researchers all use the deterministic optimization model in the existing OR planning methods, and the hospital is supposed to use dedicated ORs to serve emergency patients, or to use a fixed portion of the capacity to perform emergency operations (Lamiri et al., 2008). Moreover, in hospitals, balancing the operational costs and the service level is hard. In the problems of OR planning and scheduling, the constraints are mainly about the availability, applicability, and usability of resources, including facilities resources. A set of resource combinations is open to certain cases at certain times in certain places, while others may be unavailable or inapplicable. Only a few researchers pay attention to resource uncertainty that results from patient length of stay (LOS). Hence, this study aims to incorporate demand uncertainty, namely surgery duration and patient LOS.

1.4.3 Performance measures

Various performances criteria are used to evaluate operating room planning and scheduling problems. The structure and scope of an OR mathematical model may be limited to these criteria (Rahimi & Gandomi., 2020). According to Cardoen et al. (2010), they distinguished between eight main performance measures, such as, waiting time, throughput, utilization, leveling, make-span, patient deferrals, financial measures, and preferences. In this study, we focus on two critical healthcare performance measures namely: waiting list clearance time (waiting time and throughput) and total incurred cost (financial measures). Henceforth, operating room block planning and scheduling aims at minimizing the conflicting costs of operating room overtime, as well as patient waiting time for surgery while accounting for the penalty cost for exceeding operating room capacity.

1.5 Objectives

The following are the main objectives of this study:

1) To develop a mathematical model that minimizes both the total absolute deviation of the time required to clear the surgical backlog for all Surgical Specialties (SSs) and the overall costs associated with operating room (OR) block allocation over the planning period.
2) To allocate OR blocks across multiple SSs in a way that balances resource utilization and equity in patient access.
3) To prioritize patients within each surgical specialty using a multi-criteria decision-making (MCDM) approach that accounts for various clinical and operational factors (e.g., urgency, waiting time, expected surgery duration, ICU/ward resource consumption).
4) To analyze the trade-off between time-based and cost-based performance in OR block allocation decisions.

1.6 Scope of Research

This study focuses on improving elective surgery planning at the tactical and operational levels in a hospital setting through a two-phase framework:

1) **Phase 1** – OR Block Allocation: A mathematical model is developed to allocate OR blocks to various Surgical Specialties (SSs) under demand uncertainty. The aim is to minimize the total absolute deviation in the time required to clear patient backlogs and reduce OR operational costs, while ensuring efficient and equitable use of critical resources (OR time, ICU beds, surgical ward beds).
2) **Phase 2** – Patient Prioritization: Once blocks are allocated to each department, patients on the waiting list are prioritized using a multi-criteria decision-making (MCDM) approach to ensure that patients with higher urgency and greater need are treated first. This step addresses sequencing decisions within each specialty rather than detailed scheduling across the OR timetable.

The following issues are addressed to achieve these goals:

1) Develop a mathematical model to determine the optimal number of OR blocks allocated to each surgical specialty that minimizes operating costs and the deviation in backlog clearance time.
2) Use MCDM methods (e.g., AHP, TOPSIS, or similar) to prioritize patients for surgery within each specialty based on predefined criteria.
3) Perform scenario analysis to examine how different planning strategies affect the trade-off between time and cost.
4) Explore fairness scenarios where some specialties may be given priority access (e.g., life-threatening conditions) to evaluate equity in waiting list clearance.
5) Evaluate the proposed block allocation and patient prioritization framework using computational experiments and sensitivity analysis over a planning horizon to improve the operating room's performance in terms of time and cost.

1.7 Research Assumptions

The study makes the following assumptions:

1) Dedicated Pathway for Emergencies: Emergency surgeries are handled in separate resources and are excluded from this analysis. Outpatient procedures are also excluded as they typically do not strain ICU or ward capacities.
2) Homogeneous ORs: All ORs are identical, fully equipped, and capable of handling surgeries for any specialty. Surgical team constraints are not explicitly modeled.
3) Block Scheduling Policy: A block is defined as 8 hours (8:00–16:00). A maximum of two blocks per day per OR is allowed (i.e., 16 hours from 8:00–01:00). Overtime incurs a penalty cost.
4) Resource Constraints: The study focuses on OR blocks, ICU beds, and surgical ward beds. Other resources such as lab, radiology, or outpatient nursing capacity are excluded.

5) Static Waiting List: The number of patients on the waiting list at time *t* is known and fixed. The model does not consider new arrivals and aims to clear the current backlog to return the OT to business as usual operations.
6) Sequencing Rule Baseline: Although MCDM is used for prioritization, the default comparison assumes a first-come, first-served (FCFS) rule.
7) Post-Operative Resource Usage: Post-surgery ICU stays are modeled. Patients may be downgraded to lower levels of care if ICU capacity is exceeded, with associated penalty costs.

1.8 Expected Usefulness

1) The proposed models will provide a structured admission and block allocation plan for elective surgery that minimizes variation in actual versus target utilization of critical resources.
2) The proposed multi-stage optimization framework help the decision-making more transparently.
3) The study's results will help medical and administrative staff recognize the importance of effective OR planning and patient prioritization to ensure timely care delivery and efficient resource use.

1.9 Organization of the Thesis

1) **Chapter 1** outlines the background, problem definition, objectives, scope, assumptions, and significance of the study.
2) **Chapter 2** presents a review of related literature in OR scheduling, block allocation, and patient prioritization methodologies.
3) **Chapter 3** formulates the mathematical models for OR block allocation and describes the MCDM approach for patient prioritization, along with the case study context.
4) **Chapter 4** provides computational results and scenario analyses to evaluate model performance and robustness.
5) **Chapter 5** concludes the study with key findings, contributions, limitations, and directions for future research.

CHAPTER II

LITERATURE REVIEWS

The study aims to incorporate the knowledge of medical informatics (Surgical Informatics), and Operation Research (OR) to study the integration of resource allocation and patient prioritization in Operating Theatre (OT).

2.1 Operating room planning and scheduling

The Operating room (OR) is one of the most expensive units and a central hub in the hospital system. The largest cost categories of a hospital are operating rooms and the downstream patient ward groups, averaging 33% and 31% of its total cost, respectively. It generates most of their funding, makes up most of their cost and strongly influences the use of various resources (Cardoen et al., 2010). Activities inside OR have a substantial impact in hospital system, since ORs are clearly connected with other downstream resources **(Figure 2.1.1)** for instance, the Post Anesthesia Care Unit (PACU), the Intensive Care Unit (ICU), the intermediate care unit (IMC) and general patient ward. As shown in Figure 1, after surgeries, in most cases patients are admitted to a ward. In more severe cases, patients are sent to the ICU. This is an inpatient in which patients can either be admitted to an ICU or a general ward. Patients in an ICU will be transferred to a ward before discharge. Alternatively, patients might be discharged without being sent to a ward (e.g., outpatient). Patients in the wards will be transferred to the ICU if their condition becomes unstable. Most patients leave the system only after recovering in a ward, but they might also leave the hospital directly from the ICU (e.g., if transferred to another hospital).

Hence, operating room (OR) management has remarkable impacts on the efficiency of not only OR departments themselves but also other functions of hospitals. For these reasons, the OR planning and scheduling attracted a lot of attention to managing and improving productivity.

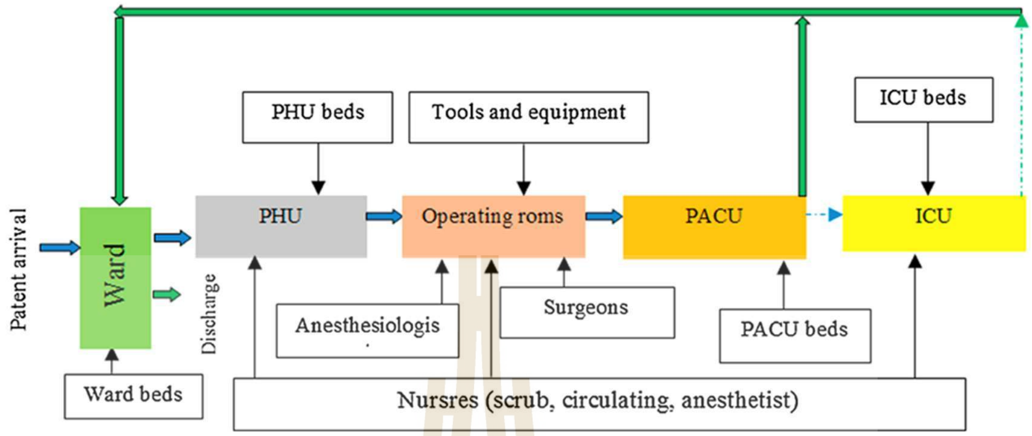

Figure 2.1.1 Operating room

2.1.1 Patients and OR suit characteristics

There are two types of classifications of patients in the OR planning and scheduling problems as shown **in Figure 2.1.2**, elective patients or non-elective patients, and inpatients or outpatients. An elective patient class stands for the patient with whom the surgery can be well planned and distinguish between inpatient and outpatient in which inpatient refer to hospitalized patients who must stay overnight, while outpatients typically enter and leave the hospital on the same day.

On the other hand, non-elective patient class groups for whom surgery is unexpected and hence need to be performed urgently and a distinction can be made between urgent and emergency surgery based on responsiveness to the patient's arrival (i.e., the waiting time till start of surgery). Whereas the surgery of emergent patients (emergencies) must be performed as soon as possible, urgent patients (urgencies) refer to non-elective patients that are sufficiently stable so that their surgery can possibly be postponed for a short period.

In an OR suit there are three policies namely, dedicated, shared and hybrid policy. A dedicated policy: was defined as a reserving OR rooms for non-elective cases only; shared policy was defined as an OR having both non-elective and elective cases. Hybrid policy: was defined as an OR blood having a mix of both dedicated and shared rooms. Duma & Aringhieri. (2019) conducted an in-depth study on how dedicated, shared and hybrid policy perform in a wide range scenario. They concluded that, while dedicated and shared policies might be preferred in certain context (dedicated policies reduce elective cancellation and shared policies result in better resources use), hybrid policies are recommended because they are better addressing the inherent trade-off between elective and emergency patient metrics.

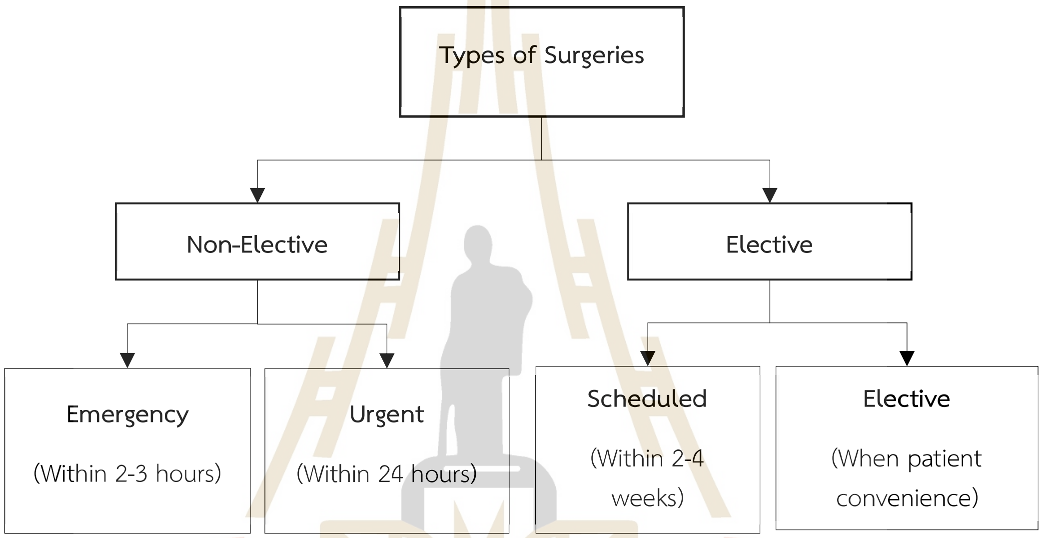

Figure 2.1.2 Patient categories

2.1.2 Decision hierarchy and Scheduling policy

OR planning and scheduling decisions can be structured into a **three-level hierarchy**: strategic, tactical, and operational (Hans et al., 2011; Beliën & Demeulemeester, 2007; Cardoen et al., 2010), as shown in **Figure 2.1.3.**

3.4.2.1 The strategic level involves long-term decisions about the healthcare system's direction, such as expanding resources (e.g., purchasing MRI machines), implementing new medical protocols, or forming partnerships with insurers. In OR management, this includes case mix planning (CMP)—deciding how to allocate total OR time among different specialties or surgical teams.

3.4.2.2 The tactical level addresses medium-term planning, particularly the development of a master surgery schedule (MSS). This schedule specifies how OR time is distributed across different departments over weeks or months.

3.4.2.3 The operational level focuses on short-term decisions, such as assigning individual surgeries to specific ORs on particular days (Jebali & Diabat, 2017). Due to upstream constraints, this level offers limited flexibility.

To operate these decisions, hospitals adopt one of three OR scheduling strategies:

1) **Block strategy**: OR time is pre-assigned in fixed blocks (e.g., 8:00–16:00) to specific departments or surgeons (Zhu et al., 2018).
2) **Open strategy**: all surgical cases compete for OR slots without pre-assigned times, promoting flexibility (Denton et al., 2007).
3) **Modified block strategy**: combines the above two to maintain managerial flexibility and efficient resource use (Zhu et al., 2018; Mullen et al., 2017).

	Medical planning	***Resource capacity planning***	***Materials planning***	***Financial planning***
Strategic	Research, development of medical protocols	Case mix planning, capacity dimensioning, workforce planning	Supply chain and warehouse design	Investment plans, contracting with insurance companies
Tactical	Treatment selection, protocol selection	Block planning, staffing, admission planning	Supplier selection, tendering	Budget and cost allocation
Offline operational	Diagnosis and planning of an individual treatment	Appointment scheduling, workforce scheduling	Materials purchasing, determining order sizes	DRG billing, cash flow analysis
Online operational	Triage, diagnosing emergencies and complications	Monitoring, emergency coordination	Rush ordering, inventory replenishing	Billing complications and changes

Figure 2.1.3. Decision hierarchy

Managing OR resources is inherently complex due to limited capacity, variable procedure durations, diverse patient needs, and the involvement of multiple stakeholders with often conflicting objectives (e.g., minimizing cost vs. maximizing patient satisfaction). Additionally, because elective cases account for up to 75% of surgeries (Hassanzadeh et al., 2022; Jebali & Diabat, 2017), careful integration of non-elective surgeries—often performed in dedicated units—is necessary to maintain efficiency (Cardoen et al., 2010; Min & Yih, 2010; Mullen et al., 2017; Neyshabouri & Berg, 2017). Ultimately, effective OR planning aims to reduce total costs and patient waiting times while maximizing resource utilization.

2.2 Patient waiting list management

Patient waiting list management is a critical component of healthcare delivery, especially in the context of surgical services where demand for services significantly exceeds supply. Ineffective and inefficient resource management in the OR department can consequently affect elective surgery waiting lists, leading to prolonged waiting times, negatively impacting patient health and satisfaction, and sometimes resulting in patients leaving before receiving treatment. Reducing patient waiting times is a critical performance indicator in healthcare systems and is crucial for patient satisfaction and loyalty to healthcare centers (Howlett & Wood, 2022). Therefore, various strategies have been employed by hospital managers to address elective patient surgical backlogs, such as increasing installed capacity, improving efficiency, and managing demand (Negash et al., 2022).

For instance, (VanBerkel & Blake, 2007) addressed waiting list problems by considering increasing installed capacity, aiming to optimize resources, and decreasing patient wait times in OR planning and scheduling procedures. They utilized discrete-event simulation to analyze the impact of changing bed capacity and OR time on throughput and waiting times. However, the option to increase capacity is limited by constraints such as budget, space, and human resources and is infeasible for some hospitals in some areas.

Comparatively, the option to improve the effectiveness and efficiency of OR management is generally more meaningful and feasible for hospitals (Abedini et al., 2016). A study by (Spratt & Kozan, 2016) considered improving efficiency by constructing a mixed-integer nonlinear programming (MINLP) approach to formulate the problem of generating MSS for managing the waiting list, adhering to staff and equipment restrictions, and ensuring timely treatment of patients.

Table 2.1 Summary of strategies in managing the waiting list

Study	Strategies	Methodology	Key findings
(VanBerkel & Blake, 2007)	Increasing Capacity	Discrete-event simulation	Increasing bed capacity and OR time can significantly impact throughput and reduce waiting times using discrete-event simulation
(Spratt & Kozan, 2016)	Improving Efficiency	Mixed-integer nonlinear programming (MINLP)	Ensured timely treatment of patients while managing resources
(Bowers, 2011)	Demand-Side Management	Model simulation	Estimated number of patients treated within target waiting time
(Powers et al., 2023)	Demand-Side Management	Dynamic priority scoring (DPS)	Focused on equitable ranking of patients
Our study	Considering all three strategies	Mathematical modeling (MINLP)	Allocate optimal resources, provide fair access time to surgical service across department, minimize total cost

Other than the above-mentioned approaches, demand-side management is critical when there is nothing much to do with the supply side. (Bowers, 2011) developed a model simulation of waiting list management that incorporated patient priority to explore the impact of seasonal variations in demand and supply on waiting times for elective surgical procedures in different specialties. The simulation estimated the number of patients who would be treated within the specified target waiting time. (Powers et al., 2023), on the other hand, proposed a dynamic priority scoring (DPS) system to rank elective surgery patients more equitably, based on a combination of waiting time and clinical factors. These two studies do not incorporate OR resource allocation into waiting list management and focus on individual patient priority settings rather than departmental as shown in **Table 2.1.**

Recently, waiting list management has received increased attention, particularly since the suspension of elective surgery due to COVID-19 pandemic. The extension of OR time has been used to reduce waiting lists by taking advantage of empty OR and existing surgical teams (Negash et al., 2022).

Unfortunately, during the peak of the pandemic, downstream resources such as ICU and MCU are redirected to use for COVID-19 patients resulting in unavailability to handle the patients flow from the OR. As a result, this led to a dramatically increased surgery backlog, and the volume of the surgery backlog accumulated from the cancellation of elective surgery remains unknown. Some studies integrated waiting list estimation and backlog clearance time projections using the simulation method. For instance, (Wang et al., 2020) estimated the backlog size in Ontario due to COVID-19 disruption and the time needed for backlog clearance utilizing forecasting and queuing models. (Oussedik et al., 2021) modeled the orthopedic pathway to estimate elective waiting list numbers and suggest recovery strategies. Furthermore, (Joshi et al., 2021) used machine learning for predictive analytics and offered real-time estimations on backlog clearance time and associated costs based on resource optimization. However, due to the ongoing pandemic, the exact size of elective surgery waiting lists remains unknown. (Abdullah et al., 2022) developed a 2-stage discrete event simulation framework to evaluate elective surgery cancellation and resumption strategies, considering the trade-offs between overutilization, extended wait times, and operational outcomes.

Efficient OR planning is critical for addressing the surgical waiting list (Barbagallo et al., 2015). As the pandemic transitions into an endemic phase, there is widespread recognition of the importance of effectively managing waiting lists and reallocating resources in OR planning. However, as reviewed summarized in **Table 2** a notable gap exists in the literature concerning the integration of elective surgery waiting list management with the allocation of OR resources. This study seeks to address this gap by examining three strategies in OR resource reallocation: increasing capacity, prioritizing surgical departments, and optimizing resource utilization within the OR system to enhance efficiency in order to minimize patient waiting time and total incurred costs.

Table 2.2 Summary of integration waiting list management and resource management

Study	Objectives	Methodology	Key findings
(Wang et al., 2020)	Estimate surgery backlog size and clearance time result from COVID-19	Forecasting and queuing models	Provided estimates for backlog size and project time for clearance, aiding in recovery planning
(Oussedik et al., 2021)	Model orthopedic pathway to estimate elective surgery waiting lists and suggest recovery strategies	Pathway modeling	Proposed strategies for managing orthopedic surgery waiting list and optimizing resources
(Joshi et al., 2021)	Use machine learning for predictive analysis to estimate backlog clearance time and associate costs	Machine learning algorithm	Offered real time estimations on clearance time and costs, facilitating resource optimization
Our study	Formulate mathematical model for managing resource and waiting list	Math modeling technique (MINLP)	Optimal resources allocation results in minimum average waiting time and costs

2.3 Performance measure

2.3.1 Patient waiting time

Long waiting lists are among the most heard complaints in general health care especially after the emergence of the COVID-19 pandemic. The concern justifies many studies aiming at decreasing the waiting times for patients (Cardoen et al., 2010). Patient throughput is another performance measure that is closely related to patient waiting time. The dependency between waiting time, and throughput on the one hand, is clearly stated in Little's Law, i.e., the average inventory in a system equals the average cycle time (which includes the waiting time and the process time) multiplied by the average throughput. The studies classified under patient throughput focus on increasing the number of treated patients which obviously leads indirectly to shorter patient waiting times or shorter waiting list clearance time. Clearance times have been estimated using queuing models before. Like clearance times, our model estimated the time required to reach the BAU workload. In our case however, the DES model allows for estimation of the entire distribution of clearance times based on actual data across all surgical groups whereas the queuing models based on Little's Law primarily estimates mean clearance times.

For instance, VanBerkel & Blake. (2007) use discrete-event simulation to examine how a change in throughput triggers a decrease in waiting time. In particular, they affect throughput by changing the capacity of beds in the wards and by changing the amount of available operating room time. Wang et al. (2020) estimate the size of the nonemergent surgical backlog owing to COVID-19 in Ontario, and the time and resources required to clear this backlog. Time series forecasting, queuing models and probabilistic sensitivity analysis were used to estimate the size of the backlog and clearance time. Joshi et al. (2021) developed a predictive analytics tool that would help evaluate different scenarios and multiple variables for clearance of surgical patient backlog during the COVID-19 pandemic. They built mathematical models for identified (1) time to clear the case backlog, (2) utilization of personal protective equipment (PPE) and (3) assessment of overtime needs. Abdullah et al. (2022) developed a 2-stage discrete events simulation (DES) based framework for the evaluation of elective surgery cancellation strategies and resumption scenarios across multiple operational outcomes. stage 1: Evaluating the Surgery Reduction Patterns and stage 2: DES model for the Evaluation of Resumption Strategies. Their modelling framework accounts for the tradeoffs between over-utilization (that can lead to significant overtime), and extended patient wait times. It is noteworthy that, for multiple surgical specialties(SSs) in the hospital system that require the same resources, the focus on solely maximizing surgical patient throughput might result in unfair access to the surgical resources and left one another behind. Therefore, to ensure fair and equal access for multiple SSs in healthcare organizations, we introduce the term "deviation of waiting list clearance time". Our goal is to minimize the deviation of waiting list clearance time among multiple SSs.

2.3.2 Minimize total costs

In the context of budget cuts domestically and in many countries' responses to an economic downturn, how to invest and distribute public resources is a pressing issue (Daniels, 2016) and OR is one of the most expensive units and a central hub in the hospital system. The largest cost categories of a hospital are operating rooms and the downstream patient ward groups, averaging 33% and 31% of its total cost, respectively. According to Fügener et al. (2014) discussed with operating room managers and indicated that there are four cost components that drive downstream costs: fixed costs, overcapacity costs, staffing costs, and additional weekend staffing costs. Moreover, additional to downstream cost, which is commonly called hospital related cost, patient related cost is another cost involved in planning and scheduling the operating room as well. For instance, Rovers et al. (2022) investigated cost incur due to long waiting time for surgery (cost of waiting per week). There is a significant cost incurred when a patient waits too long for surgery as shown in **Figure 2.3.1**

In our study we consider overtime cost of surgical block per block, overcapacity downstream ICU and waiting time cost. The patient-related costs are incurred by the long waiting time for surgery (cost per week waiting). (Rovers et al., 2022). The extra healthcare expenditure due to waiting for surgery was determined by calculating the difference in healthcareexpenditure before and after surgery. Only costs from a healthcare perspective were included, for example, extra visits to the hospital, general practitioner, physiotherapist. Net monetary loss, which is defined as the total loss of waiting another week for surgery, expressed in monetary terms.The net monetary loss is calculated by multiplying the loss in quality of life due to waiting 1 week for surgery by a threshold value, and subsequently the extra costs of waiting another week for surgery are added

The hospital-related costs are incurred by overusing surgical blocks as well as exceeding the regular SICU capacity. A fixed cost of opening a surgical block is based primarily on the staff required to support OR itself (surgeons, nurses, anesthesia, etc.). There are assumed to be fixed cost since. ORs typically planned to be open for a full day or not at all (Denton et al., 2010). This cost is neglected; we assumed all specialties incur the same amount of fixed cost when opening a surgical block.

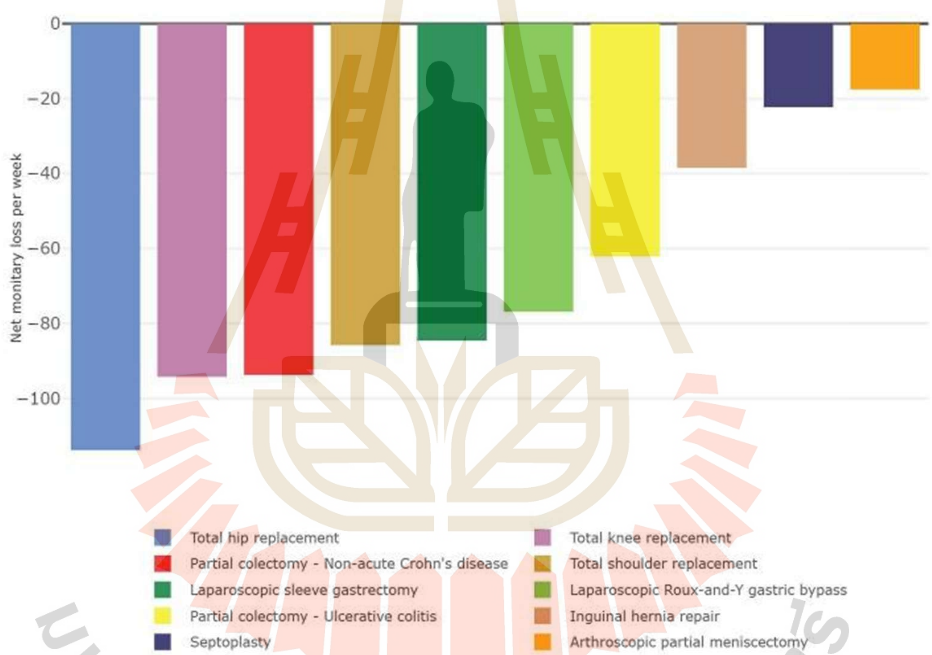

Figure 2.3.1 Surgery associated net monetary loss per week (Rovers et al., 2022).

As downstream resources (ICUs) are critically important, without an available ICU theoperation cannot be started or the existing patient in the ICU will be needed to discharge early tomake available ICU bed for incoming patients. Overcapacity costs are costs that incur due to requiring capacity beyond capacity. This situation occurs, for example when patients must be transferred to ICUs in other hospital or wrong ICU as capacity limits (depending on service level(α^i). Hence, an exceeding capacity of ICU downstream will result in penalty cost (Fügener et al.,2014). The overcapacity costs depend on the service levels α^i. The higher the service level is, thelower the overcapacity costs are. Setting the appropriate service levels α^i should be done on a strategic level and is therefore outside the scope of this study.

2.4 Multi-objective optimization

Planning and scheduling processes in OR are recognized as highly complex tasks. This complexity stems from various constraints, occasionally conflicting with their objectives, as they aim to improve quality and satisfaction while simultaneously reducing costs and managing resources effectively. However, the diverse mix of surgery cases and the individual characteristics of each patient, along with the involvement of various stakeholders with conflicting interests, poses challenges in achieving multiple objectives (Barbagallo et al., 2015).

Hence, this is a multi-objective multi-constraints (MOMC) optimization problem. The objective of all resource allocation in healthcare organizations, from an optimization perspective, is to reduce total costs and patient waiting time while maximizing resource efficiency. Various studies incorporated hospital-related costs into OR planning and scheduling. Different cost components are considered in the literature. For instance, Fügener et al. (2014) identified four cost components—fixed costs, overcapacity costs, staffing costs, and additional weekend staffing costs characterized as downstream costs. These costs significantly contribute to overall expenses in the hospital. In contrast, Zhang et al. (2019) considered two types of costs, namely, patient-related costs and hospital costs. Hospital-related costs are incurred by opening and overusing surgical blocks, as well as exceeding regular ICU capacity, while patient-related costs are incurred by scheduling and postponing surgeries.

As mentioned above, various cost components are involved in the OR block allocation problem. Different studies have incorporated various types of cost components while addressing different objectives. For instance, Denton et al. (2010)

studied optimization models for planning and scheduling multiple ORs under uncertainty. They concentrated on decisions regarding surgery-to-OR assignments, aiming to create an assignment that balances two conflicting criteria: (1) the fixed cost of opening individual OR, and (2) the total cost of overtime across all OR. Their objectives were to minimize the weighted sum of the total cost of opening an OR and the total overtime cost resulting from OR overbooking. These studies focused on individual surgeries rather than surgical departments, overlooking upstream (intake) and downstream (recovery) resources. Moreover, the authors added upstream cost and downstream cost to the fixed cost of opening OR in the model.

Lin and Li (2021) focused on the OR scheduling problem in healthcare institutions, aiming to minimize operating costs while maximizing the utilization of OR and maintaining good quality care. Two main cost components were considered, namely, waste cost (the amount of unused time in the operating room, discouraging inefficiency) and overtime-operating cost (the cost incurred when the total operating time scheduled for an operating room exceeds its regular opening hours).

Fügener et al. (2014), on the other hand, discussed the tactical MSS problem in which the block OR time was assigned to different surgical specialties. They concentrated on the effect of the MSS on patient flow to downstream inpatient care units and proposed an approach for planning the MSS to minimize downstream costs by leveling bed demand and reducing weekend bed requests.

Furthermore, Fügener (2015) integrated strategic and tactical MSS problems using mixed-integer programming (MIP). This involved incorporating downstream resources such as ICU and regular patient ward into the model to maximize hospital revenues. The model's outcome determined the number of OR blocks allocated to each surgical specialty (SS).

Rather than integrating strategic and tactical levels, Shafaei and Mozdgir (2018) developed a mathematical model to construct an MSS based on the total number of OR blocks allocated to each SS at a medium-sized hospital in Iran. From the number of OR blocks allocated, the model then reallocated OR blocks to each SS aimed at minimizing OR spare time while considering the initial set of OR block allocation at the strategic level. The proposed model was solved using a lexicographic goal programming approach. Similarly,

Lu et al. (2019) developed a multiphase OR scheduling approach that addressed two different decision levels. The first phase mainly focused on an allocation of the number of OR blocks for each SS, with the objectives of maximizing profit and minimizing overtime costs. In the second phase, the MSS model was constructed to schedule surgeries in each SS to maximize the number of scheduled patients in all OR in a certain specialty, minimize underutilization and overtime costs, and balance OR according to a standard of OR working time, simultaneously. A multi-objective linear programming (MOLP) model was used to handle the problem. To reduce the complexity of the model, downstream resources (ICU and ward) and uncertainty in surgery duration were ignored.

Patrão et al. (2022) proposed two stages of OR planning and scheduling. They introduced an integer linear programming model (ILP) that is based on patient volume in CMP at a strategic level to assign the number of OR blocks to each SS and in the tactical level, MSS, the model aimed to determine which OR blocks should be allocated to any particular SS on any particular day.

The literature shows that there is a widespread focus on combining strategic and tactical levels in OR planning and scheduling. Optimization methods are widely used in the OR context (Abdalkareem et al., 2021). However, there is less attention in OR planning and scheduling in an optimization context that simultaneously focuses on reducing total incurred costs, patient waiting time, and maximizing resource efficiency. Moreover, concerning cost considerations, OR planning and scheduling predominantly incorporate hospital-related costs (e.g., overtime cost and overcapacity penalty cost), often neglecting patient-related costs (e.g., patient waiting costs), which play a crucial role in the planning and scheduling process.

The costs incurred due to prolonged waiting times for surgery, as highlighted by Rovers et al. (2022), present a significant financial burden known as patient waiting cost. This encompasses additional healthcare expenditures, medication costs, and a decline in the quality of life for patients awaiting procedures. Patient-related costs are quantified by the expenses attributed to prolonged waiting times for surgery on a per-patient, per-week basis within each surgical department. In parallel, hospital-related costs stem from unit capacity resources exceeding, such as those in the OR, ICU, MCU, and nursing time. For instance, an unavailable ICU and MCU bed may necessitate policies like premature discharge or the creation of temporary capacity, resulting in elevated costs compared to normal operations. Hence, our study incorporates multiple aspects of cost components, encompassing patient-related costs (cost associated with waiting times) and hospital-related costs (overtime of OR and nurses and overcapacity penalty costs of ICU and MCU) in OR block allocation. It is important to incorporate both of these costs together in OR planning, since it conflicts with each other whether the patient waiting time and cost should be reduced by adding more overtime resources. Therefore, this study aims to minimize total incurred costs while simultaneously reducing patient waiting times and optimizing resource utilization efficiency.

2.5 Multi-Criteria Decision Making in Healthcare

Multi-Criteria Decision Making (MCDM) refers to a set of methodologies designed to support decisions that involve evaluating multiple, often conflicting, criteria. These methods are particularly valuable in complex environments where decisions cannot rely on a single factor. In the healthcare sector, MCDM serves as a useful framework for structuring problems, assessing alternatives, and recommending actions to improve service delivery and patient outcomes.

In recent years, healthcare systems have increasingly incorporated MCDM approaches into various aspects of management and policymaking (Amaral & Costa, 2014; Zeng et al., 2013; Kuo et al., 2012; Li et al., 2019). For example, Kuo et al. (2012) applied the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to rank healthcare failure modes in risk analysis. Zeng et al. (2013) modified the VIKOR method by introducing a data normalization approach tailored to medical datasets. Similarly, Amaral and Costa (2014) employed the PROMETHEE II method to assist decision-makers in resolving emergency department congestion.

The issue of patient prioritization is a critical concern in healthcare services, particularly for elective procedures were waiting lists are common. Li et al. (2019) emphasized that effective waiting list management requires acknowledging both the clinical urgency of patients and their broader social and personal contexts. This dual perspective underlines the importance of designing decision support systems that incorporate not only clinical guidelines but also insights from medical professionals to ensure that the most appropriate patients are scheduled for timely intervention.

Given the limitations of healthcare resources, prioritizing patients for treatment becomes a practical and ethical necessity. Several researchers have proposed frameworks using MCDM techniques to address this challenge. For instance, Rana et al. (2023) utilized fuzzy TOPSIS to develop a model for prioritizing patients awaiting elective surgeries in Chile, ensuring a more systematic and fair selection process. In another case, Solans et al. (2013) created a universal scoring system for elective surgery candidates in the Catalan public health system. Their model evaluates patients across three dimensions—clinical condition, potential benefit, and social function—through eight weighted criteria: severity of disease (23%), pain or primary symptoms (14%), rate of disease progression (15%), limitations in daily activities (14%), probability and magnitude of improvement (12%), lack of caregiving support (5%), caregiving responsibilities (8%), and limitations in work, education, or job-seeking ability (9%).

In a similar vein, Silva et al. (2021) proposed a decision support system that reflects both the clinical and social priorities of patients awaiting surgery, advocating for a comprehensive and balanced approach to prioritization. Meanwhile, Srikumar et al. (2018) introduced a general surgery prioritization framework implemented in New Zealand, aiming to enhance transparency, reliability, and fairness in surgical scheduling decisions. Their model aligns clinical judgment with equitable access, although ongoing evaluation is needed to ensure fairness in practical application.

These studies demonstrate the growing role of MCDM in supporting resource allocation and patient scheduling in healthcare. By integrating diverse factors—ranging from medical urgency to social vulnerability, MCDM tools can significantly improve the fairness and effectiveness of healthcare delivery.

CHAPTER III

RESERCH METHODOLOGY

This chapter presents the methodological framework employed to address the Operating Room (OR) resource planning and scheduling problem under uncertainty, in the context of post-pandemic surgical backlog recovery. The proposed approach comprises a two-phase decision-making model designed to (i) optimally allocate OR blocks across surgical specialties, and (ii) prioritize patients for surgery within each department using a multi-criteria decision-making (MCDM) framework.

3.1 Overview of the Proposed Framework

The methodology adopts a multi-stage, multi-objective optimization framework structured as shown in **Figure 3.1.1.**

1) Phase 1 Multi-Objective Optimization: OR Block Allocation Model

A mathematical programming model is formulated to allocate OR blocks to surgical specialties over a planning horizon. This model incorporates uncertainty in surgery durations and patient length of stay (LOS) and seeks to minimize both (a) disparities in backlog clearance time across departments and (b) total operational costs associated with overtime, delays, and resource overflow.

2) Phase 2 Multi-Criteria Decision Making: Patient Prioritization Model

Within each specialty, an MCDM technique is applied to ranked patients based on a set of clinical and operational criteria (e.g., urgency, waiting time, resource utilization). This phase aims to ensure equitable and effective use of the assigned OR time blocks, aligning prioritization with both patient need and hospital constraints.

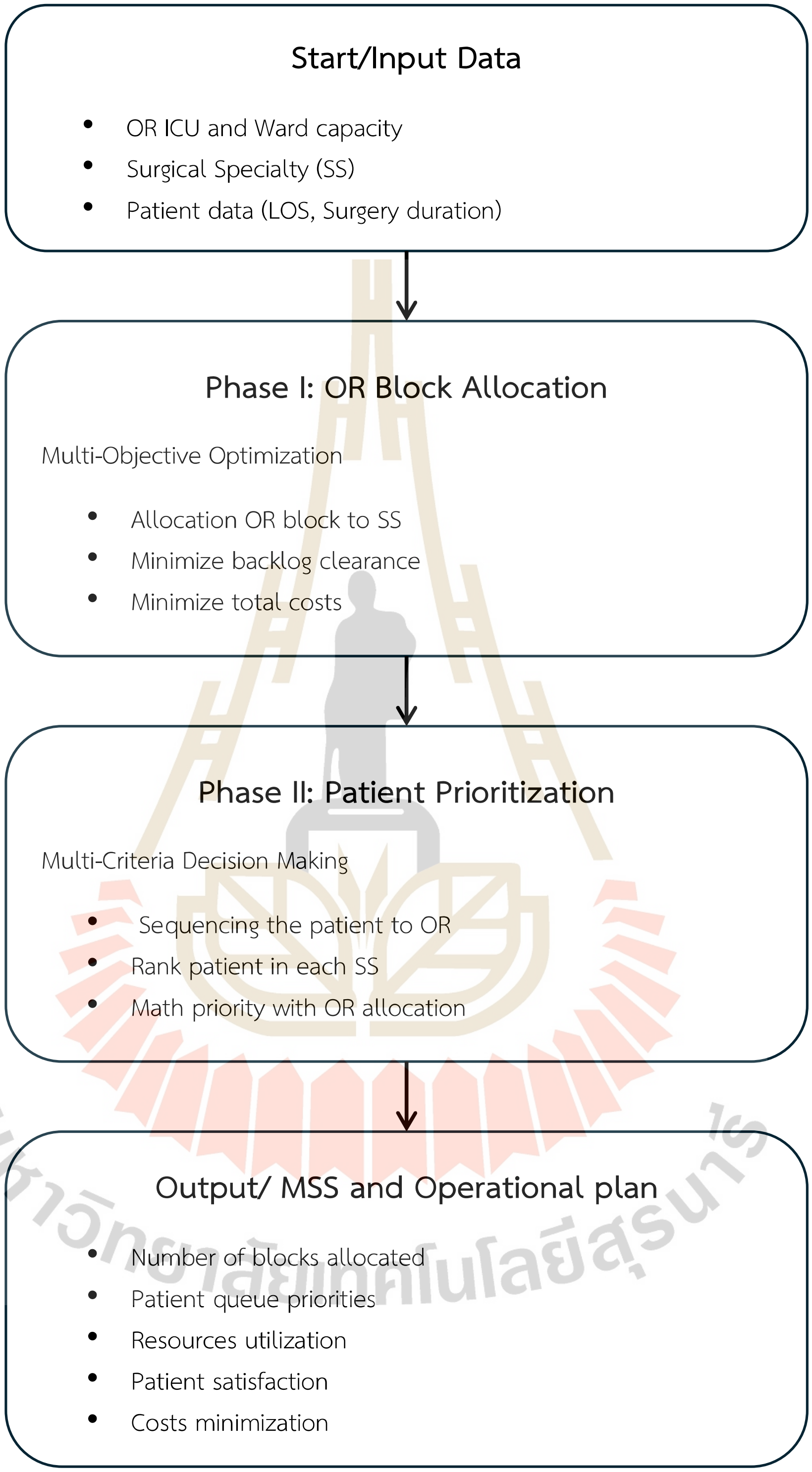

Figure 3.1.1. Proposed Framework

3.2 General Patient Flow and Resource Consideration

The general flow of patients is depicted in **Figure 3.2.1**, which illustrates the journey of a surgical patient from hospital arrival to discharge. Upon arrival, patients are first classified as elective or non-elective. Depending on their clinical condition, they may require pre-operative stays before surgery. After surgery, patients may either be treated as outpatients or require further hospitalization. Postoperative care could involve admission to the ICU or direct transfer to a surgical ward, based on the severity and type of surgery performed. All admitted patients are eventually discharged upon recovery.

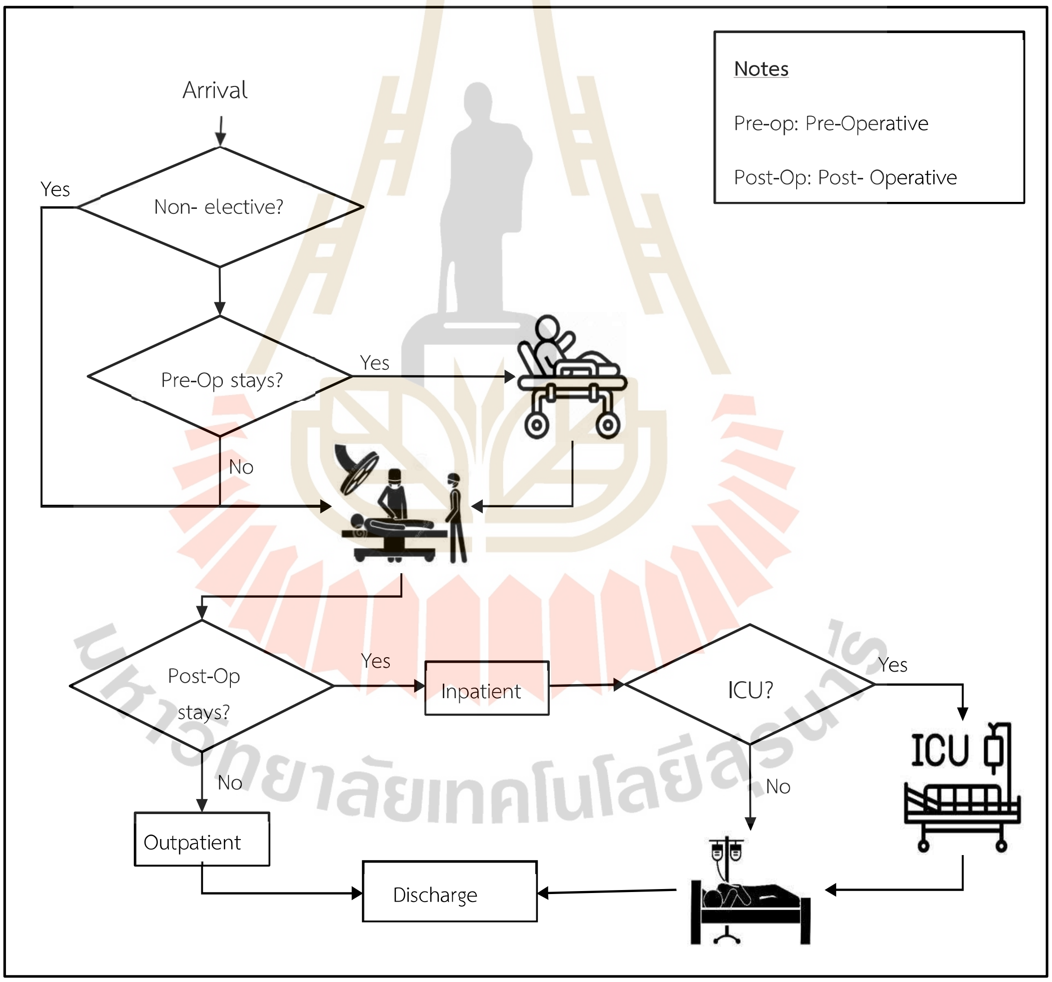

Figure 3.2.1 General Patient Flow Decision

To simplify the patient flow, this section presents the surgical patient flow and the resource structure that is used in this study. The primary goal is to allocate OR blocks efficiently across different surgical specialties (SS), considering variability in surgical duration and postoperative care needs, such as length of stay (LOS) in the ICU and surgical wards. These resources represent the primary capacity constraints in the elective surgery system. As illustrated in **Figure 3.2.2**, surgical patients utilize a sequence of resources beginning with the pre-operation stay then OR, followed by a recovery phase in either the ICU or surgical ward, depending on their clinical needs. The model assumes the availability of essential human resources, including surgical teams (surgeons, anesthetists, and support staff).

The associated costs for staff are incorporated into the fixed and variable cost components of OR block operation, including overtime utilization when applicable. Other healthcare resources—such as nursing hours, ancillary staff, laboratories, and diagnostic services—are assumed to be non-limiting and are thus excluded as constraints in the model. This assumption is consistent with similar studies and helps focus the optimization on the most critical and capacity-constrained elements of the surgical delivery system. By incorporating uncertainty in patient-level demand and focusing on resource bottlenecks, the proposed model aims to provide a robust planning tool that supports fair, efficient, and timely surgical service delivery in a post-pandemic recovery context.

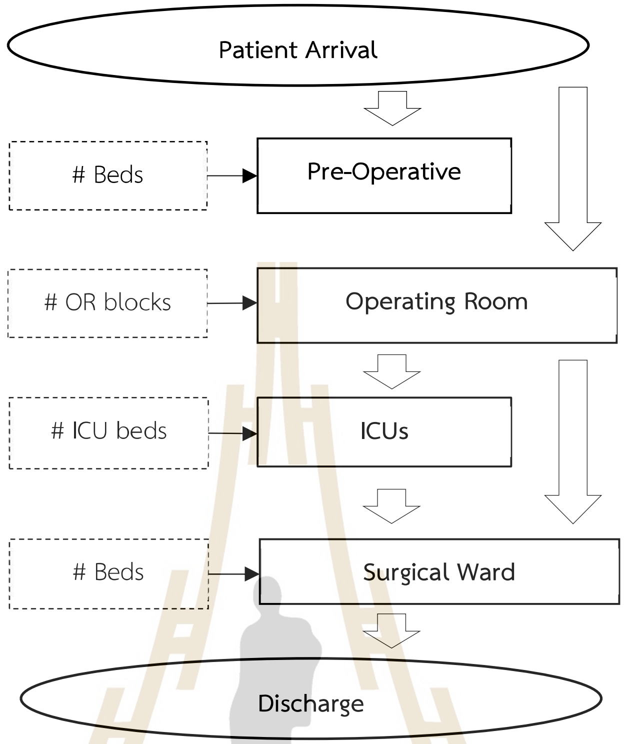

Figure 3.2.2 Patient flow and resources involved in the study

The planning model focuses on three critical and scarce resources within the surgical care pathway:

1) Operating Room (OR) Blocks – Defined as fixed time slots (typically 8 hours) allocated to surgeries.
2) ICU Beds – Required for patients needing intensive postoperative care.
3) Surgical Ward Beds – Used for routine preoperative and postoperative recovery following surgery or after ICU discharge.

3.3 Data collection

To support the development of the proposed two-phase decision-making framework, both primary and secondary data were collected from the study hospital. The data collection process was designed to ensure that all relevant clinical and operational information required for optimization modeling and patient prioritization was captured comprehensively and accurately. Figure 3.3.1 illustrates the overall data collection process and procedure.

3.3.1 Primary Data

Primary data were obtained through direct engagement with key stakeholders within the hospital, including Surgeons and Clinical Staff: Interviews and consultation sessions were conducted to gather expert input on patient care pathways, clinical urgency criteria, and the practical challenges of operating room (OR) scheduling.

Hospital Administrators and Planners: Operational priorities and resource constraints were collected. Observation and Site Visits: The research team conducted direct observations within the OR, ICU, and surgical wards to understand workflow and validate the data provided. The primary data played a crucial role in defining the criteria for patient prioritization and resource allocation, which were later used in the Multi-Criteria Decision-Making (MCDM) model.

3.3.2 Secondary Data

Secondary data were extracted from the hospital's historical databases and administrative records as well as in literature review. These included:

1) **Surgery records**: Duration, frequency, and type of surgeries performed.
2) **Patient information**: Waiting list data, lengths of stay in ICU and surgical wards, and departmental backlog levels.
3) **Resource utilization reports**: OR block usage, ICU and ward bed occupancy rates.
4) **Cost data**: Including fixed and variable costs associated with OR operations.

This data was essential for statistical analysis and the construction of the OR Block Allocation Model, where variability and uncertainty (e.g., in surgery duration or LOS) were accounted for using probabilistic modeling.

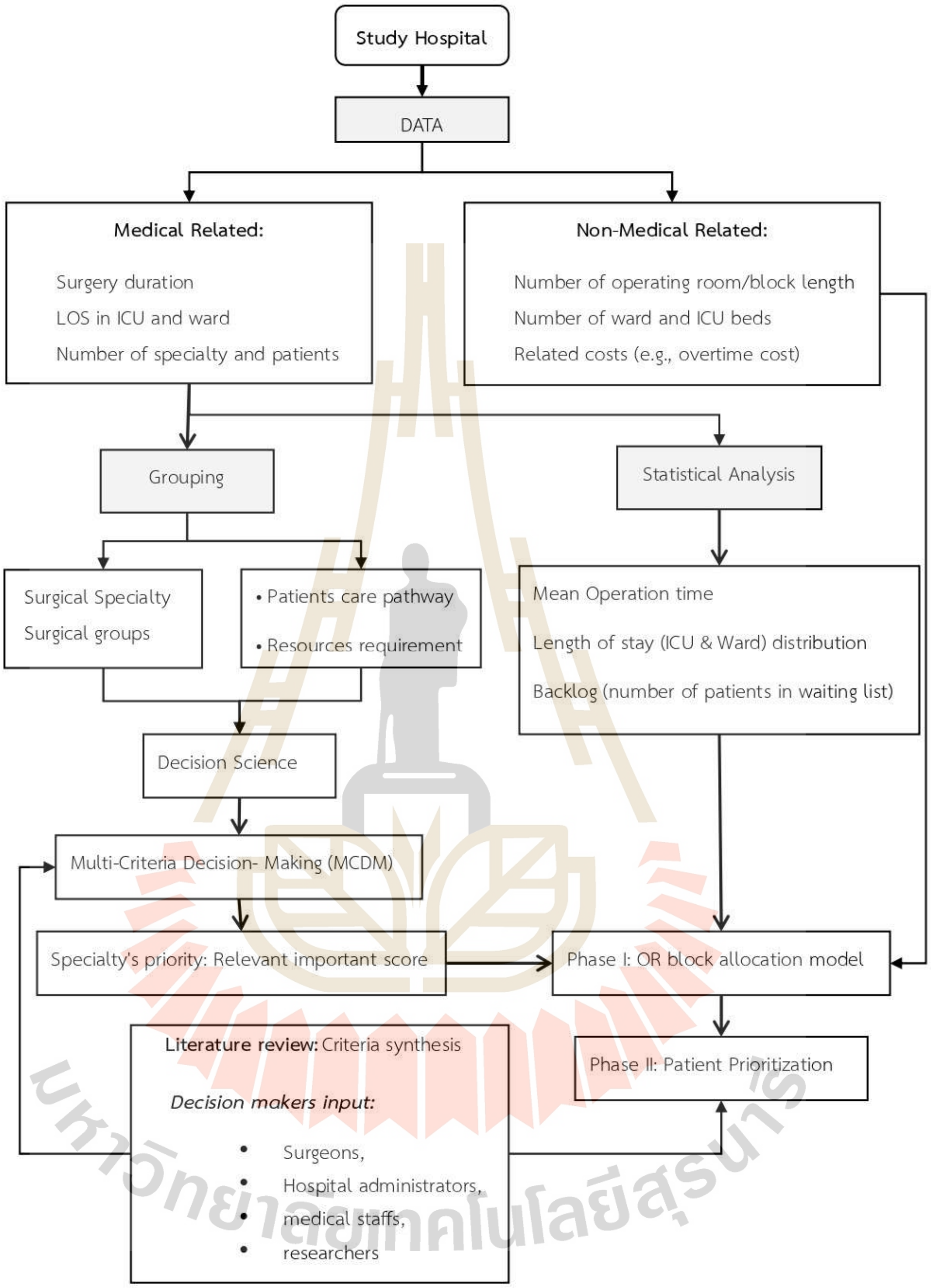

Figure 3.3.1 Data Collection Process and Procedure

3.4 Model Development

To address the OR block allocation and scheduling problem, a two-phase mathematical model is proposed:

4.1 Phase 1 Multi-Objective Optimization: OR Block Allocation Model

3.4.1.1 Research Procedure

This section describes the overall processes of the proposed mathematical model for OR resources allocation as shown in **Figure. 3.4.1.** First, parameters and decision variables are described. Then, the multi-objective optimization model is formulated and explained. We provide an overview of the mathematical model including the objective functions, constraints, and datasets from a large hospital for verifying the model and validating the model with sensitivity analysis.

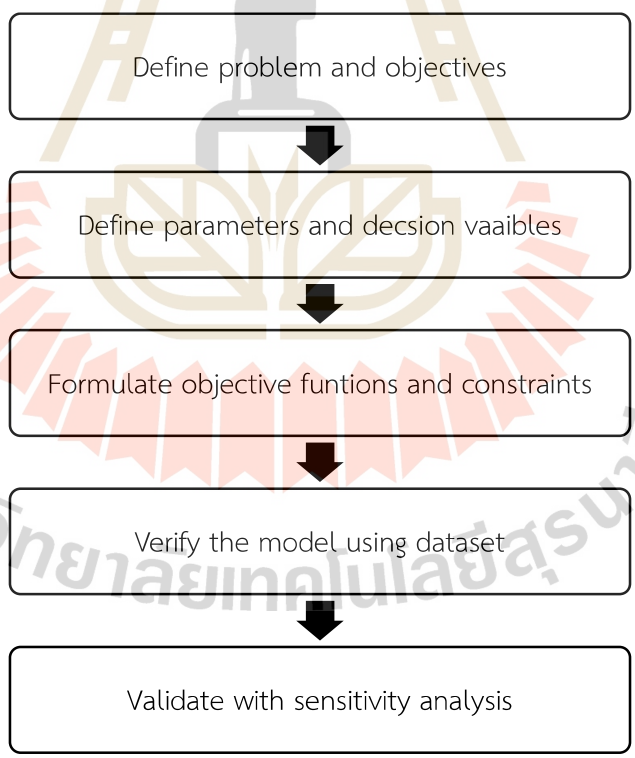

Figure 3.4.1 Overall process

The research procedure in research is categorized into 10 steps as follows:

1) Study the process and patient flow of elective surgery from literatures and collect specialty related data and non-specialty related data from studies hospital and synthesis from literatures.
2) Define parameters/ constraints relating OR block allocation problem.
3) Calculate the patient flow into downstream unit (as an input parameter of the block allocation model.
4) Develop the mathematical model of operating room block allocation problem.
5) Verify and validate the model using mathematical methods.
6) A case study of a public hospital: use the data from the hospital studied to test the model.
7) Determine the optimal block allocated to each specialty that results in such a way that the total cost is minimized and the waiting time of each patient of each specialty is optimal.
8) Develop a Master Surgery Scheduling based on allocated blocks
9) Scenario analysis as well as benefit cost analysis of the trade-off between time (waiting list clearance time) and money (total incur costs) for informing the hospital administrators at what cost the hospital should pay to increase patient satisfaction by reducing waiting time.
10) Sensitive analysis: to study how changes in specialty priority (relevant score) input parameters of a model affect the output (total cost incur and time to clear the waiting list).

We address the problem of multiple resource allocation of ORs and propose a surgery scheduling scheme for OR units. To solve this problem, a multi-phase and integrated multi-objective linear programming model is proposed. The first step is an OR resource allocation model. The goal is to optimize the allocation of OR resources to each SS during the planning period. The proposed model is a resource allocation model, which mainly focuses on the allocation of ORs block for each surgical specialty (SS). Based on the results of the first phase, the second step is the master surgical schedule (MSS) model. Hence, the main problem to be solved in our study is the allocation of number of ORs block (1 block equal to 8 hours) to different surgical specialties (SSs) belonging to the same hospital system and then developing a master surgery schedule (MSS) over a planning horizontal based on number of allocated blocks of each department.

This work proposes a mixed integer nonlinear programming model (ILP) considering integrating case-mix planning (CMP) and the master surgical scheduling (MSS) problems. The problem deals with the planning of the number of operating rooms block to be assigned to surgical specialties.

3.4.1.2 Parameters and decision variables

Notations

The following notations are used to develop the mixed integer non-linear programming (MINLP) model for the OR resources allocation problem, aiming to minimize the patient waiting time and the total cost incurred associated with OR blocks allocation.

Indices:	
T	Weekly planning horizon
t	Index of days, t=1.... T
s	Index of number of surgical departments, s=1.... S
r	Set of resources including operating room (*or*), intensive care unit (*icu*), medium care unit (*mcu*), and nursing hours (*nh*)
Parameters	
O_s	The average operation duration of surgical specialty *s*
P_s	Relative important weight of specialty *s*
μ_s	Average number of patients per OR block for specialty *s*
$l_{s,up}$	Average LOS of surgical specialty *s* patients in *MCU* before surgery
$l_{s,down}$	Average LOS of surgical specialty *s* patients in *MCU* after surgery and *ICU*
$l_{s,icu}$	Average LOS of surgical specialty *s* patients in *ICU* after surgery

$\boldsymbol{nw_s}$	Average nursing workload (in hours) require for specialty s patients in *ICU*
$\boldsymbol{C_{r,t}}$	Available capacity of resource *r* on day *t, rÎR={or,icu,mcu,nh}*
$\boldsymbol{\varphi_r}$	Maximum overtime of resources allowed for resources *r over T and T*
$\boldsymbol{U_{r,T}}$	Target utilization of resources *rÎR={or}* in planning horizon *T and T*
$\boldsymbol{Dem_s}$	Weekly demand of surgical specialty *s*
$\boldsymbol{WL_s}$	Total patients waited in each surgical department *s*
$\boldsymbol{Req_T^{max}}$	Maximum requirement number of OR blocks of specialty over *T*
$\boldsymbol{Req_T^{min}}$	Minimum requirement number of OR blocks of specialty over *T*
$\boldsymbol{WCost_s}$	Cost of waiting to surgery for patients from specialty *s*
$\boldsymbol{OCost_r}$	Cost of over capacity of resources *r*
$\boldsymbol{w_W}$	Relative weight of patient waiting time
$\boldsymbol{w_O}$	Relative weight of overtime cost
Decision variables:	
$\boldsymbol{x_{sT}}$	Number of OR blocks assign to surgical departments s in planning horizon *T*
$\boldsymbol{T_{WL,s}}$	Number of weeks required to clear patients waiting list of surgical *s*
$\boldsymbol{\partial_{TC}}$	Average number of weeks required to clear patients' waiting list in hospital
$\boldsymbol{o_{r,T}}$	Overcapacity of resources *r* needed over *T* and *T+2*
$\boldsymbol{U_{r,T}}$	Utilizations of resource *r* over *T* and *T+2*

3.4.1.3 Mathematical model

The proposed model consists of two objectives, namely, minimizing patient waiting times (1) and minimizing total incurred costs (2). In (1), involves calculating the cumulative waiting cost for all surgical departments that is needed to minimize. This is achieved by multiplying the weekly waiting cost for each surgical discipline and the number of patients on each surgical department's waiting list by the decision variable, number of weeks required to clear the patient waiting list.

3.4.1.4 Objective Functions

The model solution aims to minimize the average patient waiting time of each surgical department denoted as $T_{WL,s}$.

$$Minimize\ Z_w = \sum_{s}^{S}\sum_{t=1}^{T}\left(T_{WL,s} \cdot WCost_s \cdot WL_s\right) \tag{1}$$

$$Minimize\ Z_O = \sum_{r}^{R}\sum_{t=1}^{T}\left(o_{r,T} \cdot P_s \cdot OCost_r \cdot \partial_{TC}\right) \tag{2}$$

In (1) represents the objective function aimed at minimizing the total cost associated with patient waiting times on the surgical waiting list. In (2), the formulation comprises four cost components which are costs associated with the overcapacity of OR, ICU, MCU, and nursing workload. It computes the overall overcapacity cost of all resources by multiplying unit values of overcapacity for these resources by the unit cost and then multiplying by the average waiting list clearance time.

These two distinct formulas then can be converted into a unified objective function, as shown in (3) below. The objective function (3) is referred to as the "total incurred cost".

$$MIN\ Z = w_w \cdot Z_w + w_o \cdot Z_o \tag{3}$$

The weighing of each objective function $w_w\ and\ w_o$ can be interpreted as a reflection of the hospital's preferences toward the performance indicators. In general, different hospitals may have different priorities in weighing different performance indicators due to various factors. This model assumed that the weight of the objectives equally the same w_w = w_o =1.

3.4.1.5 Constraints

This section outlines constraints considered in our model.

$$\sum_{t=1}^{T-2} x_{sT} \leq \sum_{t=1}^{T-2} C_{r,t} \qquad \forall r \in \{or\}, \qquad \forall s \in S \tag{4}$$

$$\sum_{s=1}^{S} \left(x_{sT} \cdot \mu_s \cdot l_{s,icu}\right) \leq \sum_{t=1}^{T} C_{r,t} \quad \forall r \in \{icu\}, \qquad \forall t \in T \tag{5}$$

$$\sum_{s=1}^{S} \left\{x_{sT} \cdot \mu_s \cdot \left(l_{s,up} + l_{s,down}\right)\right\} \leq \sum_{t=1}^{T} C_{r,t} \ \forall r \in \{mcu\}, \qquad \forall t \in T \tag{6}$$

$$\sum_{s=1}^{S} \left(x_{sT} \cdot \mu_s \cdot nw_s\right) \leq \sum_{t=1}^{T} C_{r,t} \ \forall r \in \{nh\}, \qquad \forall t \in T \tag{7}$$

Constraint (4) ensures that the number of allocated OR blocks do not exceed available OR blocks in one-week planning horizon. T-2 as OR operated 5 days a week.

Constraint (5) ensures that required ICU time for all patients in planning horizons does not exceed available ICU.

Constraint (6) determines the total amount of time needed for both preoperative and postoperative stays. This constraint ensures that the number of patients admitted to the MCU following surgery and prior to surgery does not exceed available MCU beds in one-week planning horizon.

Constraint (7) is crucial for imposing constraints on the maximum allowable overtime for all resources over one-week of planning horizon. They ensure that the variables denoting overcapacity for OR blocks, ICU time, MCU and nursing time do not exceed the maximum permissible threshold of resource facilities.

It is calculated as the total supply capacity for each resource multiplied by the corresponding percentage allowance which is derived from the hospital perspective.

$$o_{r,t} \leq \varphi_r \cdot \sum_{t=1}^{T-2} C_{r,t} \quad \forall r \in \{ or \}, \quad \forall t \in T \tag{8}$$

$$o_{r,t} \leq \varphi_r \cdot \sum_{t=1}^{T-2} C_{r,t} \quad \forall r \in \{ icu, mcu, nh \}, \quad \forall t \in T-2 \tag{9}$$

To optimize the utilization of resources, including OR, ICU, MCU, and ICU nursing workload, it is essential to establish constraints that ensure that these resources are used effectively. **Constraint (10)** is formulated to set the minimum requirements for the utilization of these resources.

$$U_{r,T} \geq Req_{r,T}^{uti} \quad \forall\, r \in \{ or, icu, mcu, nh \} \tag{10}$$

Constraints (11) and **(12)** play a significant role in defining boundaries for the allocation of OR blocks to each specialty over the planning period. These constraints determine both the lower and upper limits for the number of OR blocks that should be allocated to each department. This perspective reflects the minimum and maximum service level provided to patients from less profitable surgical departments.

$$\sum_{s}^{S} \sum_{t=1}^{T-2} x_{sT} \geq Req_{s,T}^{min} \quad \forall r \tag{11}$$

$$\sum_{s}^{S} \sum_{t=1}^{T-2} x_{sT} \leq Req_{s,T}^{min} \quad \forall r \in \{or\} \tag{12}$$

The **constraint (13)** guarantees that the allocation of OR blocks must be adequate to clear the weekly demand of each specialty over the planning period.

$$\sum_{t=1}^{T-2} x_{sT} \cdot \mu_s \geq Dem_s \quad \forall s \in S \tag{13}$$

The **constraint (14)** ensures that the total number of blocks assigned to all specialties collectively must be sufficient to handle total patient throughput weekly.

In other words, the resource allocation should be capable of accommodating the combined needs of all patients across various surgical departments within a given week.

$$\sum_{t}^{T}\sum_{s}^{S}(x_{sT} \cdot \mu_s \cdot \partial_{TC}) \geq \sum_{s}^{S} Wl_s \tag{14}$$

Finally, **constraint (15)** restricts all decision variables to be positive integer values and **constraint (16)** is the non-negativity of resources utilization, overcapacity of resources r, number of weeks required to clear patients waiting list of surgical s, average number of weeks required to clear patients waiting list in hospital.

$$x_{sT} \in \mathbb{N} \quad , \quad s \in S, \qquad t = 1,2,\dots,T+2 \tag{15}$$

$$U_{r,T} \geq 0, \quad o_{r,T} \geq 0, \quad T_{WL,s} \geq 0, \quad \partial_{TC} \geq 0, \quad r \in R, t = 1 \dots . T+2 \tag{16}$$

3.4.2 Phase 2: Patient Prioritization via MCDM

This study employs a systematic approach to evaluating the potential and sustainability of HWT in Nakhon Ratchasima Province. The methodology consists of six key stages as shown in **Figure 3.4.3**.

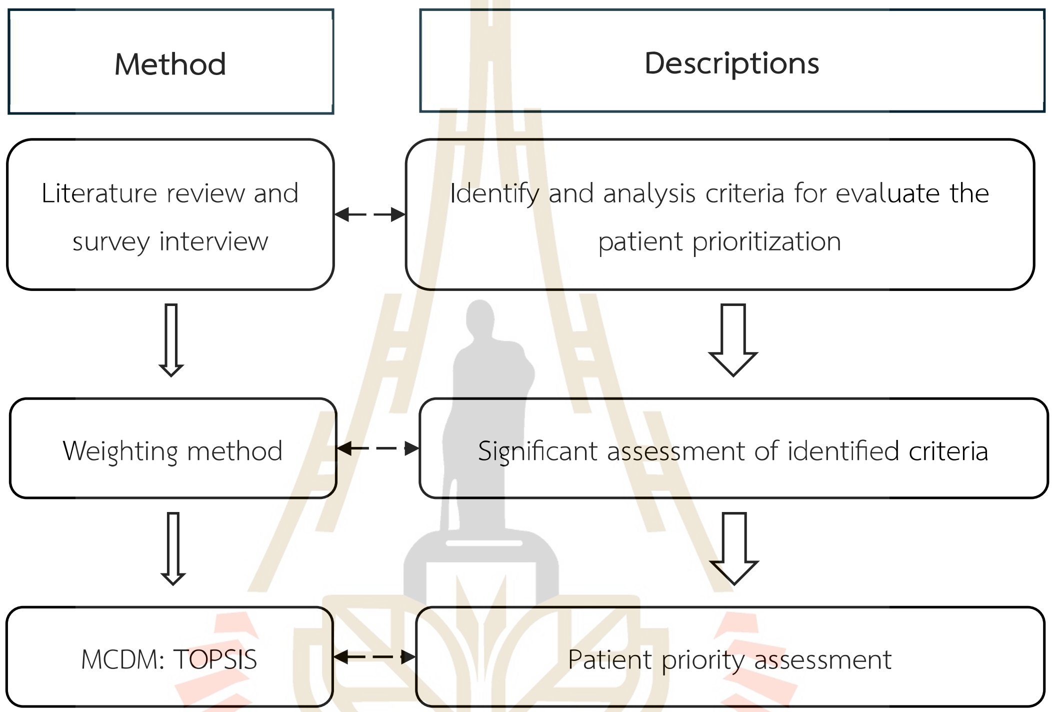

Figure 3.4.3 Research framework.

1. Literature Review and Expert Interviews/Assessment: A comprehensive literature review and expert interviews are conducted to identify and analyze the critical criteria for evaluation and assess the patient priority
2. Weighting Method for identified criteria: A weighting method is applied to prioritize the criteria and sub-criteria.
3. Multi-Criteria Decision Making (MCDM): TOPSIS is used as an MCDM approach to evaluate the patient priority. This method ranks the patient in each department based on their characteristic respected to identified criteria and sub-criteria

3.4.2.1 Criteria Identification

Literature Review and Expert Interviews/Assessment: A comprehensive literature review and expert interviews are conducted to identify and analyze the critical criteria for evaluation and assess the patient priority

3.4.2.2 *Criteria scoring*

Scoring function was applied to estimate each weight value of the sub-criteria. Experts were allowed to assess each value based on preference score e from 0 (extremely unimportant) to 10 (extremely important). The indices and parameters is shown below:

Indices	
i	index of criteria or sub-criteria, where i =1, 2,...,n
j	Index of alternatives, where j =1,2,...,m
e	Index of expert or decision-maker e=1,2,...,E
Parameters	
$x_{i,j}$	Performance score of alternative j with respect to criterion i
$\mu_{i,e}$	Preference score given by expert e to criterion i ranging from 0 (extremely unimportant) to 10 (extremely important)
w_i	Normalized weight of criterion i, calculated based on expert scores
W	Sum of all preference scores for all criteria across experts
$n_{i,j}$	Normalized value of $x_{i,j}$ in the decision matrix
$v_{i,j}$	Weighted normalized value of $x_{i,j}$
v_{ij}^{-}	Negative ideal solution vector, composed of the worst values for each criterion
v_{ij}^{+}	Positive ideal solution vector, composed of the best values for each criterion
d_j^{+}	Separation (Euclidean distance) of alternative j from the positive ideal solution
d_j^{-}	Separation of alternative j from the negative ideal solution
R_j	Relative closeness of alternative j to the ideal solution

Afterwards, the corresponding weight for each criterion i = {1, 2..., n}, wi is given by:

$$w_i = \frac{1}{W}\sum_{e=1}^{10} \mu_{i,e} \tag{17}$$

$$Where\ W = \sum_{i=1}^{n}\sum_{e=1}^{10} \mu_{i,e} \tag{18}$$

3.4.2.3 TOPSIS

(1) Calculate the normalized decision matrix. The normalized value n_{ij} is calculated as

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \quad ; \ j = 1,2, \ldots \ldots m\ ; i = 1,2, \ldots . n \tag{19}$$

(2) Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as:

$$v_{ij} = w_i \times n_{ij} \qquad ; \ j = 1,2, \ldots \ldots m\ ; i = 1,2, \ldots . n \tag{20}$$

Where w_i is the weight of the i[th] attribute or creation and criterion, and $\sum_{i=1}^{n} w_i = 1$

(3) Determine the positive ideal and negative ideal solution.

$$A^{+} = \{v_1^{+}, v_1^{+}, \ldots \ldots, v_n^{+}\} = \{(max_j\ v_{ij} | i \in I), (min_j\ v_{ij} | i \in J)\} \tag{21}$$

$$A^{-} = \{v_1^{-}, v_1^{-}, \ldots \ldots, v_n^{-}\} = \{(min_j\ v_{ij} | i \in I), (max_j\ v_{ij} | i \in J)\} \tag{22}$$

Where I is associated with benefit criteria, and J is associated with cost criteria.

(4) Calculate the separation measures using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is calculated as:

$$d_j^+ = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_{ij}^+\right)^2} \qquad ; \ j = 1,2, \dots \dots \dots \dots \dots m. \tag{23}$$

Similarly, the separation from the negative ideal solution is given as

$$d_j^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_{ij}^-\right)^2} \qquad ; \ j = 1,2, \dots \dots \dots \dots \dots m. \tag{24}$$

(5) Calculate the relative closeness to the ideal solution. The relative closeness of the alternative:

$$R_j = \frac{d_j^-}{d_j^+ + d_j^-} \qquad ; \ i = 1,2, \dots \dots , m. \tag{25}$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0$, $then$, $clearly$ $R \in [0,1]$.

(6) Rank the preference order

3.5 Numerical case study: overview of hospital dataset

The datasets for numerical analysis were collected from a large hospital with more than 5000 surgical interventions per year. There are 8 different surgical groups: ear, nose, and throat (ENT), obstetrics and gynecology (OBG), orthopedic surgeries (ORT), neurosurgery (NEU), general surgeries (GEN), vascular surgeries (VAS), cardiac surgeries (CAR), and urology surgeries (URO) in the hospital. There are 8 operating rooms, one of these is dedicated to emergency patients. As detailed in Table 3.1.

The hospital operates these OR on 8-hour surgical blocks during regular time from Monday to Friday. There are 20 ICU rooms and 35 MCU beds, which operate continuously, 24 hours a day, seven days a week. Additionally, there are 60 nurses available in the ICU. Mean surgery duration, mean LOS in the ICU and MCU (pre and postoperative stay), mean ICU nursing hours needed are adopted from historical data and statistics provided in literature.

Resources required by each surgical patient and overall resources availability are measured in hours. We assume that any patient can access any available ICU or MCU beds and MCU beds are used for both preoperative and postoperative in planning horizon.

Table 3.1 Resource requirement for each specialty

Specialty	Surgery Duration (hrs)	ICU-LOS (hrs)	MCU-LOS (hrs)		ICU nursing care (hrs)
			Pre-Op	Post-Op	
ENT	1.23	3	0	12	3
OBG	1.43	10	12	12	10
URO	1.06	7	12	12	7
GEN	1.55	6	0	24	6
VAS	2	48	24	72	48
OTH	1.78	36	12	48	36
NEU	2.67	72	24	48	72
CAR	4	72	24	72	72

Before the pandemic, OR blocks were allocated based on the number of patients in each surgical department and the limited availability of downstream facilities. As detailed in Table 3.2, the number of patients in each surgical department was assessed and the number of OR blocks assigned. Based on the current setting, over a week of planning horizontal it resulted in an average of 90% of resources being used and the average waiting time of the patient in each department is 41.32 weeks.

Table 3.2 Current OR block assignment

Specialty	No. Blocks assigned	Number of patients in waiting list	Expected Waiting time (weeks)
ENT	5	1092	36.4
OBG	3	468	31.2
URO	3	416	34.67
GEN	5	1144	31.77
VAS	3	416	52
OTH	5	1196	42.71
NEU	3	260	43.33
CAR	1	104	52

CHAPTER IV

RESULTS AND DISCUSSION

This chapter presents the numerical results of the proposed multi-stage framework for elective surgical planning and discusses its implications. The optimization model was solved using LINGO version 16.0, with real data from a tertiary hospital in Thailand. Solutions were generated within seconds, offering a practical approach to support strategic OR planning and patient scheduling under uncertainty.

In this chapter, the numerical results of the planning problem and the discussions are provided.

4.1 Stage 1: Multi-Objective OR blocks Allocation

In this section, we present the numerical experiment conducted for the deterministic operating room resource allocation (DORA) problem, along with a detailed discussion of the results obtained. The DORA model was solved using LINGO version 16, utilizing datasets obtained from the aforementioned hospital. The solution can be obtained within a few seconds, providing insights into optimal resource allocation and its impact on various metrics.

4.1.1 Comparative analysis: model solution versus current hospital setting

Figure 4.1.1 illustrates the number of OR blocks reallocated based on our model solution compared to the current allocation in the hospital. Notably, significant changes in OR block allocations have occurred across different surgical departments.

For instance, the ENT and GEN departments experienced increases from 5 to 8 blocks and from 8 to 10 blocks, respectively, while the OBG and URO departments experienced reductions from 3 to 2 blocks and from 8 to 7 blocks per week, respectively. The increase in OR blocks allocated to departments such as ENT, GEN, OTH directly address the patient waiting list demand for the surgical specialty surgical services within these specialties. By providing additional OR blocks, it can accommodate more surgeries, thereby reducing the backlog of cases and dramatically reducing average patient waiting time. Conversely, the reduction in OR blocks allocated to departments such as OBG and URO reflects a more efficient use of resources. By reallocating OR blocks from these two departments, the model solution can better match capacity with demand, thereby reducing underutilization of downstream resources and minimizing idle time in OR.

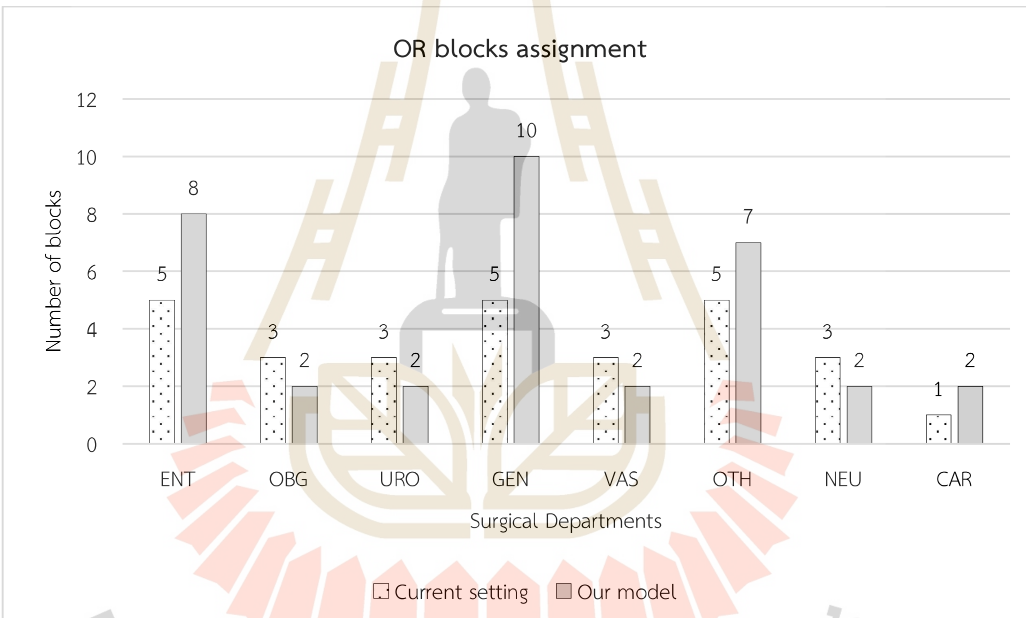

Figure. 4.1.1 Distribution of OR blocks across surgical departments

The outcomes presented in **Figure 4.1.2** show that the solution from our model substantially reduces the time required to clear the waiting list compared to the current setting. Departments such as ENT, GEN, OTH and CAR demonstrated a remarkable decrease in waiting list clearance times, transitioning from 43.68 to 27.3 weeks, 57.2 to 28.6 weeks, 59.8 to 42.71 weeks, and 52 to 26 weeks, respectively.

However, the OBG, URO, VAS and NEU departments showed an increase in waiting list clearance times, increasing from 31.2 to 46.8 weeks, 34.6 to 52 weeks, 28.88 to 43.33 weeks, respectively.

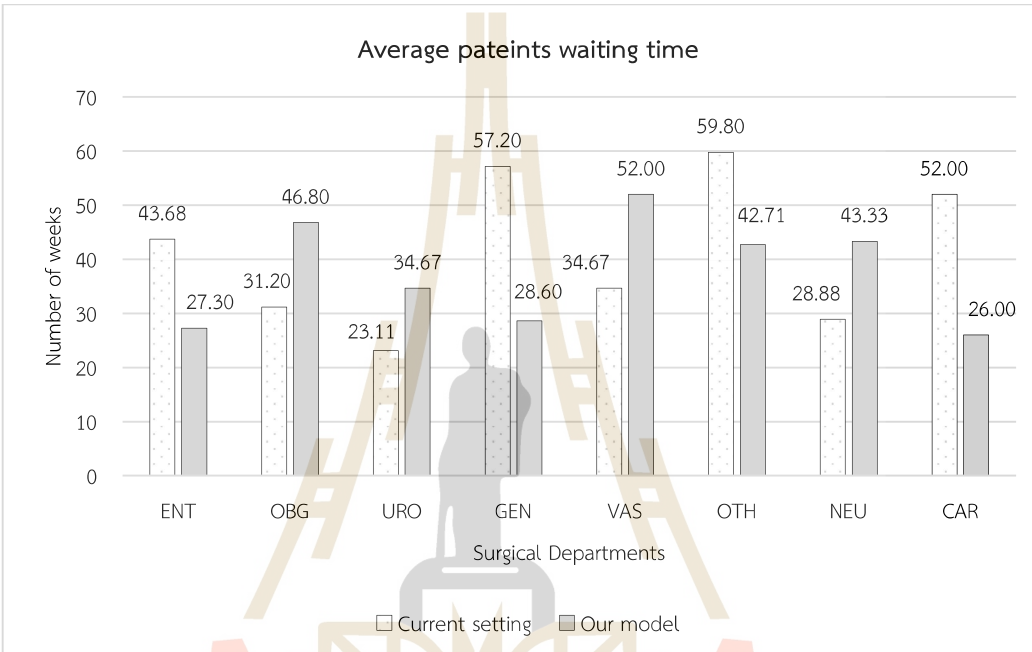

Figure. 4.1.2 Average waiting time of current setting vs our model

In addition, resource utilization across different facilities was compared between the current setting and our proposed model as shown in **Figure. 4.1.3**. The OR is 100% utilized based on our model solution while the current setting uses 80% of available capacity while downstream ICU and MCU utilization rates of 98.28% and 99.59%, compared to current resource utilization of 94% and 89.79%, respectively. And nursing time is relatively unchanged.

Table 1 shows a comparative statistical analysis between the model solution and current setting is presented. There is a notable decrease in both the objective value and average patient waiting time as well as improved resource utilization.

There is notably decrease Specifically, the mean and standard deviation patient waiting time decreased by approximately 8.81% and 28.87% respectively, while the objective value decreased by about 13.45%.

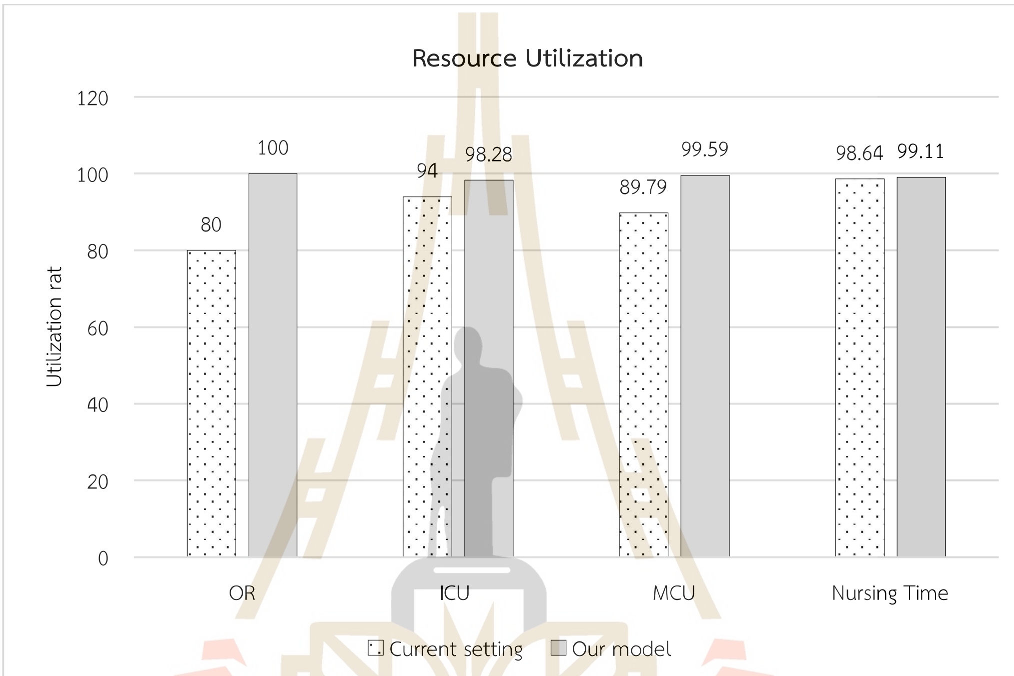

Figure. 4.1.3 Resource utilization

The mean resources utilization of resources is 99.25% and standard deviation 0.74% compared to the current hospital setting with average of 90.6% and standard deviation of 7.94%. The significant reduction in standard deviation implied that our model demonstrated better and more balance in terms of resource utilization across different resource facilities upstream and downstream.

The results highlight the effectiveness of our proposed model in optimizing OR block allocation within surgical departments. By reallocating OR blocks based on our model solution, the model solution achieved significant reductions in average patient waiting time and total incurred cost while also improving resource utilization across different resources facilities. These findings highlight the potential of modeling approaches for enhancing OR resources management and operational efficiency, ultimately leading to improved patient wait time. Although the model's solution offers improved OR resource allocation by reducing objective value, resource utilization deviation, and shortening patient waiting times across various surgical departments compared to current practices. Unfortunately, the model generates based on constrained resources and neglected the surgical department priority.

Table 4.1 Objective values of current setting vs our model

	Current setting	*Proposed Model*	*% Decrease (proposed model: current setting)*
Objective value (unit cost)	4725300	4089871	13.45%
Mean waiting time (weeks)	41.32	37.67	8.81%
Sd waiting time (weeks)	13.87	9.86	28.87%
Mean utilization (%)	90.60	99.25	8.7%
Sd utilization (%)	7.95	0.74	90%
Patient throughput	140	148	5.71%

Given the significant global burden of surgical backlog and the constraints posed by limited and costly overtime resources, it is vital for OR managers to consider prioritization techniques and allow overtime resources aid to address the surgical backlog. In scenarios where overtime is not possible due to hospital conditions, setting priorities among surgical departments becomes crucial.

This determines the order in which departments are granted access to OR blocks, impacting patient wait times and resource distribution. For instance, during crises such as pandemics or emergencies where resources are limited, decisions must be made wisely to allocate resources where they are most needed. Despite expensive overtime costs, from a crisis perspective, it is necessary to utilize overtime resources to help reduce the burden of the surgical backlog and patient waiting times. To better understand the trade-off between overtime resource allowance and additional costs incurred, the study conducts a cost-benefit analysis to assess the financial implications of such increases and strike a balance between reducing patient waiting times and considering financial aspects.

Through this analysis, hospital administrators can gain insights into the trade-offs between total additional overtime costs and average patient waiting time on the waiting list. This information provides valuable support for decision-making within hospitals regarding long-term and short-term investments in resource facilities and ensures efficient resource allocation.

For these reasons, the sensitivity analysis about surgical department priority and overtime allowances will be carried out. In the next subsection, we will continue performing sensitivity analysis with the aim of further improving the allocation of OR resources.

4.1.2 Sensitivity analysis

In this section, a comprehensive sensitivity analysis is done on two key critical parameters: surgical department priority and overtime resources allowance. OR managers should set these parameters through their strategies while other parameters such as surgery duration and patient length of stay in ICU and MCU are not under control of managers.

For generalization purposes, this study offers valuable insights to support better decision-making and alignment with hospital goals by proposing four different scenarios of prioritization setting.

1) 1.Priority based on clinical need: prioritizing departments based on their severeness.
2) Equal access: providing each department with equal right to access to resources in order to ensure fairness.
3) Tackling long waiting lists: prioritize department with long patient waiting list.

4) Prioritizing cases based on resource requirements (low and high): aims to optimize resource efficiency and utilization. Whereas, to assess the impact of overtime allowance on patient waiting time four variations in the overtime allowance are considered, ranging from 10% to 25% compared to the baseline no overtime.

The scenarios examined are as follows: Scenario 1: the overtime allowance increased by 10%; Scenario 2: 15%; Scenario 3: 20%; and Scenario 4: overtime allowance increased by 25%. These variations allow us to explore the impact of incremental changes in overtime allowances on patient waiting list clearance time as well as total overtime costs .

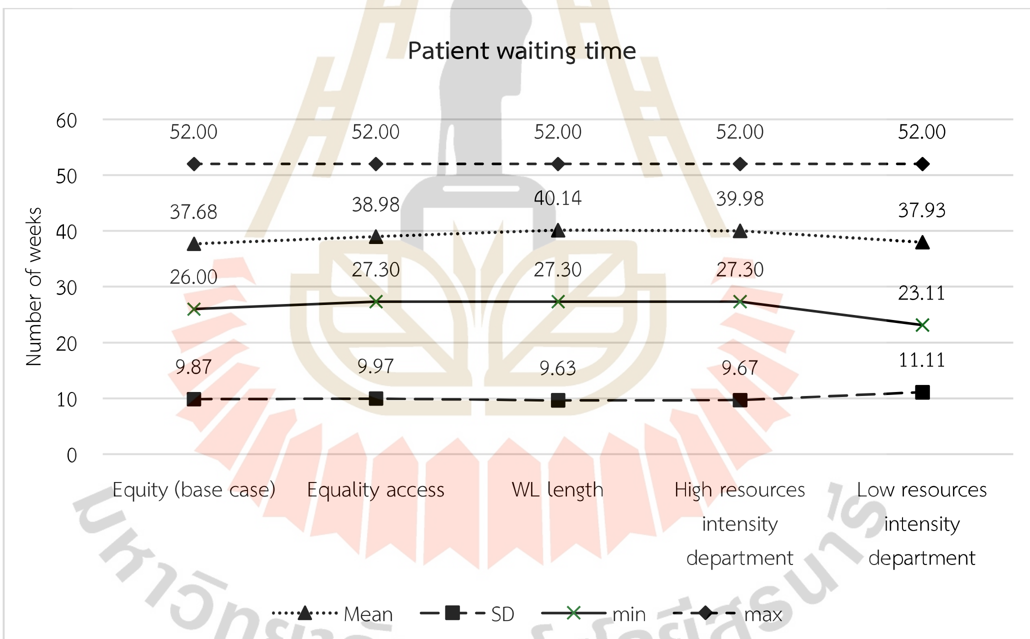

Figure. 4.1.4 Statistical analyses across scenarios

As shown in **Figure. 4.1.4**, there is no significant difference in patient waiting time in varying prioritization settings across different scenarios.

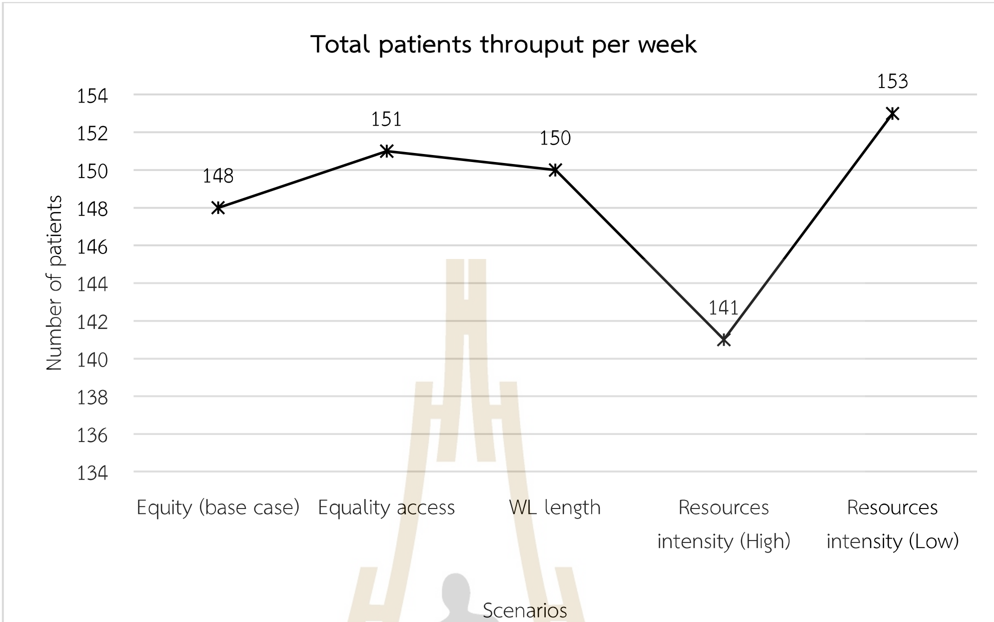

Figure 4.1.5. Patient throughput per week across scenarios

Figure 4.1.5 shows significant differences in total patient throughput across various priority settings. Based case scenario can treat 148 patients per week while scenario 2 increases throughput to 151 patients per week. This highlights the tradeoff between equity access and equality access. Scenario 3 addresses long backlogs and results in a throughput of 150 patients per week. And scenario 4 and 5 prioritizing cases based on resource requirements leads to varying throughputs, with high-resource intensity departments focusing can treating 153 patients while low-resource intensity focus treating 141 patients per week.

Additionally, there is considerable variation in resource utilization among facilities across different scenarios. Equality access, backlog concern, and low-resource intensity scenarios exhibit high variation in utilization rates. In contrast, the equity access and high-resource intensity scenarios show minimal variation in resource utilization across facilities as shown in **Figure. 4.1.6**. These scenarios provide OR managers with valuable insights into informed decision-making. By characterizing each priority scheme into different scenarios, administrators can better understand the implications of various approaches for priority-setting within surgical departments.

These insights help align priority setting practices with institutional objectives and healthcare delivery models.

They offer a deeper understanding of the trade-offs and considerations involved in allocating limited OR resources effectively while striving to meet the needs of a diverse patient population and optimize resource efficiency.

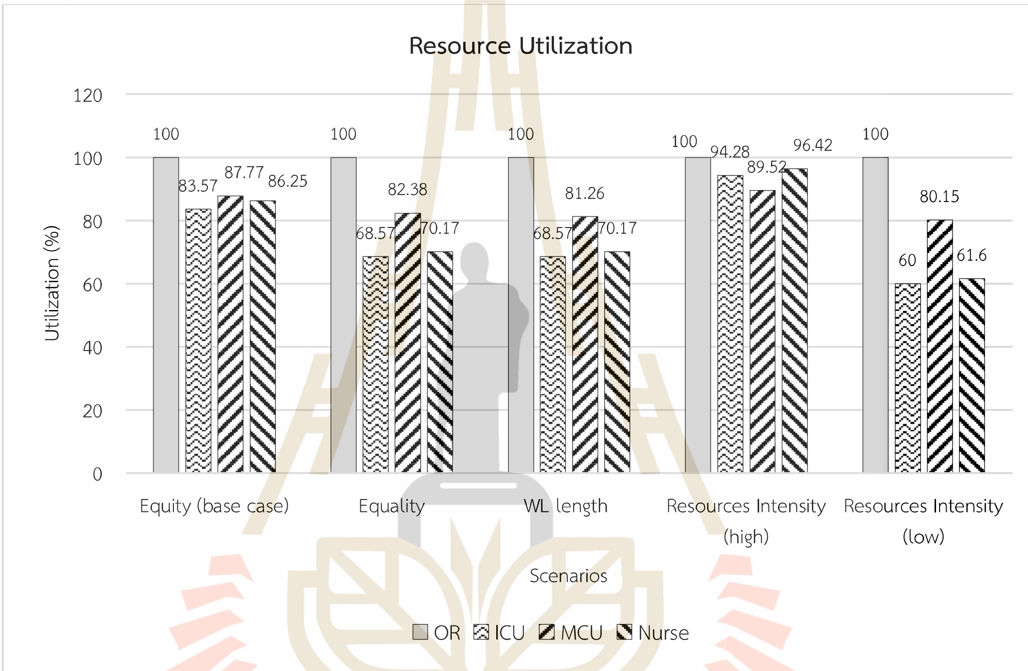

Figure 4.1.6. Resource utilization across different scenarios setting

In **Figure 4.1.7**, a notable observation arises regarding the impact of different overtime allowances on average waiting times. With a 10% increase in the overtime allowance for resources, there is a significant decrease in the average waiting time of approximately 9%, decreasing from 37.7 to 34.5 weeks. Further increases to 15% and 20% over time of the resources allowance result in smaller decreases from the base case, approximately 13.5% and 17.5%, respectively. Interestingly, when the overtime allowance is increased to 25%, there is no change in average waiting time compared to the 20% overtime allowance, which remains at approximately 1%.

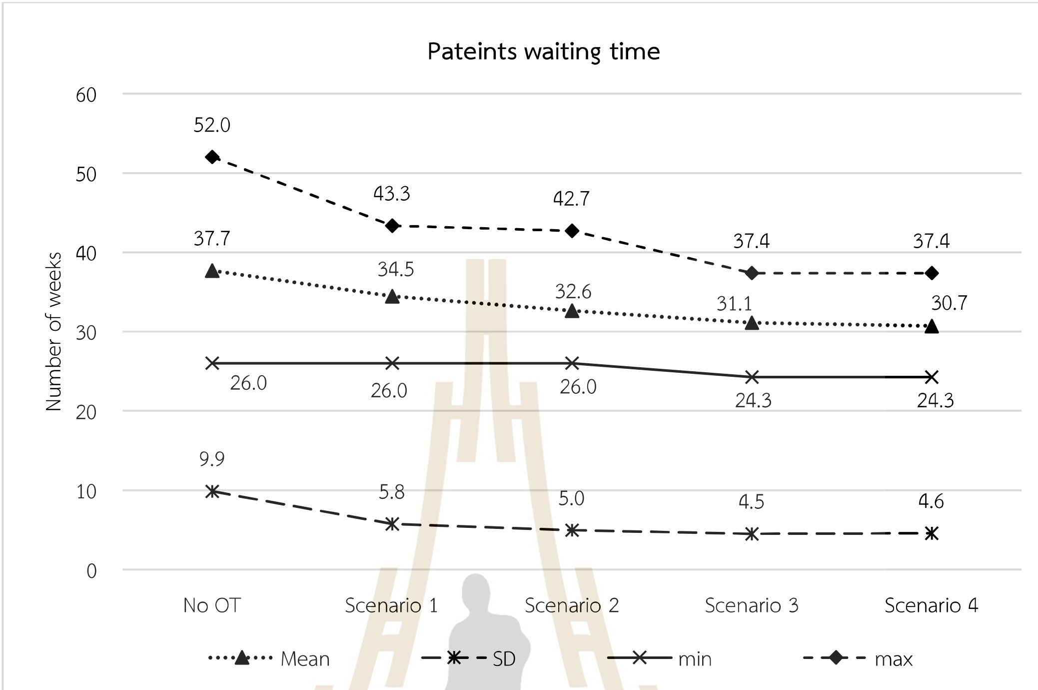

Figure. 4.1.7 Statistical analyses across scenarios

Table 2 presents the relationship between overtime allowances, waiting times, and incurred costs, emphasizing the importance of balancing resource allocation for efficient waiting list management with optimal overtime allowances. Hospital administrators can refer to this guideline to determine whether increasing operations overtime is necessary to reduce average patient waiting times. By carefully considering the trade-offs between resource utilization, waiting times, and incurred costs, administrators can make informed decisions to optimize patient care delivery while ensuring the efficient use of resources.

Table 4.2 Scenarios comparison

	No OT	*Scenario 1*	*Scenario 2*	*Scenario 3*	*Scenario 4*
Average WL clearance time (weeks)	37.7	34.5	32.6	31.1	30.7
% decrease from base case (%)	-	8.55%	13.38%	17.45%	18.50%
% increase overtime costs from 10%	-	-	136.2%	267.6%	304.4%

4.2 Stage 2: Multi Criteria Decision Making Patient Prioritization

Following the strategic allocation of operating room (OR) blocks to each surgical department in Phase 1, the second stage addresses operational-level decisions. In this phase, each department is responsible for selecting which patients from their waiting lists will be scheduled for surgery, based on the number of OR blocks allocated.

To support this decision-making process, a Multi-Criteria Decision Making (MCDM) approach is introduced. Unlike traditional first-come, first-served (FCFS) scheduling, MCDM enables a more equitable and clinically informed patient ranking by evaluating multiple criteria simultaneously. The prioritization criteria are derived from expert input and literature, incorporating both medical urgency and socio-personal factors to ensure fairness and effectiveness in scheduling decisions.

This section presents the MCDM process through a numerical case study involving ten elective surgical patients, using the TOPSIS method to illustrate how patients can be ranked objectively based on their comprehensive clinical and personal profiles.

4.2.1 Criteria Identification

To develop an effective and equitable patient prioritization framework for elective surgical services, this study adopted a structured set of criteria synthesized from established literature and existing healthcare prioritization practices. The analytical hierarchy for patient prioritization was constructed based on four overarching criteria categories: C1: Clinical and Functional Variables, C2: Expected Benefits, C3: Social Role Variables, and C4: Personal Characteristics, as proposed by Rahimi et al. (2016) and extended by Li et al. (2019), Srikunmar et al. (2018), and Silva et al. (2021).

Each of these main criteria encompasses specific sub-criteria that reflect the complexity and multifactorial nature of surgical prioritization. The sub-criteria were selected to ensure a balance between clinical necessity, potential outcome benefits, and broader socioeconomic considerations. The hierarchical structure used in this study is presented in **Figure 4.1.8**.

Clinical and Functional Variables (C1) include:

1) C11: Disease severity
2) C12: Pain
3) C13: Rate of disease progression
4) C14: Difficulty in performing daily activities

Expected Benefits (C2) include:

1) C21: Probability and degree of expected health improvement
2) C22: Risk of comorbidity development without surgery
3) Social Role Variables (C3) cover:
4) C31: Limitation in caregiving responsibilities
5) C32: Dependency level
6) C33: Geographic accessibility
7) C34: Financial capacity to undergo surgery
8) C35: Overall life impact
9) C36: Urgency based on treatment delay consequences
10) C37: Limitation in work, education, or employment participation

Personal Characteristics (C4) include:

1) C41: Age
2) C42: Gender
3) C43: Diabetes status
4) C44: Anemia
5) C45: Hypertension
6) C46: Sleep disorders

These criteria collectively serve as the input parameters for the Analytic Hierarchy Process (AHP) model developed in this study to support the prioritization of general surgical patients as shown in **Figure 8. The** prioritization outcome reflects a combination of medical urgency, potential benefits, and socio-personal considerations, ensuring that limited healthcare resources are allocated in the most impactful and ethically grounded manner.

4.2.2 Weighting method

To determine the relative importance of each criterion, a weighting methodology was employed using expert judgment through pairwise comparisons. A panel of ten decision-makers—including clinicians, hospital administrators, and public health experts—evaluated each sub-criterion using a scale of 1 to 10. The mean scores were computed, and the AHP methodology was applied to derive the final weights (Wi) for both the main criteria and their sub-components.

Main Criteria Weight Distribution: The aggregated weights for the four main criteria were as follows:

C1: Clinical and Functional Variables – 32.85%

C2: Expected Benefits – 18.98%

C3: Social Role Variables – 27.52%

C4: Personal Characteristics – 20.64%

These results indicate that clinical and functional factors were deemed most significant, comprising nearly one-third of the overall decision weight. Social role and personal characteristics also held substantial influence, underscoring the importance of a holistic approach that goes beyond clinical metrics alone.

These weights served as foundational parameters for the subsequent prioritization phase, enabling a comprehensive and objective evaluation of patient cases as shown in Table 1.

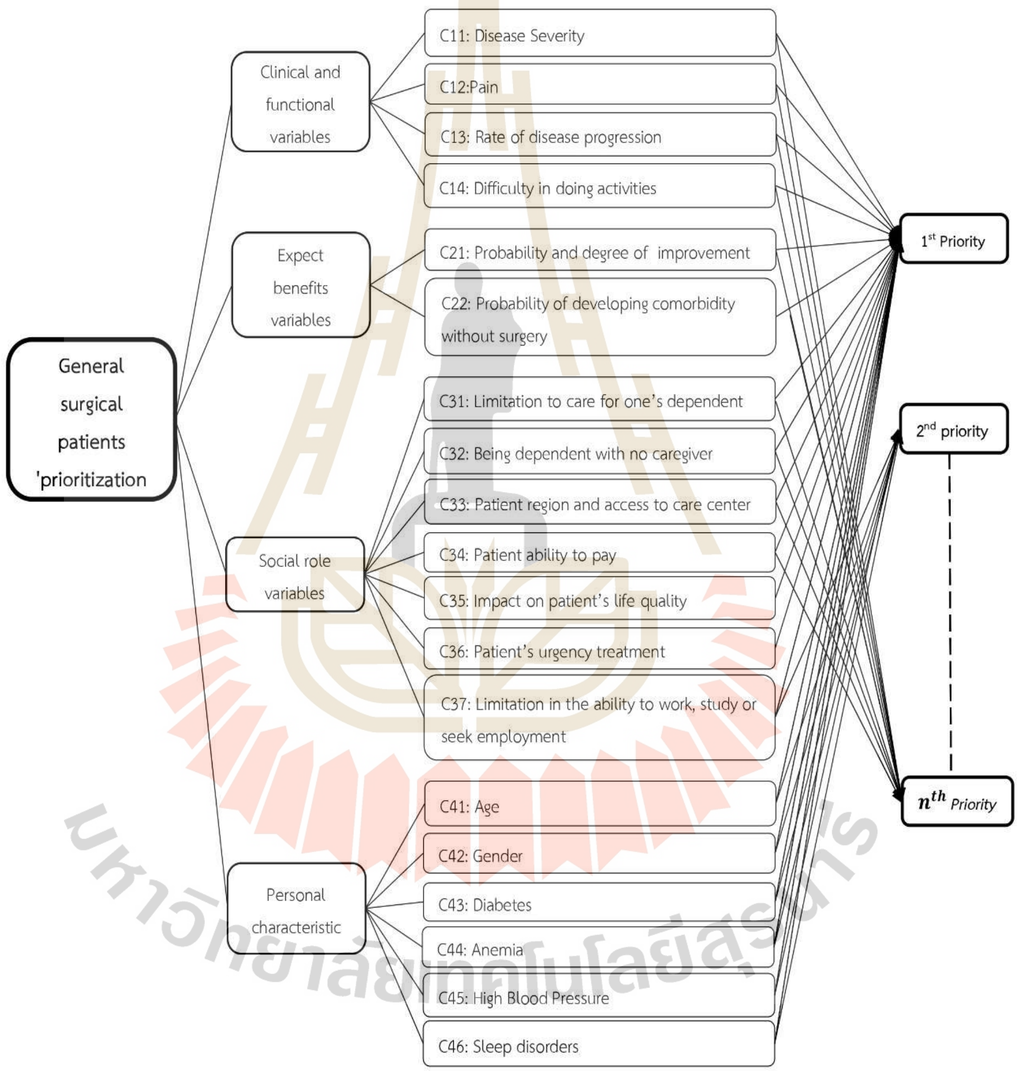

Figure 4.1.8: Analytic Hierarchy Process for General surgical patient prioritization

Table 4.3 Relevant scores assigned by 10 experts in related area to 19 criteria

Main Criteria	Criteria	1	2	3	4	5	6	7	8	9	10	Wi	Total (∑Wi)
C1: Clinical and Function	C11	10	9	8	10	8	10	10	9	9	9	0.1021	0.3285
	C12	9	8	8	8	8	8	9	8	8	7	0.0899	
	C13	8	5	5	7	8	6	8	5	7	5	0.0710	
	C14	6	7	5	5	7	7	5	6	6	5	0.0655	
C2: Expected Benefit	C21	10	9	8	10	10	7	9	10	9	9	0.1010	0.1898
	C22	7	7	7	10	7	9	9	7	10	7	0.0888	
C3: Social Role	C31	3	6	3	2	5	3	2	3	1	1	0.0322	0.2752
	C32	3	3	5	4	2	4	6	1	5	1	0.0377	
	C33	6	6	1	6	6	2	3	6	2	5	0.0477	
	C34	3	4	4	3	4	2	4	5	5	6	0.0444	
	C35	2	4	1	3	3	4	2	4	5	6	0.0377	
	C36	1	5	1	5	5	3	6	5	4	4	0.0433	
	C37	2	6	2	4	2	2	3	1	5	2	0.0322	
C4: Personal Characteristic	C41	3	5	2	3	3	1	5	2	2	5	0.0344	0.2064
	C42	5	3	3	5	4	4	2	1	2	1	0.0333	
	C43	2	4	2	3	4	2	3	4	5	2	0.0344	
	C44	5	5	5	2	5	5	4	5	4	5	0.0499	
	C45	4	1	1	1	1	5	1	3	4	3	0.0266	
	C46	5	2	4	1	1	1	1	2	5	3	0.0277	

4.2.3 TOPSIS Method for Patient Ranking

To generate the final prioritization of patients, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed. This method evaluates each alternative by measuring its Euclidean distance from both an ideal best and an ideal worst solution, thereby identifying the most suitable option through relative closeness to the ideal point.

Ten patient cases were evaluated using the sub-criteria identified and weighted in the previous phase. The raw clinical and demographic data for each patient are presented in Table 4.3.

Using the weighted normalized decision matrix shown in Table 4.5, the TOPSIS model calculated the Euclidean distance of each patient from the ideal best (d^{+}) and ideal worst (d^{-}) solutions. These distances were then used to compute the relative closeness (Rj) to the ideal solution, which determines the final patient ranking. Results are summarized in Table 4.4.

Table 4.4 Basic patient information and clinical evaluation

Patient No	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
1	4	2	5	5	7	68	1	0	1	0	1	0	0	30	0	1	0	1	1
2	4	3	1	2	86	86	1	1	1	1	1	1	1	21	1	1	1	1	0
3	1	4	3	5	87	46	1	1	1	0	0	1	0	41	0	1	1	0	1
4	3	3	1	5	35	99	0	0	1	0	0	0	0	75	0	1	0	1	0
5	2	0	5	1	14	26	0	1	0	0	0	1	1	69	1	1	1	0	1
6	5	1	1	4	13	21	0	1	1	0	0	1	0	47	1	1	1	1	0
7	2	4	1	3	47	40	1	1	1	1	0	1	1	44	0	1	1	1	1
8	2	1	2	1	58	54	1	1	1	0	0	1	1	19	1	0	1	0	0
9	4	1	1	1	32	72	1	0	1	1	1	0	0	76	0	0	1	0	1
10	3	2	2	2	55	54	1	0	0	1	1	0	1	70	1	0	1	0	1

Table 4.5 Weighted normalized matrix

Patient No	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
1	0.039	0.022	0.043	0.033	0.005	0.034	0.013	0.000	0.010	0.000	0.014	0.000	0.000	0.007	0.000	0.013	0.000	0.015	0.015
2	0.039	0.033	0.009	0.013	0.055	0.043	0.013	0.018	0.010	0.014	0.014	0.017	0.016	0.005	0.018	0.013	0.012	0.015	0.000
3	0.010	0.044	0.026	0.033	0.056	0.023	0.013	0.018	0.010	0.000	0.000	0.017	0.000	0.009	0.000	0.013	0.012	0.000	0.015
4	0.029	0.033	0.009	0.033	0.023	0.049	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.017	0.000	0.013	0.000	0.015	0.000
5	0.020	0.000	0.043	0.007	0.009	0.013	0.000	0.018	0.000	0.000	0.000	0.017	0.016	0.016	0.018	0.013	0.012	0.000	0.015
6	0.049	0.011	0.009	0.026	0.008	0.010	0.000	0.018	0.010	0.000	0.000	0.017	0.000	0.011	0.018	0.013	0.012	0.015	0.000
7	0.020	0.044	0.009	0.020	0.030	0.020	0.013	0.018	0.010	0.014	0.000	0.017	0.016	0.010	0.000	0.013	0.012	0.015	0.015
8	0.020	0.011	0.017	0.007	0.037	0.027	0.013	0.018	0.010	0.000	0.000	0.017	0.016	0.004	0.018	0.000	0.012	0.000	0.000
9	0.039	0.011	0.009	0.007	0.021	0.036	0.013	0.000	0.010	0.014	0.014	0.000	0.000	0.017	0.000	0.000	0.012	0.000	0.015
10	0.029	0.022	0.017	0.013	0.035	0.027	0.013	0.000	0.000	0.014	0.014	0.000	0.016	0.016	0.018	0.000	0.012	0.000	0.015

Table 4.6 Euclidean distance and relative closeness & rank

Patient No	d^{+}	d^{-}	Rj	Patient Rank
1	0.072	0.070	0.493	6
2	0.047	0.094	0.665	1
3	0.061	0.087	0.586	2
4	0.070	0.075	0.515	4
5	0.089	0.058	0.394	10
6	0.085	0.061	0.420	9
7	0.066	0.074	0.528	3
8	0.073	0.061	0.454	7
9	0.078	0.061	0.439	8
10	0.063	0.066	0.511	5

The results show a different prioritization order compared to the hospital's current first-come, first-served scheduling. For example, Patient No. 5 is ranked 10th by TOPSIS, while the hospital's traditional system prioritized them 5th. This discrepancy illustrates that using different decision-making frameworks—MCDM vs. staff judgment—may lead to inconsistencies.

The main advantage of the MCDM approach is its ability to interpret multiple criteria simultaneously, which human decision-makers may not easily process due to cognitive limitations. Staff may rely on experience and intuition, allowing for faster but potentially less systematic decisions.

The use of the TOPSIS method in a non-urgent healthcare service setting can improve patient satisfaction by enabling more objective and meaningful prioritization, potentially improving patients' preoperative conditions. However, integrating this framework into daily practice would require computational infrastructure and staff training, implying a need for investment and planning.

Overall, this study demonstrates that a systematic decision-making approach using TOPSIS can enhance elective surgical patient prioritization, particularly where detailed patient information is available, and the healthcare system aims to optimize resource allocation.

The ranking of the patient from the TOPSIS model was calculated based on the biopsychosocial aspects used in this study. While its rank was found to be different compared to the current first-come first-serve procedure from real case. For instance, TOPSIS ranked patient no.5 as the 10th order while the current procedure was given at the 5th order. The difference of results between two frameworks (MCDM and staff) implies that using different decision-making methods may lead to inconstancy in the decision process. Staff can make decisions more rapidly than using the MCDM model because they use their experience while MCDM must calculate based on the recorded data.

MCDM tends to provide the results more concisely because it can interpret the results based on multiple criteria in which staff cannot achieve this ability. The satisfaction of the patient may be increased due to the ability to make a proper prioritization which can improve the overall health of each patient before surgery. The MCDM framework required to be operated on a computing device which may lead to investment consideration in the future. However, the non-urgent healthcare service setting can be beneficial from incorporating MCDM framework for elective surgical patient prioritization in advance because the care service can gather the scheduled patient data to improve the planning of the resources utilization in the healthcare service setting more appropriately.

The main challenge in scheduling elective surgical patients is to manage patient prioritization based on multiple biopsychosocial criteria. This research demonstrates a decision-making framework, using both MCDM method and TOPSIS technique, to support elective surgical

patient prioritization based on multiple biopsychosocial criteria. A case study was presented to illustrate numerical examples of the framework based on the data in a non-urgent healthcare service setting. Results were presented to exemplify a consequence of the elective surgical patient prioritization framework in this study. The satisfaction of the patient is increased due to the ability in making a decisive prioritization which can improve overall health of each patient before surgery. The non-urgent healthcare service setting can gather the scheduled patient data to from the MCDM framework to improve the planning of the resources utilization in the healthcare service setting more appropriately.

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research presents a multi-stage, multi-objective optimization framework for operating room (OR) resource planning and scheduling, designed to address operational challenges in the post-pandemic healthcare context. The study introduces the DORA model, which integrates strategic OR block allocation with tactical patient prioritization under uncertainty. The primary aim is to enhance hospital efficiency while balancing clinical effectiveness and cost considerations.

The model was evaluated using real-world data from a major hospital in Thailand, involving eight surgical departments.

<u>**Phase 1**</u>: The model demonstrated significant improvements over existing scheduling practices. Key outcomes include:

1) A 7% reduction in average patient waiting time, from 40.5 weeks to 37.67 weeks.
2) A 5% decrease in overall hospital costs, from 4.27 million to 4.08 million THB.
3) More balanced resource utilization across ORs, ICUs, MCUs, and nursing staff.
4) Improved fairness in OR block allocation, reducing disparities among departments.

Sensitivity analysis revealed the model's adaptability under overcapacity conditions. A 20% overcapacity buffer was identified as optimal for balancing cost efficiency with service continuity during demand surges, such as those experienced during COVID-19. Scenario analysis further emphasized the trade-offs between returning to standard operations and temporarily allowing overcapacity, offering practical guidance for hospital administrators.

This stage provides a data-driven, uncertainty-aware decision-support tool to assist hospital managers in OR planning, resource reallocation, and patient prioritization—supporting resilience in surgical service delivery during and beyond healthcare disruptions.

<u>Phase 2</u>: The second phase applied the TOPSIS method to prioritize elective surgical patients. The results revealed a divergence from the hospital's current first-come, first-served (FCFS) system. For example, Patient No. 5 was ranked 5th under the FCFS method but 10th using TOPSIS. This discrepancy underscores the variability in prioritization outcomes when contrasting subjective clinical judgments with data-driven multi-criteria decision-making (MCDM) approaches.

A key strength of MCDM methods such as TOPSIS lies in their ability to consider multiple biopsychosocial criteria simultaneously. In contrast, human decision-makers often rely on experience and intuition, which, while expedient, may lack systematic rigor. TOPSIS provides a structured and objective evaluation framework, potentially improving fairness and consistency in patient prioritization.

Integrating this approach into routine elective surgery scheduling—particularly in non-urgent healthcare settings—can enhance resource utilization and patient satisfaction. By aligning prioritization with individual needs, such models may also lead to improved preoperative outcomes. However, effective implementation will require computational tools, staff training, and organizational change. Despite these initial costs, the long-term benefits of improved planning and patient-centered care justify the adoption of such decision-support tools.

In summary, this study demonstrates that a TOPSIS-based MCDM framework can complement or potentially outperform traditional FCFS systems by offering a more balanced, data-informed approach to elective surgery prioritization.

5.2 Applications

The findings of this study offer several real-world applications:

1) Hospital resource planning: Enables dynamic allocation of OR blocks and ICU/MCU capacities across departments.
2) Surgical backlog management: Assists hospitals in efficiently reducing elective surgery backlogs.
3) Policy development: Provides evidence-based recommendations for optimal overcapacity thresholds under uncertain demand.
4) Decision-support systems: The model can be integrated into hospital information systems for short- and long-term OR planning.
5) Post-crisis recovery strategies: Informs recovery planning efforts following healthcare disruptions such as pandemics or natural disasters.

5.3 Recommendations for Future Work

While the proposed framework shows promising results, several areas warrant further exploration:

1) Incorporate dynamic demand forecasting: Utilize predictive analytics or machine learning to account for fluctuating patient inflows.
2) Stochastic and robust optimization: Develop formulations that better capture uncertainties in surgery durations, patient arrivals, and cancellations.
3) Heuristic and metaheuristic algorithms: Enhance computational efficiency and scalability for application in large-scale healthcare systems.
4) Real-time decision-making: Investigate the use of digital twins or simulation-based optimization for adaptive scheduling.
5) Integration with Electronic Health Records (EHRs): Automate prioritization using real-time clinical data to improve personalization.
6) Patient-centered outcomes: Include satisfaction, recovery quality, and equity as added optimization goals.

5.4 Limitations

Despite its promising contributions, this study acknowledges the following limitations:

1) **Excludes emergency/outpatient surgeries:** Focuses only on elective cases, assuming others are managed separately.
2) **Homogeneous OR assumption:** All operating rooms are treated the same, ignoring specialty-specific needs.
3) **Static waiting list:** Does not account for new patients arriving over time.
4) **Limited resource scope:** Models only key resources (ORs, ICU beds, surgical wards), omitting others like anesthesia teams, PACU, labs, and imaging.
5) **Simplified scheduling:** Uses fixed 8-hour OR blocks, excluding real-world variations.
6) **Predictable recovery needs assumed:** Post-op demands are treated as known, overlooking patient variability.
7) **Limited real-time clinical input:** Prioritization relies on fixed criteria, not evolving patient conditions.
8) **Narrow fairness scope:** Analyzes block allocation fairness but omits broader equity factors (e.g., insurance, socioeconomic status).
9) **Scalability issues:** As an NP-hard problem, large-scale use may need heuristics or real-time methods.

Despite these limitations, the proposed framework offers a solid foundation for improving elective surgery planning and can be further developed to support comprehensive hospital operations.

REFERENCES

1. Abdullah, H. R., Lam, S. S., Ang, B. Y., Pourghaderi, A., Nguyen, F. N., Matchar, D. B., et al. (2022). Resuming elective surgery after COVID-19: A simulation modelling framework for guiding the phased opening of Operating Rooms. International Journal of Medical Informatics, 158, 104665. https://doi.org/10.1016/j.ijmedinf.2021.104665
2. Abdullah, R. M., Luo, W., Zhang, N., Zhu, X., & Bai, K. (2022). Evaluation of elective surgery cancellation strategies during COVID-19 using a two-stage DES framework. Health Care Management Science, 25(2), 255–271. https://doi.org/10.1007/s10729-021-09555-0
3. Abedini, A., Ye, H., & Li, W. (2016). Operating room planning under surgery type and priority constraints. Procedia Manufacturing, 5, 15–25. https://doi.org/10.1016/j.promfg.2016.08.005
4. Angelis, A., Kanavos, P., & Montibeller, G. (2016). Resource Allocation and Priority Setting in health care: A multi-criteria decision analysis problem of value? Global Policy, 8, 76–83. https://doi.org/10.1111/1758-5899.12387
5. Badalov, E., Blackler, L., Scharf, A. E., Matsoukas, K., Chawla, S., Voigt, L. P., & Kuflik. (2022). Covid-19 double jeopardy: The overwhelming impact of the social determinants of health. International Journal for Equity in Health, 21(1). https://doi.org/10.1186/s12939-022-01629-0
6. Barbagallo, S., Corradi, L., de Ville de Goyet, J., Iannucci, M., Porro, I., Rosso, N., et al. (2015). Optimization and planning of Operating Theatre Activities: An original definition of pathways and Process Modeling. BMC Medical Informatics and Decision Making, 15(1). https://doi.org/10.1186/s12911-015-0161-7
7. Bowers, J. A. (2011). Simulating waiting list management. Health Care Management Science, 14(3), 292–298. https://doi.org/10.1007/s10729-011-9171-x

8. Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. European Journal of Operational Research, 201(3), 921–932. https://doi.org/10.1016/j.ejor.2009.04.011
9. Daniels, N. (2016). Just health: Meeting health needs fairly. Cambridge University Press. https://doi.org/10.1017/CBO9781316423927
10. Denton, B. T., Miller, A. J., Balasubramanian, H. J., & Huschka, T. R. (2010). Optimal allocation of surgery blocks to operating rooms under uncertainty. Operations Research, 58(4-part-1), 802–816. https://doi.org/10.1287/opre.1090.0791
11. Frank, L., Concannon, T. W., & Patel, K. V. (2020). Health Care Resource Allocation Decision-making During a Pandemic. Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/research_reports/RRA326-1.html
12. Fügener, A., Hans, E. W., Kolisch, R., Kortbeek, N., & Vanberkel, P. T. (2014). Master surgery scheduling with consideration of multiple downstream units. European Journal of Operational Research, 239(1), 227–236. https://doi.org/10.1016/j.ejor.2014.05.009
13. Hassanzadeh, H., Boyle, J., Khanna, S., Biki, B., & Syed, F. (2022). Daily surgery caseload prediction: Towards improving operating theatre efficiency. BMC Medical Informatics and Decision Making, 22(1). https://doi.org/10.1186/s12911-022-01893-8
14. Howlett, N. C., & Wood, R. M. (2022). Modeling the recovery of elective waiting lists following covid-19: Scenario projections for England. Value in Health, 25(11), 1805–1813. https://doi.org/10.1016/j.jval.2022.06.016
15. Jebali, A., & Diabat, A. (2017). A chance-constrained operating room planning with elective and emergency cases under downstream capacity constraints. Computers & Industrial Engineering, 114, 329–344. https://doi.org/10.1016/j.cie.2017.07.015
16. Joshi, D., Jalali, A., Whipple, T., Rehman, M., & Ahumada, L. M. (2021). "P3": An Adaptive Modeling tool for post-covid-19 restart of surgical services. JAMIA Open, 4(2). https://doi.org/10.1093/jamiaopen/ooab016

17. Joshi, M., Ghassemi, P., Liao, J. M., & Choudhry, D. K. (2021). Predictive analytics model for surgical backlog clearance due to COVID-19. Journal of Medical Systems, 45, 77. https://doi.org/10.1007/s10916-021-01717-w
18. Lamiri, M., Augusto, V., & Xie, X. (2008). Patients scheduling in a hospital operating theatre. 2008 IEEE International Conference on Automation Science and Engineering. https://doi.org/10.1109/coase.2008.4626529
19. Lopreite, M., & Zhu, Z. (2020). The effects of ageing population on health expenditure and economic growth in China: A Bayesian-Var Approach. Social Science & Medicine, 265, 113513. https://doi.org/10.1016/j.socscimed.2020.113513
20. Mehta, A., Awuah, W. A., Ng, J. C., Kundu, M., Yarlagadda, R., Sen, M., Nansubuga, E. P., Abdul-Rahman, T., & Hasan, M. M. (2022). Elective surgeries during and after the COVID-19 pandemic: Case burden and physician shortage concerns. Annals of Medicine and Surgery, 81, 104395. https://doi.org/10.1016/j.amsu.2022.104395
21. Min, D., & Yih, Y. (2010). Scheduling elective surgery under uncertainty and downstream capacity constraints. European Journal of Operational Research, 206(3), 642–652. https://doi.org/10.1016/j.ejor.2010.03.014
22. Mullen, M. G., Michaels, A. D., Mehaffey, J. H., Guidry, C. A., Turrentine, F. E., Hedrick, T. L., et al. (2017). Risk associated with complications and mortality after urgent surgery vs elective and emergency surgery. JAMA Surgery, 152(8), 768. https://doi.org/10.1001/jamasurg.2017.0918
23. Negash, S., Anberber, E., Ayele, B., Ashebir, Z., Abate, A., Bitew, S., et al. (2022). Operating room efficiency in a low-resource setting: A pilot study from a large tertiary referral center in Ethiopia. Patient Safety in Surgery, 16(1). https://doi.org/10.1186/s13037-021-00314-5
24. Neyshabouri, S., & Berg, B. P. (2017). Two-stage robust optimization approach to elective surgery and downstream capacity planning. European Journal of Operational Research, 260(1), 21–40. https://doi.org/10.1016/j.ejor.2016.11.04
25. Oussedik, S., MacIntyre, S., Gray, J., McMeekin, P., Clement, N. D., & Deehan, D. J. (2021). Elective orthopaedic cancellations due to the COVID-19 pandemic:

Where are we now, and where are we heading? Bone & Joint Open, 2(2), 103–110. https://doi.org/10.1302/2633-1462.22.bjo-2020-0161.r1

26. Powers, J., McGree, J. M., Grieve, D., Aseervatham, R., Ryan, S., & Corry, P. (2023). Managing surgical waiting lists through dynamic priority scoring. Health Care Management Science, 26(3), 533–557. https://doi.org/10.1007/s10729-023-09648-1
27. Spratt, B., & Kozan, E. (2016). Waiting list management through Master Surgical Schedules: A case study. Operations Research for Health Care, 10, 49–64. https://doi.org/10.1016/j.orhc.2016.07.002
28. VanBerkel, P. T., & Blake, J. T. (2007). A comprehensive simulation for wait time reduction and capacity planning applied in general surgery. Health Care Management Science, 10(4), 373–385. https://doi.org/10.1007/s10729-007-9035-6
29. Vancroonenburg, W., Smet, P., & Vanden Berghe, G. (2015). A two-phase heuristic approach to multi-day surgical case scheduling considering generalized resource constraints. Operations Research for Health Care, 7, 27–39. https://doi.org/10.1016/j.orhc.2015.09.010
30. Wang, J., Vahid, S., Eberg, M., Milroy, S., Milkovich, J., Wright, F. C., et al. (2020). Clearing the surgical backlog caused by COVID-19 in Ontario: A time series modelling study. Canadian Medical Association Journal, 192(44). https://doi.org/10.1503/cmaj.201521
31. Rovers, M. M., Wijn, S. R., Grutters, J. P., Metsemakers, S. J., Vermeulen, R. J., van der Pennen, R., et al. (2022). Development of a decision analytical framework to prioritise operating room capacity: Lessons learnt from an empirical example on delayed elective surgeries during the COVID-19 pandemic in a hospital in the Netherlands. BMJ Open, 12(4). https://doi.org/10.1136/bmjopen-2021-054110

APPENDIX I

LINGO PROGRAMMING RESULTS

Table 1 Current Setting

```
Global optimal solution found.
Objective value:                              4725300.
Infeasibilities:                              0.000000
Total solver iterations:                             0
Elapsed runtime seconds:                          0.06

Model Class:                                        LP

Total variables:                      8
Nonlinear variables:                  0
Integer variables:                    0

Total constraints:                   17
Nonlinear constraints:                0

Total nonzeros:                      20
Nonlinear nonzeros:                   0
```

Variable	Value	Reduced Cost
NUMBER_OR	7.000000	0.000000
DAYOPEN_OR	5.000000	0.000000
OR_BLOCK_HOURS	8.000000	0.000000
NUMBER_ICU	20.00000	0.000000
DAYOPEN_ICU	7.000000	0.000000
ICU_HOURS_OPERATE	24.00000	0.000000
NUMBER_MCU	35.00000	0.000000
DAYOPEN_MCU	7.000000	0.000000
MCU_HOURS_OPERATE	24.00000	0.000000
NUMBER_NURSE	60.00000	0.000000
WORKING_SHIFT	3.000000	0.000000
HOURINSHIFT	8.000000	0.000000
DAYWORK_ICUNURSE	7.000000	0.000000
WEIGHT_WL	1.000000	0.000000
WEIGHT_OT	1.000000	0.000000
OCOST_OR	400.0000	0.000000
OCOST_ICU	15.00000	0.000000
OCOST_MCU	5.000000	0.000000
OCOST_NURSE	4.000000	0.000000
DAILY_BLOCKSUPPLY	7.000000	0.000000
WEEKLY_ORBLOCKSUPPLY	35.00000	0.000000
ICUSUPPLY	3360.000	0.000000
MCUSUPPLY	5880.000	0.000000
NURSETIMESUPPY	1120.000	0.000000
DEMAND_WEEKLY_TPT	98.00000	0.000000
TOTAL_PATIENTS_ALLDEP	5096.000	0.000000
OICU	0.000000	619.7750
OMCU	0.000000	206.5917
OOR	0.000000	16527.33
ONURSE	0.000000	165.2733
AVERAGE_CLEARINGTIME	41.31833	0.000000
TOTALBLOCK_ASSIGN	28.00000	0.000000
TOTAL_ICU_TIME	3168.600	0.000000
TOTAL_MCUDOWN_TIME	4092.000	0.000000
TOTAL_MCUUP_TIME	1188.000	0.000000
TOTAL_ICU_NURSE_TIME	1104.867	0.000000
OR_UTILIZATION	80.00000	0.000000
ICU_UTILIZATION	94.30357	0.000000
MCU_UTILIZATION	89.79592	0.000000
ONURSE_UTILIZATION	98.64881	0.000000
TOTAL_PATIENTS_ASSIGNED	121.0000	0.000000
TOTAL_WAITING_COST	4725300.	0.000000
TOTAL_OOR_COST	0.000000	0.000000
TOTAL_OICU_COST	0.000000	0.000000
TOTAL_OMCU_COST	0.000000	0.000000
TOTAL_ONURSE_NURSE	0.000000	0.000000
WAITCOST(ENT)	10.00000	0.000000

WAITCOST(OBGYN)	17.00000	0.000000
WAITCOST(URO)	6.000000	0.000000
WAITCOST(GEN)	16.00000	0.000000
WAITCOST(VAS)	45.00000	0.000000
WAITCOST(ORT)	22.00000	0.000000
WAITCOST(NEU)	50.00000	0.000000
WAITCOST(CAR)	55.00000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBGYN)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBGYN)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBGYN)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBGYN)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBGYN)	24.00000	0.000000
REQICUDOWN(URO)	19.20000	0.000000
REQICUDOWN(GEN)	15.00000	0.000000
REQICUDOWN(VAS)	48.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	24.00000	0.000000
REQMCUDOWN(OBGYN)	12.00000	0.000000
REQMCUDOWN(URO)	24.00000	0.000000
REQMCUDOWN(GEN)	24.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	48.00000	0.000000
REQMCUDOWN(NEU)	48.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBGYN)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBGYN)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000
MIN_WEEKLYASSIGN(GEN)	1.000000	0.000000
MIN_WEEKLYASSIGN(VAS)	1.000000	0.000000

```
     MIN_WEEKLYASSIGN( ORT)        1.000000           0.000000
     MIN_WEEKLYASSIGN( NEU)        1.000000           0.000000
     MIN_WEEKLYASSIGN( CAR)        1.000000           0.000000
     MAX_WEEKLYASSIGN( ENT)        28.00000           0.000000
   MAX_WEEKLYASSIGN( OBGYN)        28.00000           0.000000
     MAX_WEEKLYASSIGN( URO)        28.00000           0.000000
     MAX_WEEKLYASSIGN( GEN)        28.00000           0.000000
     MAX_WEEKLYASSIGN( VAS)        28.00000           0.000000
     MAX_WEEKLYASSIGN( ORT)        28.00000           0.000000
     MAX_WEEKLYASSIGN( NEU)        28.00000           0.000000
     MAX_WEEKLYASSIGN( CAR)        28.00000           0.000000
         REQNURSETIME( ENT)        3.000000           0.000000
       REQNURSETIME( OBGYN)        24.00000           0.000000
         REQNURSETIME( URO)        19.20000           0.000000
         REQNURSETIME( GEN)        15.00000           0.000000
         REQNURSETIME( VAS)        84.00000           0.000000
         REQNURSETIME( ORT)        36.00000           0.000000
         REQNURSETIME( NEU)        46.00000           0.000000
         REQNURSETIME( CAR)        46.00000           0.000000
           LOWER_TIME( ENT)        1.000000           0.000000
         LOWER_TIME( OBGYN)        1.000000           0.000000
           LOWER_TIME( URO)        1.000000           0.000000
           LOWER_TIME( GEN)        1.000000           0.000000
           LOWER_TIME( VAS)        1.000000           0.000000
           LOWER_TIME( ORT)        1.000000           0.000000
           LOWER_TIME( NEU)        1.000000           0.000000
           LOWER_TIME( CAR)        1.000000           0.000000
           UPPER_TIME( ENT)        104.0000           0.000000
         UPPER_TIME( OBGYN)        104.0000           0.000000
           UPPER_TIME( URO)        104.0000           0.000000
           UPPER_TIME( GEN)        104.0000           0.000000
           UPPER_TIME( VAS)        104.0000           0.000000
           UPPER_TIME( ORT)        104.0000           0.000000
           UPPER_TIME( NEU)        104.0000           0.000000
           UPPER_TIME( CAR)        104.0000           0.000000
               ASSIGN( ENT)        5.000000           0.000000
             ASSIGN( OBGYN)        3.000000           0.000000
               ASSIGN( URO)        3.000000           0.000000
               ASSIGN( GEN)        5.000000           0.000000
               ASSIGN( VAS)        3.000000           0.000000
               ASSIGN( ORT)        5.000000           0.000000
               ASSIGN( NEU)        3.000000           0.000000
               ASSIGN( CAR)        1.000000           0.000000
        TIMEELIMINATE( ENT)        43.68000           0.000000
      TIMEELIMINATE( OBGYN)        31.20000           0.000000
        TIMEELIMINATE( URO)        23.11111           0.000000
        TIMEELIMINATE( GEN)        57.20000           0.000000
        TIMEELIMINATE( VAS)        34.66667           0.000000
        TIMEELIMINATE( ORT)        59.80000           0.000000
        TIMEELIMINATE( NEU)        28.88889           0.000000
        TIMEELIMINATE( CAR)        52.00000           0.000000

                        Row    Slack or Surplus      Dual Price
                          1        0.000000           0.000000
                          2        0.000000           0.000000
                          3        0.000000           0.000000
                          4        0.000000           0.000000
                          5        0.000000           0.000000
                          6        0.000000           0.000000
                          7        0.000000           0.000000
                          8        4725300.          -1.000000
                          9        0.000000           0.000000
                         10        7.000000           0.000000
                         11        0.000000           0.000000
                         12        191.4000           0.000000
                         13        0.000000           0.000000
                         14        0.000000           0.000000
                         15        600.0000           0.000000
```

16	0.000000	0.000000
17	15.13333	0.000000
18	0.000000	0.000000
19	0.000000	0.000000
20	0.000000	0.000000
21	0.000000	0.000000
22	50.00000	0.000000
23	64.30357	0.000000
24	59.79592	0.000000
25	68.64881	0.000000
26	0.000000	0.000000
27	0.000000	-436.8000
28	0.000000	-530.4000
29	0.000000	-138.6667
30	0.000000	-915.2000
31	0.000000	-1560.000
32	0.000000	-1315.600
33	0.000000	-1444.444
34	0.000000	-2860.000
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	0.000000	0.000000
39	0.000000	0.000000
40	0.000000	0.000000
41	0.000000	0.000000
42	0.000000	0.000000
43	0.000000	0.000000
44	0.000000	0.000000

Table 2 Our Study

Local optimal solution found.	
Objective value:	4089871.
Objective bound:	4089871.
Infeasibilities:	0.3273435E-04
Extended solver steps:	147
Total solver iterations:	11898
Elapsed runtime seconds:	0.81
Model Class:	MINLP
Total variables:	36
Nonlinear variables:	21
Integer variables:	8
Total constraints:	62
Nonlinear constraints:	13
Total nonzeros:	162
Nonlinear nonzeros:	29

Variable	Value	Reduced Cost
NUMBER_OR	7.000000	0.000000
DAYOPEN_OR	5.000000	0.000000
OR_BLOCK_HOURS	8.000000	0.000000
NUMBER_ICU	20.00000	0.000000
DAYOPEN_ICU	7.000000	0.000000
ICU_HOURS_OPERATE	24.00000	0.000000
NUMBER_MCU	35.00000	0.000000
DAYOPEN_MCU	7.000000	0.000000
MCU_HOURS_OPERATE	24.00000	0.000000
NUMBER_NURSE	60.00000	0.000000
WORKING_SHIFT	3.000000	0.000000
HOURINSHIFT	8.000000	0.000000
DAYWORK_ICUNURSE	7.000000	0.000000
WEIGHT_WL	1.000000	0.000000
WEIGHT_OT	1.000000	0.000000
OCOST_OR	400.0000	0.000000
OCOST_ICU	15.00000	0.000000
OCOST_MCU	5.000000	0.000000
OCOST_NURSE	4.000000	0.000000
DAILY_BLOCKSUPPLY	7.000000	0.000000
WEEKLY_ORBLOCKSUPPLY	35.00000	0.000000
ICUSUPPLY	3360.000	0.000000
MCUSUPPLY	5880.000	0.000000
NURSETIMESUPPY	1120.000	0.000000
DEMAND_WEEKLY_TPT	98.00000	0.000000
TOTAL_PATIENTS_ALLDEP	5096.000	0.000000
OICU	0.000000	0.000000
OMCU	0.000000	0.000000
OOR	0.000000	0.000000
ONURSE	0.000000	150.7071
AVERAGE_CLEARINGTIME	37.67678	0.000000
TOTALBLOCK_ASSIGN	35.00000	0.000000
TOTAL_ICU_TIME	3302.400	0.000000
TOTAL_MCUDOWN_TIME	4824.000	0.000000
TOTAL_MCUUP_TIME	1032.000	0.000000
TOTAL_ICU_NURSE_TIME	1110.133	0.000000
OR_UTILIZATION	100.0000	0.000000
ICU_UTILIZATION	98.28571	0.000000
MCU_UTILIZATION	99.59184	0.000000
ONURSE_UTILIZATION	99.11905	0.000000
TOTAL_PATIENTS_ASSIGNED	148.0000	0.000000
TOTAL_WAITING_COST	4089871.	0.000000
TOTAL_OOR_COST	0.000000	0.000000
TOTAL_OICU_COST	0.000000	1.000000
TOTAL_OMCU_COST	0.000000	1.000000

TOTAL_ONURSE_NURSE	0.000000	0.000000
WAITCOST(ENT)	10.00000	0.000000
WAITCOST(OBGYN)	17.00000	0.000000
WAITCOST(URO)	6.000000	0.000000
WAITCOST(GEN)	16.00000	0.000000
WAITCOST(VAS)	45.00000	0.000000
WAITCOST(ORT)	22.00000	0.000000
WAITCOST(NEU)	50.00000	0.000000
WAITCOST(CAR)	55.00000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBGYN)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBGYN)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBGYN)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBGYN)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBGYN)	24.00000	0.000000
REQICUDOWN(URO)	19.20000	0.000000
REQICUDOWN(GEN)	15.00000	0.000000
REQICUDOWN(VAS)	48.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	24.00000	0.000000
REQMCUDOWN(OBGYN)	12.00000	0.000000
REQMCUDOWN(URO)	24.00000	0.000000
REQMCUDOWN(GEN)	24.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	48.00000	0.000000
REQMCUDOWN(NEU)	48.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBGYN)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBGYN)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000

```
  MIN_WEEKLYASSIGN( GEN)        1.000000          0.000000
  MIN_WEEKLYASSIGN( VAS)        1.000000          0.000000
  MIN_WEEKLYASSIGN( ORT)        1.000000          0.000000
  MIN_WEEKLYASSIGN( NEU)        1.000000          0.000000
  MIN_WEEKLYASSIGN( CAR)        1.000000          0.000000
  MAX_WEEKLYASSIGN( ENT)        28.00000          0.000000
MAX_WEEKLYASSIGN( OBGYN)        28.00000          0.000000
  MAX_WEEKLYASSIGN( URO)        28.00000          0.000000
  MAX_WEEKLYASSIGN( GEN)        28.00000          0.000000
  MAX_WEEKLYASSIGN( VAS)        28.00000          0.000000
  MAX_WEEKLYASSIGN( ORT)        28.00000          0.000000
  MAX_WEEKLYASSIGN( NEU)        28.00000          0.000000
  MAX_WEEKLYASSIGN( CAR)        28.00000          0.000000
      REQNURSETIME( ENT)        3.000000          0.000000
    REQNURSETIME( OBGYN)        24.00000          0.000000
      REQNURSETIME( URO)        19.20000          0.000000
      REQNURSETIME( GEN)        15.00000          0.000000
      REQNURSETIME( VAS)        84.00000          0.000000
      REQNURSETIME( ORT)        36.00000          0.000000
      REQNURSETIME( NEU)        46.00000          0.000000
      REQNURSETIME( CAR)        46.00000          0.000000
        LOWER_TIME( ENT)        1.000000          0.000000
      LOWER_TIME( OBGYN)        1.000000          0.000000
        LOWER_TIME( URO)        1.000000          0.000000
        LOWER_TIME( GEN)        1.000000          0.000000
        LOWER_TIME( VAS)        1.000000          0.000000
        LOWER_TIME( ORT)        1.000000          0.000000
        LOWER_TIME( NEU)        1.000000          0.000000
        LOWER_TIME( CAR)        1.000000          0.000000
        UPPER_TIME( ENT)        104.0000          0.000000
      UPPER_TIME( OBGYN)        104.0000          0.000000
        UPPER_TIME( URO)        104.0000          0.000000
        UPPER_TIME( GEN)        104.0000          0.000000
        UPPER_TIME( VAS)        104.0000          0.000000
        UPPER_TIME( ORT)        104.0000          0.000000
        UPPER_TIME( NEU)        104.0000          0.000000
        UPPER_TIME( CAR)        104.0000          0.000000
            ASSIGN( ENT)        8.000000          37095.57
          ASSIGN( OBGYN)        2.000000         -111810.1
            ASSIGN( URO)        2.000000          31096.03
            ASSIGN( GEN)        10.00000          22010.62
            ASSIGN( VAS)        2.000000         -412359.4
            ASSIGN( ORT)        7.000000         -86196.78
            ASSIGN( NEU)        2.000000         -207306.3
            ASSIGN( CAR)        2.000000          0.000000
     TIMEELIMINATE( ENT)        27.30000          0.000000
   TIMEELIMINATE( OBGYN)        46.80000          0.000000
     TIMEELIMINATE( URO)        34.66667          0.000000
     TIMEELIMINATE( GEN)        28.60000          0.000000
     TIMEELIMINATE( VAS)        52.00000          0.000000
     TIMEELIMINATE( ORT)        42.71429          0.000000
     TIMEELIMINATE( NEU)        43.33333          0.000000
     TIMEELIMINATE( CAR)        25.99999          0.000000

                     Row    Slack or Surplus      Dual Price
                       1        0.000000          0.000000
                       2        0.000000          74360.07
                       3        0.000000          0.000000
                       4        0.000000          0.000000
                       5        0.000000          0.000000
                       6        0.000000          0.000000
                       7        0.000000          0.000000
                       8        4089871.         -1.000000
                       9        0.000000         -74360.07
                      10        0.000000          74360.07
                      11        7.000000          0.000000
                      12        1.000000          0.000000
                      13        1.000000          0.000000
```

14	9.000000	0.000000
15	1.000000	0.000000
16	6.000000	0.000000
17	1.000000	0.000000
18	1.000000	0.000000
19	20.00000	0.000000
20	26.00000	0.000000
21	26.00000	0.000000
22	18.00000	0.000000
23	26.00000	0.000000
24	21.00000	0.000000
25	26.00000	0.000000
26	26.00000	0.000000
27	0.000000	0.000000
28	57.60000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	24.00000	0.000000
32	0.000000	0.000000
33	9.866667	0.000000
34	0.000000	59289.36
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	70.00000	0.000000
39	68.28571	0.000000
40	69.59184	0.000000
41	69.11905	0.000000
42	0.000000	0.000000
43	50.00000	0.000000
44	19.00000	0.000000
45	1.000000	0.000000
46	4.000000	0.000000
47	18.00000	0.000000
48	0.000000	0.000000
49	5.000000	0.000000
50	1.000000	0.000000
51	2.000000	0.000000
52	0.000000	-273.0000
53	0.000000	-795.5996
54	0.000000	-208.0001
55	0.000000	-457.6000
56	0.000000	-2339.999
57	0.000000	-939.7142
58	0.000000	-2166.666
59	-0.3273435E-04	-1430.001
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	1.000000
67	0.000000	1.000000
68	0.000000	0.000000
69	0.000000	0.000000

Table 3 Equity

```
Local optimal solution found.
Objective value:                              4089871.
Objective bound:                              4089871.
Infeasibilities:                            0.3273435E-04
Extended solver steps:                            147
Total solver iterations:                        16674
Elapsed runtime seconds:                         0.80

Model Class:                                    MINLP

Total variables:                    36
Nonlinear variables:                21
Integer variables:                   8

Total constraints:                  78
Nonlinear constraints:              13

Total nonzeros:                    178
Nonlinear nonzeros:                 29


                              Variable           Value        Reduced Cost
                             NUMBER_OR        7.000000            0.000000
                            DAYOPEN_OR        5.000000            0.000000
                        OR_BLOCK_HOURS        8.000000            0.000000
                            NUMBER_ICU        20.00000            0.000000
                           DAYOPEN_ICU        7.000000            0.000000
                    ICU_HOURS_OPERATE        24.00000            0.000000
                            NUMBER_MCU        35.00000            0.000000
                           DAYOPEN_MCU        7.000000            0.000000
                    MCU_HOURS_OPERATE        24.00000            0.000000
                          NUMBER_NURSE        60.00000            0.000000
                         WORKING_SHIFT        3.000000            0.000000
                          HOURINSHIFT        8.000000            0.000000
                      DAYWORK_ICUNURSE        7.000000            0.000000
                             WEIGHT_WL        1.000000            0.000000
                             WEIGHT_OT        1.000000            0.000000
                              OCOST_OR        400.0000            0.000000
                             OCOST_ICU        15.00000            0.000000
                             OCOST_MCU        5.000000            0.000000
                           OCOST_NURSE        4.000000            0.000000
                    DAILY_BLOCKSUPPLY        7.000000            0.000000
                 WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                            ICUSUPPLY        3360.000            0.000000
                            MCUSUPPLY        5880.000            0.000000
                       NURSETIMESUPPY        1120.000            0.000000
                     DEMAND_WEEKLY_TPT       98.00000            0.000000
                  TOTAL_PATIENTS_ALLDEP      5096.000            0.000000
                                  OICU        0.000000            0.000000
                                  OMCU        0.000000            0.000000
                                   OOR        0.000000            0.000000
                                ONURSE        0.000000            150.7071
                 AVERAGE_CLEARINGTIME        37.67678            0.000000
                    TOTALBLOCK_ASSIGN        35.00000            0.000000
                       TOTAL_ICU_TIME        3302.400            0.000000
                   TOTAL_MCUDOWN_TIME        4824.000            0.000000
                     TOTAL_MCUUP_TIME        1032.000            0.000000
                 TOTAL_ICU_NURSE_TIME        1110.133            0.000000
                       OR_UTILIZATION        100.0000            0.000000
                      ICU_UTILIZATION        98.28571            0.000000
                      MCU_UTILIZATION        99.59184            0.000000
                   ONURSE_UTILIZATION        99.11905            0.000000
               TOTAL_PATIENTS_ASSIGNED       148.0000            0.000000
                    TOTAL_WAITING_COST       4089871.            0.000000
                        TOTAL_OOR_COST        0.000000            0.000000
                       TOTAL_OICU_COST        0.000000            1.000000
                       TOTAL_OMCU_COST        0.000000            1.000000
```

```
    TOTAL_ONURSE_NURSE        0.000000            0.000000
        WAITCOST( ENT)        10.00000            0.000000
        WAITCOST( OBG)        17.00000            0.000000
        WAITCOST( URO)        6.000000            0.000000
        WAITCOST( GEN)        16.00000            0.000000
        WAITCOST( VAS)        45.00000            0.000000
        WAITCOST( ORT)        22.00000            0.000000
        WAITCOST( NEU)        50.00000            0.000000
        WAITCOST( CAR)        55.00000            0.000000
   WEEKLY_DEMAND( ENT)        21.00000            0.000000
   WEEKLY_DEMAND( OBG)        9.000000            0.000000
   WEEKLY_DEMAND( URO)        8.000000            0.000000
   WEEKLY_DEMAND( GEN)        22.00000            0.000000
   WEEKLY_DEMAND( VAS)        8.000000            0.000000
   WEEKLY_DEMAND( ORT)        23.00000            0.000000
   WEEKLY_DEMAND( NEU)        5.000000            0.000000
   WEEKLY_DEMAND( CAR)        2.000000            0.000000
    WAITING_LIST( ENT)        1092.000            0.000000
    WAITING_LIST( OBG)        468.0000            0.000000
    WAITING_LIST( URO)        416.0000            0.000000
    WAITING_LIST( GEN)        1144.000            0.000000
    WAITING_LIST( VAS)        416.0000            0.000000
    WAITING_LIST( ORT)        1196.000            0.000000
    WAITING_LIST( NEU)        260.0000            0.000000
    WAITING_LIST( CAR)        104.0000            0.000000
      EFFICIENCY( ENT)        5.000000            0.000000
      EFFICIENCY( OBG)        5.000000            0.000000
      EFFICIENCY( URO)        6.000000            0.000000
      EFFICIENCY( GEN)        4.000000            0.000000
      EFFICIENCY( VAS)        4.000000            0.000000
      EFFICIENCY( ORT)        4.000000            0.000000
      EFFICIENCY( NEU)        3.000000            0.000000
      EFFICIENCY( CAR)        2.000000            0.000000
     SURGERY_DUR( ENT)        1.233000            0.000000
     SURGERY_DUR( OBG)        1.433000            0.000000
     SURGERY_DUR( URO)        1.060000            0.000000
     SURGERY_DUR( GEN)        1.550000            0.000000
     SURGERY_DUR( VAS)        2.000000            0.000000
     SURGERY_DUR( ORT)        1.780000            0.000000
     SURGERY_DUR( NEU)        2.670000            0.000000
     SURGERY_DUR( CAR)        4.000000            0.000000
      REQICUDOWN( ENT)        3.000000            0.000000
      REQICUDOWN( OBG)        24.00000            0.000000
      REQICUDOWN( URO)        19.20000            0.000000
      REQICUDOWN( GEN)        15.00000            0.000000
      REQICUDOWN( VAS)        48.00000            0.000000
      REQICUDOWN( ORT)        36.00000            0.000000
      REQICUDOWN( NEU)        72.00000            0.000000
      REQICUDOWN( CAR)        72.00000            0.000000
      REQMCUDOWN( ENT)        24.00000            0.000000
      REQMCUDOWN( OBG)        12.00000            0.000000
      REQMCUDOWN( URO)        24.00000            0.000000
      REQMCUDOWN( GEN)        24.00000            0.000000
      REQMCUDOWN( VAS)        72.00000            0.000000
      REQMCUDOWN( ORT)        48.00000            0.000000
      REQMCUDOWN( NEU)        48.00000            0.000000
      REQMCUDOWN( CAR)        72.00000            0.000000
        REQMCUUP( ENT)        0.000000            0.000000
        REQMCUUP( OBG)        12.00000            0.000000
        REQMCUUP( URO)        12.00000            0.000000
        REQMCUUP( GEN)        0.000000            0.000000
        REQMCUUP( VAS)        24.00000            0.000000
        REQMCUUP( ORT)        12.00000            0.000000
        REQMCUUP( NEU)        24.00000            0.000000
        REQMCUUP( CAR)        24.00000            0.000000
 MIN_WEEKLYASSIGN( ENT)       1.000000            0.000000
 MIN_WEEKLYASSIGN( OBG)       1.000000            0.000000
 MIN_WEEKLYASSIGN( URO)       1.000000            0.000000
```

```
  MIN_WEEKLYASSIGN( GEN)        1.000000            0.000000
  MIN_WEEKLYASSIGN( VAS)        1.000000            0.000000
  MIN_WEEKLYASSIGN( ORT)        1.000000            0.000000
  MIN_WEEKLYASSIGN( NEU)        1.000000            0.000000
  MIN_WEEKLYASSIGN( CAR)        1.000000            0.000000
  MAX_WEEKLYASSIGN( ENT)        28.00000            0.000000
  MAX_WEEKLYASSIGN( OBG)        28.00000            0.000000
  MAX_WEEKLYASSIGN( URO)        28.00000            0.000000
  MAX_WEEKLYASSIGN( GEN)        28.00000            0.000000
  MAX_WEEKLYASSIGN( VAS)        28.00000            0.000000
  MAX_WEEKLYASSIGN( ORT)        28.00000            0.000000
  MAX_WEEKLYASSIGN( NEU)        28.00000            0.000000
  MAX_WEEKLYASSIGN( CAR)        28.00000            0.000000
      REQNURSETIME( ENT)        3.000000            0.000000
      REQNURSETIME( OBG)        24.00000            0.000000
      REQNURSETIME( URO)        19.20000            0.000000
      REQNURSETIME( GEN)        15.00000            0.000000
      REQNURSETIME( VAS)        84.00000            0.000000
      REQNURSETIME( ORT)        36.00000            0.000000
      REQNURSETIME( NEU)        46.00000            0.000000
      REQNURSETIME( CAR)        46.00000            0.000000
        LOWER_TIME( ENT)        1.000000            0.000000
        LOWER_TIME( OBG)        1.000000            0.000000
        LOWER_TIME( URO)        1.000000            0.000000
        LOWER_TIME( GEN)        1.000000            0.000000
        LOWER_TIME( VAS)        1.000000            0.000000
        LOWER_TIME( ORT)        1.000000            0.000000
        LOWER_TIME( NEU)        1.000000            0.000000
        LOWER_TIME( CAR)        1.000000            0.000000
        UPPER_TIME( ENT)        104.0000            0.000000
        UPPER_TIME( OBG)        104.0000            0.000000
        UPPER_TIME( URO)        104.0000            0.000000
        UPPER_TIME( GEN)        104.0000            0.000000
        UPPER_TIME( VAS)        104.0000            0.000000
        UPPER_TIME( ORT)        104.0000            0.000000
        UPPER_TIME( NEU)        104.0000            0.000000
        UPPER_TIME( CAR)        104.0000            0.000000
            ASSIGN( ENT)        8.000000            37095.57
            ASSIGN( OBG)        2.000000           -111810.1
            ASSIGN( URO)        2.000000            31096.03
            ASSIGN( GEN)        10.00000            22010.62
            ASSIGN( VAS)        2.000000           -412359.4
            ASSIGN( ORT)        7.000000           -86196.78
            ASSIGN( NEU)        2.000000           -207306.3
            ASSIGN( CAR)        2.000000            0.000000
     TIMEELIMINATE( ENT)        27.30000            0.000000
     TIMEELIMINATE( OBG)        46.80000            0.000000
     TIMEELIMINATE( URO)        34.66667            0.000000
     TIMEELIMINATE( GEN)        28.60000            0.000000
     TIMEELIMINATE( VAS)        52.00000            0.000000
     TIMEELIMINATE( ORT)        42.71429            0.000000
     TIMEELIMINATE( NEU)        43.33333            0.000000
     TIMEELIMINATE( CAR)        25.99999            0.000000

                   Row    Slack or Surplus      Dual Price
                     1        0.000000            0.000000
                     2        0.000000            74360.07
                     3        0.000000            0.000000
                     4        0.000000            0.000000
                     5        0.000000            0.000000
                     6        0.000000            0.000000
                     7        0.000000            0.000000
                     8        4089871.           -1.000000
                     9        0.000000           -74360.07
                    10        0.000000            74360.07
                    11        7.000000            0.000000
                    12        1.000000            0.000000
                    13        1.000000            0.000000
```

14	9.000000	0.000000
15	1.000000	0.000000
16	6.000000	0.000000
17	1.000000	0.000000
18	1.000000	0.000000
19	20.00000	0.000000
20	26.00000	0.000000
21	26.00000	0.000000
22	18.00000	0.000000
23	26.00000	0.000000
24	21.00000	0.000000
25	26.00000	0.000000
26	26.00000	0.000000
27	0.000000	0.000000
28	57.60000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	24.00000	0.000000
32	0.000000	0.000000
33	9.866667	0.000000
34	0.000000	59289.36
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	70.00000	0.000000
39	68.28571	0.000000
40	69.59184	0.000000
41	69.11905	0.000000
42	0.000000	0.000000
43	50.00000	0.000000
44	19.00000	0.000000
45	1.000000	0.000000
46	4.000000	0.000000
47	18.00000	0.000000
48	0.000000	0.000000
49	5.000000	0.000000
50	1.000000	0.000000
51	2.000000	0.000000
52	0.000000	-273.0000
53	0.000000	-795.5996
54	0.000000	-208.0001
55	0.000000	-457.6000
56	0.000000	-2339.999
57	0.000000	-939.7142
58	0.000000	-2166.666
59	-0.3273435E-04	-1430.001
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	1.000000
67	0.000000	1.000000
68	0.000000	0.000000
69	0.000000	0.000000
70	26.30000	0.000000
71	45.80000	0.000000
72	33.66667	0.000000
73	27.60000	0.000000
74	51.00000	0.000000
75	41.71429	0.000000
76	42.33333	0.000000
77	24.99999	0.000000
78	76.70000	0.000000
79	57.20000	0.000000
80	69.33333	0.000000
81	75.40000	0.000000

82	52.00000	0.000000
83	61.28571	0.000000
84	60.66667	0.000000
85	78.00001	0.000000

Table 4 Equality

```
Local optimal solution found.
Objective value:                              4976012.
Objective bound:                              4976012.
Infeasibilities:                              0.000000
Extended solver steps:                              17
Total solver iterations:                          5677
Elapsed runtime seconds:                          0.48

Model Class:                                     MINLP

Total variables:                    36
Nonlinear variables:                21
Integer variables:                   8

Total constraints:                  78
Nonlinear constraints:              13

Total nonzeros:                    178
Nonlinear nonzeros:                 29
```

Variable	Value	Reduced Cost
NUMBER_OR	7.000000	0.000000
DAYOPEN_OR	5.000000	0.000000
OR_BLOCK_HOURS	8.000000	0.000000
NUMBER_ICU	20.00000	0.000000
DAYOPEN_ICU	7.000000	0.000000
ICU_HOURS_OPERATE	24.00000	0.000000
NUMBER_MCU	35.00000	0.000000
DAYOPEN_MCU	7.000000	0.000000
MCU_HOURS_OPERATE	24.00000	0.000000
NUMBER_NURSE	60.00000	0.000000
WORKING_SHIFT	3.000000	0.000000
HOURINSHIFT	8.000000	0.000000
DAYWORK_ICUNURSE	7.000000	0.000000
WEIGHT_WL	1.000000	0.000000
WEIGHT_OT	1.000000	0.000000
OCOST_OR	400.0000	0.000000
OCOST_ICU	15.00000	0.000000
OCOST_MCU	5.000000	0.000000
OCOST_NURSE	4.000000	0.000000
DAILY_BLOCKSUPPLY	7.000000	0.000000
WEEKLY_ORBLOCKSUPPLY	35.00000	0.000000
ICUSUPPLY	3360.000	0.000000
MCUSUPPLY	5880.000	0.000000
NURSETIMESUPPY	1120.000	0.000000
DEMAND_WEEKLY_TPT	98.00000	0.000000
TOTAL_PATIENTS_ALLDEP	5096.000	0.000000
OICU	0.000000	0.000000
OMCU	0.000000	0.000000
OOR	0.000000	0.000000
ONURSE	0.000000	0.000000
AVERAGE_CLEARINGTIME	38.97679	0.000000
TOTALBLOCK_ASSIGN	35.00000	0.000000
TOTAL_ICU_TIME	3278.400	0.000000
TOTAL_MCUDOWN_TIME	4740.000	0.000000
TOTAL_MCUUP_TIME	1044.000	0.000000
TOTAL_ICU_NURSE_TIME	1119.467	0.000000
OR_UTILIZATION	100.0000	0.000000
ICU_UTILIZATION	97.57143	0.000000
MCU_UTILIZATION	98.36735	0.000000
ONURSE_UTILIZATION	99.95238	0.000000
TOTAL_PATIENTS_ASSIGNED	151.0000	0.000000
TOTAL_WAITING_COST	4976012.	0.000000
TOTAL_OOR_COST	0.000000	0.000000
TOTAL_OICU_COST	0.000000	1.000000
TOTAL_OMCU_COST	0.000000	1.000000

TOTAL_ONURSE_NURSE	0.000000	1.000000
WAITCOST(ENT)	27.50000	0.000000
WAITCOST(OBGYN)	27.50000	0.000000
WAITCOST(URO)	27.50000	0.000000
WAITCOST(GEN)	27.50000	0.000000
WAITCOST(VAS)	27.50000	0.000000
WAITCOST(ORT)	27.50000	0.000000
WAITCOST(NEU)	27.50000	0.000000
WAITCOST(CAR)	27.50000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBGYN)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBGYN)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBGYN)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBGYN)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBGYN)	24.00000	0.000000
REQICUDOWN(URO)	19.20000	0.000000
REQICUDOWN(GEN)	15.00000	0.000000
REQICUDOWN(VAS)	48.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	24.00000	0.000000
REQMCUDOWN(OBGYN)	12.00000	0.000000
REQMCUDOWN(URO)	24.00000	0.000000
REQMCUDOWN(GEN)	24.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	48.00000	0.000000
REQMCUDOWN(NEU)	48.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBGYN)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBGYN)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000

```
    MIN_WEEKLYASSIGN( GEN)        1.000000            0.000000
    MIN_WEEKLYASSIGN( VAS)        1.000000            0.000000
    MIN_WEEKLYASSIGN( ORT)        1.000000            0.000000
    MIN_WEEKLYASSIGN( NEU)        1.000000            0.000000
    MIN_WEEKLYASSIGN( CAR)        1.000000            0.000000
    MAX_WEEKLYASSIGN( ENT)        28.00000            0.000000
  MAX_WEEKLYASSIGN( OBGYN)        28.00000            0.000000
    MAX_WEEKLYASSIGN( URO)        28.00000            0.000000
    MAX_WEEKLYASSIGN( GEN)        28.00000            0.000000
    MAX_WEEKLYASSIGN( VAS)        28.00000            0.000000
    MAX_WEEKLYASSIGN( ORT)        28.00000            0.000000
    MAX_WEEKLYASSIGN( NEU)        28.00000            0.000000
    MAX_WEEKLYASSIGN( CAR)        28.00000            0.000000
        REQNURSETIME( ENT)        3.000000            0.000000
      REQNURSETIME( OBGYN)        24.00000            0.000000
        REQNURSETIME( URO)        19.20000            0.000000
        REQNURSETIME( GEN)        15.00000            0.000000
        REQNURSETIME( VAS)        84.00000            0.000000
        REQNURSETIME( ORT)        36.00000            0.000000
        REQNURSETIME( NEU)        46.00000            0.000000
        REQNURSETIME( CAR)        46.00000            0.000000
          LOWER_TIME( ENT)        1.000000            0.000000
        LOWER_TIME( OBGYN)        1.000000            0.000000
          LOWER_TIME( URO)        1.000000            0.000000
          LOWER_TIME( GEN)        1.000000            0.000000
          LOWER_TIME( VAS)        1.000000            0.000000
          LOWER_TIME( ORT)        1.000000            0.000000
          LOWER_TIME( NEU)        1.000000            0.000000
          LOWER_TIME( CAR)        1.000000            0.000000
          UPPER_TIME( ENT)        104.0000            0.000000
        UPPER_TIME( OBGYN)        104.0000            0.000000
          UPPER_TIME( URO)        104.0000            0.000000
          UPPER_TIME( GEN)        104.0000            0.000000
          UPPER_TIME( VAS)        104.0000            0.000000
          UPPER_TIME( ORT)        104.0000            0.000000
          UPPER_TIME( NEU)        104.0000            0.000000
          UPPER_TIME( CAR)        104.0000            0.000000
              ASSIGN( ENT)        8.000000            52439.27
            ASSIGN( OBGYN)        3.000000            21068.58
              ASSIGN( URO)        2.000000           -43376.47
              ASSIGN( GEN)        10.00000            64941.05
              ASSIGN( VAS)        2.000000           -142523.0
              ASSIGN( ORT)        7.000000           -45779.40
              ASSIGN( NEU)        2.000000            0.000000
              ASSIGN( CAR)        1.000000            0.000000
       TIMEELIMINATE( ENT)        27.30000            0.000000
     TIMEELIMINATE( OBGYN)        31.20000            0.000000
       TIMEELIMINATE( URO)        34.66667            0.000000
       TIMEELIMINATE( GEN)        28.60000            0.000000
       TIMEELIMINATE( VAS)        52.00000            0.000000
       TIMEELIMINATE( ORT)        42.71429            0.000000
       TIMEELIMINATE( NEU)        43.33333            0.000000
       TIMEELIMINATE( CAR)        52.00000            0.000000

                       Row    Slack or Surplus      Dual Price
                         1        0.000000            0.000000
                         2        0.000000            154916.7
                         3        0.000000            0.000000
                         4        0.000000            0.000000
                         5        0.000000            0.000000
                         6        0.000000            0.000000
                         7        0.000000            0.000000
                         8        4976012.           -1.000000
                         9        0.000000           -154916.7
                        10        0.000000            154916.7
                        11        7.000000            0.000000
                        12        2.000000            0.000000
                        13        1.000000            0.000000
```

14	9.000000	0.000000
15	1.000000	0.000000
16	6.000000	0.000000
17	1.000000	0.000000
18	0.000000	-6196.667
19	20.00000	0.000000
20	25.00000	0.000000
21	26.00000	0.000000
22	18.00000	0.000000
23	26.00000	0.000000
24	21.00000	0.000000
25	26.00000	0.000000
26	27.00000	0.000000
27	0.000000	0.000000
28	81.60000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	96.00000	0.000000
32	0.000000	0.000000
33	0.5333333	0.000000
34	0.000000	139326.0
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	70.00000	0.000000
39	67.57143	0.000000
40	68.36735	0.000000
41	69.95238	0.000000
42	0.000000	0.000000
43	53.00000	0.000000
44	19.00000	0.000000
45	6.000000	0.000000
46	4.000000	0.000000
47	18.00000	0.000000
48	0.000000	0.000000
49	5.000000	0.000000
50	1.000000	0.000000
51	0.000000	0.000000
52	0.000000	-750.7501
53	0.000000	-858.0003
54	0.000000	-953.3329
55	0.000000	-786.5001
56	0.000000	-1429.999
57	0.000000	-1174.643
58	0.000000	-1191.667
59	0.000000	-1430.000
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	1.000000
67	0.000000	1.000000
68	0.000000	1.000000
69	0.000000	0.000000
70	26.30000	0.000000
71	30.20000	0.000000
72	33.66667	0.000000
73	27.60000	0.000000
74	51.00000	0.000000
75	41.71429	0.000000
76	42.33333	0.000000
77	51.00000	0.000000
78	76.70000	0.000000
79	72.80000	0.000000
80	69.33333	0.000000
81	75.40000	0.000000

82	52.00000	0.000000
83	61.28571	0.000000
84	60.66667	0.000000
85	52.00000	0.000000

Table 5 Waiting List Length Priority

```
Local optimal solution found.
Objective value:                              6207235.
Objective bound:                              6207235.
Infeasibilities:                              0.5241136E-04
Extended solver steps:                             11
Total solver iterations:                         1982
Elapsed runtime seconds:                         0.29

Model Class:                                     MINLP

Total variables:                     36
Nonlinear variables:                 21
Integer variables:                    8

Total constraints:                   78
Nonlinear constraints:               13

Total nonzeros:                     178
Nonlinear nonzeros:                  29


                              Variable           Value        Reduced Cost
                             NUMBER_OR        7.000000            0.000000
                            DAYOPEN_OR        5.000000            0.000000
                        OR_BLOCK_HOURS        8.000000            0.000000
                            NUMBER_ICU        20.00000            0.000000
                           DAYOPEN_ICU        7.000000            0.000000
                    ICU_HOURS_OPERATE         24.00000            0.000000
                            NUMBER_MCU        35.00000            0.000000
                           DAYOPEN_MCU        7.000000            0.000000
                    MCU_HOURS_OPERATE         24.00000            0.000000
                          NUMBER_NURSE        60.00000            0.000000
                         WORKING_SHIFT        3.000000            0.000000
                           HOURINSHIFT        8.000000            0.000000
                      DAYWORK_ICUNURSE        7.000000            0.000000
                             WEIGHT_WL        1.000000            0.000000
                             WEIGHT_OT        1.000000            0.000000
                              OCOST_OR        400.0000            0.000000
                             OCOST_ICU        15.00000            0.000000
                             OCOST_MCU        5.000000            0.000000
                           OCOST_NURSE        4.000000            0.000000
                    DAILY_BLOCKSUPPLY         7.000000            0.000000
                   WEEKLY_ORBLOCKSUPPLY       35.00000            0.000000
                             ICUSUPPLY        3360.000            0.000000
                             MCUSUPPLY        5880.000            0.000000
                       NURSETIMESUPPY         1120.000            0.000000
                     DEMAND_WEEKLY_TPT        98.00000            0.000000
                    TOTAL_PATIENTS_ALLDEP     5096.000            0.000000
                                  OICU        0.000000            0.000000
                                  OMCU        0.000000            0.000000
                                   OOR        0.000000            0.000000
                                ONURSE        0.000000            0.000000
                   AVERAGE_CLEARINGTIME       40.13750            0.000000
                     TOTALBLOCK_ASSIGN        35.00000            0.000000
                        TOTAL_ICU_TIME        2776.000            0.000000
                    TOTAL_MCUDOWN_TIME        4344.000            0.000000
                      TOTAL_MCUUP_TIME        1080.000            0.000000
                  TOTAL_ICU_NURSE_TIME        856.0000            0.000000
                        OR_UTILIZATION        100.0000            0.000000
                       ICU_UTILIZATION        82.61905            0.000000
                       MCU_UTILIZATION        92.24490            0.000000
                    ONURSE_UTILIZATION        76.42857            0.000000
                TOTAL_PATIENTS_ASSIGNED       150.0000            0.000000
                    TOTAL_WAITING_COST        6207235.            0.000000
                        TOTAL_OOR_COST        0.000000            0.000000
                       TOTAL_OICU_COST        0.000000            1.000000
                       TOTAL_OMCU_COST        0.000000            1.000000
```

```
         TOTAL_ONURSE_NURSE        0.000000            1.000000
             WAITCOST( ENT)        45.00000            0.000000
           WAITCOST( OBGYN)        22.00000            0.000000
             WAITCOST( URO)        22.00000            0.000000
             WAITCOST( GEN)        45.00000            0.000000
             WAITCOST( VAS)        22.00000            0.000000
             WAITCOST( ORT)        45.00000            0.000000
             WAITCOST( NEU)        10.00000            0.000000
             WAITCOST( CAR)        10.00000            0.000000
        WEEKLY_DEMAND( ENT)        21.00000            0.000000
      WEEKLY_DEMAND( OBGYN)        9.000000            0.000000
        WEEKLY_DEMAND( URO)        8.000000            0.000000
        WEEKLY_DEMAND( GEN)        22.00000            0.000000
        WEEKLY_DEMAND( VAS)        8.000000            0.000000
        WEEKLY_DEMAND( ORT)        23.00000            0.000000
        WEEKLY_DEMAND( NEU)        5.000000            0.000000
        WEEKLY_DEMAND( CAR)        2.000000            0.000000
         WAITING_LIST( ENT)        1092.000            0.000000
       WAITING_LIST( OBGYN)        468.0000            0.000000
         WAITING_LIST( URO)        416.0000            0.000000
         WAITING_LIST( GEN)        1144.000            0.000000
         WAITING_LIST( VAS)        416.0000            0.000000
         WAITING_LIST( ORT)        1196.000            0.000000
         WAITING_LIST( NEU)        260.0000            0.000000
         WAITING_LIST( CAR)        104.0000            0.000000
           EFFICIENCY( ENT)        5.000000            0.000000
         EFFICIENCY( OBGYN)        5.000000            0.000000
           EFFICIENCY( URO)        6.000000            0.000000
           EFFICIENCY( GEN)        4.000000            0.000000
           EFFICIENCY( VAS)        4.000000            0.000000
           EFFICIENCY( ORT)        4.000000            0.000000
           EFFICIENCY( NEU)        3.000000            0.000000
           EFFICIENCY( CAR)        2.000000            0.000000
         SURGERY_DUR( ENT)         1.233000            0.000000
       SURGERY_DUR( OBGYN)         1.433000            0.000000
         SURGERY_DUR( URO)         1.060000            0.000000
         SURGERY_DUR( GEN)         1.550000            0.000000
         SURGERY_DUR( VAS)         2.000000            0.000000
         SURGERY_DUR( ORT)         1.780000            0.000000
         SURGERY_DUR( NEU)         2.670000            0.000000
         SURGERY_DUR( CAR)         4.000000            0.000000
          REQICUDOWN( ENT)         3.000000            0.000000
        REQICUDOWN( OBGYN)         10.00000            0.000000
          REQICUDOWN( URO)         7.000000            0.000000
          REQICUDOWN( GEN)         6.000000            0.000000
          REQICUDOWN( VAS)         48.00000            0.000000
          REQICUDOWN( ORT)         36.00000            0.000000
          REQICUDOWN( NEU)         72.00000            0.000000
          REQICUDOWN( CAR)         72.00000            0.000000
          REQMCUDOWN( ENT)         12.00000            0.000000
        REQMCUDOWN( OBGYN)         12.00000            0.000000
          REQMCUDOWN( URO)         12.00000            0.000000
          REQMCUDOWN( GEN)         24.00000            0.000000
          REQMCUDOWN( VAS)         72.00000            0.000000
          REQMCUDOWN( ORT)         48.00000            0.000000
          REQMCUDOWN( NEU)         48.00000            0.000000
          REQMCUDOWN( CAR)         72.00000            0.000000
            REQMCUUP( ENT)         0.000000            0.000000
          REQMCUUP( OBGYN)         12.00000            0.000000
            REQMCUUP( URO)         12.00000            0.000000
            REQMCUUP( GEN)         0.000000            0.000000
            REQMCUUP( VAS)         24.00000            0.000000
            REQMCUUP( ORT)         12.00000            0.000000
            REQMCUUP( NEU)         24.00000            0.000000
            REQMCUUP( CAR)         24.00000            0.000000
     MIN_WEEKLYASSIGN( ENT)        1.000000            0.000000
   MIN_WEEKLYASSIGN( OBGYN)        1.000000            0.000000
     MIN_WEEKLYASSIGN( URO)        1.000000            0.000000
```

```
    MIN_WEEKLYASSIGN( GEN)        1.000000          0.000000
    MIN_WEEKLYASSIGN( VAS)        1.000000          0.000000
    MIN_WEEKLYASSIGN( ORT)        1.000000          0.000000
    MIN_WEEKLYASSIGN( NEU)        1.000000          0.000000
    MIN_WEEKLYASSIGN( CAR)        1.000000          0.000000
    MAX_WEEKLYASSIGN( ENT)        28.00000          0.000000
  MAX_WEEKLYASSIGN( OBGYN)        28.00000          0.000000
    MAX_WEEKLYASSIGN( URO)        28.00000          0.000000
    MAX_WEEKLYASSIGN( GEN)        28.00000          0.000000
    MAX_WEEKLYASSIGN( VAS)        28.00000          0.000000
    MAX_WEEKLYASSIGN( ORT)        28.00000          0.000000
    MAX_WEEKLYASSIGN( NEU)        28.00000          0.000000
    MAX_WEEKLYASSIGN( CAR)        28.00000          0.000000
        REQNURSETIME( ENT)        3.000000          0.000000
      REQNURSETIME( OBGYN)        10.00000          0.000000
        REQNURSETIME( URO)        7.000000          0.000000
        REQNURSETIME( GEN)        6.000000          0.000000
        REQNURSETIME( VAS)        48.00000          0.000000
        REQNURSETIME( ORT)        36.00000          0.000000
        REQNURSETIME( NEU)        46.00000          0.000000
        REQNURSETIME( CAR)        46.00000          0.000000
          LOWER_TIME( ENT)        1.000000          0.000000
        LOWER_TIME( OBGYN)        1.000000          0.000000
          LOWER_TIME( URO)        1.000000          0.000000
          LOWER_TIME( GEN)        1.000000          0.000000
          LOWER_TIME( VAS)        1.000000          0.000000
          LOWER_TIME( ORT)        1.000000          0.000000
          LOWER_TIME( NEU)        1.000000          0.000000
          LOWER_TIME( CAR)        1.000000          0.000000
          UPPER_TIME( ENT)        104.0000          0.000000
        UPPER_TIME( OBGYN)        104.0000          0.000000
          UPPER_TIME( URO)        104.0000          0.000000
          UPPER_TIME( GEN)        104.0000          0.000000
          UPPER_TIME( VAS)        104.0000          0.000000
          UPPER_TIME( ORT)        104.0000          0.000000
          UPPER_TIME( NEU)        104.0000          0.000000
          UPPER_TIME( CAR)        104.0000          0.000000
              ASSIGN( ENT)        8.000000          14078.60
            ASSIGN( OBGYN)        2.000000         -59157.27
              ASSIGN( URO)        2.000000          23134.06
              ASSIGN( GEN)        9.000000          0.000000
              ASSIGN( VAS)        2.000000         -56182.87
              ASSIGN( ORT)        9.000000         -16899.96
              ASSIGN( NEU)        2.000000          125435.5
              ASSIGN( CAR)        1.000000          0.000000
       TIMEELIMINATE( ENT)        27.30000          0.000000
     TIMEELIMINATE( OBGYN)        46.80000          0.000000
       TIMEELIMINATE( URO)        34.66667          0.000000
       TIMEELIMINATE( GEN)        31.77778          0.000000
       TIMEELIMINATE( VAS)        52.00000          0.000000
       TIMEELIMINATE( ORT)        33.22222          0.000000
       TIMEELIMINATE( NEU)        43.33333          0.000000
       TIMEELIMINATE( CAR)        52.00000          0.000000

                       Row    Slack or Surplus      Dual Price
                         1        0.000000          0.000000
                         2        0.000000          181768.9
                         3        0.000000          0.000000
                         4        0.000000          0.000000
                         5        0.000000          0.000000
                         6        0.000000          0.000000
                         7        0.000000          0.000000
                         8        6207235.         -1.000000
                         9        0.000000         -181768.9
                        10        0.000000          181768.9
                        11        7.000000          0.000000
                        12        1.000000          0.000000
                        13        1.000000          0.000000
```

14	8.000000	0.000000
15	1.000000	0.000000
16	8.000000	0.000000
17	1.000000	0.000000
18	0.000000	-127688.9
19	20.00000	0.000000
20	26.00000	0.000000
21	26.00000	0.000000
22	19.00000	0.000000
23	26.00000	0.000000
24	19.00000	0.000000
25	26.00000	0.000000
26	27.00000	0.000000
27	0.000000	0.000000
28	584.0000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	456.0000	0.000000
32	0.000000	0.000000
33	264.0000	0.000000
34	0.000000	165713.9
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	70.00000	0.000000
39	52.61905	0.000000
40	62.24490	0.000000
41	46.42857	0.000000
42	0.000000	0.000000
43	52.00000	0.000000
44	19.00000	0.000000
45	1.000000	0.000000
46	4.000000	0.000000
47	14.00000	0.000000
48	0.000000	0.000000
49	13.00000	0.000000
50	1.000000	0.000000
51	0.000000	0.000000
52	0.000000	-1228.500
53	0.000000	-1029.599
54	0.000000	-762.6670
55	-0.5241136E-04	-1430.000
56	0.000000	-1143.999
57	0.000000	-1495.000
58	0.000000	-433.3336
59	0.000000	-520.0000
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	1.000000
67	0.000000	1.000000
68	0.000000	1.000000
69	0.000000	0.000000
70	26.30000	0.000000
71	45.80000	0.000000
72	33.66667	0.000000
73	30.77778	0.000000
74	51.00000	0.000000
75	32.22222	0.000000
76	42.33333	0.000000
77	51.00000	0.000000
78	76.70000	0.000000
79	57.20000	0.000000
80	69.33333	0.000000
81	72.22222	0.000000

82	52.00000	0.000000
83	70.77778	0.000000
84	60.66667	0.000000
85	52.00000	0.000000

Table 6 Resource intensity (high first)

```
Local optimal solution found.
Objective value:                              3893881.
Objective bound:                              3893881.
Infeasibilities:                              0.1217824E-03
Extended solver steps:                             61
Total solver iterations:                         8816
Elapsed runtime seconds:                         0.55

Model Class:                                    MINLP

Total variables:                     36
Nonlinear variables:                 21
Integer variables:                    8

Total constraints:                   78
Nonlinear constraints:               13

Total nonzeros:                     178
Nonlinear nonzeros:                  29


                              Variable           Value        Reduced Cost
                             NUMBER_OR        7.000000            0.000000
                            DAYOPEN_OR        5.000000            0.000000
                        OR_BLOCK_HOURS        8.000000            0.000000
                            NUMBER_ICU        20.00000            0.000000
                           DAYOPEN_ICU        7.000000            0.000000
                     ICU_HOURS_OPERATE        24.00000            0.000000
                            NUMBER_MCU        35.00000            0.000000
                           DAYOPEN_MCU        7.000000            0.000000
                     MCU_HOURS_OPERATE        24.00000            0.000000
                          NUMBER_NURSE        60.00000            0.000000
                         WORKING_SHIFT        3.000000            0.000000
                           HOURINSHIFT        8.000000            0.000000
                      DAYWORK_ICUNURSE        7.000000            0.000000
                             WEIGHT_WL        1.000000            0.000000
                             WEIGHT_OT        1.000000            0.000000
                              OCOST_OR        400.0000            0.000000
                             OCOST_ICU        15.00000            0.000000
                             OCOST_MCU        5.000000            0.000000
                           OCOST_NURSE        4.000000            0.000000
                     DAILY_BLOCKSUPPLY        7.000000            0.000000
                  WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                             ICUSUPPLY        3360.000            0.000000
                             MCUSUPPLY        5880.000            0.000000
                        NURSETIMESUPPY        1120.000            0.000000
                    DEMAND_WEEKLY_TPT         98.00000            0.000000
                  TOTAL_PATIENTS_ALLDEP       5096.000            0.000000
                                  OICU        0.000000            599.7892
                                  OMCU        0.000000            0.000000
                                   OOR        0.000000            15994.38
                                ONURSE        0.000000            0.000000
                  AVERAGE_CLEARINGTIME        39.98596            0.000000
                     TOTALBLOCK_ASSIGN        33.00000            0.000000
                        TOTAL_ICU_TIME        3338.400            0.000000
                    TOTAL_MCUDOWN_TIME        4728.000            0.000000
                      TOTAL_MCUUP_TIME        1104.000            0.000000
                  TOTAL_ICU_NURSE_TIME        1113.467            0.000000
                        OR_UTILIZATION        94.28571            0.000000
                       ICU_UTILIZATION        99.35714            0.000000
                       MCU_UTILIZATION        99.18367            0.000000
                    ONURSE_UTILIZATION        99.41667            0.000000
                TOTAL_PATIENTS_ASSIGNED       141.0000            0.000000
                    TOTAL_WAITING_COST        3893881.            0.000000
                        TOTAL_OOR_COST        0.000000            0.000000
                       TOTAL_OICU_COST        0.000000            0.000000
                       TOTAL_OMCU_COST        0.000000            1.000000
```

```
              TOTAL_ONURSE_NURSE        0.000000            1.000000
                  WAITCOST( ENT)        10.00000            0.000000
                WAITCOST( OBGYN)        10.00000            0.000000
                  WAITCOST( URO)        10.00000            0.000000
                  WAITCOST( GEN)        10.00000            0.000000
                  WAITCOST( VAS)        30.00000            0.000000
                  WAITCOST( ORT)        30.00000            0.000000
                  WAITCOST( NEU)        60.00000            0.000000
                  WAITCOST( CAR)        60.00000            0.000000
             WEEKLY_DEMAND( ENT)        21.00000            0.000000
           WEEKLY_DEMAND( OBGYN)        9.000000            0.000000
             WEEKLY_DEMAND( URO)        8.000000            0.000000
             WEEKLY_DEMAND( GEN)        22.00000            0.000000
             WEEKLY_DEMAND( VAS)        8.000000            0.000000
             WEEKLY_DEMAND( ORT)        23.00000            0.000000
             WEEKLY_DEMAND( NEU)        5.000000            0.000000
             WEEKLY_DEMAND( CAR)        2.000000            0.000000
              WAITING_LIST( ENT)        1092.000            0.000000
            WAITING_LIST( OBGYN)        468.0000            0.000000
              WAITING_LIST( URO)        416.0000            0.000000
              WAITING_LIST( GEN)        1144.000            0.000000
              WAITING_LIST( VAS)        416.0000            0.000000
              WAITING_LIST( ORT)        1196.000            0.000000
              WAITING_LIST( NEU)        260.0000            0.000000
              WAITING_LIST( CAR)        104.0000            0.000000
                EFFICIENCY( ENT)        5.000000            0.000000
              EFFICIENCY( OBGYN)        5.000000            0.000000
                EFFICIENCY( URO)        6.000000            0.000000
                EFFICIENCY( GEN)        4.000000            0.000000
                EFFICIENCY( VAS)        4.000000            0.000000
                EFFICIENCY( ORT)        4.000000            0.000000
                EFFICIENCY( NEU)        3.000000            0.000000
                EFFICIENCY( CAR)        2.000000            0.000000
              SURGERY_DUR( ENT)         1.233000            0.000000
            SURGERY_DUR( OBGYN)         1.433000            0.000000
              SURGERY_DUR( URO)         1.060000            0.000000
              SURGERY_DUR( GEN)         1.550000            0.000000
              SURGERY_DUR( VAS)         2.000000            0.000000
              SURGERY_DUR( ORT)         1.780000            0.000000
              SURGERY_DUR( NEU)         2.670000            0.000000
              SURGERY_DUR( CAR)         4.000000            0.000000
               REQICUDOWN( ENT)         3.000000            0.000000
             REQICUDOWN( OBGYN)         24.00000            0.000000
               REQICUDOWN( URO)         19.20000            0.000000
               REQICUDOWN( GEN)         15.00000            0.000000
               REQICUDOWN( VAS)         48.00000            0.000000
               REQICUDOWN( ORT)         36.00000            0.000000
               REQICUDOWN( NEU)         72.00000            0.000000
               REQICUDOWN( CAR)         72.00000            0.000000
               REQMCUDOWN( ENT)         24.00000            0.000000
             REQMCUDOWN( OBGYN)         12.00000            0.000000
               REQMCUDOWN( URO)         24.00000            0.000000
               REQMCUDOWN( GEN)         24.00000            0.000000
               REQMCUDOWN( VAS)         72.00000            0.000000
               REQMCUDOWN( ORT)         48.00000            0.000000
               REQMCUDOWN( NEU)         48.00000            0.000000
               REQMCUDOWN( CAR)         72.00000            0.000000
                 REQMCUUP( ENT)         0.000000            0.000000
               REQMCUUP( OBGYN)         12.00000            0.000000
                 REQMCUUP( URO)         12.00000            0.000000
                 REQMCUUP( GEN)         0.000000            0.000000
                 REQMCUUP( VAS)         24.00000            0.000000
                 REQMCUUP( ORT)         12.00000            0.000000
                 REQMCUUP( NEU)         24.00000            0.000000
                 REQMCUUP( CAR)         24.00000            0.000000
         MIN_WEEKLYASSIGN( ENT)         1.000000            0.000000
       MIN_WEEKLYASSIGN( OBGYN)         1.000000            0.000000
         MIN_WEEKLYASSIGN( URO)         1.000000            0.000000
```

```
     MIN_WEEKLYASSIGN( GEN)        1.000000            0.000000
     MIN_WEEKLYASSIGN( VAS)        1.000000            0.000000
     MIN_WEEKLYASSIGN( ORT)        1.000000            0.000000
     MIN_WEEKLYASSIGN( NEU)        1.000000            0.000000
     MIN_WEEKLYASSIGN( CAR)        1.000000            0.000000
     MAX_WEEKLYASSIGN( ENT)        28.00000            0.000000
   MAX_WEEKLYASSIGN( OBGYN)        28.00000            0.000000
     MAX_WEEKLYASSIGN( URO)        28.00000            0.000000
     MAX_WEEKLYASSIGN( GEN)        28.00000            0.000000
     MAX_WEEKLYASSIGN( VAS)        28.00000            0.000000
     MAX_WEEKLYASSIGN( ORT)        28.00000            0.000000
     MAX_WEEKLYASSIGN( NEU)        28.00000            0.000000
     MAX_WEEKLYASSIGN( CAR)        28.00000            0.000000
         REQNURSETIME( ENT)        3.000000            0.000000
       REQNURSETIME( OBGYN)        24.00000            0.000000
         REQNURSETIME( URO)        19.20000            0.000000
         REQNURSETIME( GEN)        15.00000            0.000000
         REQNURSETIME( VAS)        84.00000            0.000000
         REQNURSETIME( ORT)        36.00000            0.000000
         REQNURSETIME( NEU)        46.00000            0.000000
         REQNURSETIME( CAR)        46.00000            0.000000
           LOWER_TIME( ENT)        1.000000            0.000000
         LOWER_TIME( OBGYN)        1.000000            0.000000
           LOWER_TIME( URO)        1.000000            0.000000
           LOWER_TIME( GEN)        1.000000            0.000000
           LOWER_TIME( VAS)        1.000000            0.000000
           LOWER_TIME( ORT)        1.000000            0.000000
           LOWER_TIME( NEU)        1.000000            0.000000
           LOWER_TIME( CAR)        1.000000            0.000000
           UPPER_TIME( ENT)        104.0000            0.000000
         UPPER_TIME( OBGYN)        104.0000            0.000000
           UPPER_TIME( URO)        104.0000            0.000000
           UPPER_TIME( GEN)        104.0000            0.000000
           UPPER_TIME( VAS)        104.0000            0.000000
           UPPER_TIME( ORT)        104.0000            0.000000
           UPPER_TIME( NEU)        104.0000            0.000000
           UPPER_TIME( CAR)        104.0000            0.000000
               ASSIGN( ENT)        8.000000           -37264.49
             ASSIGN( OBGYN)        2.000000           -109511.9
               ASSIGN( URO)        2.000000           -72106.59
               ASSIGN( GEN)        7.000000           -66772.23
               ASSIGN( VAS)        2.000000           -324479.7
               ASSIGN( ORT)        8.000000           -167626.8
               ASSIGN( NEU)        3.000000           -150222.1
               ASSIGN( CAR)        1.000000           -324479.4
        TIMEELIMINATE( ENT)        27.30000            0.000000
      TIMEELIMINATE( OBGYN)        46.80000            0.000000
        TIMEELIMINATE( URO)        34.66667            0.000000
        TIMEELIMINATE( GEN)        40.85714            0.000000
        TIMEELIMINATE( VAS)        52.00000            0.000000
        TIMEELIMINATE( ORT)        37.37500            0.000000
        TIMEELIMINATE( NEU)        28.88889            0.000000
        TIMEELIMINATE( CAR)        52.00000            0.000000

                        Row    Slack or Surplus      Dual Price
                          1        0.000000            0.000000
                          2        0.000000            0.000000
                          3        0.000000            0.000000
                          4        0.000000            0.000000
                          5        0.000000            0.000000
                          6        0.000000            0.000000
                          7        0.000000            0.000000
                          8        3893881.           -1.000000
                          9        0.000000            0.000000
                         10        2.000000            0.000000
                         11        7.000000            0.000000
                         12        1.000000            0.000000
                         13        1.000000            0.000000
```

14	6.000000	0.000000
15	1.000000	0.000000
16	7.000000	0.000000
17	2.000000	0.000000
18	0.000000	0.000000
19	20.00000	0.000000
20	26.00000	0.000000
21	26.00000	0.000000
22	21.00000	0.000000
23	26.00000	0.000000
24	20.00000	0.000000
25	25.00000	0.000000
26	27.00000	0.000000
27	0.000000	0.000000
28	21.60000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	48.00000	0.000000
32	0.000000	0.000000
33	6.533333	0.000000
34	0.000000	0.000000
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	64.28571	0.000000
39	69.35714	0.000000
40	69.18367	0.000000
41	69.41667	0.000000
42	0.000000	0.000000
43	43.00000	0.000000
44	19.00000	0.000000
45	1.000000	0.000000
46	4.000000	0.000000
47	6.000000	0.000000
48	0.000000	0.000000
49	9.000000	0.000000
50	4.000000	0.000000
51	0.000000	0.000000
52	-0.3037080E-06	-273.0000
53	0.000000	-467.9998
54	0.000000	-346.6665
55	-0.1217824E-03	-408.5714
56	0.000000	-1559.999
57	-0.5662741E-08	-1121.250
58	0.000000	-1733.333
59	0.000000	-3119.997
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	0.000000
67	0.000000	1.000000
68	0.000000	1.000000
69	0.000000	0.000000
70	26.30000	0.000000
71	45.80000	0.000000
72	33.66667	0.000000
73	39.85714	0.000000
74	51.00000	0.000000
75	36.37500	0.000000
76	27.88889	0.000000
77	51.00000	0.000000
78	76.70000	0.000000
79	57.20000	0.000000
80	69.33333	0.000000
81	63.14286	0.000000

82	52.00000	0.000000
83	66.62500	0.000000
84	75.11111	0.000000
85	52.00000	0.000000

Table 7 Resource intensity (low first)

```
Local optimal solution found.
Objective value:                              5309079.
Objective bound:                              5309079.
Infeasibilities:                              0.1121629E-03
Extended solver steps:                              19
Total solver iterations:                          3458
Elapsed runtime seconds:                          0.35

Model Class:                                     MINLP

Total variables:                    36
Nonlinear variables:                21
Integer variables:                   8

Total constraints:                  78
Nonlinear constraints:              13

Total nonzeros:                    178
Nonlinear nonzeros:                 29


                          Variable           Value        Reduced Cost
                         NUMBER_OR        7.000000            0.000000
                        DAYOPEN_OR        5.000000            0.000000
                    OR_BLOCK_HOURS        8.000000            0.000000
                        NUMBER_ICU        20.00000            0.000000
                       DAYOPEN_ICU        7.000000            0.000000
                ICU_HOURS_OPERATE        24.00000            0.000000
                        NUMBER_MCU        35.00000            0.000000
                       DAYOPEN_MCU        7.000000            0.000000
                MCU_HOURS_OPERATE        24.00000            0.000000
                      NUMBER_NURSE        60.00000            0.000000
                     WORKING_SHIFT        3.000000            0.000000
                      HOURINSHIFT        8.000000            0.000000
                  DAYWORK_ICUNURSE        7.000000            0.000000
                         WEIGHT_WL        1.000000            0.000000
                         WEIGHT_OT        1.000000            0.000000
                          OCOST_OR        400.0000            0.000000
                         OCOST_ICU        15.00000            0.000000
                         OCOST_MCU        5.000000            0.000000
                       OCOST_NURSE        4.000000            0.000000
                DAILY_BLOCKSUPPLY        7.000000            0.000000
             WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                        ICUSUPPLY        3360.000            0.000000
                        MCUSUPPLY        5880.000            0.000000
                  NURSETIMESUPPY        1120.000            0.000000
                DEMAND_WEEKLY_TPT        98.00000            0.000000
             TOTAL_PATIENTS_ALLDEP        5096.000            0.000000
                              OICU        0.000000            0.000000
                              OMCU        0.000000            0.000000
                               OOR        0.000000            0.000000
                            ONURSE        0.000000            0.000000
             AVERAGE_CLEARINGTIME        37.92956            0.000000
                TOTALBLOCK_ASSIGN        35.00000            0.000000
                   TOTAL_ICU_TIME        2550.000            0.000000
                TOTAL_MCUDOWN_TIME        4140.000            0.000000
                 TOTAL_MCUUP_TIME        1116.000            0.000000
             TOTAL_ICU_NURSE_TIME        748.6667            0.000000
                   OR_UTILIZATION        100.0000            0.000000
                  ICU_UTILIZATION        75.89286            0.000000
                  MCU_UTILIZATION        89.38776            0.000000
               ONURSE_UTILIZATION        66.84524            0.000000
           TOTAL_PATIENTS_ASSIGNED        153.0000            0.000000
                TOTAL_WAITING_COST        5309079.            0.000000
                    TOTAL_OOR_COST        0.000000            0.000000
                   TOTAL_OICU_COST        0.000000            1.000000
                   TOTAL_OMCU_COST        0.000000            1.000000
```

TOTAL_ONURSE_NURSE	0.000000	1.000000
WAITCOST(ENT)	40.00000	0.000000
WAITCOST(OBGYN)	40.00000	0.000000
WAITCOST(URO)	40.00000	0.000000
WAITCOST(GEN)	40.00000	0.000000
WAITCOST(VAS)	21.00000	0.000000
WAITCOST(ORT)	21.00000	0.000000
WAITCOST(NEU)	10.00000	0.000000
WAITCOST(CAR)	10.00000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBGYN)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBGYN)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBGYN)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBGYN)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBGYN)	4.000000	0.000000
REQICUDOWN(URO)	7.000000	0.000000
REQICUDOWN(GEN)	5.000000	0.000000
REQICUDOWN(VAS)	60.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	12.00000	0.000000
REQMCUDOWN(OBGYN)	12.00000	0.000000
REQMCUDOWN(URO)	12.00000	0.000000
REQMCUDOWN(GEN)	12.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	60.00000	0.000000
REQMCUDOWN(NEU)	72.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBGYN)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBGYN)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000

```
   MIN_WEEKLYASSIGN( GEN)        1.000000          0.000000
   MIN_WEEKLYASSIGN( VAS)        1.000000          0.000000
   MIN_WEEKLYASSIGN( ORT)        1.000000          0.000000
   MIN_WEEKLYASSIGN( NEU)        1.000000          0.000000
   MIN_WEEKLYASSIGN( CAR)        1.000000          0.000000
   MAX_WEEKLYASSIGN( ENT)        28.00000          0.000000
 MAX_WEEKLYASSIGN( OBGYN)        28.00000          0.000000
   MAX_WEEKLYASSIGN( URO)        28.00000          0.000000
   MAX_WEEKLYASSIGN( GEN)        28.00000          0.000000
   MAX_WEEKLYASSIGN( VAS)        28.00000          0.000000
   MAX_WEEKLYASSIGN( ORT)        28.00000          0.000000
   MAX_WEEKLYASSIGN( NEU)        28.00000          0.000000
   MAX_WEEKLYASSIGN( CAR)        28.00000          0.000000
       REQNURSETIME( ENT)        3.000000          0.000000
     REQNURSETIME( OBGYN)        4.000000          0.000000
       REQNURSETIME( URO)        7.000000          0.000000
       REQNURSETIME( GEN)        5.000000          0.000000
       REQNURSETIME( VAS)        48.00000          0.000000
       REQNURSETIME( ORT)        36.00000          0.000000
       REQNURSETIME( NEU)        46.00000          0.000000
       REQNURSETIME( CAR)        46.00000          0.000000
         LOWER_TIME( ENT)        1.000000          0.000000
       LOWER_TIME( OBGYN)        1.000000          0.000000
         LOWER_TIME( URO)        1.000000          0.000000
         LOWER_TIME( GEN)        1.000000          0.000000
         LOWER_TIME( VAS)        1.000000          0.000000
         LOWER_TIME( ORT)        1.000000          0.000000
         LOWER_TIME( NEU)        1.000000          0.000000
         LOWER_TIME( CAR)        1.000000          0.000000
         UPPER_TIME( ENT)        104.0000          0.000000
       UPPER_TIME( OBGYN)        104.0000          0.000000
         UPPER_TIME( URO)        104.0000          0.000000
         UPPER_TIME( GEN)        104.0000          0.000000
         UPPER_TIME( VAS)        104.0000          0.000000
         UPPER_TIME( ORT)        104.0000          0.000000
         UPPER_TIME( NEU)        104.0000          0.000000
         UPPER_TIME( CAR)        104.0000          0.000000
             ASSIGN( ENT)        8.000000          4200.820
           ASSIGN( OBGYN)        3.000000         -41429.01
             ASSIGN( URO)        3.000000          25069.14
             ASSIGN( GEN)        9.000000         -8313.453
             ASSIGN( VAS)        2.000000         -73876.92
             ASSIGN( ORT)        7.000000          0.000000
             ASSIGN( NEU)        2.000000          96925.47
             ASSIGN( CAR)        1.000000          0.000000
      TIMEELIMINATE( ENT)        27.30000          0.000000
    TIMEELIMINATE( OBGYN)        31.19999          0.000000
      TIMEELIMINATE( URO)        23.11111          0.000000
      TIMEELIMINATE( GEN)        31.77778          0.000000
      TIMEELIMINATE( VAS)        52.00000          0.000000
      TIMEELIMINATE( ORT)        42.71429          0.000000
      TIMEELIMINATE( NEU)        43.33333          0.000000
      TIMEELIMINATE( CAR)        52.00000          0.000000

                      Row    Slack or Surplus      Dual Price
                        1        0.000000          0.000000
                        2        0.000000          153258.9
                        3        0.000000          0.000000
                        4        0.000000          0.000000
                        5        0.000000          0.000000
                        6        0.000000          0.000000
                        7        0.000000          0.000000
                        8        5309079.         -1.000000
                        9        0.000000         -153258.9
                       10        0.000000          153258.9
                       11        7.000000          0.000000
                       12        2.000000          0.000000
                       13        2.000000          0.000000
```

14	8.000000	0.000000
15	1.000000	0.000000
16	6.000000	0.000000
17	1.000000	0.000000
18	0.000000	-99178.86
19	20.00000	0.000000
20	25.00000	0.000000
21	25.00000	0.000000
22	19.00000	0.000000
23	26.00000	0.000000
24	21.00000	0.000000
25	26.00000	0.000000
26	27.00000	0.000000
27	0.000000	0.000000
28	810.0000	0.000000
29	0.000000	0.000000
30	0.000000	0.000000
31	624.0000	0.000000
32	0.000000	0.000000
33	371.3333	0.000000
34	0.000000	138087.0
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	0.000000
38	70.00000	0.000000
39	45.89286	0.000000
40	59.38776	0.000000
41	36.84524	0.000000
42	0.000000	0.000000
43	55.00000	0.000000
44	19.00000	0.000000
45	6.000000	0.000000
46	10.00000	0.000000
47	14.00000	0.000000
48	0.000000	0.000000
49	5.000000	0.000000
50	1.000000	0.000000
51	0.000000	0.000000
52	0.000000	-1092.000
53	-0.1121629E-03	-1248.000
54	0.000000	-924.4448
55	0.000000	-1271.111
56	0.000000	-1091.999
57	0.000000	-897.0000
58	0.000000	-433.3336
59	0.000000	-520.0000
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	1.000000
67	0.000000	1.000000
68	0.000000	1.000000
69	0.000000	0.000000
70	26.30000	0.000000
71	30.19999	0.000000
72	22.11111	0.000000
73	30.77778	0.000000
74	51.00000	0.000000
75	41.71429	0.000000
76	42.33333	0.000000
77	51.00000	0.000000
78	76.70000	0.000000
79	72.80001	0.000000
80	80.88889	0.000000
81	72.22222	0.000000

82	52.00000	0.000000
83	61.28571	0.000000
84	60.66667	0.000000
85	52.00000	0.000000

Table 8 Overtime allowance 10%

```
Local optimal solution found.
Objective value:                              3928452.
Objective bound:                              3928452.
Infeasibilities:                              0.000000
Extended solver steps:                              35
Total solver iterations:                          6461
Elapsed runtime seconds:                          0.52

Model Class:                                     MINLP

Total variables:                     36
Nonlinear variables:                 21
Integer variables:                    8

Total constraints:                   78
Nonlinear constraints:               13

Total nonzeros:                     178
Nonlinear nonzeros:                  29


                       Variable           Value        Reduced Cost
                      NUMBER_OR        7.000000            0.000000
                     DAYOPEN_OR        5.000000            0.000000
                 OR_BLOCK_HOURS        8.000000            0.000000
                     NUMBER_ICU        20.00000            0.000000
                    DAYOPEN_ICU        7.000000            0.000000
              ICU_HOURS_OPERATE        24.00000            0.000000
                     NUMBER_MCU        35.00000            0.000000
                    DAYOPEN_MCU        7.000000            0.000000
              MCU_HOURS_OPERATE        24.00000            0.000000
                   NUMBER_NURSE        60.00000            0.000000
                  WORKING_SHIFT        3.000000            0.000000
                    HOURINSHIFT        8.000000            0.000000
                DAYWORK_ICUNURSE       7.000000            0.000000
                      WEIGHT_WL        1.000000            0.000000
                      WEIGHT_OT        1.000000            0.000000
                       OCOST_OR        350.0000            0.000000
                      OCOST_ICU        20.00000            0.000000
                      OCOST_MCU        5.000000            0.000000
                    OCOST_NURSE        4.000000            0.000000
              DAILY_BLOCKSUPPLY        7.000000            0.000000
           WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                      ICUSUPPLY        3360.000            0.000000
                      MCUSUPPLY        5880.000            0.000000
                 NURSETIMESUPPY        1120.000            0.000000
              DEMAND_WEEKLY_TPT        98.00000            0.000000
           TOTAL_PATIENTS_ALLDEP       5096.000            0.000000
                           OICU        134.4000            0.000000
                           OMCU        288.0000            0.000000
                            OOR        0.000000            12058.85
                         ONURSE        102.1333            0.000000
            AVERAGE_CLEARINGTIME       34.45387            0.000000
              TOTALBLOCK_ASSIGN        35.00000            0.000000
                 TOTAL_ICU_TIME        3494.400            0.000000
             TOTAL_MCUDOWN_TIME        4980.000            0.000000
               TOTAL_MCUUP_TIME        1188.000            0.000000
           TOTAL_ICU_NURSE_TIME        1222.133            0.000000
                 OR_UTILIZATION        100.0000            0.000000
                ICU_UTILIZATION        104.0000            0.000000
                MCU_UTILIZATION        104.8980            0.000000
             ONURSE_UTILIZATION        109.1190            0.000000
         TOTAL_PATIENTS_ASSIGNED       149.0000            0.000000
              TOTAL_WAITING_COST       3772151.            0.000000
                  TOTAL_OOR_COST       0.000000            0.000000
                 TOTAL_OICU_COST       92612.00            0.000000
                 TOTAL_OMCU_COST       49613.57            0.000000
```

```
TOTAL_ONURSE_NURSE        14075.55        0.000000
     WAITCOST( ENT)       10.00000        0.000000
     WAITCOST( OBG)       17.00000        0.000000
     WAITCOST( URO)       6.000000        0.000000
     WAITCOST( GEN)       16.00000        0.000000
     WAITCOST( VAS)       45.00000        0.000000
     WAITCOST( ORT)       22.00000        0.000000
     WAITCOST( NEU)       50.00000        0.000000
     WAITCOST( CAR)       55.00000        0.000000
WEEKLY_DEMAND( ENT)       21.00000        0.000000
WEEKLY_DEMAND( OBG)       9.000000        0.000000
WEEKLY_DEMAND( URO)       8.000000        0.000000
WEEKLY_DEMAND( GEN)       22.00000        0.000000
WEEKLY_DEMAND( VAS)       8.000000        0.000000
WEEKLY_DEMAND( ORT)       23.00000        0.000000
WEEKLY_DEMAND( NEU)       5.000000        0.000000
WEEKLY_DEMAND( CAR)       2.000000        0.000000
 WAITING_LIST( ENT)       1092.000        0.000000
 WAITING_LIST( OBG)       468.0000        0.000000
 WAITING_LIST( URO)       416.0000        0.000000
 WAITING_LIST( GEN)       1144.000        0.000000
 WAITING_LIST( VAS)       416.0000        0.000000
 WAITING_LIST( ORT)       1196.000        0.000000
 WAITING_LIST( NEU)       260.0000        0.000000
 WAITING_LIST( CAR)       104.0000        0.000000
   EFFICIENCY( ENT)       5.000000        0.000000
   EFFICIENCY( OBG)       5.000000        0.000000
   EFFICIENCY( URO)       6.000000        0.000000
   EFFICIENCY( GEN)       4.000000        0.000000
   EFFICIENCY( VAS)       4.000000        0.000000
   EFFICIENCY( ORT)       4.000000        0.000000
   EFFICIENCY( NEU)       3.000000        0.000000
   EFFICIENCY( CAR)       2.000000        0.000000
  SURGERY_DUR( ENT)       1.233000        0.000000
  SURGERY_DUR( OBG)       1.433000        0.000000
  SURGERY_DUR( URO)       1.060000        0.000000
  SURGERY_DUR( GEN)       1.550000        0.000000
  SURGERY_DUR( VAS)       2.000000        0.000000
  SURGERY_DUR( ORT)       1.780000        0.000000
  SURGERY_DUR( NEU)       2.670000        0.000000
  SURGERY_DUR( CAR)       4.000000        0.000000
   REQICUDOWN( ENT)       3.000000        0.000000
   REQICUDOWN( OBG)       24.00000        0.000000
   REQICUDOWN( URO)       19.20000        0.000000
   REQICUDOWN( GEN)       15.00000        0.000000
   REQICUDOWN( VAS)       48.00000        0.000000
   REQICUDOWN( ORT)       36.00000        0.000000
   REQICUDOWN( NEU)       72.00000        0.000000
   REQICUDOWN( CAR)       72.00000        0.000000
   REQMCUDOWN( ENT)       24.00000        0.000000
   REQMCUDOWN( OBG)       12.00000        0.000000
   REQMCUDOWN( URO)       24.00000        0.000000
   REQMCUDOWN( GEN)       24.00000        0.000000
   REQMCUDOWN( VAS)       72.00000        0.000000
   REQMCUDOWN( ORT)       48.00000        0.000000
   REQMCUDOWN( NEU)       48.00000        0.000000
   REQMCUDOWN( CAR)       72.00000        0.000000
     REQMCUUP( ENT)       0.000000        0.000000
     REQMCUUP( OBG)       12.00000        0.000000
     REQMCUUP( URO)       12.00000        0.000000
     REQMCUUP( GEN)       0.000000        0.000000
     REQMCUUP( VAS)       24.00000        0.000000
     REQMCUUP( ORT)       12.00000        0.000000
     REQMCUUP( NEU)       24.00000        0.000000
     REQMCUUP( CAR)       24.00000        0.000000
MIN_WEEKLYASSIGN( ENT)    1.000000        0.000000
MIN_WEEKLYASSIGN( OBG)    1.000000        0.000000
MIN_WEEKLYASSIGN( URO)    1.000000        0.000000
```

MIN_WEEKLYASSIGN(GEN)	1.000000	0.000000
MIN_WEEKLYASSIGN(VAS)	1.000000	0.000000
MIN_WEEKLYASSIGN(ORT)	1.000000	0.000000
MIN_WEEKLYASSIGN(NEU)	1.000000	0.000000
MIN_WEEKLYASSIGN(CAR)	1.000000	0.000000
MAX_WEEKLYASSIGN(ENT)	28.00000	0.000000
MAX_WEEKLYASSIGN(OBG)	28.00000	0.000000
MAX_WEEKLYASSIGN(URO)	28.00000	0.000000
MAX_WEEKLYASSIGN(GEN)	28.00000	0.000000
MAX_WEEKLYASSIGN(VAS)	28.00000	0.000000
MAX_WEEKLYASSIGN(ORT)	28.00000	0.000000
MAX_WEEKLYASSIGN(NEU)	28.00000	0.000000
MAX_WEEKLYASSIGN(CAR)	28.00000	0.000000
REQNURSETIME(ENT)	3.000000	0.000000
REQNURSETIME(OBG)	24.00000	0.000000
REQNURSETIME(URO)	19.20000	0.000000
REQNURSETIME(GEN)	15.00000	0.000000
REQNURSETIME(VAS)	84.00000	0.000000
REQNURSETIME(ORT)	36.00000	0.000000
REQNURSETIME(NEU)	46.00000	0.000000
REQNURSETIME(CAR)	46.00000	0.000000
LOWER_TIME(ENT)	1.000000	0.000000
LOWER_TIME(OBG)	1.000000	0.000000
LOWER_TIME(URO)	1.000000	0.000000
LOWER_TIME(GEN)	1.000000	0.000000
LOWER_TIME(VAS)	1.000000	0.000000
LOWER_TIME(ORT)	1.000000	0.000000
LOWER_TIME(NEU)	1.000000	0.000000
LOWER_TIME(CAR)	1.000000	0.000000
UPPER_TIME(ENT)	104.0000	0.000000
UPPER_TIME(OBG)	104.0000	0.000000
UPPER_TIME(URO)	104.0000	0.000000
UPPER_TIME(GEN)	104.0000	0.000000
UPPER_TIME(VAS)	104.0000	0.000000
UPPER_TIME(ORT)	104.0000	0.000000
UPPER_TIME(NEU)	104.0000	0.000000
UPPER_TIME(CAR)	104.0000	0.000000
ASSIGN(ENT)	8.000000	-7502.050
ASSIGN(OBG)	3.000000	20234.26
ASSIGN(URO)	2.000000	68790.78
ASSIGN(GEN)	8.000000	-23691.25
ASSIGN(VAS)	3.000000	-8983.019
ASSIGN(ORT)	7.000000	-16830.20
ASSIGN(NEU)	2.000000	-101562.4
ASSIGN(CAR)	2.000000	54797.23
TIMEELIMINATE(ENT)	27.30000	0.000000
TIMEELIMINATE(OBG)	31.20000	0.000000
TIMEELIMINATE(URO)	34.66667	0.000000
TIMEELIMINATE(GEN)	35.75000	0.000000
TIMEELIMINATE(VAS)	34.66667	0.000000
TIMEELIMINATE(ORT)	42.71429	0.000000
TIMEELIMINATE(NEU)	43.33333	0.000000
TIMEELIMINATE(CAR)	26.00000	0.000000

Row	Slack or Surplus	Dual Price
1	0.000000	0.000000
2	0.000000	0.000000
3	0.000000	689.0774
4	0.000000	172.2693
5	0.000000	137.8155
6	0.000000	0.000000
7	0.000000	0.000000
8	3928452.	-1.000000
9	0.000000	0.000000
10	0.000000	0.000000
11	7.000000	0.000000
12	2.000000	0.000000
13	1.000000	0.000000

14	7.000000	0.000000
15	2.000000	0.000000
16	6.000000	0.000000
17	1.000000	0.000000
18	1.000000	0.000000
19	20.00000	0.000000
20	25.00000	0.000000
21	26.00000	0.000000
22	20.00000	0.000000
23	25.00000	0.000000
24	21.00000	0.000000
25	26.00000	0.000000
26	26.00000	0.000000
27	0.000000	-689.0774
28	0.000000	689.0774
29	0.000000	-172.2693
30	0.000000	-172.2693
31	0.000000	172.2693
32	0.000000	-137.8155
33	0.000000	137.8155
34	3.500000	0.000000
35	201.6000	0.000000
36	300.0000	0.000000
37	9.866667	0.000000
38	70.00000	0.000000
39	74.00000	0.000000
40	74.89796	0.000000
41	79.11905	0.000000
42	0.000000	0.000000
43	51.00000	0.000000
44	19.00000	0.000000
45	6.000000	0.000000
46	4.000000	0.000000
47	10.00000	0.000000
48	4.000000	0.000000
49	5.000000	0.000000
50	1.000000	0.000000
51	2.000000	0.000000
52	0.000000	-287.1767
53	0.000000	-568.2047
54	0.000000	-255.2558
55	0.000000	-589.7208
56	0.000000	-1607.255
57	0.000000	-959.9666
58	0.000000	-2261.177
59	0.000000	-1571.768
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	0.000000
67	0.000000	0.000000
68	0.000000	0.000000
69	0.000000	-4536.541
70	26.30000	0.000000
71	30.20000	0.000000
72	33.66667	0.000000
73	34.75000	0.000000
74	33.66667	0.000000
75	41.71429	0.000000
76	42.33333	0.000000
77	25.00000	0.000000
78	76.70000	0.000000
79	72.80000	0.000000
80	69.33333	0.000000
81	68.25000	0.000000

82	69.33333	0.000000
83	61.28571	0.000000
84	60.66667	0.000000
85	78.00000	0.000000

Table 9 Overtime allowance 15%

```
Local optimal solution found.
Objective value:                              3923421.
Objective bound:                              3923421.
Infeasibilities:                              0.4303414E-02
Extended solver steps:                             41
Total solver iterations:                         8423
Elapsed runtime seconds:                         0.79

Model Class:                                    MINLP

Total variables:                     36
Nonlinear variables:                 21
Integer variables:                    8

Total constraints:                   78
Nonlinear constraints:               13

Total nonzeros:                     178
Nonlinear nonzeros:                  29


                                Variable           Value        Reduced Cost
                               NUMBER_OR        7.000000            0.000000
                              DAYOPEN_OR        5.000000            0.000000
                          OR_BLOCK_HOURS        8.000000            0.000000
                              NUMBER_ICU        20.00000            0.000000
                             DAYOPEN_ICU        7.000000            0.000000
                      ICU_HOURS_OPERATE        24.00000            0.000000
                              NUMBER_MCU        35.00000            0.000000
                             DAYOPEN_MCU        7.000000            0.000000
                      MCU_HOURS_OPERATE        24.00000            0.000000
                            NUMBER_NURSE        60.00000            0.000000
                           WORKING_SHIFT        3.000000            0.000000
                             HOURINSHIFT        8.000000            0.000000
                        DAYWORK_ICUNURSE        7.000000            0.000000
                               WEIGHT_WL        1.000000            0.000000
                               WEIGHT_OT        1.000000            0.000000
                                OCOST_OR        350.0000            0.000000
                               OCOST_ICU        20.00000            0.000000
                               OCOST_MCU        5.000000            0.000000
                             OCOST_NURSE        4.000000            0.000000
                      DAILY_BLOCKSUPPLY        7.000000            0.000000
                   WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                               ICUSUPPLY        3360.000            0.000000
                               MCUSUPPLY        5880.000            0.000000
                         NURSETIMESUPPY        1120.000            0.000000
                      DEMAND_WEEKLY_TPT        98.00000            0.000000
                    TOTAL_PATIENTS_ALLDEP       5096.000            0.000000
                                    OICU        395.4000            0.000000
                                    OMCU        480.0000            0.000000
                                     OOR        1.000000            0.000000
                                  ONURSE        163.1333            0.000000
                   AVERAGE_CLEARINGTIME        32.63929            0.000000
                      TOTALBLOCK_ASSIGN        36.00000            0.000000
                          TOTAL_ICU_TIME        3755.400            0.000000
                      TOTAL_MCUDOWN_TIME        5100.000            0.000000
                        TOTAL_MCUUP_TIME        1260.000            0.000000
                    TOTAL_ICU_NURSE_TIME        1283.133            0.000000
                          OR_UTILIZATION        102.8571            0.000000
                         ICU_UTILIZATION        111.7679            0.000000
                         MCU_UTILIZATION        108.1633            0.000000
                      ONURSE_UTILIZATION        114.5655            0.000000
                  TOTAL_PATIENTS_ASSIGNED       151.0000            0.000000
                      TOTAL_WAITING_COST        3554253.            0.000000
                          TOTAL_OOR_COST        11423.75            0.000000
                         TOTAL_OICU_COST        258111.5            0.000000
                         TOTAL_OMCU_COST        78334.29            0.000000
```

```
             TOTAL_ONURSE_NURSE        21298.22            0.000000
                 WAITCOST( ENT)        10.00000            0.000000
                 WAITCOST( OBG)        17.00000            0.000000
                 WAITCOST( URO)        6.000000            0.000000
                 WAITCOST( GEN)        16.00000            0.000000
                 WAITCOST( VAS)        45.00000            0.000000
                 WAITCOST( ORT)        22.00000            0.000000
                 WAITCOST( NEU)        50.00000            0.000000
                 WAITCOST( CAR)        55.00000            0.000000
            WEEKLY_DEMAND( ENT)        21.00000            0.000000
            WEEKLY_DEMAND( OBG)        9.000000            0.000000
            WEEKLY_DEMAND( URO)        8.000000            0.000000
            WEEKLY_DEMAND( GEN)        22.00000            0.000000
            WEEKLY_DEMAND( VAS)        8.000000            0.000000
            WEEKLY_DEMAND( ORT)        23.00000            0.000000
            WEEKLY_DEMAND( NEU)        5.000000            0.000000
            WEEKLY_DEMAND( CAR)        2.000000            0.000000
             WAITING_LIST( ENT)        1092.000            0.000000
             WAITING_LIST( OBG)        468.0000            0.000000
             WAITING_LIST( URO)        416.0000            0.000000
             WAITING_LIST( GEN)        1144.000            0.000000
             WAITING_LIST( VAS)        416.0000            0.000000
             WAITING_LIST( ORT)        1196.000            0.000000
             WAITING_LIST( NEU)        260.0000            0.000000
             WAITING_LIST( CAR)        104.0000            0.000000
               EFFICIENCY( ENT)        5.000000            0.000000
               EFFICIENCY( OBG)        5.000000            0.000000
               EFFICIENCY( URO)        6.000000            0.000000
               EFFICIENCY( GEN)        4.000000            0.000000
               EFFICIENCY( VAS)        4.000000            0.000000
               EFFICIENCY( ORT)        4.000000            0.000000
               EFFICIENCY( NEU)        3.000000            0.000000
               EFFICIENCY( CAR)        2.000000            0.000000
             SURGERY_DUR( ENT)         1.233000            0.000000
             SURGERY_DUR( OBG)         1.433000            0.000000
             SURGERY_DUR( URO)         1.060000            0.000000
             SURGERY_DUR( GEN)         1.550000            0.000000
             SURGERY_DUR( VAS)         2.000000            0.000000
             SURGERY_DUR( ORT)         1.780000            0.000000
             SURGERY_DUR( NEU)         2.670000            0.000000
             SURGERY_DUR( CAR)         4.000000            0.000000
              REQICUDOWN( ENT)         3.000000            0.000000
              REQICUDOWN( OBG)         24.00000            0.000000
              REQICUDOWN( URO)         19.20000            0.000000
              REQICUDOWN( GEN)         15.00000            0.000000
              REQICUDOWN( VAS)         48.00000            0.000000
              REQICUDOWN( ORT)         36.00000            0.000000
              REQICUDOWN( NEU)         72.00000            0.000000
              REQICUDOWN( CAR)         72.00000            0.000000
              REQMCUDOWN( ENT)         24.00000            0.000000
              REQMCUDOWN( OBG)         12.00000            0.000000
              REQMCUDOWN( URO)         24.00000            0.000000
              REQMCUDOWN( GEN)         24.00000            0.000000
              REQMCUDOWN( VAS)         72.00000            0.000000
              REQMCUDOWN( ORT)         48.00000            0.000000
              REQMCUDOWN( NEU)         48.00000            0.000000
              REQMCUDOWN( CAR)         72.00000            0.000000
                REQMCUUP( ENT)         0.000000            0.000000
                REQMCUUP( OBG)         12.00000            0.000000
                REQMCUUP( URO)         12.00000            0.000000
                REQMCUUP( GEN)         0.000000            0.000000
                REQMCUUP( VAS)         24.00000            0.000000
                REQMCUUP( ORT)         12.00000            0.000000
                REQMCUUP( NEU)         24.00000            0.000000
                REQMCUUP( CAR)         24.00000            0.000000
        MIN_WEEKLYASSIGN( ENT)         1.000000            0.000000
        MIN_WEEKLYASSIGN( OBG)         1.000000            0.000000
        MIN_WEEKLYASSIGN( URO)         1.000000            0.000000
```

```
MIN_WEEKLYASSIGN( GEN)        1.000000         0.000000
MIN_WEEKLYASSIGN( VAS)        1.000000         0.000000
MIN_WEEKLYASSIGN( ORT)        1.000000         0.000000
MIN_WEEKLYASSIGN( NEU)        1.000000         0.000000
MIN_WEEKLYASSIGN( CAR)        1.000000         0.000000
MAX_WEEKLYASSIGN( ENT)        28.00000         0.000000
MAX_WEEKLYASSIGN( OBG)        28.00000         0.000000
MAX_WEEKLYASSIGN( URO)        28.00000         0.000000
MAX_WEEKLYASSIGN( GEN)        28.00000         0.000000
MAX_WEEKLYASSIGN( VAS)        28.00000         0.000000
MAX_WEEKLYASSIGN( ORT)        28.00000         0.000000
MAX_WEEKLYASSIGN( NEU)        28.00000         0.000000
MAX_WEEKLYASSIGN( CAR)        28.00000         0.000000
    REQNURSETIME( ENT)        3.000000         0.000000
    REQNURSETIME( OBG)        24.00000         0.000000
    REQNURSETIME( URO)        19.20000         0.000000
    REQNURSETIME( GEN)        15.00000         0.000000
    REQNURSETIME( VAS)        84.00000         0.000000
    REQNURSETIME( ORT)        36.00000         0.000000
    REQNURSETIME( NEU)        46.00000         0.000000
    REQNURSETIME( CAR)        46.00000         0.000000
      LOWER_TIME( ENT)        1.000000         0.000000
      LOWER_TIME( OBG)        1.000000         0.000000
      LOWER_TIME( URO)        1.000000         0.000000
      LOWER_TIME( GEN)        1.000000         0.000000
      LOWER_TIME( VAS)        1.000000         0.000000
      LOWER_TIME( ORT)        1.000000         0.000000
      LOWER_TIME( NEU)        1.000000         0.000000
      LOWER_TIME( CAR)        1.000000         0.000000
      UPPER_TIME( ENT)        104.0000         0.000000
      UPPER_TIME( OBG)        104.0000         0.000000
      UPPER_TIME( URO)        104.0000         0.000000
      UPPER_TIME( GEN)        104.0000         0.000000
      UPPER_TIME( VAS)        104.0000         0.000000
      UPPER_TIME( ORT)        104.0000         0.000000
      UPPER_TIME( NEU)        104.0000         0.000000
      UPPER_TIME( CAR)        104.0000         0.000000
          ASSIGN( ENT)        7.000000        -13521.67
          ASSIGN( OBG)        3.000000         17117.75
          ASSIGN( URO)        2.000000         59118.28
          ASSIGN( GEN)        9.000000        -752.0167
          ASSIGN( VAS)        3.000000        -18608.82
          ASSIGN( ORT)        7.000000        -18325.22
          ASSIGN( NEU)        3.000000         54881.73
          ASSIGN( CAR)        2.000000         48022.67
   TIMEELIMINATE( ENT)        31.20000         0.000000
   TIMEELIMINATE( OBG)        31.20000         0.000000
   TIMEELIMINATE( URO)        34.66667         0.000000
   TIMEELIMINATE( GEN)        31.77778         0.000000
   TIMEELIMINATE( VAS)        34.66667         0.000000
   TIMEELIMINATE( ORT)        42.71428         0.000000
   TIMEELIMINATE( NEU)        28.88889         0.000000
   TIMEELIMINATE( CAR)        26.00000         0.000000

                 Row    Slack or Surplus      Dual Price
                   1        0.000000         0.000000
                   2        0.000000         11423.75
                   3        0.000000         652.7858
                   4        0.000000         163.1964
                   5        0.000000         130.5572
                   6        0.000000         0.000000
                   7        0.000000         0.000000
                   8        3923421.        -1.000000
                   9        0.000000        -11423.75
                  10        0.000000         11423.75
                  11        6.000000         0.000000
                  12        2.000000         0.000000
                  13        1.000000         0.000000
```

14	8.000000	0.000000
15	2.000000	0.000000
16	6.000000	0.000000
17	2.000000	0.000000
18	1.000000	0.000000
19	21.00000	0.000000
20	25.00000	0.000000
21	26.00000	0.000000
22	19.00000	0.000000
23	25.00000	0.000000
24	21.00000	0.000000
25	25.00000	0.000000
26	26.00000	0.000000
27	0.000000	-652.7858
28	0.000000	652.7858
29	0.000000	-163.1964
30	0.000000	-163.1964
31	0.000000	163.1964
32	0.000000	-130.5572
33	0.000000	130.5572
34	4.250000	0.000000
35	108.6000	0.000000
36	402.0000	0.000000
37	4.866667	0.000000
38	72.85714	0.000000
39	81.76786	0.000000
40	78.16327	0.000000
41	84.56548	0.000000
42	0.000000	0.000000
43	53.00000	0.000000
44	14.00000	0.000000
45	6.000000	0.000000
46	4.000000	0.000000
47	14.00000	0.000000
48	4.000000	0.000000
49	5.000000	0.000000
50	4.000000	0.000000
51	2.000000	0.000000
52	0.000000	-352.3947
53	0.000000	-624.6546
54	0.000000	-325.8182
55	0.000000	-547.7171
56	0.000000	-1677.817
57	-0.4643414E-04	-990.2076
58	0.000000	-1601.536
59	0.000000	-1783.455
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	-0.6526840E-03	0.000000
66	-0.4303414E-02	0.000000
67	-0.1989578E-02	0.000000
68	-0.2868943E-03	0.000000
69	0.000000	-11310.53
70	30.20000	0.000000
71	30.20000	0.000000
72	33.66667	0.000000
73	30.77778	0.000000
74	33.66667	0.000000
75	41.71428	0.000000
76	27.88889	0.000000
77	25.00000	0.000000
78	72.80000	0.000000
79	72.80000	0.000000
80	69.33333	0.000000
81	72.22222	0.000000

82	69.33333	0.000000
83	61.28572	0.000000
84	75.11111	0.000000
85	78.00000	0.000000

Table 10 Overtime allowance 20%

```
Local optimal solution found.
Objective value:                              3912646.
Objective bound:                              3912646.
Infeasibilities:                              0.000000
Extended solver steps:                              29
Total solver iterations:                          5488
Elapsed runtime seconds:                          0.38

Model Class:                                     MINLP

Total variables:                    36
Nonlinear variables:                21
Integer variables:                   8

Total constraints:                  78
Nonlinear constraints:              13

Total nonzeros:                    178
Nonlinear nonzeros:                 29


                        Variable           Value        Reduced Cost
                       NUMBER_OR        7.000000            0.000000
                      DAYOPEN_OR        5.000000            0.000000
                  OR_BLOCK_HOURS        8.000000            0.000000
                      NUMBER_ICU        20.00000            0.000000
                     DAYOPEN_ICU        7.000000            0.000000
               ICU_HOURS_OPERATE        24.00000            0.000000
                      NUMBER_MCU        35.00000            0.000000
                     DAYOPEN_MCU        7.000000            0.000000
               MCU_HOURS_OPERATE        24.00000            0.000000
                    NUMBER_NURSE        60.00000            0.000000
                   WORKING_SHIFT        3.000000            0.000000
                     HOURINSHIFT        8.000000            0.000000
                DAYWORK_ICUNURSE        7.000000            0.000000
                       WEIGHT_WL        1.000000            0.000000
                       WEIGHT_OT        1.000000            0.000000
                        OCOST_OR        350.0000            0.000000
                       OCOST_ICU        20.00000            0.000000
                       OCOST_MCU        5.000000            0.000000
                     OCOST_NURSE        4.000000            0.000000
               DAILY_BLOCKSUPPLY        7.000000            0.000000
            WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                       ICUSUPPLY        3360.000            0.000000
                       MCUSUPPLY        5880.000            0.000000
                 NURSETIMESUPPY         1120.000            0.000000
               DEMAND_WEEKLY_TPT        98.00000            0.000000
             TOTAL_PATIENTS_ALLDEP      5096.000            0.000000
                            OICU        569.4000            0.000000
                            OMCU        960.0000            0.000000
                             OOR        4.000000            0.000000
                          ONURSE        221.1333            0.000000
            AVERAGE_CLEARINGTIME        31.10521            0.000000
               TOTALBLOCK_ASSIGN        39.00000            0.000000
                  TOTAL_ICU_TIME        3929.400            0.000000
              TOTAL_MCUDOWN_TIME        5532.000            0.000000
                TOTAL_MCUUP_TIME        1308.000            0.000000
            TOTAL_ICU_NURSE_TIME        1341.133            0.000000
                  OR_UTILIZATION        111.4286            0.000000
                 ICU_UTILIZATION        116.9464            0.000000
                 MCU_UTILIZATION        116.3265            0.000000
              ONURSE_UTILIZATION        119.7440            0.000000
          TOTAL_PATIENTS_ASSIGNED       165.0000            0.000000
              TOTAL_WAITING_COST        3338054.            0.000000
                  TOTAL_OOR_COST        43547.29            0.000000
                 TOTAL_OICU_COST        354226.1            0.000000
                 TOTAL_OMCU_COST        149305.0            0.000000
```

TOTAL_ONURSE_NURSE	27513.59	0.000000
WAITCOST(ENT)	10.00000	0.000000
WAITCOST(OBG)	17.00000	0.000000
WAITCOST(URO)	6.000000	0.000000
WAITCOST(GEN)	16.00000	0.000000
WAITCOST(VAS)	45.00000	0.000000
WAITCOST(ORT)	22.00000	0.000000
WAITCOST(NEU)	50.00000	0.000000
WAITCOST(CAR)	55.00000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBG)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBG)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBG)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBG)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBG)	24.00000	0.000000
REQICUDOWN(URO)	19.20000	0.000000
REQICUDOWN(GEN)	15.00000	0.000000
REQICUDOWN(VAS)	48.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	24.00000	0.000000
REQMCUDOWN(OBG)	12.00000	0.000000
REQMCUDOWN(URO)	24.00000	0.000000
REQMCUDOWN(GEN)	24.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	48.00000	0.000000
REQMCUDOWN(NEU)	48.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBG)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBG)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000

```
MIN_WEEKLYASSIGN( GEN)        1.000000            0.000000
MIN_WEEKLYASSIGN( VAS)        1.000000            0.000000
MIN_WEEKLYASSIGN( ORT)        1.000000            0.000000
MIN_WEEKLYASSIGN( NEU)        1.000000            0.000000
MIN_WEEKLYASSIGN( CAR)        1.000000            0.000000
MAX_WEEKLYASSIGN( ENT)        28.00000            0.000000
MAX_WEEKLYASSIGN( OBG)        28.00000            0.000000
MAX_WEEKLYASSIGN( URO)        28.00000            0.000000
MAX_WEEKLYASSIGN( GEN)        28.00000            0.000000
MAX_WEEKLYASSIGN( VAS)        28.00000            0.000000
MAX_WEEKLYASSIGN( ORT)        28.00000            0.000000
MAX_WEEKLYASSIGN( NEU)        28.00000            0.000000
MAX_WEEKLYASSIGN( CAR)        28.00000            0.000000
    REQNURSETIME( ENT)        3.000000            0.000000
    REQNURSETIME( OBG)        24.00000            0.000000
    REQNURSETIME( URO)        19.20000            0.000000
    REQNURSETIME( GEN)        15.00000            0.000000
    REQNURSETIME( VAS)        84.00000            0.000000
    REQNURSETIME( ORT)        36.00000            0.000000
    REQNURSETIME( NEU)        46.00000            0.000000
    REQNURSETIME( CAR)        46.00000            0.000000
      LOWER_TIME( ENT)        1.000000            0.000000
      LOWER_TIME( OBG)        1.000000            0.000000
      LOWER_TIME( URO)        1.000000            0.000000
      LOWER_TIME( GEN)        1.000000            0.000000
      LOWER_TIME( VAS)        1.000000            0.000000
      LOWER_TIME( ORT)        1.000000            0.000000
      LOWER_TIME( NEU)        1.000000            0.000000
      LOWER_TIME( CAR)        1.000000            0.000000
      UPPER_TIME( ENT)        104.0000            0.000000
      UPPER_TIME( OBG)        104.0000            0.000000
      UPPER_TIME( URO)        104.0000            0.000000
      UPPER_TIME( GEN)        104.0000            0.000000
      UPPER_TIME( VAS)        104.0000            0.000000
      UPPER_TIME( ORT)        104.0000            0.000000
      UPPER_TIME( NEU)        104.0000            0.000000
      UPPER_TIME( CAR)        104.0000            0.000000
          ASSIGN( ENT)        9.000000            3834.135
          ASSIGN( OBG)        3.000000            2422.555
          ASSIGN( URO)        2.000000            37636.76
          ASSIGN( GEN)        9.000000           -7149.916
          ASSIGN( VAS)        3.000000           -39014.37
          ASSIGN( ORT)        8.000000            10054.23
          ASSIGN( NEU)        3.000000            37157.62
          ASSIGN( CAR)        2.000000            29768.47
   TIMEELIMINATE( ENT)        24.26667            0.000000
   TIMEELIMINATE( OBG)        31.20000            0.000000
   TIMEELIMINATE( URO)        34.66667            0.000000
   TIMEELIMINATE( GEN)        31.77778            0.000000
   TIMEELIMINATE( VAS)        34.66667            0.000000
   TIMEELIMINATE( ORT)        37.37500            0.000000
   TIMEELIMINATE( NEU)        28.88889            0.000000
   TIMEELIMINATE( CAR)        26.00000            0.000000

                  Row    Slack or Surplus      Dual Price
                    1        0.000000            0.000000
                    2        0.000000            10886.82
                    3        0.000000            622.1043
                    4        0.000000            155.5261
                    5        0.000000            124.4209
                    6        0.000000            0.000000
                    7        0.000000            0.000000
                    8        3912646.           -1.000000
                    9        0.000000           -10886.82
                   10        0.000000            10886.82
                   11        8.000000            0.000000
                   12        2.000000            0.000000
                   13        1.000000            0.000000
```

14	8.000000	0.000000
15	2.000000	0.000000
16	7.000000	0.000000
17	2.000000	0.000000
18	1.000000	0.000000
19	19.00000	0.000000
20	25.00000	0.000000
21	26.00000	0.000000
22	19.00000	0.000000
23	25.00000	0.000000
24	20.00000	0.000000
25	25.00000	0.000000
26	26.00000	0.000000
27	0.000000	-622.1043
28	0.000000	622.1043
29	0.000000	-155.5261
30	0.000000	-155.5261
31	0.000000	155.5261
32	0.000000	-124.4209
33	0.000000	124.4209
34	3.000000	0.000000
35	102.6000	0.000000
36	216.0000	0.000000
37	2.866667	0.000000
38	81.42857	0.000000
39	86.94643	0.000000
40	86.32653	0.000000
41	89.74405	0.000000
42	0.000000	0.000000
43	67.00000	0.000000
44	24.00000	0.000000
45	6.000000	0.000000
46	4.000000	0.000000
47	14.00000	0.000000
48	4.000000	0.000000
49	9.000000	0.000000
50	4.000000	0.000000
51	2.000000	0.000000
52	0.000000	-293.9793
53	0.000000	-684.3379
54	0.000000	-400.4223
55	0.000000	-572.5851
56	0.000000	-1752.421
57	0.000000	-894.4084
58	0.000000	-1701.008
59	0.000000	-2007.267
60	0.000000	0.000000
61	0.000000	0.000000
62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	0.000000
67	0.000000	0.000000
68	0.000000	0.000000
69	0.000000	-18472.52
70	23.26667	0.000000
71	30.20000	0.000000
72	33.66667	0.000000
73	30.77778	0.000000
74	33.66667	0.000000
75	36.37500	0.000000
76	27.88889	0.000000
77	25.00000	0.000000
78	79.73333	0.000000
79	72.80000	0.000000
80	69.33333	0.000000
81	72.22222	0.000000

82	69.33333	0.000000
83	66.62500	0.000000
84	75.11111	0.000000
85	78.00000	0.000000

Table 11 Overtime allowance 25%

```
Local optimal solution found.
Objective value:                              3911936.
Objective bound:                              3911936.
Infeasibilities:                              0.000000
Extended solver steps:                              32
Total solver iterations:                          6534
Elapsed runtime seconds:                          0.62

Model Class:                                     MINLP

Total variables:                     36
Nonlinear variables:                 21
Integer variables:                    8

Total constraints:                   78
Nonlinear constraints:               13

Total nonzeros:                     178
Nonlinear nonzeros:                  29


                              Variable           Value        Reduced Cost
                             NUMBER_OR        7.000000            0.000000
                            DAYOPEN_OR        5.000000            0.000000
                        OR_BLOCK_HOURS        8.000000            0.000000
                            NUMBER_ICU        20.00000            0.000000
                           DAYOPEN_ICU        7.000000            0.000000
                    ICU_HOURS_OPERATE         24.00000            0.000000
                            NUMBER_MCU        35.00000            0.000000
                           DAYOPEN_MCU        7.000000            0.000000
                    MCU_HOURS_OPERATE         24.00000            0.000000
                          NUMBER_NURSE        60.00000            0.000000
                         WORKING_SHIFT        3.000000            0.000000
                           HOURINSHIFT        8.000000            0.000000
                      DAYWORK_ICUNURSE        7.000000            0.000000
                             WEIGHT_WL        1.000000            0.000000
                             WEIGHT_OT        1.000000            0.000000
                              OCOST_OR        350.0000            0.000000
                             OCOST_ICU        20.00000            0.000000
                             OCOST_MCU        5.000000            0.000000
                           OCOST_NURSE        4.000000            0.000000
                     DAILY_BLOCKSUPPLY        7.000000            0.000000
                  WEEKLY_ORBLOCKSUPPLY        35.00000            0.000000
                             ICUSUPPLY        3360.000            0.000000
                             MCUSUPPLY        5880.000            0.000000
                        NURSETIMESUPPY        1120.000            0.000000
                     DEMAND_WEEKLY_TPT        98.00000            0.000000
                   TOTAL_PATIENTS_ALLDEP      5096.000            0.000000
                                  OICU        629.4000            0.000000
                                  OMCU        1056.000            0.000000
                                   OOR        5.000000            0.000000
                                ONURSE        241.1333            0.000000
                  AVERAGE_CLEARINGTIME        30.70799            0.000000
                    TOTALBLOCK_ASSIGN         40.00000            0.000000
                        TOTAL_ICU_TIME        3989.400            0.000000
                    TOTAL_MCUDOWN_TIME        5628.000            0.000000
                      TOTAL_MCUUP_TIME        1308.000            0.000000
                  TOTAL_ICU_NURSE_TIME        1361.133            0.000000
                        OR_UTILIZATION        114.2857            0.000000
                       ICU_UTILIZATION        118.7321            0.000000
                       MCU_UTILIZATION        117.9592            0.000000
                    ONURSE_UTILIZATION        121.5298            0.000000
                TOTAL_PATIENTS_ASSIGNED       169.0000            0.000000
                    TOTAL_WAITING_COST        3279888.            0.000000
                        TOTAL_OOR_COST        53738.98            0.000000
                       TOTAL_OICU_COST        386552.1            0.000000
                       TOTAL_OMCU_COST        162138.2            0.000000
```

TOTAL_ONURSE_NURSE	29618.88	0.000000
WAITCOST(ENT)	10.00000	0.000000
WAITCOST(OBG)	17.00000	0.000000
WAITCOST(URO)	6.000000	0.000000
WAITCOST(GEN)	16.00000	0.000000
WAITCOST(VAS)	45.00000	0.000000
WAITCOST(ORT)	22.00000	0.000000
WAITCOST(NEU)	50.00000	0.000000
WAITCOST(CAR)	55.00000	0.000000
WEEKLY_DEMAND(ENT)	21.00000	0.000000
WEEKLY_DEMAND(OBG)	9.000000	0.000000
WEEKLY_DEMAND(URO)	8.000000	0.000000
WEEKLY_DEMAND(GEN)	22.00000	0.000000
WEEKLY_DEMAND(VAS)	8.000000	0.000000
WEEKLY_DEMAND(ORT)	23.00000	0.000000
WEEKLY_DEMAND(NEU)	5.000000	0.000000
WEEKLY_DEMAND(CAR)	2.000000	0.000000
WAITING_LIST(ENT)	1092.000	0.000000
WAITING_LIST(OBG)	468.0000	0.000000
WAITING_LIST(URO)	416.0000	0.000000
WAITING_LIST(GEN)	1144.000	0.000000
WAITING_LIST(VAS)	416.0000	0.000000
WAITING_LIST(ORT)	1196.000	0.000000
WAITING_LIST(NEU)	260.0000	0.000000
WAITING_LIST(CAR)	104.0000	0.000000
EFFICIENCY(ENT)	5.000000	0.000000
EFFICIENCY(OBG)	5.000000	0.000000
EFFICIENCY(URO)	6.000000	0.000000
EFFICIENCY(GEN)	4.000000	0.000000
EFFICIENCY(VAS)	4.000000	0.000000
EFFICIENCY(ORT)	4.000000	0.000000
EFFICIENCY(NEU)	3.000000	0.000000
EFFICIENCY(CAR)	2.000000	0.000000
SURGERY_DUR(ENT)	1.233000	0.000000
SURGERY_DUR(OBG)	1.433000	0.000000
SURGERY_DUR(URO)	1.060000	0.000000
SURGERY_DUR(GEN)	1.550000	0.000000
SURGERY_DUR(VAS)	2.000000	0.000000
SURGERY_DUR(ORT)	1.780000	0.000000
SURGERY_DUR(NEU)	2.670000	0.000000
SURGERY_DUR(CAR)	4.000000	0.000000
REQICUDOWN(ENT)	3.000000	0.000000
REQICUDOWN(OBG)	24.00000	0.000000
REQICUDOWN(URO)	19.20000	0.000000
REQICUDOWN(GEN)	15.00000	0.000000
REQICUDOWN(VAS)	48.00000	0.000000
REQICUDOWN(ORT)	36.00000	0.000000
REQICUDOWN(NEU)	72.00000	0.000000
REQICUDOWN(CAR)	72.00000	0.000000
REQMCUDOWN(ENT)	24.00000	0.000000
REQMCUDOWN(OBG)	12.00000	0.000000
REQMCUDOWN(URO)	24.00000	0.000000
REQMCUDOWN(GEN)	24.00000	0.000000
REQMCUDOWN(VAS)	72.00000	0.000000
REQMCUDOWN(ORT)	48.00000	0.000000
REQMCUDOWN(NEU)	48.00000	0.000000
REQMCUDOWN(CAR)	72.00000	0.000000
REQMCUUP(ENT)	0.000000	0.000000
REQMCUUP(OBG)	12.00000	0.000000
REQMCUUP(URO)	12.00000	0.000000
REQMCUUP(GEN)	0.000000	0.000000
REQMCUUP(VAS)	24.00000	0.000000
REQMCUUP(ORT)	12.00000	0.000000
REQMCUUP(NEU)	24.00000	0.000000
REQMCUUP(CAR)	24.00000	0.000000
MIN_WEEKLYASSIGN(ENT)	1.000000	0.000000
MIN_WEEKLYASSIGN(OBG)	1.000000	0.000000
MIN_WEEKLYASSIGN(URO)	1.000000	0.000000

```
 MIN_WEEKLYASSIGN( GEN)        1.000000          0.000000
 MIN_WEEKLYASSIGN( VAS)        1.000000          0.000000
 MIN_WEEKLYASSIGN( ORT)        1.000000          0.000000
 MIN_WEEKLYASSIGN( NEU)        1.000000          0.000000
 MIN_WEEKLYASSIGN( CAR)        1.000000          0.000000
 MAX_WEEKLYASSIGN( ENT)        28.00000          0.000000
 MAX_WEEKLYASSIGN( OBG)        28.00000          0.000000
 MAX_WEEKLYASSIGN( URO)        28.00000          0.000000
 MAX_WEEKLYASSIGN( GEN)        28.00000          0.000000
 MAX_WEEKLYASSIGN( VAS)        28.00000          0.000000
 MAX_WEEKLYASSIGN( ORT)        28.00000          0.000000
 MAX_WEEKLYASSIGN( NEU)        28.00000          0.000000
 MAX_WEEKLYASSIGN( CAR)        28.00000          0.000000
     REQNURSETIME( ENT)        3.000000          0.000000
     REQNURSETIME( OBG)        24.00000          0.000000
     REQNURSETIME( URO)        19.20000          0.000000
     REQNURSETIME( GEN)        15.00000          0.000000
     REQNURSETIME( VAS)        84.00000          0.000000
     REQNURSETIME( ORT)        36.00000          0.000000
     REQNURSETIME( NEU)        46.00000          0.000000
     REQNURSETIME( CAR)        46.00000          0.000000
       LOWER_TIME( ENT)        1.000000          0.000000
       LOWER_TIME( OBG)        1.000000          0.000000
       LOWER_TIME( URO)        1.000000          0.000000
       LOWER_TIME( GEN)        1.000000          0.000000
       LOWER_TIME( VAS)        1.000000          0.000000
       LOWER_TIME( ORT)        1.000000          0.000000
       LOWER_TIME( NEU)        1.000000          0.000000
       LOWER_TIME( CAR)        1.000000          0.000000
       UPPER_TIME( ENT)        104.0000          0.000000
       UPPER_TIME( OBG)        104.0000          0.000000
       UPPER_TIME( URO)        104.0000          0.000000
       UPPER_TIME( GEN)        104.0000          0.000000
       UPPER_TIME( VAS)        104.0000          0.000000
       UPPER_TIME( ORT)        104.0000          0.000000
       UPPER_TIME( NEU)        104.0000          0.000000
       UPPER_TIME( CAR)        104.0000          0.000000
           ASSIGN( ENT)        9.000000          2618.511
           ASSIGN( OBG)        3.000000         -1714.561
           ASSIGN( URO)        2.000000          31520.83
           ASSIGN( GEN)        10.00000          5086.155
           ASSIGN( VAS)        3.000000         -44667.15
           ASSIGN( ORT)        8.000000          6986.049
           ASSIGN( NEU)        3.000000          32260.67
           ASSIGN( CAR)        2.000000          24626.62
    TIMEELIMINATE( ENT)        24.26667          0.000000
    TIMEELIMINATE( OBG)        31.20000          0.000000
    TIMEELIMINATE( URO)        34.66667          0.000000
    TIMEELIMINATE( GEN)        28.60000          0.000000
    TIMEELIMINATE( VAS)        34.66667          0.000000
    TIMEELIMINATE( ORT)        37.37500          0.000000
    TIMEELIMINATE( NEU)        28.88889          0.000000
    TIMEELIMINATE( CAR)        26.00000          0.000000

                   Row    Slack or Surplus      Dual Price
                     1        0.000000          0.000000
                     2        0.000000          10747.80
                     3        0.000000          614.1598
                     4        0.000000          153.5399
                     5        0.000000          122.8320
                     6        0.000000          0.000000
                     7        0.000000          0.000000
                     8        3911936.         -1.000000
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                    11        8.000000          0.000000
                    12        2.000000          0.000000
                    13        1.000000          0.000000
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46	4.000000	0.000000
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53	0.000000	-701.9208
54	0.000000	-422.4015
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56	0.000000	-1774.401
57	0.000000	-902.6506
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62	0.000000	0.000000
63	0.000000	0.000000
64	0.000000	0.000000
65	0.000000	0.000000
66	0.000000	0.000000
67	0.000000	0.000000
68	0.000000	0.000000
69	0.000000	-20582.52
70	23.26667	0.000000
71	30.20000	0.000000
72	33.66667	0.000000
73	27.60000	0.000000
74	33.66667	0.000000
75	36.37500	0.000000
76	27.88889	0.000000
77	25.00000	0.000000
78	79.73333	0.000000
79	72.80000	0.000000
80	69.33333	0.000000
81	75.40000	0.000000

82	69.33333	0.000000
83	66.62500	0.000000
84	75.11111	0.000000
85	78.00000	0.000000

APPENDIX II

LIST OF PUBLICATIONS

1. Jittamai, P.; Toek, S.; Phengarree, K.; Kongkanjana, K.; Chanlawong, N. Multi-Criteria Decision-Making for Assessing and Evaluating Health and Wellness Tourism Destination Potential Using the 6AsTD Framework: A Case Study of Nakhon Ratchasima Province, Thailand. Sustainability 2025, 17, 4995. https://doi.org/10.3390/su17114995

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Article

Multi-Criteria Decision-Making for Assessing and Evaluating Health and Wellness Tourism Destination Potential Using the 6AsTD Framework: A Case Study of Nakhon Ratchasima Province, Thailand

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Abstract: Health and wellness tourism is a rapidly expanding segment of the global tourism industry, driven by increasing consumer awareness of well-being and lifestyle enhancement. As the demand for wellness travel grows, destinations are expected to offer high standards of safety, hygiene, rehabilitation, and holistic experiences. This study aims to identify and evaluate the key attributes and determinants for developing health and wellness tourism destinations by applying the 6As Tourism Development framework: Attractions, Accessibility, Amenities, Activities, Available Packages, and Ancillary Services. A multi-criteria decision-making approach, specifically the TOPSIS, was employed to assess destination potential through a case study of Nakhon Ratchasima Province, Thailand. The results indicate that Attractions, Accessibility, and Amenities are the top three priorities for wellness tourists. Sub-criteria such as natural scenery, cultural significance, accessibility for all, safety, and accommodation quality are particularly influential. Three districts in Nakhon Ratchasima were found to exhibit distinct strengths—Pak Chong is best suited for rehabilitative tourism (e.g., aroma and water therapy), aligning with mind and nutrition wellness components; Wang Nam Khiao is ideal for ecotourism and cultural experiences, supporting environmental and nutritional dimensions; while Mueang Nakhon Ratchasima excels in sports tourism, supporting physical and nutritional well-being. The study offers practical insights for policymakers and tourism stakeholders to design sustainable, visitor-centered wellness destinations. The proposed framework supports strategic planning and resource allocation for health-focused tourism development.

Keywords: health and wellness tourism (HWT); multi-criteria decision-making (MCDM); 6As tourism destination (6AsTD); TOPSIS

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1. Introduction

The diversification of global tourism in recent decades has given rise to specialized forms of travel, among which health and wellness tourism (HWT) has gained increasing prominence. This form of tourism promotes physical, mental, and spiritual well-being through various types of travel experiences and the combination of traditional travel experiences with health-oriented activities [1]. According to the Global Wellness Economy Monitor [2], the wellness economy reached an unprecedented $6.3 trillion in 2023, with projections estimating growth to nearly $9.0 trillion by 2028. HWT not only benefits the tourism industry but also stimulates various other industries, such as transportation, food, accommodation, entertainment, etc. [3]. It could be seen that wellness tourism is a large umbrella that potentially includes various business sectors, including culture and food exploration, nature expenditure, fitness activities, spas, yoga, and meditation. For example, the food industry could become healthy food services, and sightseeing activities in natural scenery could become sport trips [4].

HWT encompasses a wide range of activities, not only spa and yoga sessions but also unique cultural traditions, historical sites, traditional and healthy foods, and natural resources such as hot springs and mountains [5]. The form of health and wellness treatment promoted for tourists in each country tends to be different, depending on the destination, local resources, or social circumstances of the destination. For example, natural health practices, including homeopathy, are most prevalent in the United States, Europe, the Middle East, Australia, New Zealand, and various South Pacific nations. According to the Global Wellness Institute [6], in Southeast Asian countries, the focus is on healing that ties spirituality and alternative therapies by promoting activities that improve well-being through the surrounding environment. In addition, it is worth noting that Western travelers are increasingly drawn to Eastern philosophies and therapies available in various Asian countries, including shiatsu and onsen (hot springs) in Japan acupuncture, reflexology, tui na, and tai chi in China, Ayurvedic practices in India, and traditional Thai massage in Thailand [7]. In addition to the availability of diverse philosophies and therapies, the affordability of health and wellness treatments in Asian countries is a significant factor motivating Western tourists to visit the region. Consequently, Asia has emerged as a global leader in HWT, leading to intense competition among Asian countries.

Hekmat et al. [8] demonstrated that an increasing number of consumers perceive HWT tourism as a holistic experience. This perspective emphasizes not only the significance of products directly associated with health and wellness treatments but also the importance of leisure activities, safety and hygiene, accessibility, recreation, and cultural experiences. For these reasons, to stay competitive and attract tourists, understanding the core attributes and determinants of health and wellness destinations from the tourists' perspective is crucial for developing sustainable and successful HWT destinations [9,10]. The competitiveness of a wellness tourism destination means the readiness of an area to facilitate the development, improvement, or changes, and the appeal of that area to attract wellness tourists [11].

In this context, there is a need to identify the attributes and determinants that are most important for tourists when selecting destinations. Based on this premise, many researchers, policymakers, and practitioners consider the significance of destination competitiveness and its attributes' effects in planning and developing a tourism destination [12].

Hence, this study aims to develop a framework for assessing and evaluating health and wellness tourism destinations. This study leverages the 6As tourism destination development framework (6AsDT) from Buhalis [13] and Buhalis and Amaranggana [14]—comprising Attractions, Accessibility, Amenities, Activities, Available Packages, and Ancillary Services—to examine the key attributes and determinants that shape service quality and visitor satisfaction.

Based on an identified set of attributes and determinants of HWT destinations, the study proposed a framework for assessing and evaluating the HWT destinations based on identified attributes and determinants using a Multi-Criteria Decision-Making (MCDM) approach, specifically the TOPSIS. A case study of Nakhon Ratchasima, Thailand, is conducted to verify and validate the attributes and determinants, offering empirical insights into health and wellness destination development and assessment.

This paper is structured into five main sections. Section 1 presents the study's background and introduction. Section 2 reviews existing literature on health and wellness tourism, along with methodologies for assessing and identifying the potential of tourism destinations. Section 3 outlines the methodology employed in this study. First, a literature review and expert interviews helped identify attributes and determinants within the 6AsTD. Second, a mean-based thresholding technique was used to filter unnecessary attributes and determinants. Third, a weighting method prioritized these sub-criteria. Finally, the TOPSIS method was applied to rank tourism activities across districts. Section 4 explores the implications of the study's findings. Section 5 summarizes the study's conclusions, encapsulating the core insights and implications of the research.

2. Literature Review

2.1. Health and Wellness Tourism (HWT)

Health and Wellness Tourism (HWT) encompasses travel experiences focused on improving or maintaining physical, mental, and spiritual well-being through a range of holistic activities. It frequently intersects with other forms of niche tourism, such as cultural, culinary, and eco-tourism, offering a comprehensive approach to well-being. This industry drives economic growth by creating jobs, supporting local products, and empowering women. It also connects to health practices, helping to revive traditional wellness methods and improve mental health. In addition, HWT helps protect natural and cultural heritage, supports the environment, and promotes sustainable tourism [3].

In general, HWT is classified into two main types: Health Promotion Tourism, which emphasizes preventive health practices in natural and cultural environments, and Health Healing Tourism, which is centered on medical treatments and rehabilitation efforts. According to Liao et al. [15], the health benefits of wellness tourism can be classified into four main areas: physical fitness, mental well-being, quality of life, and environmental health.

Existing research divides HWT into two main fields: medical and well-being tourism. The medical aspect focuses on illness, surgery, and therapeutic treatments within biological research, while the well-being aspect takes a broader approach, emphasizing the balance of mind, body, spirit, environment, and overall quality of life [16].

Majeed and Gon Kim [17] further categorize HWT based on the health conditions of the tourists into two groups: those with non-critical disease conditions and those with critical health conditions. Tourists with non-critical health conditions often seek conventional medical treatments or alternative therapies like yoga, meditation, massage, and wellness check-ups in health resorts, temples, or natural environments.

Conversely, wellness tourists with serious health conditions, such as those receiving cancer treatment, can benefit from a blend of conventional medical care and complementary health therapies. These travelers often engage in therapeutic activities, including spending time in natural settings or participating in gentle exercises like walking or breathing techniques. Hartwell et al. [16] highlighted three essential areas of wellness tourism research: destinations focused on health and well-being, the influence of tourism on the health of local communities, and its impact on the well-being of tourists. More recently, Kongtaveesawas et al. [18] highlighted that HWT experiences involve physical activities aimed at enhancing both physical and mental health. Their study also emphasized environmental concerns, which align with the widely accepted PMSE wellness tourism experience framework, covering physical, mental, spiritual, and environmental aspects.

Nonetheless, the perceived values and expectations from the destinations of customers are varied and different experience concepts in terms of cultural diversification. Hence, understanding the general attributes and determinants of health and wellness destinations is crucial for developing sustainable and successful destinations.

2.2. Health and Wellness Tourism (HWT) in Thailand

The tourism industry is a crucial driver of Thailand's economy, contributing significantly to both domestic and international markets. In recent years, Thailand has experienced steady growth in its tourism sector, marked by a consistent rise in international tourist arrivals and an increase in average spending per trip, with an annual growth rate of approximately 2%. Thailand remains a popular destination for tourists from developed countries due to its relatively low costs [19]. In 2018 alone, the country generated nearly USD 3.5 billion in tourism revenue. Wellness services contribute around 3% of Thailand's GDP, with 90% of this figure derived from the beauty, anti-aging, and preventive medicine sectors, while the remaining 10% comes from spa treatment businesses [20]. To stay competitive in the global tourism market, Thailand has increasingly focused on developing high-value products and services, particularly in the HWT sector. This niche market has gained momentum as global awareness of health and well-being continues to grow. The demand for holistic health practices, such as yoga, meditation, and traditional healing methods, has risen significantly, further highlighting the potential of HWT. According to the Global Wellness Economy Monitor [21], Thailand ranks fourth in the Asia-Pacific region for its wellness tourism market size. Csirmaz and Pető [22] noted that many countries in the region have rich resources and traditions that can be incorporated into health and wellness tourism. Examples include the Japanese and Korean bath cultures, Indonesian body treatments, Thai massage techniques, and the Southeast Asian cosmetic industry. Acknowledging this potential, HWT has become a key focus of Thailand's national development strategies, including the 20-year National Strategic Plan (2018–2037) and the Bio-Circular-Green (BCG) economic model. These strategies highlight the significance of HWT in increasing national revenue and enhancing service quality to align with international standards.

In Thailand, HWT is a thriving alternative tourism sector, integrating the country's natural resources, cultural heritage, and health traditions to promote overall well-being. Popular HWT programs include Traditional Thai Medicine Tours, which showcase traditional Thai massage techniques at landmarks like Wat Pho, and Herbal Cuisine Tours, where tourists explore herbal wisdom through culinary experiences and participate in yoga and meditation. Additionally, Rural Herbal Medicine Tours allow travelers to learn from local herbalists, while Natural Agriculture Tours offer insights into sustainable farming practices, such as growing chemical-free vegetables, based on the King Rama IX sufficiency economy philosophy. According to Kongtaveesawas et al. [18], the characteristics of HWT in Thailand consist of four main key characteristics, namely, Physical Attributes: Activities like spa treatments and detox programs that enhance physical health; Mental Attributes: Experiences that promote mental well-being, such as mindfulness and relaxation techniques; Spiritual Attributes: Opportunities for spiritual growth, including meditation and cultural practices; Environmental Attributes: The importance of the destination's atmosphere, including hygiene and local culture. Other wellness experiences in Thailand include Hot Spring and Mineral Bath Tours, which offer relaxation at natural hot spring resorts, and Meditation and Spiritual Retreats, which provide guided meditation sessions in serene monasteries. For those seeking to connect with nature, Nature and Biodiversity Tours invite travelers to national parks and forests, where activities like hiking and herbal foraging are combined with wellness services [23]. These diverse offerings emphasize Thailand's commitment to integrating natural, cultural, and health-focused elements, promoting holistic well-being for travelers. The growing appeal of HWT brings significant economic, social, and environmental benefits to destinations, attracting a broad range of travelers and contributing to sustainable tourism development.

2.3. Tourism Destination Development: The 6AsTD Framework and Multi-Criteria Decision-Making (MCDM)

2.3.1. The 6AsTD Framework in Tourism Destination Development

The 6AsTD framework is a widely used model for evaluating tourism destinations, focusing on six critical components: Attractions, Accessibility, Amenities, Available Packages, Activities, and Ancillary Services [13,14]. Each component consists of several sub-criteria that contribute to a destination's success, offering a holistic perspective from the tourist's viewpoint. Numerous studies have adopted the 6AsTD framework to guide strategic planning and resource allocation.

Based on the review literature on the 6AsTD framework, the criteria and sub-criteria of the six key components of the 6AsTD framework are defined as follows: Attractions (A1): This component focuses on features that draw visitors to the destination, such as natural landscapes (A11), artificial tourism sites (A12), cultural attractions (A13), and special events (A14). Accessibility (A2): This evaluates how easy it is for tourists to access the destination, considering transportation routes (A21), terminals (A22), and both internal (A23) and external (A24) public transportation options. Amenities (A3): Amenities include necessary facilities such as lodging (A31), restaurants (A32), public utilities (A33), and shopping centers (A34), ensuring tourist comfort. Available Packages (A4): The availability and variety of tour packages, such as guided tours (A41), organized packages (A42), and special interest tours (A43), contribute to the destination's appeal. Activities (A5): This component assesses the range of activities, from sightseeing to adventure sports and cultural experiences, that engage tourists during their visit. Ancillary Services (A6): Supporting services such as communication channels (A61), internet access (A62), financial services (A63), medical services (A64), and postal services (A65) are crucial for enhancing the tourist experience [24–30].

2.3.2. Multi-Criteria Decision-Making (MCDM) in Tourism Studies

Decision-making in tourism often involves evaluating multiple, sometimes conflicting, criteria. MCDM techniques provide systematic and robust tools for comparing alternatives based on various qualitative and quantitative factors. Several studies have applied the 6AsTD framework in conjunction with MCDM techniques. For example, Arif et al. [24] combined the 6AsTD framework with the TOPSIS method to prioritize tourism destinations based on the destination's attributes, providing a comprehensive analysis of tourism potential. In another study, Arif et al. [25] integrated the 6AsTD framework with blockchain technology to rate tourism destinations using data collected from tourists, enabling more accurate and decentralized destination evaluations. Arif et al. [26] applied the 6AsTD framework to develop a Multi-Criteria Recommender System (MCRS), which utilizes rating values between users to provide recommendations for selecting tourist destinations. Similarly, Agustan et al. [27] employed the 6AsTD framework with TOPSIS to assess local governments' priorities for destination development in Wakatobi, Indonesia. The analysis highlighted the significance of each 6AsTD component in determining tourism potential. Each variable within these components was evaluated, revealing important insights into the strengths and weaknesses of the destination. Other studies have applied the pure 6As framework to different tourism contexts. Govekar et al. [28] used the framework to develop a model for smart beach management, emphasizing sustainable and innovative strategies. Additionally, Agustina Riski and Wulandari [29] applied the 6As framework to assess the educational tourism potential of Desa Coklat Bali, demonstrating its versatility across different types of destinations. Lopes and Rodríguez-López [30] conducted a study to rank wellness tourism destinations in Northern Portugal using MCDM methods, specifically the PROMETHEE and GAIA approaches. These tools assist tourism experts and planners in identifying optimal destinations. Unlike the 6AsTD framework, the study utilizes the Travel and Tourism Development Index (TTDI), which comprises five subindexes: enabling environment, tourism policy and conditions, infrastructure, tourism demand drivers, and sustainability.

Among the various MCDM methods, TOPSIS has emerged as one of the most popular approaches. TOPSIS ranks alternatives based on their distance to an ideal (best) and anti-ideal (worst) solution, making it highly suitable for tourism destination evaluation where both strengths and weaknesses must be considered simultaneously [24,27]. The selection of TOPSIS in this study is based on several reasons: It provides clear and interpretable rankings of alternatives as well as can handle multiple criteria effectively, and is computationally efficient. Moreover, TOPSIS supports quantitative integration of expert judgments, making it ideal for studies like this one that rely on stakeholders and expert inputs. Other MCDM methods, such as AHP, PROMETHEE, and GAIA, have their own merits, but they often involve more complex pairwise comparisons or assumptions not as well suited to the structure of this study. Hence, TOPSIS is selected for its simplicity, compatibility with 6AsTD, and demonstrated effectiveness in tourism-related decision-making contexts. It has been widely validated in tourism research, including applications involving the 6AsTD framework [24,27].

The 6AsTD framework has proven to be an effective tool for evaluating and developing tourism destinations, particularly when integrated with MCDM methods specifically. In the context of HWT, this study aims to identify the critical attributes and determinants within the 6AsTD essential for developing and accessing HWT destinations. Experts' insights into the tourism industry, related stakeholders, tourists, etc., gathered through a survey questionnaire, will be utilized to evaluate the sub-criteria within each primary variable of the 6AsTD framework.

3. Methodology

3.1. Study Design and Method

This study adopts an exploratory, mixed-methods design aimed at identifying, assessing, and prioritizing key attributes and determinants of HWT destinations. A case study in Nakhon Ratchasima Province is used to test the framework. The research does not involve hypothesis testing but is grounded in a systematic framework to support decision-making in HWT development.

The methodological approach integrates both qualitative and quantitative components to ensure a comprehensive evaluation. Qualitative data were obtained through expert interviews, focus group discussions, and a literature review to identify relevant criteria based on the 6AsTD framework. Quantitative data were collected through structured surveys using a Likert scale, enabling the prioritization of criteria and the evaluation of site suitability through a Multi-Criteria Decision-Making (MCDM) process. The methodology consists of four key stages as shown in Figure 1.

1. Literature Review and Expert Interviews/Assessment: A comprehensive literature review and expert interviews are conducted to identify and analyze the attributes and determinants of the Tourism Destination Framework (6AsTD), providing a basis for assessing and evaluating the potential of HWT in a given region.
2. Mean-based thresholding: A mean-based threshold is used to estimate the unnecessary attributes and determinants of 6AsTD based on the expert judgment of the Linkert scale of 1–5 (not necessary to most necessary).
3. Weighting method for attributes and determinants of 6AsTD: A weighting method is applied to prioritize the sub-criteria within the 6AsTD framework. This process involves expert judgment, statistical techniques, or a combination of both

to ensure an objective and reliable prioritization of factors influencing wellness tourism development.

4. Multi-Criteria Decision-Making (MCDM): TOPSIS is used as an MCDM approach to evaluate assessing and evaluating the suitability of HWT activities in each location. This method ranks tourism activities based on their proximity to an ideal solution, ensuring a data-driven decision-making process.

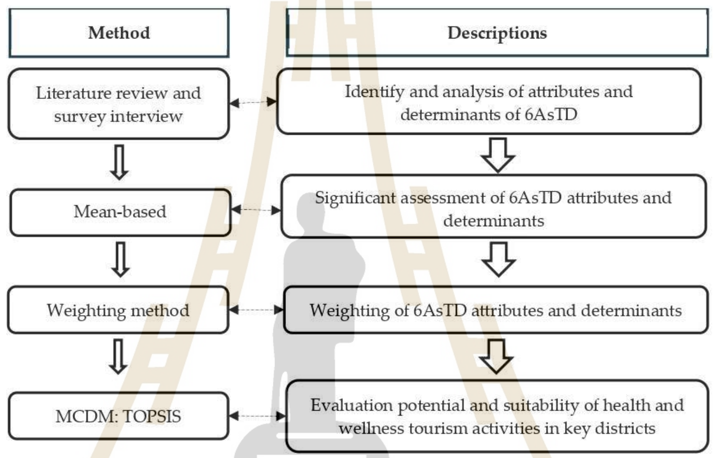
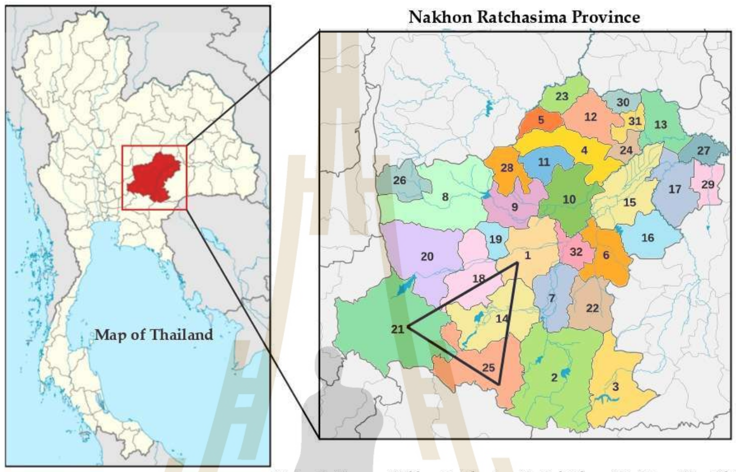


Figure 1. Research framework.

3.2. Study Area

Nakhon Ratchasima, Thailand's largest province by area and population, spans 20,493 square kilometers and houses over 2.6 million residents. Its geographical diversity, including mountainous landscapes, cultural sites, and urban centers, positions it as a strong contender for HWT development. The province already supports traditional Thai medicine, herbal food tourism, natural agriculture, hot springs, and eco-tourism, providing a strong foundation for an integrated HWT supply chain.

The study focuses on three key districts—Mueang Nakhon Ratchasima, Wang Nam Khiao, and Pak Chong—selected for their diverse HWT offerings (Figure 2). These districts represent a cross-section of the province's tourism landscape, ensuring a comprehensive assessment of the sector's potential. Each district has been chosen for its unique characteristics. These include a combination of modern urban amenities, cultural and traditional wellness practices, ecological attractions, sustainable agriculture, organic health products, and a variety of wellness-focused facilities such as resorts, hot springs, and spas. Across the districts in the province, eight HWT activities were selected and analyzed in this study, namely, Ecotourism, Cultural Tourism, Food Tourism, Culinary Tourism, Sport City, Cycling Tourism, Aroma Therapy, and Water Therapy. The selection is based on multiple factors, including tourist preferences from the survey, the region's unique characteristics, theoretical frameworks on health and wellness tourism, and the provincial policy for tourism development.



Notes: 1. Mueang Nakhon Ratchasima 21. Pak Chong 25. Wang Nam Khiao

Figure 2. Map of the study area.

3.3. Data Collected

3.3.1. Type of Data Collected

The data collection process in this study was structured to systematically assess and evaluate the potential and sustainability of HWT in Nakhon Ratchasima Province.

Primary data were collected through participatory surveys and semi-structured interviews, targeting key stakeholders such as tourism service providers, local authorities, and tourists. The interviews, conducted with HWT experts, local government representatives, and community leaders, offered qualitative insights into the internal and external factors affecting the region's tourism landscape, contributing to a deeper understanding of strategic priorities.

Secondary data were sourced through a literature review, which analyzed the sub-criteria of 6AsTD. This review, along with expert interviews and assessments, identified attributes and determinants relevant to the potential of health and wellness destinations. The literature also provided context for sustainability, wellness tourism trends, and supply chain management, ensuring a robust theoretical foundation.

3.3.2. Data Collection Procedures

The data collection process in this study was structured to systematically assess and evaluate the potential and sustainability of health and wellness tourism (HWT) in Nakhon Ratchasima Province through both qualitative and quantitative methods.

Phase 1: Criteria Identification, Elimination, and Weighting

Primary data in the initial phase was collected from two key groups using participatory surveys and structured group discussions: (1) 30 general health and wellness tourists and (2) 20 experts from tourism government agencies and academic institutions. These participants were selected using purposive sampling, based on their experience and familiarity with general tourism and HWT. Participants were first asked to identify sub-criteria under the 6As Tourism Destination (6AsTD) framework. They were guided by a list of attributes and determinants identified through a prior literature review and their own opinion. Redundant or overlapping sub-criteria were then consolidated. To refine this list, the same respondents rated the importance of each sub-criterion using a 5-point Likert scale. A simple mean threshold was applied to eliminate sub-criteria with scores below the overall mean. The resulting final set of sub-criteria was subsequently rated again using a 10-point Likert scale to determine their relative importance (weights). These weights served as inputs for the MCDM process in later stages.

Phase 2: District-Level Evaluation of Tourism Activities

In the second phase, data were collected through field-level surveys involving 50 participants in Nakhon Ratchasima province. This group included tourists, community members, HWT service providers, and local government officials. Participants were selected using a mix of purposive and randomized sampling to ensure relevant experience while avoiding sampling bias. Participants evaluated local HWT activities based on the finalized and weighted sub-criteria. Their ratings were used as input for the TOPSIS analysis, facilitating a comparative assessment of HWT development potential across the districts. Table 1 shows a summary of participants' demographics and sampling methods.

Table 1. Summary of participant demographics' and sampling methods.

Participant Group	No. of Participants	Gender (M/F)	Age Range (Years)	Occupation/ Role	Sampling Method
Group 1: Criteria Identification and Weighting					
Health and Wellness Tourists	30	14/16	25–60	General tourists with an interest in health and wellness	Purposive
Experts (Government and Academia)	20	11/9	30–65	Tourism officials, researchers, consultants	Purposive
Group 2: District-Level Evaluation					
Tourists	10	5/5	20–55	Domestic visitors	Random
Local Community Members	15	6/9	25–65	Shopkeepers, wellness providers	Random
HWT service providers	15	8/7	30–60	Spa owners, resort managers, retreat operators	Random
Local Officials	10	6/4	35–60	District tourism officers	Purposive

3.4. Multi-Criteria Decision-Making (MCDM)

MCDM is a method dealing with making a decision based on multiple criteria. It is aimed at supporting structuring, analyzing, and recommending alternative solutions to assist decision-makers in several service sectors, including the tourism industry. This study employs an MCDM method, specifically TOPSIS, to evaluate the suitability of tourism destinations and their support for HWT activities. The details of the methodology are outlined below.

3.4.1. Criteria Identification

To effectively assess the potential and suitability of a destination for health and wellness tourism, it is crucial to break down the broad categories of the 6AsTD Framework into more specific sub-criteria tailored to this niche market. The 6AsTD framework, which includes Attractions, Accessibility, Amenities, Available Packages, Activities, and Ancillary Services, serves as a comprehensive tool for evaluating tourism destinations by Buhalis [13]. However, for a focused analysis of health and wellness tourism, it is essential to identify sub-criteria that reflect the specific needs and preferences of wellness travelers.

In this study, sub-criteria are identified based on insights from existing literature, tourism expert interviews, and a focus group of wellness tourists. These sub-criteria will ensure that each dimension of the 6AsTD framework is contextualized for the health and wellness sector. By identifying these sub-criteria, this research aims to provide a more comprehensive and sector-specific application of the 6AsTD framework. The result is a set of tailored indicators that will be used to evaluate the region's potential and suitability for health and wellness activities for developing a competitive HWT offering.

3.4.2. Mean-Based Thresholding

Mean-based Thresholding, the average (mean) score or rating of each sub-criterion, C_i, is calculated based on an expert and focus group of wellness tourist evaluations S_{ij}. A predefined threshold, typically based on the average score $\overline{S_i}$ is used to determine the relevance of each sub-criterion. Sub-criteria C_i that have a mean score $\overline{S_i}$ below the threshold (T) are eliminated, as they are considered less significant. This approach helps in simplifying the decision-making process by focusing only on the most important factors. The result of this approach will be further used in the next section.

The process of Mean-based Thresholding can be outlined in a sequence of steps as follows:

(1) Mean Score Calculation:

$$\overline{S_i} = \frac{1}{m}\sum_{j=1}^{m} S_{ij}\ ;\ i = 1, 2, \ldots, n\ j = 1, 2, \ldots, m \tag{1}$$

(2) Threshold Definition:
Let T represent the **threshold value**, which is typically based on the overall average of all mean scores across sub-criteria. This can be calculated as follows:

$$T = \frac{1}{n}\sum_{i=1}^{n} \overline{S_i}\ ;\ i = 1, 2, \ldots, n \tag{2}$$

(3) Elimination of Less Important Sub-criteria:
Sub-criteria with a mean score $\overline{S_i}$ below the threshold T are considered less significant and are eliminated from further analysis. Formally, a sub-criterion C_i is eliminated if:

$$\overline{S_i} < T \tag{3}$$

Only sub-criteria C_i that satisfy $\overline{S_i} > T$ will be retained for further analysis.

(4) Final Decision-Making Model
The final set of weighted sub-criteria forms the input for the subsequent analysis. This ensures that only the most relevant sub-criteria (those with a mean score above the threshold) contribute to the decision-making process, simplifying the evaluation while focusing on key factors.

3.4.3. Criteria Scoring

Scoring function was applied to estimate each weight value of the sub-criteria. Experts were allowed to assess each value based on preference score e from 0 (extremely unimportant) to 10 (extremely important). Afterwards, the corresponding weight for each criterion i = {1, 2, . . . , n}, w_i is given by the following:

$$w_i = \frac{1}{W}\sum_{e=1}^{10} \mu_{i,e} \tag{4}$$

$$Where\ W = \sum_{i=1}^{n}\sum_{e=1}^{10} \mu_{i,e} \tag{5}$$

3.4.4. Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS)

TOPSIS is a multi-criteria decision-making method designed to identify the optimal option from a set of alternatives. The fundamental concept is to choose the alternative that is closest to the ideal solution and furthest from the worst possible option. The TOPSIS methodology involves a series of steps, as detailed by Jahanshahloo et al. [31]:

(1) Calculate the normalized decision matrix. The normalized value n_{ij} is calculated as follows:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} {x_{ij}}^2}};\ j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n \tag{6}$$

(2) Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as follows:

$$v_{ij} = w_i \times n_{ij};\ j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n \tag{7}$$

where w_i is the weight of the ith attribute or creation and criterion, and $\sum_{i=1}^{n} w_i = 1$

(3) Determine the positive ideal and negative ideal solution.

$$A^+ = \left\{v_1^+, v_1^+, \ldots\ldots, v_n^+\right\} = \left\{\left(max_j\, v_{ij} \middle| i \in I\right), \left(min_j\, v_{ij} \middle| i \in J\right)\right\} \tag{8}$$

$$A^- = \left\{v_1^-, v_1^-, \ldots\ldots, v_n^-\right\} = \left\{\left(min_j\, v_{ij} \middle| i \in I\right), \left(max_j\, v_{ij} \middle| i \in J\right)\right\} \tag{9}$$

where I is associated with benefit criteria, and J is associated with cost criteria.

(4) Calculate the separation measures using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is calculated as follows:

$$d_j^+ = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_{ij}^+\right)^2};\ j = 1, 2, \ldots\ldots\ldots\ldots\ldots m. \tag{10}$$

Similarly, the separation from the negative ideal solution is given as follows:

$$d_j^- = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_{ij}^-\right)^2};\ j = 1, 2, \ldots\ldots\ldots\ldots\ldots m. \tag{11}$$

(5) Calculate the relative closeness to the ideal solution. The relative closeness of the alternative:

$$R_j = \frac{d_j^-}{d_j^+ + d_j^-};\ i = 1, 2, \ldots\ldots, m. \tag{12}$$

Since $d_j^- \geq 0$ *and* $d_j^+ \geq 0$, *then, clearly* $R \in [0, 1]$.

(6) Rank the preference order

4. Results and Discussion

4.1. Analysis of 6AsTD Framework

4.1.1. Identified Criteria

This study employed the 6AsTD, proposed by Buhalis [13], as the foundation for evaluating the potential of locations for HWT. Each of the components represents a key dimension in determining the suitability of a destination for health- and wellness-oriented experiences. To identify specific sub-criteria under each component, a multi-method approach was applied, combining an extensive literature review, expert interviews, tourist surveys, and internal brainstorming discussions within the research team. This approach ensured both theoretical depth and practical relevance.

The literature review drew on various academic sources, including the works of [18,24–30,32,33], which provided valuable insights into the essential elements influencing HWT destinations. These were further refined through in-depth discussions with tourism professionals and feedback from tourists, which helped validate the real-world applicability of the identified criteria. Brainstorming sessions among the research team also contributed to shaping and finalizing the list of sub-criteria.

As a result, a total of 39 attributes and determinants were identified and categorized under the six components of the 6AsTD framework. Within the Attractions component, five sub-criteria were determined, namely natural scenery or environment, cultural significance, health and wellness appeal, uniqueness of experience, and the presence of artificial tourism sites. Under Accessibility, six key sub-criteria were recognized, which include proximity to public transport hubs, quality of infrastructure, availability of transportation, accessibility for all users, ease of accessing information, and convenience in booking. The Amenities category also comprised six sub-criteria: availability of accommodation options such as resorts or hotels, dining and nutrition services, recreational facilities including sauna and steam rooms, safety and hygiene standards, opportunities for health-related shopping, and access to fitness facilities and public parks. In the case of Available Packages, seven sub-criteria were synthesized. These include a variety of wellness-focused packages, the possibility of customization, cost-effectiveness, appropriate duration, such as weekend or two-day packages, comprehensiveness of health packages, availability of coaching or expert-led programs, and the inclusion of group-based activities like aerobic dance. Similarly, seven sub-criteria were identified for the Activities component, including physical wellness activities such as sports or yoga, the level of engagement they offer, innovativeness such as plastic surgery options, special events with knowledge-sharing or storytelling elements, natural therapy activities like forest bathing or health-oriented hiking, mental therapy programs, and nutrition-focused activities. Lastly, the Ancillary Services component comprised eight sub-criteria, which cover health and wellness support services, the availability of local guides and experts, medical services, complementary services, financial services such as ATMs and banks, postal services, internet access including free Wi-Fi, and communication infrastructure such as mobile signal availability.

Altogether, these 39 sub-criteria offer a comprehensive assessment tool for determining the critical attributes and determinants for identifying the region's potential in supporting HWT initiatives. They form a solid foundation for subsequent stages of analysis and decision-making in destination planning and development. Table 2 presents a detailed summary of these attributes and determinants categorized under each of the six components of the 6AsTD framework.

Table 2. Summarizes the attributes and determinants for each of the 6AsTD.

Main Criteria	Sub-Criteria
Attractions:	Natural Scenery/Environment
	Cultural Significance
	Health and Wellness Appeal
	Uniqueness of Experience
	Artificial tourism sites
Accessibility:	Proximity to Public Transport Hubs
	Quality of Infrastructure
	Availability of Transportation
	Accessibility for All
	Accessibility for information
	Easily for booking
Amenities:	Accommodation Options (resort/hotel)
	Dining and Nutrition
	Recreational Facilities (sauna/stream)
	Safety and Hygiene
	Health-related Shopping
	Fitness and public park
Available Packages:	Variety of Packages (wellness activities)
	Customization Options
	Cost-Effectiveness
	Duration (e.g., 2 days package)
	Comprehensive Health Package
	Health Programs with Coaching/Experts
	Group packages (Aerobic dance)
Activities:	Physical Wellness activities (Sport/Yoga)
	Engagement Level
	Innovativeness (plastic surgery etc.)
	Special events (Knowledge/storytelling)
	Natural Therapy Activities (Forest Bathing, Health-Oriented Hiking, etc.)
	Mental therapy
	Nutritional Activities
Ancillary Services:	Health and Wellness Support
	Local Guides and Experts
	Medical Services
	Complementary Services
	Financial services (ATM/bank)
	Postal services
	Internet access (free WI-FI)
	Communication channels (signal call)

4.1.2. Thresholding Results

Following the identification of relevant attributes and determinants within the 6AsTD framework, a mean-based thresholding technique was employed to refine the list of sub-criteria. This process aimed to eliminate elements deemed less significant based on perceptions of two focused respondent groups: health and wellness tourists and experts.

Participants were asked to evaluate each of the 39 sub-criteria using a five-point Likert scale, where a score of 1 represented "not necessary", and a score of 5 indicated "most necessary". The mean score for each sub-criterion was calculated. A threshold value of T = 3.19 was established to differentiate between significant and insignificant sub-criteria. Any sub-criterion with a mean score below this threshold was excluded from further consideration.

For instance, the sub-criterion "Artificial Tourism Sites" received an average score of 1.50 and was subsequently eliminated. In total, 15 sub-criteria were excluded from the analysis, resulting in a more concise and focused list of sub-criteria that better reflects stakeholder priorities. These retained sub-criteria are aligned with the six components of the 6AsTD framework and are considered suitable for further weight methods. Table 3 presents the evaluation results, including mean scores, threshold comparison, and the final decision regarding each sub-criterion. The remaining sub-criteria to be used in the next analytical phase are illustrated in Figure 3.

Table 3. Mean-based threshold sub-criteria elimination.

Main Criteria	Sub-Criteria	Mean $\overline{S_i}$	Threshold T	Result
Attractions:	Natural Scenery/Environment	4.62	3.19	Retained
	Cultural Significance	3.52	3.19	Retained
	Health and Wellness Appeal	4.4	3.19	Retained
	Uniqueness of Experience	4.34	3.19	Retained
	Artificial tourism sites	1.5	3.19	Eliminated
Accessibility:	Proximity to Public Transport Hubs	1.82	3.19	Eliminated
	Quality of Infrastructure	3.58	3.19	Retained
	Availability of Transportation	4.46	3.19	Retained
	Accessibility for All	4.44	3.19	Retained
	Accessibility for information	3.54	3.19	Retained
	Easily for booking	2.18	3.19	Eliminated
Amenities:	Accommodation Options (resort/hotel)	4.44	3.19	Retained
	Dining and Nutrition	3.5	3.19	Retained
	Recreational Facilities (sauna/stream)	3.54	3.19	Retained
	Safety and Hygiene	4.54	3.19	Retained
	Health-related Shopping	2.12	3.19	Eliminated
	Fitness and public park	1.98	3.19	Eliminated
Available Packages:	Variety of Packages (wellness activities)	3.36	3.19	Retained
	Customization Options	4.6	3.19	Retained
	Cost-Effectiveness	4.44	3.19	Retained
	Duration (e.g., 2 days package)	3.54	3.19	Retained
	Comprehensive Health Package	2	3.19	Eliminated

Table 3. *Cont.*

Main Criteria	Sub-Criteria	Mean $\overline{S_i}$	Threshold T	Result
Available Packages:	Health Programs with Coaching/Experts	2.06	3.19	Eliminated
	Group packages (Aerobic dance)	2.06	3.19	Eliminated
Activities:	Physical Wellness activities (Sport/Yoga)	3.44	3.19	Retained
	Engagement Level	4.52	3.19	Retained
	Innovativeness (plastic surgery etc.)	1.46	3.19	Eliminated
	Special events (Knowledge/storytelling)	1.56	3.19	Eliminated
	Natural Therapy Activities (Forest Bathing, Nature Therapy, Health-Oriented Hiking)	4.4	3.19	Retained
	Mental therapy	1.88	3.19	Eliminated
	Nutritional Activities	3.64	3.19	Retained
Ancillary Services:	Health and Wellness Support	4.6	3.19	Retained
	Local Guides and Experts	1.96	3.19	Eliminated
	Medical Services	4.52	3.19	Retained
	Complementary Services	1.56	3.19	Eliminated
	Financial services (ATM/bank)	1.52	3.19	Eliminated
	Postal services	1.48	3.19	Eliminated
	Internet access (free WI-FI)	3.54	3.19	Retained
	Communication channels (signal call)	3.46	3.19	Retained

4.1.3. Weighting Criteria

To systematically prioritize the various factors influencing the assessment and development of HWT destinations, a weighting methodology was applied to the attributes and determinants retained from the 6AsTD framework. This process incorporated both quantitative statistical techniques and qualitative judgments derived from two focus groups—one comprising health and wellness tourists and the other consisting of domain experts. This integration ensured a balanced and robust evaluation of the relative importance of each criterion.

Initially, participants rated each of the retained sub-criteria. These preliminary scores were subsequently refined through a statistical weighting approach, designed to reflect the relative significance of each factor. The final weights thus represent a composite measure derived from empirical participant ratings, enhancing both objectivity and reliability in the evaluation process. This method allowed for a comprehensive understanding of how each attribute and determinant contributes to the overall development of an HWT destination.

The results of the weighting analysis are presented in Table 4, which displays the relative weights assigned to each criterion. Among the six main components of the 6AsTD framework, Attractions emerged as the most influential factor, receiving the highest overall weight of 0.19808, followed by Accessibility (0.17992) and Amenities (0.16672). Conversely, Available Packages (0.13552) and Ancillary Services (0.11193) received the lowest weights, indicating their relatively lower influence in the assessment framework. At the sub-criteria level, Natural Scenery/Environment and Cultural Significance, under the Attractions category, were identified as the most critical attributes, with weights of 0.05457 and 0.05137, respectively. Within the Accessibility component, the sub-criterion Accessibility for All held considerable significance with a weight of 0.05377. In the Amenities dimension, Safety and Hygiene (0.05477) and Accommodation Options (0.05157) emerged as key priorities.

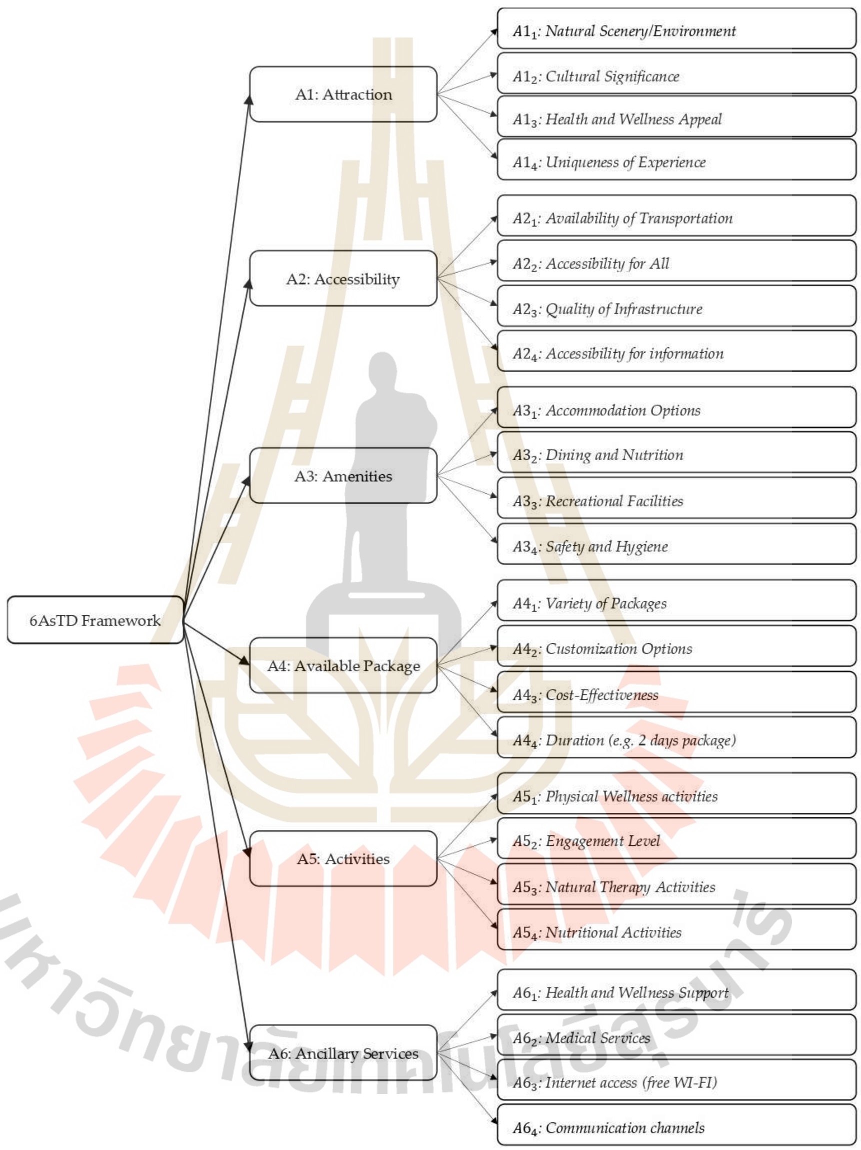


Figure 3. Final 6AsTD sub-criteria.

Table 4. Criteria scoring.

Main Criteria	Sub-Criteria	Wi	Total Sum
A1: Attraction	A11: Natural Scenery/Environment	0.05457	0.19808
	A12: Cultural Significance	0.05137	
	A13: Health and Wellness Appeal	0.04817	
	A14: Uniqueness of Experience	0.04397	
A2: Accessibility	A21: Quality of Infrastructure	0.04177	0.18589
	A22: Availability of Transportation	0.04357	
	A23: Accessibility for All	0.05377	
	A24: Accessibility for information	0.04677	
A3: Amenities	A31: Accommodation Options	0.05157	0.18989
	A32: Dining and Nutrition	0.04617	
	A33: Recreational Facilities	0.03738	
	A34: Safety and Hygiene	0.05477	
A4: Available Package	A41: Variety of Packages	0.03338	0.13552
	A42: Customization Options	0.02978	
	A43: Cost-Effectiveness	0.04657	
	A44: Duration	0.02578	
A5: Activities	A51: Physical Wellness activities	0.05137	0.17869
	A52: Engagement Level	0.04138	
	A53: Natural Therapy Activities	0.04357	
	A54: Nutritional Activities	0.04237	
A6: Ancillary Services	A61: Health and Wellness Support	0.04078	0.11193
	A62: Medical Services	0.03518	
	$A6_3$: Internet access	0.01839	
	$A6_4$: Communication channels	0.01759	

These findings are consistent with previous research [18,32,33]. For instance, Mikulić et al. [32] found that natural beauty, personal safety, quality of accommodation, and cultural tourism offerings exerted the strongest influence on wellness tourist satisfaction. The present study further corroborates these results by demonstrating the centrality of environmental quality, security, and cultural value in determining HWT destination appeal.

4.2. MCDM-TOPSIS

To further evaluate and prioritize the suitability of HWT activities across different districts in Nakhon Ratchasima Province, this study applied the TOPSIS. Using the set of weighted criteria derived from Section 4.1.3, experts were invited to assess the relative suitability of eight HWT activities across three distinct locations. These activities were evaluated based on a comprehensive set of criteria, including tourist preferences, accessibility, environmental sustainability, and development potential.

The TOPSIS method was employed to compute the Relative Closeness Coefficient (R_j) which indicates how close each activity-location alternative is to the ideal solution while maximizing its distance from the negative-ideal solution. This structured and objective approach enables decision-makers to rank the alternatives effectively, thereby supporting the identification of the most appropriate strategies for sustainable tourism development.

Pak Chong District demonstrates the highest Relative Closeness (R_j) values for activities primarily associated with therapeutic and rehabilitative health tourism. As presented in Table 5, Water Therapy (R_j = 0.01372), Aroma Therapy (R_j = 0.01439), Culinary Tourism (R_j = 0.00565), and Food Tourism (R_j = 0.00693) rank as the most suitable HWT activities in this district. The high scores of Water Therapy and Aroma Therapy, in particular, underscore Pak Chong's significant potential to serve as a wellness tourism hub, especially for activities that promote physical rehabilitation and mental rejuvenation.

Table 5. TOPSIS evaluation of health and wellness tourism activities in Pak Chong.

	Activities	D_j-	D_j+	R_j
Pak Chong	1. Ecotourism	0.001145288	0.004126516	−0.00184
	2. Cultural Tourism	0.000225765	0.007336432	−0.00688
	3. Food Tourism	0.004063259	0.001200834	0.00693
	4. Culinary Tourism	0.003547864	0.001448603	0.00565
	5. Sport City	0.000242247	0.007297193	−0.00681
	6. Cycling Tourism	0.000426958	0.006216822	−0.00536
	7. Aroma Therapy	0.007298298	0.000210557	0.01439
	8. Water Therapy	0.00698267	0.000246973	0.01372

This finding is well-aligned with the district's natural and environmental assets, such as geothermal springs, herbal plantations, and traditional spa facilities, which contribute directly to the appeal and viability of health-oriented tourism. The alignment between the district's natural characteristics and the top-ranked activities emphasizes the strategic opportunity for targeted development of health and wellness experiences in Pak Chong.

Wang Nam Khiao District displays the highest Relative Closeness (R_j) values for Ecotourism (R_j = 0.97048) and Cultural Tourism (R_j = 0.97735), followed by Culinary Tourism (R_j = 0.69367) and Food Tourism (R_j = 0.72227) as shown in Table 6. The exceptionally high scores for Ecotourism and Cultural Tourism indicate that Wang Nam Khiao is particularly well-suited for tourism development rooted in sustainability and cultural heritage. These results align with the district's rich ecological assets and well-preserved local traditions. The presence of lush natural landscapes, biodiversity, and community-led tourism initiatives provides a robust foundation for promoting ecotourism. Concurrently, the strong cultural identity of local communities supports the development of cultural tourism as a vehicle for preserving indigenous knowledge and fostering meaningful tourist engagement. Together, these factors position Wang Nam Khiao as a model destination for integrated HWT with an emphasis on environmental and cultural sustainability.

Table 6. TOPSIS evaluation of health and wellness tourism activities in Wang Nam Khiao.

	Activities	D_j-	D_j+	R_j
Wang Nam Khiao	1. Ecotourism	0.007317158	0.000222569	0.97048
	2. Cultural Tourism	0.007534903	0.000174574	0.97735
	3. Food Tourism	0.003674549	0.001412912	0.72227
	4. Culinary Tourism	0.0034606	0.001528184	0.69367
	5. Sport City	0.000287344	0.006931184	0.03980
	6. Cycling Tourism	0.00034611	0.006552783	0.05016
	7. Aroma Therapy	0.000558324	0.005125303	0.09823
	8. Water Therapy	0.000558324	0.005125303	0.09823

Mueang Nakhon Ratchasima District emerges as the most suitable location for sports and rehabilitative health tourism, particularly in activities such as Sport City (R_j = 0.95335), Cycling Tourism (R_j = 0.97112), Culinary Tourism (R_j = 0.63238), and Food Tourism (R_j = 0.71809), as detailed in Table 7. The district's established sports infrastructure, including professional-grade venues, training facilities, and extensive cycling routes, supports its capacity to host regional and international sporting events. These assets collectively position Mueang Nakhon Ratchasima as a strategic hub for sports-based wellness tourism, combining physical activity with holistic health experiences.

Table 7. TOPSIS evaluation of health and wellness tourism activities in Mueang.

	Activities	D_j-	D_j+	R_j
Mueang Nakhon Ratchasima	1. Ecotourism	0.000297666	0.006843805	0.04168
	2. Cultural Tourism	0.000257886	0.007113465	0.03498
	3. Food Tourism	0.003610517	0.0014174	0.71809
	4. Culinary Tourism	0.003081732	0.001791508	0.63238
	5. Sport City	0.006611754	0.000323538	0.95335
	6. Cycling Tourism	0.007162599	0.000213022	0.97112
	7. Aroma Therapy	0.001272773	0.003820796	0.24988
	8. Water Therapy	0.001170336	0.004106051	0.22181

The comparative ranking of high-potential wellness tourism activities across the three districts—Pak Chong, Wang Nam Khiao, and Mueang Nakhon Ratchasima—reveals distinct strengths and specialized tourism assets unique to each area. Pak Chong demonstrates comparative advantages in therapeutic and rehabilitative activities, Wang Nam Khiao excels in ecotourism and cultural tourism, while Mueang Nakhon Ratchasima leads in sports-based and active wellness, as shown in Table 8 and Figure 4.

Table 8. Attributes of health and wellness triangle of Nakhon Ratchasima Province.

EMBN Model	Mueang (B-N)	Wang Nam Khiao (E-N)	Pak Chong (M-N)
E = Environment Clean air, pollution-free		✓	
M = Mind Good mental health, relaxation from stress			✓
B = Physical Body Physical health	✓		
N = Nutrition Healthy food	✓	✓	✓

A particularly salient observation is the consistent appearance of Food Tourism and Culinary Tourism among the top four activities in all three districts. This recurring pattern suggests that food- and nutrition-based tourism may serve as a strategic linkage, enabling the formation of an integrated wellness tourism network across the province. The shared emphasis on health-conscious culinary experiences and the utilization of locally sourced ingredients presents an opportunity to unify district-level strengths into a coherent provincial tourism identity. By capitalizing on this commonality, Nakhon Ratchasima can advance a holistic and sustainable wellness tourism model that not only leverages local resources and cultural assets but also promotes regional collaboration, inclusive development, and long-term destination competitiveness. Like the four dimensions of the PMSE experience framework, namely, physical, mental, spiritual, and environmental, that holistically served as a mechanism toward wellness tourism in Thailand context [18]. The results of this study show that Nakhon Ratchasima is the capital of the HWT hub, with a key strength of the Nakhon Ratchasima area emphasizing four aspects of health and wellness tourism: environment (E), mind (M), physical body health (B), and nutrition (N).

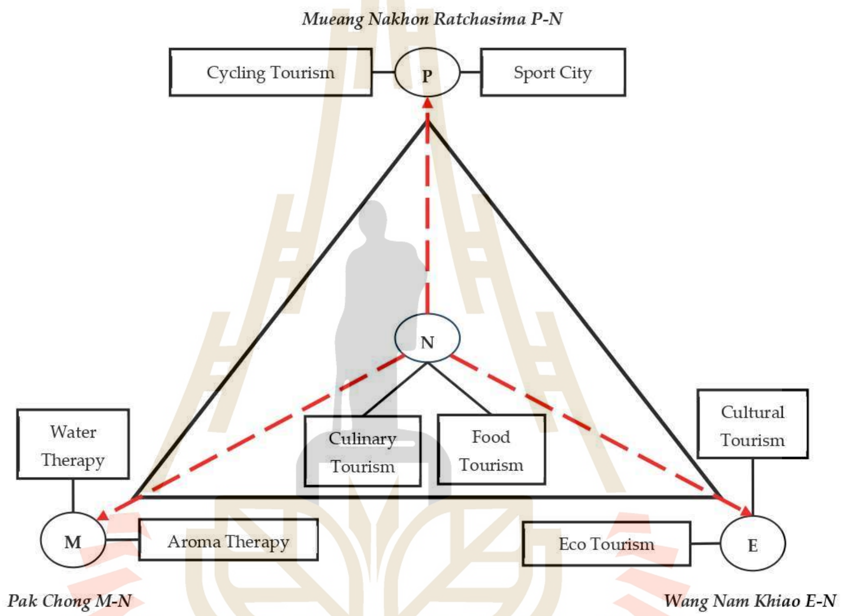


Figure 4. EMBN health and wellness attribute of Nakhon Ratchasima.

5. Conclusions

This study presents a comprehensive approach to assessing and evaluating health and wellness tourism (HWT) destination potential by integrating the 6AsTD framework with a multi-criteria decision-making (MCDM) approach, specifically the TOPSIS method. The findings are twofold. First, the study identifies and structures the key attributes and determinants influencing tourist satisfaction in HWT destinations. By adapting the general 6As tourism framework—Attractions, Accessibility, Amenities, Activities, Available Packages, and Ancillary Services—to the context of HWT, this research offers a contextualized and holistic understanding of the elements contributing to successful HWT destinations. Among the six criteria, Attractions, Accessibility, and Amenities emerged as the top priorities for HWT tourists. Within these, critical attributes and determinants such as natural scenery/environment, health and wellness appeal, universal accessibility, transportation availability, and safety and hygiene significantly influence tourist satisfaction, aligned with [32,33]. Second, the study integrates these findings into the TOPSIS evaluation model to assess and rank HWT activities and locations. This integration allows for a detailed assessment of each location's suitability for specific health and wellness activities and broader strategic positioning, while also identifying areas for improvement based on the 6AsTD framework.

Empirical results show that different districts within Nakhon Ratchasima Province exhibit distinct HWT potential, aligned with the EMBN model—Environment, Mind, Physical Body, and Nutrition. For instance, Wang Nam Khiao District excels in eco-tourism, cultural experiences, and health-focused culinary tourism, aligning with the Environment and Nutrition dimensions. Pak Chong District is recognized for its health and wellness services, such as aromatherapy, traditional Thai massage, herbal steam, and hot spring therapies, reflecting the Mind and Nutrition dimensions. Meanwhile, Mueang District focuses on physical wellness through its sports city initiative, promoting cycling, physical activity, and health-focused cuisine, thus fitting under the Physical Body and Nutrition dimensions. Additionally, the province demonstrates strong capabilities in various forms of health and wellness, supported by medical professionals, hospitals, and high-standard accommodation, positioning Nakhon Ratchasima as a competitive destination for HWT. Its affordability compared to Bangkok further enhances its appeal. By integrating eco-tourism with wellness and medical services, the province can evolve into a comprehensive HWT destination.

The study's contributions span theoretical, practical, and managerial domains: *Theoretical Contribution:* This study demonstrates that the 6AsTD framework can be effectively adapted to the HWT context, providing a solid theoretical foundation for evaluating and developing health and wellness destinations. The combination of 6AsTD and MCDM-TOPSIS offers a promising analytical framework for structured decision-making in wellness tourism development. In comparison to Kongtaveesawas et al. [18], who emphasized spiritual and environmental elements in wellness tourism development in northern Thailand, our findings highlight a stronger emphasis on physical and nutritional wellness dimensions in the Nakhon Ratchasima case, reflecting the province's distinctive policy focus and resource endowments. This contrast underscores the framework's flexibility across different regional contexts. *Practical Contribution:* The findings are valuable for stakeholders such as the Thailand Tourism Authority and regional offices (e.g., Nakhon Ratchasima Tourism Authority), as well as businesses involved in health and wellness services. They offer guidance for shaping policies and designing compelling tourism experiences. Consistent with Praprom & Laipaporn [34], the study reinforces the importance of innovating new wellness tourism services to increase attractiveness and value. It also supports the development of wellness programs reflecting holistic attributes—physical, mental, spiritual, and environmental—as emphasized by Kongtaveesawas et al. [18]. *Managerial Contribution:* The research provides practical insights for experience design and strategic destination management within the Thai context. It recommends that findings be used to guide strategic planning, particularly in positioning Nakhon Ratchasima as a multidimensional health capital through various forms of health and wellness activities. By operating the 6AsTD framework within an MCDM-TOPSIS model, the study delivers a decision-support tool that enables policy-makers, tourism planners, and local businesses to prioritize development efforts, allocate resources effectively, and tailor marketing strategies toward high-impact wellness dimensions. Effective policy development should capitalize on these strengths. Moreover, this study suggests general policy actions for HWT destination managers and firms to improve overall tourist satisfaction. Special attention should be paid to the determinants with the strongest association with perceived destination attractiveness, especially complementary services that enhance wellness experiences.

Limitations and Future Research Directions

This research is not without limitations. First, the study's sample of tourists and experts was limited to Thailand, which may restrict the generalizability of the findings. Different regions and age groups may hold differing perspectives toward HWT destinations [33]. Second, the multi-step process involving various groups in attribute identification, weighting, and evaluation may introduce biases or inconsistencies. Lastly, the evaluation of HWT activities was conducted solely by experts, omitting input from tourists and local residents, which may overlook important user-centered insights.

Future studies should consider incorporating dynamic criteria, tourist segmentation, and seasonal variations to refine destination assessment and strategic planning. As highlighted by But & Ap [35], the impact of tourism depends heavily on both traveler and destination characteristics. However, the influence of tourists' personal attributes remains underexplored, particularly since many health and wellness tourists may be coping with illness or chronic conditions. Exploring these effects can deepen our understanding of tourist behavior and destination impact. Additional research could investigate other factors not covered in this study that may influence destination choice, tourist satisfaction, and competitiveness. Exploring aspects such as personalization, wellness program pricing, and cross-border wellness mobility may yield valuable insights for both domestic and international markets.

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References

1. Pan, H.; Mi, H.; Chen, Y.; Chen, Z.; Zhou, W. Measurement and evaluation of the development level of health and wellness tourism from the perspective of high-quality development. *Sustainability* **2024**, *16*, 8082. [CrossRef]
2. Global Wellness Institute. 2024 Global Wellness Economy Monitor. Global Wellness Institute. 2024. Available online: https://globalwellnessinstitute.org/industry-research/2024-global-wellness-economy-monitor/ (accessed on 28 January 2025).
3. Andreu, M.G.; Font-Barnet, A.; Roca, M.E. Wellness tourism—New challenges and opportunities for tourism in Salou. *Sustainability* **2021**, *13*, 8246. [CrossRef]

4. Chaopreecha, J.; Tovankasame, N.; Wae-Esor, E. Tourists' Behavior and Expectations in Wellness Tourism: A Study of Phuket, Thailand. *J. Int. Stud. Prince Songkla Univ.* **2024**, *14*, 12–25. Available online: https://so03.tci-thaijo.org/index.php/jis/article/view/272331 (accessed on 20 February 2025).
5. Thojampa, S.; Klankhajhon, S.; Kumpeera, K.; Mongkholkham, C.; Ellen Mawn, B. The development of a Wellness Tourism Program in Thailand: A community-based participatory action research approach with an empowerment theoretical framework. *J. Ners* **2023**, *18*, 291–298. [CrossRef]
6. Global Wellness Institute. 2022 The Global Wellness Economy: Country Rankings. 2022. Available online: https://globalwellnessinstitute.org/industryresearch/2022-global-wellness-economy-country-rankings/ (accessed on 20 February 2025).
7. Heung, V.C.; Kucukusta, D. Wellness tourism in China: Resources, development and marketing. *Int. J. Tour. Res.* **2012**, *15*, 346–359. [CrossRef]
8. Hekmat, N.; Marques, J.A.; Quintela, J.; Ramazanova, M. Wellness tourism from consumers' perspective—An exploratory analysis. *Int. Conf. Tour. Res.* **2022**, *15*, 554–560. [CrossRef]
9. Han, H.; Kiatkawsin, K.; Jung, H.; Kim, W. The role of Wellness Spa Tourism Performance in Building Destination Loyalty: The case of Thailand. *J. Travel Tour. Mark.* **2017**, *35*, 595–610. [CrossRef]
10. Han, H.; Kiatkawsin, K.; Kim, W.; Lee, S. Investigating customer loyalty formation for wellness spa: Individualism vs. collectivism. *Int. J. Hosp. Manag.* **2017**, *67*, 11–23. [CrossRef]
11. Pathumporn, J.; Nakapaksin, S. Participatory Action Research Model for Sustainable Community Based Tourism Development. *Int. J. Bus. Adm. Stud.* **2015**, *1*, 89–93. [CrossRef]
12. Mior Shariffuddin, N.S.; Azinuddin, M.; Hanafiah, M.H.; Wan Mohd Zain, W.M. A comprehensive review of tourism destination competitiveness (TDC) literature. *Compet. Rev. Int. Bus. J.* **2022**, *33*, 787–819. [CrossRef]
13. Buhalis, D. Marketing is the competitive destination of the future. *Tour. Manag.* **2000**, *21*, 97–116. [CrossRef]
14. Buhalis, D.; Amaranggana, A. Smart tourism destinations. In Proceedings of the Information and Communication Technologies in Tourism, Dublin, Ireland, 21–24 January 2014; pp. 553–564. [CrossRef]
15. Liao, C.; Zuo, Y.; Xu, S.; Law, R.; Zhang, M. Dimensions of the health benefits of Wellness Tourism: A Review. *Front. Psychol.* **2023**, *13*, 1071578. [CrossRef] [PubMed]
16. Hartwell, H.; Fyall, A.; Willis, C.; Page, S.; Ladkin, A.; Hemingway, A. Progress in tourism and Destination Wellbeing Research. *Curr. Issues Tour.* **2016**, *21*, 1830–1892. [CrossRef]
17. Majeed, S.; Gon Kim, W. Emerging trends in wellness tourism: A scoping review. *J. Hosp. Tour. Insights* **2022**, *6*, 853–873. [CrossRef]
18. Kongtaveesawas, N.; Prasarnphanich, P.; Sinthupinyo, S.; Ashton, A.S. Attribute framework validation for wellness tourism within the context of Thailand. *Sustainability* **2022**, *14*, 5953. [CrossRef]
19. Zhong, L.; Deng, B.; Morrison, A.M.; Coca-Stefaniak, J.A.; Yang, L. Medical, health and Wellness Tourism Research—A review of the literature (1970–2020) and research agenda. *Int. J. Environ. Res. Public Health* **2021**, *18*, 10875. [CrossRef]
20. KBank Identifies Ventures as Four Game Changers in Thai Medical Tourism. Kbank. Available online: https://www.kasikornbank.com/en/news/pages/medical-hub.aspx (accessed on 20 February 2025).
21. Global Wellness Institute. Global Wellness Tourism Economy. 2018. Available online: https://globalwellnessinstitute.org/wp-content/uploads/2018/11/GWI_GlobalWellnessTourismEconomyReport.pdf (accessed on 20 February 2025).
22. Csirmaz, É.; Pető, K. International trends in recreational and wellness tourism. *Procedia Econ. Financ.* **2015**, *32*, 755–762. [CrossRef]
23. The Official Website of Tourism Authority of Thailand. Available online: https://www.tourismthailand.org/home (accessed on 20 February 2025).
24. Arif, Y.M.; Nugroho, S.M.; Hariadi, M. Selection of tourism destinations is a priority using 6ASTD framework and Topsis. In Proceedings of the 2019 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI) 2019, Yogyakarta, Indonesia, 5–6 December 2019; pp. 346–351. [CrossRef]
25. Arif, Y.M.; Nurhayati, H.; Harini, S.; Susiki Nugroho, S.M.; Hariadi, M. Decentralized tourism destinations rating system using 6ASTD framework and Blockchain. In Proceedings of the 2020 International Conference on Smart Technology and Applications (ICoSTA) 2020, Surabaya, Indonesia, 20 February 2020; pp. 1–6. [CrossRef]
26. Arif, Y.M.; Putra, D.D.; Khan, N. Selecting tourism site using 6 as tourism destinations framework based multi-criteria Recommender System. *Appl. Inf. Syst. Manag. AISM* **2023**, *6*, 7–12. [CrossRef]
27. Agustan; Rianse, U.; Sukotjo, E.; Faslih, A. Exploration and implementation of a smart tourism destination with the 6As Framework & Topsis (case study: Wakatobi, Indonesia). *Sci. Rev. Eng. Environ. Sci. SREES* **2024**, *33*, 419–442. [CrossRef]
28. Govekar, S.; Dayanand, M.S.; Dsouza, E.P. Optimizing beach tourism through smart solutions: A comprehensive review of smart technologies and sustainable strategies. *Rev. Tur. Stud. Cercet. Tur.* **2024**, *38*, 1–10.
29. Agustina Riski, G.A.; Wulandari, G.A. Identification of destination's attributes in Desa Coklat Bali as educational tourism destinations in Tabanan Regency. *J. Manaj. Pelayanan Hotel* **2022**, *6*, 633. [CrossRef]
30. Lopes, A.P.; Rodríguez-López, N. Application of a decision-making tool for ranking wellness tourism destinations. *Sustainability* **2022**, *14*, 15498. [CrossRef]

31. Jahanshahloo, G.R.; Lotfi, F.H.; Izadikhah, M. An algorithmic method to extend topsis for decision-making problems with interval data. *Appl. Math. Comput.* **2006**, *175*, 1375–1384. [CrossRef]
32. Medina-Muñoz, D.R.; Medina-Muñoz, R.D. The attractiveness of wellness destinations: An important performance-satisfaction approach. *Int. J. Tour. Res.* **2013**, *16*, 521–533. [CrossRef]
33. Mikulić, J.; Šerić, M.; Krešić, D. Asymmetric effects of wellness destination and Wellness Facility Attributes on Tourist Satisfaction. *Tour. Rev.* **2023**, *79*, 969–980. [CrossRef]
34. Praprom, C.; Laipaporn, J. Betong: A potential wellness tourism destination in the Deep South of Thailand. *GeoJournal Tour. Geosites* **2023**, *46*, 55–62. [CrossRef]
35. But, J.W.; Ap, J. The impacts of Casino Tourism Development on Macao residents' livelihood. *Worldw. Hosp. Tour. Themes* **2017**, *9*, 260–273. [CrossRef]

2. 3rd World Conference on Engineering and Technology (WORLDCET) 10-12 June 22 | Vienna, Austria : Multi-Criteria Decision-Making Model for Elective Surgical Patient Prioritization in Non-Urgent Healthcare Service Setting

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Multi-Criteria Decision-Making Model for Elective Surgical Patient Prioritization in Non-Urgent Healthcare Service Setting

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Abstract.

Elective surgery is an important procedure in which the patient can be scheduled in advance. A main challenge in scheduling elective surgical patients is to properly manage patient prioritization in order to improve overall health of each patient before surgery, by applying several biopsychosocial aspects in the decision process. Thus, this research aims to demonstrate a decision-making framework to support elective surgical patient prioritization, using Multi-Criteria Decision-Making (MCDM) method and scoring method for weighting associated criteria conducted from the literature. Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) was applied to formulate the elective surgical patient prioritization model and develop a decision framework in the patient scheduling procedure. A case study was presented to illustrate numerical example of the framework based on the data in a non-urgent healthcare service setting. Results were presented to exemplify a consequence of the elective surgical patient prioritization framework in this study. The discussion is also provided based on the prospect of balancing patient satisfaction and medical resources utilization in advance in the healthcare service setting.

Keywords: Patient Prioritization; Elective Surgery, Multi-Criteria Decision-Making (MCDM), Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS)

1. Introduction

Elective surgery is an important procedure in which the patient can be scheduled in advance. A main challenge in scheduling elective surgical patients is to properly manage patient prioritization to improve overall health of each patient before the surgery. A poor decision-making in such procedure may lead to obstacles in patient satisfaction and medical resources utilization in a healthcare service setting. Thus, patient prioritization has been a prior issue in the elective surgery context in which each patient is facilitated to gain entry to and to receive care and service from healthcare system. Correspondingly, it is essential to enhance an ability to make a proper decision in the elective surgical patient prioritization to improve such process in terms of patient satisfaction and medical resources utilization in the healthcare service setting.

The crucial manner in prioritizing elective surgical patients is to associate not only clinical aspect of the patient but also other criteria such as biopsychosocial factors. Most of the decision-making in elective surgical patient prioritization relied on clinical criteria such as main disease, severity, mobility, and similar characteristics (Solans et al., 2013); (Rahimi et al., 2016); (Srikunmar et al.,2018) and (Silva et al.,2021). However, biopsychosocial factors such as health benefit, social, and individual aspects, play an important role in the elective surgical patient prioritization. Clinical criteria can be applied to measure the current health condition while probability of the improvement and comorbidity can be evaluated through benefit aspect to determine the chance of health outcome of each elective patient. While individual criteria are also important to be defined such as age, gender, and personal medical conditions because these could directly affect patient prioritization on urgency treatment. Social aspect is used to evaluate activities of daily living after the surgery as well. Therefore, applying multiple biopsychosocial criteria is necessary to support patient prioritization in order to enhance decision-making process more decisively.

Thus, this research aims to utilize a Multi-Criteria Decision-Making (MCDM) method to demonstrate a decision-making framework based on multiple biopsychosocial criteria to enhance elective surgical patient prioritization. Associated criteria used in the framework are addressed and scoring technique is conducted based on the adjustment of the professionals in the context. A practical MCDM technique is addressed to formulate the patient prioritization model for the elective surgery using the data at a non-urgent healthcare service setting as a case study in order to illustrate numerical example of the results. Furthermore, discussion is also provided from the proposed framework to briefly describe the prospect of balancing patient satisfaction and medical resources utilization in the healthcare service setting.

2. Methodology

MCDM is a method dealing with making a decision based on multiple criteria. It is aimed to support the structuring, analyze, and recommend alternative solution to assist decision makers in several service sectors, including healthcare. This research utilizes an MCDM method, using Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) to formulate the elective surgical patient prioritization model to develop the decision framework in the patient scheduling procedure. The methodology details are described as follows.

2.1 Criteria

Four main criteria incorporated in this study were synthesized from the literature and practices in the area, including qualitative and quantitative sets, namely, C1: clinical and function variables; C2: expected benefits; C3: social variables; and C4: personal characteristic (Rahimi et al., 2016). Furthermore, we adopted the sub-criteria under each main criterion from (Rahimi et al., 2016); (Li et al., 2019); (Srikunmar et al., 2018) and (Silva et al., 2021). Analytical hierarchy process (AHP) for elective surgical patient prioritization can be illustrated in Figure 1.

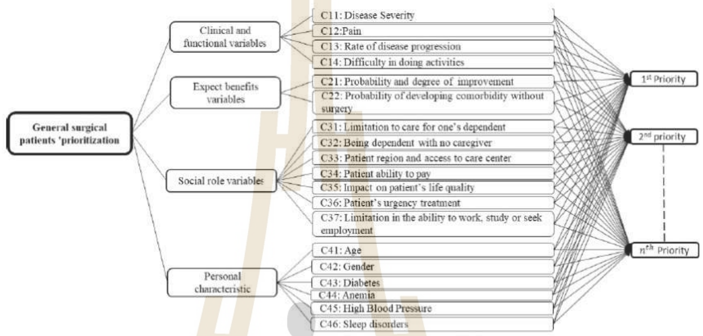

Figure 1: Analytic Hierarchy Process for General surgical patient prioritization

2.2 Criteria scoring

Scoring function was applied to estimate each weight value. Experts were allowed to assess each value based on preference score from 0 (extremely unimportant) to 10 (extremely important). Afterwards, the corresponding weight for each criterion i ={1, 19}, w_i is given by:

$$w_i = \frac{1}{W} \sum_{e=1}^{10} \mu_{i,e} \tag{1}$$

$$\text{Where } W = \sum_{i=1}^{19} \sum_{e=1}^{10} \mu_{i,e} \tag{2}$$

2.3 TOPSIS

TOPSIS is a multiple criteria method to identify solutions from a finite set of alternatives. The basic principle is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The procedure of TOPSIS can be expressed in a series of steps as follows (Jahanshaloo et al.,2006):

(1) Calculate the normalized decision matrix. The normalized value n_{ij} is calculated as

$$n_{ij} = x_{ij} / \sqrt{\sum_{j=1}^{m} x_{ij}^2} \text{ ,j=1, 2, …, m; i=1, 2, …, n.} \tag{3}$$

(2) Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as:

$$v_{ij} = w_i * n_{ij} \text{ , j=1, 2, …, m; i=1, 2, …, n.} \tag{4}$$

Where w_i is the weight of the i^{th} attribute or criterion, and $\sum_{i=1}^{n} w_i = 1$

(3) Determine the positive ideal and negative ideal solution.

$$A^+ = \{v_1^+, v_2^+, ..., v_n^+\} = \{(max_j v_{ij} | i \in I), (min_j v_{ij} | i \in J) \tag{5}$$

$$A^- = \{v_1^-, v_2^-, ..., v_n^-\} = \{(min_j v_{ij} | i \in I), (max_j v_{ij} | i \in J) \tag{6}$$

where I is associated with benefit criteria, and J is associated with cost criteria.

(4) Calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as:

$$d_j^+ = \left\{\sum_{i=1}^{n}(v_{ij} - v_i^+)^2\right\}^{\frac{1}{2}}, \text{ j=1, 2, …., m.} \quad (7)$$

Similarly, the separation from the negative ideal solution is given as

$$d_j^+ = \left\{\sum_{i=1}^{n}(v_{ij} - v_i^-)^2\right\}^{\frac{1}{2}} \text{ , j=1, 2, …., m.} \quad (8)$$

(5) Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_j with respect to A+ is defined as:

$$R_j = \frac{d_j^-}{d_j^+ + d_j^-} \quad , i = 1, 2, \dots, m. \quad (9)$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0, then, clearly$ $R_j \in [0,1]$.

(6) Rank the preference order.

3. Results

3.1 Weighting method

The average relevant scores were evaluated with clinical and function approximate one-third while expected benefit accounted for 19%, social role for 27%, and personal characteristic around 20%. The average relevant scores are shown in Table 1.

Table 1: Relevant scores assigned by 10 experts in related area to 19 criteria

Main criteria	Criteria/ Expert	Expert judgement										Wi	Total Sum for main criteria
		1	2	3	4	5	6	7	8	9	10		
C1: Clinical and function	*C11*	10	9	8	10	8	10	10	9	9	9	***0.1021***	0.3285
	C12	9	8	8	8	8	8	9	8	8	7	***0.0899***	
	C13	8	5	5	7	8	6	8	5	7	5	***0.0710***	
	C14	6	7	5	5	7	7	5	6	6	5	***0.0655***	
C2: Expected benefit	*C21*	10	9	8	10	10	7	9	10	9	9	***0.1010***	0.1898
	C22	7	7	7	10	7	9	9	7	10	7	***0.0888***	
C3: Social Role	*C31*	3	6	3	2	5	3	2	3	1	1	***0.0322***	0.2752
	C32	3	3	5	4	2	4	6	1	5	1	***0.0377***	
	C33	6	6	1	6	6	2	3	6	2	5	***0.0477***	
	C34	3	4	4	3	4	2	4	5	5	6	***0.0444***	
	C35	2	4	1	3	3	4	2	4	5	6	***0.0377***	
	C36	1	5	1	5	5	3	6	5	4	4	***0.0433***	
	C37	2	6	2	4	2	2	3	1	5	2	***0.0322***	
C4: Personal characteristic	*C41*	3	5	2	3	3	1	5	2	2	5	***0.0344***	0.2064
	C42	5	3	3	5	4	4	2	1	2	1	***0.0333***	
	C43	2	4	2	3	4	2	3	4	5	2	***0.0344***	
	C44	5	5	5	2	5	5	4	5	4	5	***0.0499***	
	C45	4	1	1	1	1	5	1	3	4	3	***0.0266***	
	C46	5	2	4	1	1	1	1	2	5	3	***0.0277***	

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3.2 TOPSIS

A case study is presented to illustrate numerical example of the framework based on the data in a non-urgent healthcare service setting. The data in the queue were used to prioritize the schedule for elective surgery, and compare with the first-come, first-serve procedure from real case.

Numerical example for illustration

Basic patient information and clinical evaluation was presented in Table 3, with respected to the 19 criteria. For criteria C11 to C14, five scale scoring method (0 less; 5 most) was used. While C21 and C22 used percentage as an expression of probability and C41 was ages of the patient. The other criteria were binary with YES (1) and NO (0).

Table 2: Basic patient information and clinical evaluation

Patient rank	Basic patient data/clinical info																		
	C11	*C12*	*C13*	*C14*	*C21*	*C22*	*C31*	*C32*	*C33*	*C34*	*C35*	*C36*	*C37*	*C41*	*C42*	*C43*	*C44*	*C45*	*C46*
1	4	2	5	5	7	68	1	0	1	0	1	0	0	30	0	1	0	1	1
2	4	3	1	2	86	86	1	1	1	1	1	1	1	21	1	1	1	1	0
3	1	4	3	5	87	46	1	1	1	0	0	1	0	41	0	1	1	0	1
4	3	3	1	5	35	99	0	0	1	0	0	0	0	75	0	1	0	1	0
5	2	0	5	1	14	26	0	1	0	0	0	1	1	69	1	1	1	0	1
6	5	1	1	4	13	21	0	1	1	0	0	1	0	47	1	1	1	1	0
7	2	4	1	3	47	40	1	1	1	1	0	1	1	44	0	1	1	1	1
8	2	1	2	1	58	54	1	1	1	0	0	1	1	19	1	0	1	0	0
9	4	1	1	1	32	72	1	0	1	1	1	0	0	76	0	0	1	0	1
10	3	2	2	2	55	54	1	0	0	1	1	0	1	70	1	0	1	0	1

Ten patients were in the waiting list for elective surgery. Personal and clinical data were collected by the physician with respect to all variable. Eq. (3) was used to normalize the matrix to be input in Eq. (4) for the calculation of its weight to each criteria variable with respect to table 2 and results were shown in table 3.

Table 3: Weighted normalize matrix

Rank	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
1	0.039	0.022	0.043	0.033	0.005	0.034	0.013	0.000	0.010	0.000	0.014	0.000	0.000	0.007	0.000	0.013	0.000	0.015	0.015
2	0.039	0.033	0.009	0.013	0.055	0.043	0.013	0.018	0.010	0.014	0.014	0.017	0.016	0.005	0.018	0.013	0.012	0.015	0.000
3	0.010	0.044	0.026	0.033	0.056	0.023	0.013	0.018	0.010	0.000	0.000	0.017	0.000	0.009	0.000	0.013	0.012	0.000	0.015
4	0.029	0.033	0.009	0.033	0.023	0.049	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.017	0.000	0.013	0.000	0.015	0.000
5	0.020	0.000	0.043	0.007	0.009	0.013	0.000	0.018	0.000	0.000	0.000	0.017	0.016	0.016	0.018	0.013	0.012	0.000	0.015
6	0.049	0.011	0.009	0.026	0.008	0.010	0.000	0.018	0.010	0.000	0.000	0.017	0.000	0.011	0.018	0.013	0.012	0.015	0.000
7	0.020	0.044	0.009	0.020	0.030	0.020	0.013	0.018	0.010	0.014	0.000	0.017	0.016	0.010	0.000	0.013	0.012	0.015	0.015
8	0.020	0.011	0.017	0.007	0.037	0.027	0.013	0.018	0.010	0.000	0.000	0.017	0.016	0.004	0.018	0.000	0.012	0.000	0.000
9	0.039	0.011	0.009	0.007	0.021	0.036	0.013	0.000	0.010	0.014	0.014	0.000	0.000	0.017	0.000	0.000	0.012	0.000	0.015
10	0.029	0.022	0.017	0.013	0.035	0.027	0.013	0.000	0.000	0.014	0.014	0.000	0.016	0.016	0.018	0.000	0.012	0.000	0.015

Eqs. (5) & (6) were used to generate the best ideal solution for each variable as shown in table 4.

Table 4: Ideal best solutions

	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45	C46
A+	0.049	0.044	0.043	0.033	0.056	0.049	0.013	0.018	0.010	0.014	0.014	0.017	0.016	0.017	0.018	0.013	0.012	0.015	0.015
A-	0.010	0.000	0.009	0.007	0.005	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000

Lastly, Eqs. (7) & (8) were used to obtain Euclidean distance from the best ideal solution and then Eq. (9) was used to calculate the relative closeness and rank the patient priority on their performance score as presented in table 5.

Table 5: Euclidean distance and the relative closeness & rank

Patient	d+	d-	Rj	Rank
1	0.072	0.070	0.493	6
2	0.047	0.094	0.665	1
3	0.061	0.087	0.586	2
4	0.070	0.075	0.515	4
5	0.089	0.058	0.394	10
6	0.085	0.061	0.420	9
7	0.066	0.074	0.528	3
8	0.073	0.061	0.454	7
9	0.078	0.061	0.439	8
10	0.063	0.066	0.511	5

4. Discussions

The ranking of the patient from the TOPSIS model was calculated based on the biopsychosocial aspects used in this study. While its rank was found to be different compared to the current first-come first-serve procedure from real case. For instance, TOPSIS ranked patient no.5 as the 10th order while the current procedure was given at the 5th order. The different of results between two frameworks (MCDM and staff) implies that using different decision-making method may lead to inconstancy in the decision process. Staff are able to make decision more rapidly than using the MCDM model because they use their experience while MCDM has to calculate based on the recorded data.

MCDM tends to provide the result more concisely because it can interpret the results based on multiple criteria in which staff cannot achieve this ability. The satisfaction of the patient may be increased due to the ability in making a proper prioritization which can improve overall health of each patient before surgery. The MCDM framework required to be operated in a computing device which may lead to investment consideration in the future. However, the non-urgent healthcare service setting can be beneficial from incorporating MCDM framework for elective surgical patient prioritization in advance because the care service can gather the scheduled patient data to improve the planning of the resources utilization in the healthcare service setting more appropriately.

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5. Conclusion

A main challenge in scheduling elective surgical patient is to manage a patient prioritization based on multiple biopsychosocial criteria. This research demonstrates a decision-making framework, using both MCDM method and TOPSIS technique, to support elective surgical patient prioritization based on multiple biopsychosocial criteria. A case study was presented to illustrate numerical example of the framework based on the data in a non-urgent healthcare service setting. Results were presented to exemplify a consequence of the elective surgical patient prioritization framework in this study. The satisfaction of the patient is increased due to the ability in making a decisive prioritization which can improve overall health of each patient before surgery. The non-urgent healthcare service setting can gather the scheduled patient data to from the MCDM framework to improve the planning of the resources utilization in the healthcare service setting more appropriately.

References:

Jahanshahloo, G. R., Lotfi, F. H., & Izadikhah, M. (2006). An algorithmic method to extend topsis for decision-making problems with interval data. *Applied Mathematics and Computation*, *175*(2), 1375–1384. https://doi.org/10.1016/j.amc.2005.08.048

Li, J., Luo, L., Wu, X., Liao, C., Liao, H., & Shen, W. (2019). Prioritizing the elective surgery patient admission in a Chinese public tertiary hospital using the hesitant fuzzy linguistic Oreste method. *Applied Soft Computing*, *78*, 407–419. https://doi.org/10.1016/j.asoc.2019.02.001

Rahimi, S. A., Jamshidi, A., Ruiz, A., & Ait-Kadi, D. (2016). Multi-criteria decision making approaches to prioritize surgical patients. *Springer Proceedings in Mathematics & Statistics*, 25–34. https://doi.org/10.1007/978-3-319-35132-2_3

Silva-Aravena, F., Álvarez-Miranda, E., Astudillo, C. A., González-Martínez, L., & Ledezma, J. G. (2021). Patients' prioritization on surgical waiting lists: A decision support system. *Mathematics*, *9*(10), 1097. https://doi.org/10.3390/math9101097

Solans-Domènech, M., Adam, P., Tebé, C., & Espallargues, M. (2013). Developing a universal tool for the prioritization of patients waiting for elective surgery. *Health Policy*, *113*(1-2), 118–126. https://doi.org/10.1016/j.healthpol.2013.07.006

Srikumar, G., Eglinton, T., & MacCormick, A. D. (2020). Development of the general Surgery Prioritisation tool implemented in New Zealand in 2018. *Health Policy*, *124*(10), 1043–1049. https://doi.org/10.1016/j.healthpol.2020.07.018

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