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MULTI-FIDELITY SIMULATION FRAMEWORK FOR THE STRATEGIC POOLING OF SURGICAL ASSETS

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ABSTRACT

This study describes a multi-fidelity simulation framework integrating a high-fidelity discrete event simulation (DES) model with a machine learning (ML)-based low-fidelity model to optimize operating theatre (OT) scheduling in a major public hospital in Singapore. The high-fidelity DES model is trained and validated with real-world data and the low-fidelity model is trained and validated with synthetic data derived from simulation runs with the DES model. The high-fidelity model captures system complexities and uncertainties while the low-fidelity model facilitates policy optimization via the multi-objective non-dominated sorting genetic algorithm (NSGA-II). The optimization algorithm can identify Pareto-optimal policies under varying open access (OA) periods and strategies. Pareto optimal policies are derived across the dual objectives in maximizing OT utilization (OTU) and minimizing waiting time to surgery (WTS). These policies support *post-hoc* evaluation within an integrated decision support system (DSS).

1 INTRODUCTION

Operating Theatres (OTs) are critical facilities that allow surgical cases to be performed safely and effectively. Performing such surgical cases involves the coordination of several resources and processes, such as surgeons, nurses, surgical supplies, operating theatre facilities and utilities and processes such as scheduling of surgical cases and the intra-operative and post-operative management of patients. OTs have been proven to be the largest cost center as well as the main revenue generator in hospitals (Denton et al., 2007).

Integrated planning systems for OTs have been reported in a number of studies which looked at different levels of planning, namely, strategic, tactical and operational (Rachuba et al., 2024). OT operations planning involves addressing planning problems across the strategic, tactical and operational planning horizons involving: (1) Session Planning Problem (SPP); (2) Master Surgical Schedule Problem (MSSP), and; Surgical Case Assignment Problem (SCAP) (Heider et al., 2022) (see Figure 1). The scheduling and allocation of OT resources is hierarchical and multi-dimensional in nature, requiring the constant tradeoffs between the effectiveness in resource usage and patient outcomes, whilst working within operational constraints and addressing stakeholders' concerns.

OT Utilization (OTU) and Wait Time to Surgery (WTS) are two important metrics to evaluate the performance of OT systems (Gür & Eren, 2018). OTU is defined as the proportion of time OT slots are utilized over the amount of time they are available for service, evaluated over daily and weekly utilization horizons. WTS is defined as the time when an OT request is made till the surgery date. WTS causes disutility to patients due to delayed benefits from treatments and worsened clinical outcomes.

Discrete events simulation (DES) models have been applied to a number of healthcare operational problems. DES is able to capture with high-fidelity, the detailed system configurations and operational behaviours of stakeholders in a complex system(Vázquez-Serrano et al., 2021). DES models are utilized to evaluate alternative scenarios and policies in a virtual environment prior to the actual policy implementation and/or realization of uncertain scenarios.

This paper presents a high-fidelity DES model that is developed for an OT complex in a large public acute care hospital in Singapore. To enable time-sensitive planning and policy optimization, a low-fidelity machine learning (ML) model is trained with the DES-generated synthetic data. By learning from large-scale simulation experiments, the low-fidelity ML model can estimate the impact of various scheduling policies on outcomes with high accuracy. Metaheuristic optimization based on Genetic Algorithms (GA) is then used to determine optimal policies via the low-resolution model. The multifidelity modelling framework is integrated within a decision support system (DSS) is demonstrated to support decision making for SCAP and MSSP.

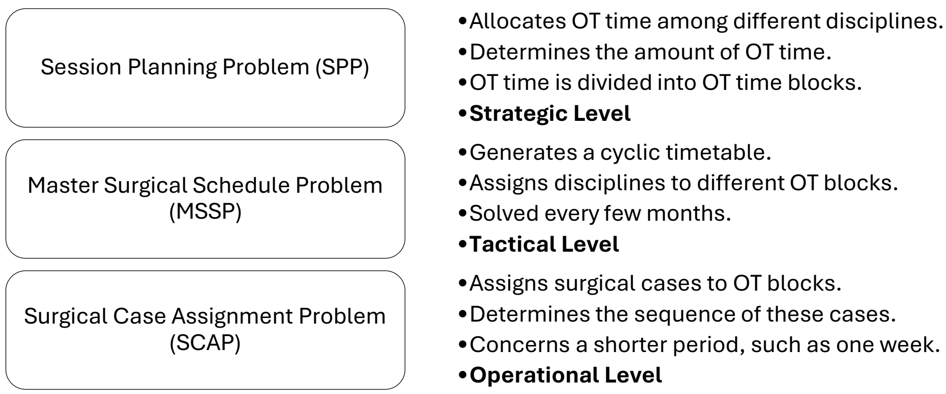


Figure 1: Conceptual decision making and planning hierarchy in OT management

2 RELATED LITERATURE

A number of OT decision problems across various planning horizons have been tackled using the DES paradigm (Al Amin et al., 2025). These models have been focused on various aspects of OT scheduling (e.g., operational case assignment problem, evaluation of block allocation policies, capacity expansion, amongst others (Dexter et al., 1999; Van Houdenhoven et al., 2007; VanBerkel & Blake, 2007). Decision heuristics for assigning surgical cases have also been explored (Akbarzadeh et al., 2020).

Mathematical programming (MP) approaches have been developed to address the MSSP by pre-allocating specific OTs among different disciplines according to surgery demand, surgery duration and no-show rates. Robust optimization approaches have also been utilized to maximize OT capacity utilization and minimize overtime by considering uncertainty in surgery durations (Zhu et al., 2019). Multiple objective programming approaches that considered scheduling attributes, such as surgeon preferences and staff availability, have been reported in the literature (Fallahpour et al., 2024). Policies which involve resource pooling and the sharing of OTs among surgeons have also been reported(Batun et al., 2011).

DSS have been developed for various purposes, such as in the evaluation of safety, efficiency and continuity of care (Al Amin et al., 2025; Chen et al., 2023; Feng et al., 2024). MP models in some DSS may impede adequate consideration of system uncertainties and limited policy flexibilities (Al Amin et al., 2025). DES modelling can better capture the system uncertainties and complexities and frequently used in scenario analysis (Al Amin et al., 2025). Our study is among the first to combine a high-fidelity DES model trained on real hospital data with a low-fidelity machine learning surrogate model to enable scalable policy optimization. This integrated pipeline addresses a major limitation in simulation optimization—computational cost—by enabling tractable exploration of a large policy space through a surrogate-assisted genetic algorithm. System interdependencies, complexities and dynamic uncertainties can be adequately considered within such a framework.

3 STUDY SETTING

Our study utilized historical data from completed surgical cases conducted in the OTs of a major public hospital in Singapore from July 1, 2016, to December 31, 2017. Data for this study was extracted from the study hospital's(SH's) Electronic Medical Record (EMR) system, powered by Sunrise™ Clinical Manager (Allscripts, Illinois, USA). The DES model was developed based on data collected over the period from 1 July 2016 to 31 December 2017. Data from 01 Jul 2016 – 31 Dec 2016 was used to estimate the input parameters for the simulation model. As a full year of independent holdout data was necessary for validation to assess generalizability across annual seasonal and scheduling patterns, model validation was conducted with the remaining dataset.

The study data contains 77,753 cases and includes 23 elective OTs that are used by 18 surgical disciplines. Surgeon and OT allocation schedules and the MSS were collected over the same period. The detailed process understanding was developed through in-depth interviews with nurses, surgeons, anaesthetists and scheduling staff. This study does not require formal ethical review because it involves the use of health information that is not individually identifiable, hence does not meet the definition of human biomedical research (SingHealth Centralised Institutional Review Board Ref No. 2018/2558).

The high-level schematic of the scheduling process is shown in Figure 2. Details of the baseline operating policies are described as follows:

(1) Operating hours of the OTs are from 0815 hours to 1700 hours with a total of 525 minutes per day of usable OT time.
(2) Patients arrive at the Emergency Department (ED) or the hospital's Specialist Outpatient Clinics (SOCs) and attend a medical consultation with a clinician. If they require surgical treatment, a surgery request is made to the listing nurse who then searches for an available OT slot to list.
(3) OT slots are assigned to surgical disciplines by the day of the week. Surgeons are unable to list their surgical cases into non-allocated slots.
(4) The choice of an OT slot depends on a number of factors, such as surgeon's availability, estimated surgical duration and the urgency of the surgery.
(5) After the surgical case has been listed or scheduled into a particular OT slot, it can be cancelled or rescheduled to another date.
(6) When a surgical case requires a longer time to be performed, subsequent cases will be delayed or postponed.
(7) Hospitalization could occur a day before or on the day of surgery. If the patient requires admission to one of the intensive care (ICU) or high dependency (HD) units, a bed will be secured prior to the operation.
(8) Various processes must be synchronized (e.g., portering, cleaning, post-anesthesia care units). Supporting logistics such as diagnostic radiology equipment, MRI, specialized anesthetic procedures, robotic equipment, etc, must be available on standby for every surgery where it is necessary.

Patient Arrival:
- Follows MSS
- Discipline-specific demand patterns

Enters Listed Duration:
- Based on surgery requests
- Listing nurse enters listing duration

Surgery Case Assignment to Blocks:
- Listing nurse checks availability of slots
- OT block is selected based on: Urgency of surgery; Surgeon availability; Patient availability

Surgery Durations:
- Surgery takes place if not postponed/cancelled
- Start and end time noted in the EMR
- If Actual Durations > Listed Duration, then next surgery is pushed back
    - If delayed surgery does not fulfil criteria (e.g., fasting duration), surgery will be pushed back
    - Else Duration == Listed Duration (next surgery will not be brought forward)

Figure 2: Schematic of the surgical case assignment process

4 METHODOLOGY

DES models allow policy and decision makers to carefully evaluate new policies effectively before implementation. However, large scale DES models are computationally expensive to run. This limits the ability to derive optimal designs via a simulation optimization (SO) approach (Amaran et al., 2016). To enhance computational tractability, we propose a multifidelity approach that incorporates a lower-fidelity, machine learning-based predictive model to approximate slot rankings for policy optimization. The conceptual architecture of this multifidelity simulation framework is illustrated in Figure 3.

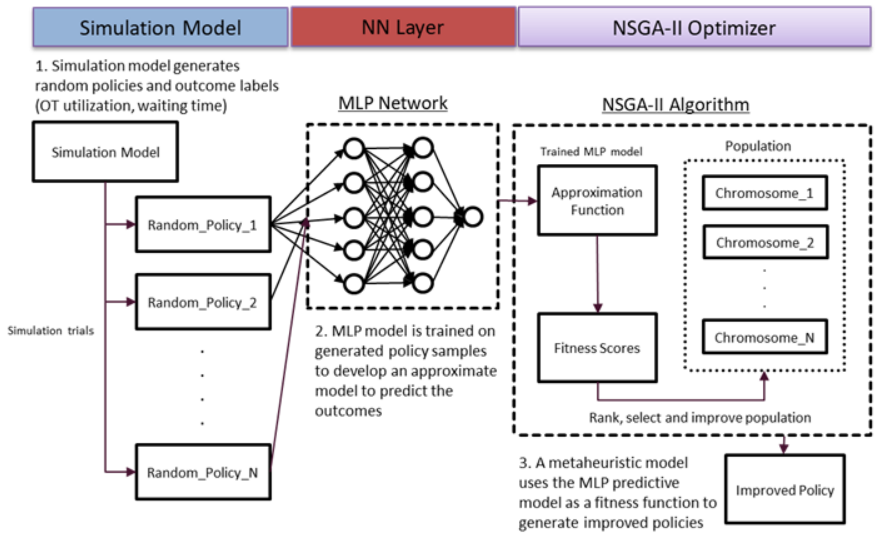


Figure 3: Multi-fidelity Simulation Optimization Approach for OT Management (NSGA-II: the non-dominated sorting genetic algorithm (Deb et al., 2002))

4.1 High Fidelity Model

A high-fidelity DES simulation model (HFM) was developed using Python with operational data from the SH's OT management system and the EMR. A high-level class diagram which captures the flow of salient information across various stakeholders and scheduling subsystems in Unified Modeling Language (UML) is shown in Figure 4. Input parameters (surgical durations and caseloads) and outcome measures (OTU and WTS) across the OTs and surgical disciplines were validated against the historical data using the baseline scenario. Other than the outcome measures of OTU and WTS, secondary indicators related to the average number of patients waiting for surgeries and cases listed were also compared with the historical data. Non-parametric bootstrap confidence intervals (95%) for the simulated results were compared against the historical statistics. The Kolmogorov-Smirnov non-parametric test was used to compare the difference in the actual and simulated empirical distributions of the outcome measures. A simulation warm-up period of 3 months was assumed, and identical random seeds were used in the simulation model for the validation studies. Identical random seeds in the simulation model were used to compare the results across all the scenarios. Verification of the model was conducted with the domain experts and the entire model development process involved surgical and OT process experts(Banks, 2010). Model validation involved the evaluation of dimensional consistency, behaviors under extreme conditions and behavioral sensibilities (Banks, 2010; Law, 2015). The model was validated with data from 1 Jan 2017 – 31 Dec 2017. Considering simulation warm-up period, outcome statistics were collected from month 4 onwards.

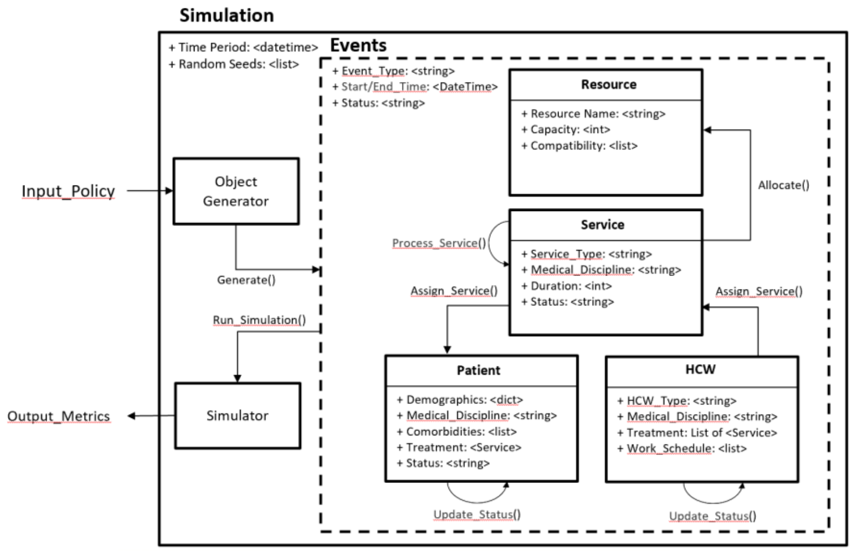


Figure 4. Simplified UML diagram depicting the information flows and input parameters in the HFM

4.2 Low Fidelity Model and Genetic Algorithm

The HFM forms the backbone of the DSS for policy evaluation. The HFM can be used to evaluate alternative policies and scenarios as it directly captures the intricate interdependencies within the OR system. Synthetic data can also be generated from multiple simulation runs to train a low-fidelity machine learning (ML) model. This model learns the relationships between input parameters, alternative policies and the outcome measures. The LFM leverages on a multilayer perceptron (MLP) neural network architecture (Haykin, 1999) to capture the functional relationship from synthetic data derived from the simulation experiments. The MLP models predict two key outcome measures—OTU and WTS. The synthetic dataset derived from simulation experiments consisted of 1,000 randomly generated policies, with an 80%-20% training-test split. Each model was trained over 100 epochs with architectures specifically designed for their respective target metrics.

As a low-resolution approximation, the OTU and WTS based LFMs can be used as the fitness functions for metaheuristic optimization algorithms (e.g., genetic algorithm, tabu search, and particle swarm optimization) (Abdel-Basset et al., 2018). These algorithms iteratively refine scheduling policies by ranking, selecting, and evolving policy solutions. To enable multi-objective optimization across WTS and OTU based objectives (minimizing WTS, maximizing OTU, and workload balancing), the non-dominated sorting genetic algorithm (NSGA-II)(Deb et al., 2002) was used to derive Pareto optimal policies to support *a posteriori* decision making (Miettinen, 1998). The optimization process efficiently navigates the complex solution space, identifying optimal or near-optimal policies that align with hospital objectives and stakeholder preferences. These Pareto optimal policies are then used to guide decision makers towards the best non-inferior decision alternatives in an *a posteriori* decision support system(Miettinen, 1998).

4.3 Policy Analysis

In the baseline policy, OTs slots are allocated to individual surgeons and departments according to the Master Surgical Schedule (MSS). The MSS is a monthly recurring schedule which details the allocation of OTs by the day of the week and/or the week of the month. OT slots which are not utilized cannot be released to a non-allocated surgeon or department except for mutually agreeable ad-hoc schedule swaps. The alternative policies considered the Open Access (OA) policy. Under the OA policy, unused OT slots were consolidated and made available (on a mandatory basis) by the “participating” departments for other departments to list their cases. The OA policy augments the cyclic timetable generated for the MSS and relaxes the scheduling constraints of any predetermined MSS. In the most extreme scenario, all the OT resources could be pooled (not just "participating" department).

The key considerations when designing OA policies are: (1) the period of OA; (2) the OT-discipline combinations in functional groupings open for OA, and; (3) the strategy in the assigning cases. The OA period is defined as the period when the unused slots are consolidated and made available till the actual day of surgery. Functional groupings of the OTs and surgical disciplines involved in the OA program is an important consideration. Two alternative functional groupings were proposed in consultation with subject-matter experts (SMEs) (e.g., OT management, scheduling team, nurses and surgeons). These policies are:

Policy 1: 7 OTs and 3 surgical disciplines participated in an OA pilot over varying OA periods when the unutilized surgical slots for these OT-surgical department combinations were released for OA across different OA periods.

Policy 2: 2 functional groupings, with 3 surgical disciplines and 10 OTs in the first functional group, and; 6 disciplines and 8 OTs in the second functional group were released for OA across different OA periods.

The performance of these SME-guided OA policies was compared against the optimal policy derived from the NSGA-II optimization approach. To determine the effects of the OA periods on the outcome measures, varying time periods for OA in 24-hour intervals from 0 hours (No OA) to 240 hours were evaluated.

4.4 Decision Support System

The consideration of multiple stakeholders' preferences and the need for agility to respond to various modes of operations and minor policy adjustments necessitate an integrated DSS. The DSS supports the optimization of the MSS while simultaneously incorporating pre-defined heuristics for SCAP (e.g., first-come-first served, FCFS). A high-level architecture was developed for the DSS. The proposed architecture can be easily incorporated with the existing enterprise data warehouse (see Figure 5). Interactive dashboards for key stakeholders (e.g., management, surgeons, anaesthetists, OT management staff) were developed. The dashboards provide information and guidance on the suitability of schedules, as well as to maintain the quality of the final schedules under a modified block scheduling approach where OT slots can be open for OA booking ahead of the day of operations. The dashboards include allows decision makers to visualize policy scenarios, compare key metrics, and explore trade-offs interactively.

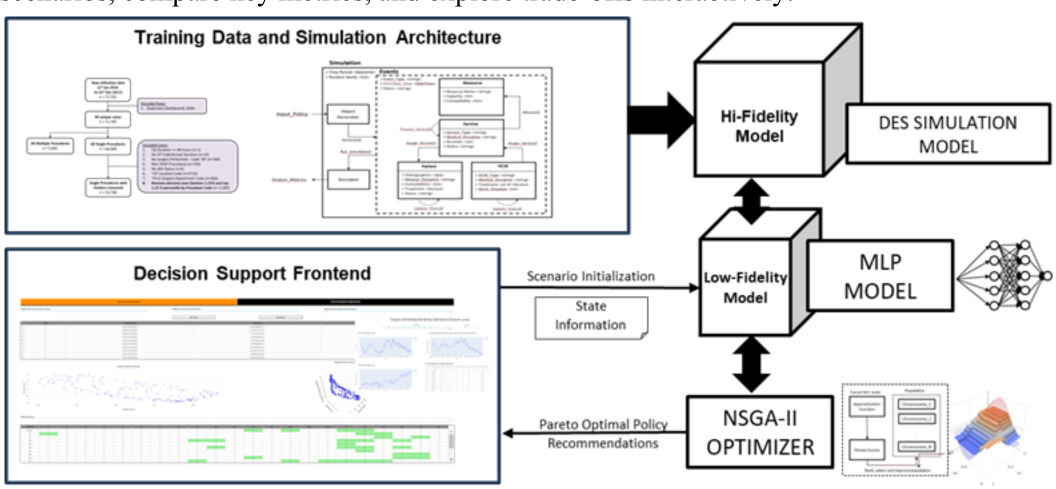


Figure 5: Implementation framework for the DSS with NSGA-II optimizer (Note: Centralized Healthcare Resource Optimization & Management (CHROME) open-source codebase can be found here: https://hsrc-projects.github.io/chrome-project/site/index.html)

5 RESULTS

Data from 01 Jul 2016 – 31 Dec 2016 was used to estimate the input parameters for the simulation model. The model was validated with data from 1 Jan 2017 – 31 Dec 2017. Summary statistics for the cleaned data set from 16 surgical disciplines across 22 OTs is shown in Table 1.

Table 1. Summary statistics for across: (a) Operating theatre; (b) Clinical disciplines

(a)

OT Code	*Number of Cases*	*Mean OTU (SD) / %*	*Median Duration (IQR) / mins*
L1	1811	87.3% (13.1%)	120 (62.5)
L2	2133	88.8% (14.3%)	115 (65)
L3	1421	83.6% (20.2%)	145 (140)
L4	1690	84.8% (17.2%)	120 (65)
L5	1290	79.7% (23.0%)	175 (185)
L6	924	80.2% (23.9%)	275 (197.5)
L7	1339	76.5% (23.0%)	130 (115)
L8	1747	77.2% (24.0%)	105 (100)
M1	1503	84.9% (21.2%)	135 (105)
M2	1732	88.5% (17.6%)	145 (88.5)
M3	535	68.0% (26.5%)	235 (227.5)
M4	1808	84.5% (16.7%)	115 (70)
M5	1537	74.4% (29.4%)	111.5 (106.25)
OT22	1171	81.5% (23.2%)	150 (167.5)
OT24	2063	77.5% (24.4%)	75 (65)
OT25	1870	83.3% (20.0%)	95 (95)
R1	1739	78.0% (20.9%)	85 (90)
R4	1330	85.0% (19.2%)	130 (115)
R5	1002	80.6% (20.4%)	152.5 (250)
R6	1584	80.1% (23.7%)	125 (126.25)
R7	1241	78.2% (27.1%)	190 (340)
R8	1543	79.2% (20.3%)	105 (70)

(b)

Clinical Discipline	*Median WTS (IQR) / days*	*Median Duration (IQR) / mins*
Breast Surgery	7.4 (9.0)	125 (95)
Colorectal Surgery	9.5 (12.8)	190 (205)
Otorhinolaryngology	2.5 (5.0)	115 (105)
Head and Neck	10.9 (18.4)	135 (126.25)
Hand Surgery	2.6 (6.3)	65 (85)
Hepato-Pancreato-Biliary Surgery	6.4 (9.2)	140 (195)
Neurosurgery	5.5 (12.0)	227.5 (231.25)
Obstetrics and Gynaecology	6.4 (10.2)	80 (80)
Oral and Maxillofacial Surgery	11.3 (21.8)	247.5 (251.25)
Orthopaedic Surgery	2.6 (7.0)	120 (70)
Plastic Surgery	6.3 (11.6)	165 (330)
Respiratory and Critical Care	5.4 (4.8)	105 (53.75)
Surgical Oncology	6.5 (12.3)	180 (157.5)
Upper Gastrointestinal and Bariatric	10.9 (16.0)	135 (110)
Urology	31.3 (41.8)	283.5 (103.75)
Vascular Surgery	10.3 (18.3)	100 (90)

For the model validation, the HFM results were compared against historical OTU and WTS estimates based on the baseline policy (Table 2). 95% non-parametric bootstrap intervals were found acceptable across all the OTs for the average OTU and WTS measures. Differences between the actual and simulated empirical distributions of these measures were also found to be insignificant.

Table 2. Actual against simulated aggregated OTU and WTS measures for baseline scenario

		Simulated Results		
	Actual	Simulated	Lower Bound	Upper Bound
Average OTU rates	82.6%	82.3%	80.9%	83.7%
Average WTS	9.5	9.0	8.1	9.8

For policy 1, Figures 6(a) and (b) shows that the mean OT utilization rates for the affected OTs increased from 77.7% at baseline to 82.7% at 240 hours (of OA) while mean waiting time to surgery decreased from 10.3 days to 5.3 days respectively. For policy 2, Figures 6(c) and (d) reveal that mean OT utilization increased from 81.7% to 86.9% and waiting time decreased from 9.5 days to 7.9 days. The results show that the marginal improvements in the outcomes decreased with the OA period, where near optimal improvements are already observed at OA period of 120-144 hours.

The OTU LFM model featured a deep neural network(DNN) with 2,067,457 trainable parameters, leveraging multiple dense layers of 1024, 512, and 256 neurons interspersed with dropouts. In contrast, the WTS LFM model adopted a relatively simpler DNN with 1,231,873 parameters, using dense layers with 512 neurons and dropout layers to maintain generalization. The architectures for the OTU and WTS DNN are shown in Table 3. The performance of both models was evaluated using mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) for the test data. The OTU model achieved an MAE of 0.0025, and a MAPE of 0.29%. The WTS model exhibited an MAE of 0.129 days, and a MAPE of 2.79%. These results indicate reasonable predictive capability.

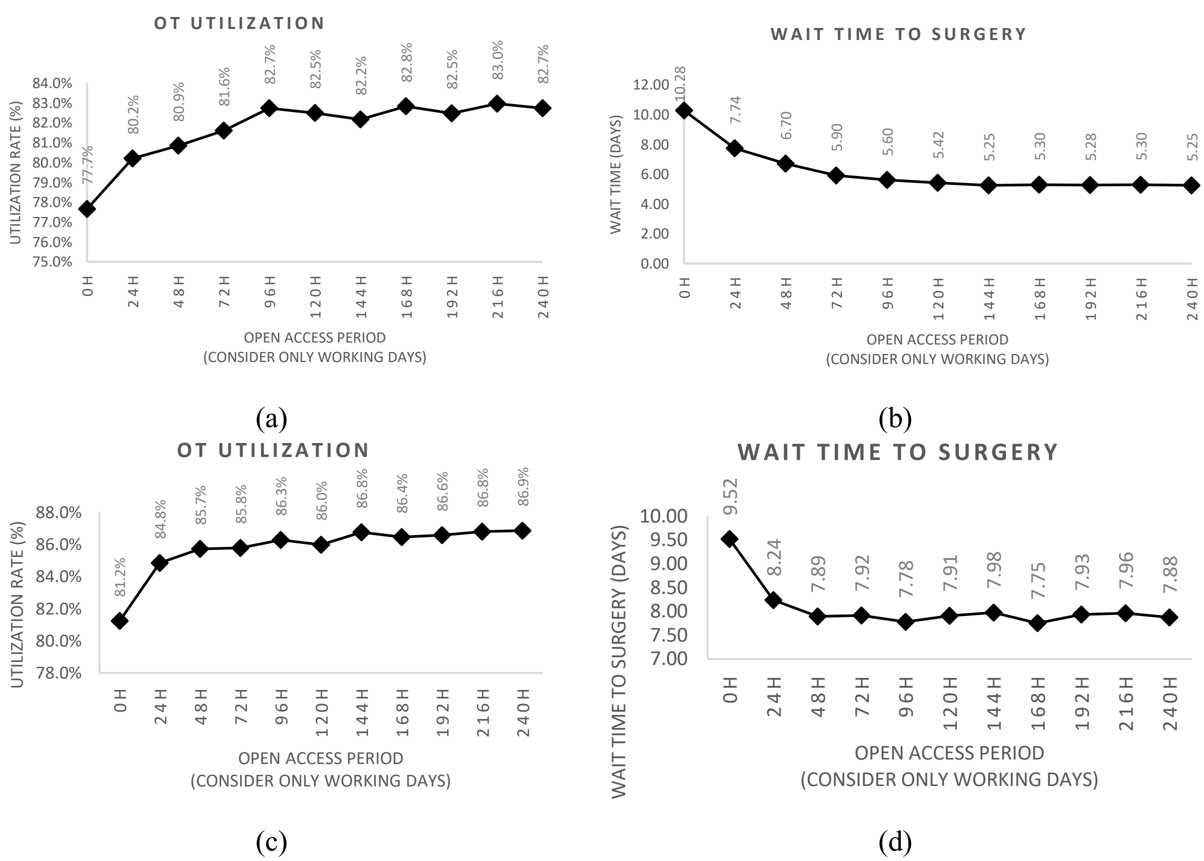
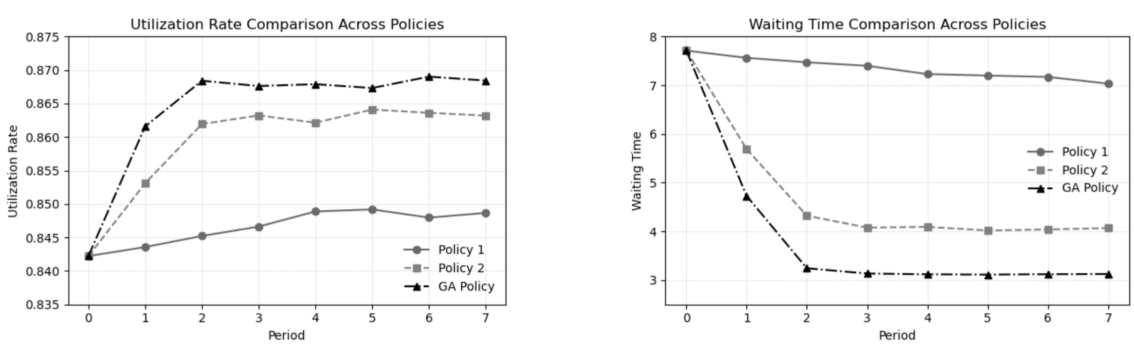


Figure 6: Impact of varying OA periods on OTU and WTS for: (a), (b) Policy 1, and; (c), (d) Policy 2.

The comparisons of OTU and WTS across OA periods from 0 to 7 days for scenarios 1 and 2 (SME-based policies) vs the GA results are shown in Figure 7. The GA-optimized OA policies outperformed both SME-based policies, resulting in higher utilization rates (Figure 7(a)) while ensuring lower waiting times (Figure 7(b)). The underperformance of SME-based policies is likely due to the rigidity in the pre-specified slot release mechanisms. The GA policy is able to evaluate alternative allocation of open access slots using the LFM for both OTU and WTS efficiently. The joint consideration of both OTU maximization and WTS minimization requires a tradeoff between conflicting objectives. As OTU improves, WTS will inevitably rise due to the uncertainties in the system (e.g., arrival rate and service durations) (Green, 2006). These tradeoffs can be captured via a plot of the Pareto frontier across different preference weights assigned to each of these objectives. This is implemented via the NSGA-II optimizer (see Figure 8). The optimal objective values defining the Pareto optimal frontier translates to a set of possible open access policies that can be presented to the decision makers for further deliberation in an *a posteriori* decision approach as the preference weights need not be defined *a priori* (Miettinen, 1998).

Table 3: (a) LFM for OTU; (b) LFM for WTS

(a)			(b)		
Layer (type)	**Output Shape**	**# Parameters**	**Layer (type)**	**Output Shape**	**# Parameters**
input_24 (Input Layer)	(None, 352)	0	input_38 (Input Layer)	(None, 352)	0
dense_137 (Dense)	(None, 1024)	361,472	dense_211 (Dense)	(None, 512)	180,768
dropout_70 (Dropout)	(None, 1024)	0	dense_212 (Dense)	(None, 512)	262,656
dense_138 (Dense)	(None, 1024)	1,049,600	dropout_133 (Dropout)	(None, 512)	0
dropout_71 (Dropout)	(None, 1024)	0	dense_213 (Dense)	(None, 512)	262,656
dense_139 (Dense)	(None, 512)	524,800	dropout_134 (Dropout)	(None, 512)	0
dropout_72 (Dropout)	(None, 512)	0	dense_214 (Dense)	(None, 512)	262,656
dense_140 (Dense)	(None, 256)	131,328	dropout_135 (Dropout)	(None, 512)	0
dense_141 (Dense)	(None, 1)	257	dense_215 (Dense)	(None, 512)	262,656
			dropout_136 (Dropout)	(None, 512)	0
			dense_216 (Dense)	(None, 1)	513
Total params		**2,067,457**	**Total params**		**1,231,873**
Trainable params		**2,067,457**	**Trainable params**		**1,231,873**



(a) (b)

Figure 7. Comparison of Policies 1 and 2 with GA optimized policy for: (a) OTU; (b) WTS

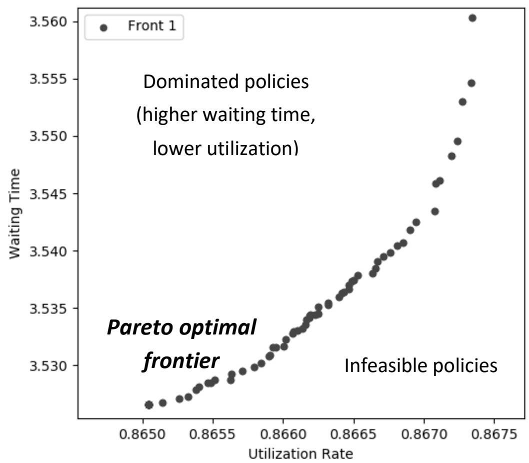


Figure 8. Pareto optimal frontier generated by the NSGA-II algorithm

6 DISCUSSION

Allowing for flexibility beyond the OA policies defined by SMEs, the multi-objective GA-optimized OA policies showed improvements in both the OTU and WTS. As compared with most studies in the literature on OT optimization (Al Amin et al., 2025), our framework focused on OA-slot scheduling that is embedded in a DSS which can enable hospital administrators to interactively explore Pareto-optimal policies. The DSS allows the decision maker to decide on an optimal combination of OA slots and OA periods via *a posteriori* approach. The costs of longer OA periods may not be commensurate with the improvements in OTU and WTS. Extended OA periods can result in implementation difficulties and resistance in adoption.

MLP are well-suited for modelling high-dimensional non-linear functions(Haykin, 1999). While simpler models (linear regression, decision trees, and random forests) provided quicker training times and better interpretability, they underperformed significantly in prediction accuracy. Although interpretability is important, our surrogate model is not intended for direct clinical explanation, but rather as an intermediate component in an optimization pipeline to evaluate policy trade-offs. Interpretability of results is addressed via the Pareto optimal policy recommendations with process metrics relevant to decision makers.

The current simulation model captured the interdependencies across 22 elective OTs and 16 surgical disciplines. The SH serves 38% of all surgical needs of Singaporeans seeking surgical services in the public healthcare system. Improvement in OTU and WTS within the SH will have a potential impact on approximately 180,000 patients annually(Ang et al., 2017). Future work could also incorporate economic evaluation to account for cost-effective trade-offs, enabling more holistic decision-making across clinical and financial objectives.

By integrating MLP, DES-based policy evaluation, and the NSGA-II approach, the DSS facilitates a robust, adaptive, and intelligent OR scheduling system. Compared to existing studies(Al Amin et al., 2025), our approach is one of the first implementations that integrates DES-based realism with MLP surrogates to support multi-objective optimization in OT resource pooling. This comprehensive approach ensures optimal resource utilization while maintaining high-quality patient care and operational efficiency. As hospitals face growing patient volumes and resource constraints, the DSS equipped with predictive analytics and optimization capabilities offers a scalable and sustainable solution for improving OT management.

The HFM offers a ready platform for the *in silico* evaluation of alternative OT scheduling policies. The LFM offers an efficient alternative to explore the multidimensional solution space in search of optimal policies via metaheuristic optimization approach. A digital twin hospital system (DTHS) can be developed to leverage on both the HFM for the evaluation of alternative scenarios and the LFM for multiobjective optimization across OTU and WTS (Sharma et al., 2022). The DTHS should be capable of real-time decision analytics, predictive modeling, and simulation-based scenario testing to support efficient decision-making.

7 CONCLUSION

This study proposed a multi-fidelity simulation framework to enhance OT management. By integrating a HFM with a DNN-based LFM coupled with GA optimization, the framework effectively supports data-driven decision-making for OT scheduling over COVID-19 (Abdullah et al., 2022; Lam et al., 2022). The DSS enables the exploration of alternative OA policies and provides decision-makers with recommendations that consider the tradeoffs between OTU and WTS. Results demonstrate that the NSGA-II optimal OA policies outperform expert-defined OA policies. This framework offers a practical and scalable approach towards the development of large-scale DTHS for OT management. Future work will focus on integrating real-time data streams and external validation of the framework for other study hospitals.

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