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.

Phase 2: 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.