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Operating Room Scheduling Optimization Under Surgeon and Nurse Constraints Using Genetic Algorithm

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ABSTRACT

Operating room scheduling is a complex problem due to the limited availability of surgeons, nurses, and operating rooms, as well as the variability in surgery durations. Inaccurate predictions or scheduling may cause conflicts such as overlapping surgeon schedules, violations of contamination level restrictions, and unavailability of nurses or rooms, ultimately reducing the quality of hospital services. This study integrates multiprocedure surgery duration prediction using machine learning with scheduling optimization based on genetic algorithms. The prediction model considers the American Society of Anesthesiologists (ASA) physical status classification, patient profiles, and sets of surgical procedures variables. Scheduling optimization employs a lexicographic approach with three main objectives: minimizing patient waiting time, nurse overtime, and operating room idle time, while ensuring surgeon presence during critical phases and nurse availability according to shifts. The results show that the Catboost algorithm achieves the best prediction performance. Incorporating the ASA variable reduces prediction errors by 33.880 minutes in MAE and 55.575 minutes in RMSE compared to model without the ASA feature. The optimization model successfully eliminates all scheduling conflicts, ensuring full compliance with medical procedure constraints. Recovery bed utilization remains efficient, with a maximum of five units used, representing less than 50% of the total capacity.

Keywords: Operating Room Scheduling; Surgery Duration Prediction; Surgeon Presence.

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1. INTRODUCTION

Surgery is an essential component of hospital care [1]. Operating rooms are among the most expensive facilities and contribute significantly to hospital revenue, with approximately 40% of hospital expenditures attributed to operating rooms and more than 60% of hospitalized patients requiring surgical procedures [2]. The operating room is considered one of the hospital's critical sectors and a primary driver of hospital operations, improving the efficiency and effectiveness of operating room utilization is crucial [3]. Operating rooms function not only as critical clinical care units but also as major cost centers and primary sources of hospital revenue. Ineffective and inefficient utilization of operating rooms can be observed in several situations, such as excessive overtime among operating room medical staff, which significantly increases hospital operational costs. In addition, idle time of both operating rooms and medical personnel contributes to higher operational expenses and reduced hospital profitability. The cancellation of surgical procedures and schedule delays resulting from inadequate management of medical staff working hours and limited availability of facilities and infrastructure, such as operating rooms and recovery rooms, can negatively affect the quality of patient care. In such situations, patient waiting time becomes a critical issue that must be carefully addressed, particularly given patients' medical conditions and the urgency of surgical interventions.

Efficiency and effectiveness can be achieved through proper operating room scheduling, as scheduling and planning are vital tools to enhance operating room performance and meet patient demand [3]. Surgical case scheduling involves assigning a specific time and day for each operation while considering the availability of resources such as operating rooms, surgeons, nurses, and equipment. Factors influencing surgical case scheduling include case attributes (e.g., priority and start time), resource availability, and surgical duration [1]. Inefficient scheduling can lead to a reduction in the quality of patient care and an increase in operational costs. These issues highlight the importance of effective operating room scheduling as a key managerial mechanism to balance operational efficiency with patient care quality. Operating room scheduling primarily focuses on elective patients, who represent one of the main sources of hospital revenue; thus, effective scheduling is essential to prevent cancellations or delays that could negatively impact hospital performance [4]. Elective patients are those scheduled for surgery, with predefined resources and operation start times [5]. A well-designed elective patient scheduling model can maximize patient satisfaction and minimize idle time [6].

The scheduling model used in this study applies a no wait constraint, which ensures that there is no waiting time between the completion of surgery in the Operating Room (OR) and the start of recovery in the recovery room. According to the no-wait constraint in the surgical procedure flow, congestion may occur in the recovery room when a surgical procedure in the operating room is completed but no recovery beds are available to accommodate the patient [7]. A patient can only enter the operating room stage once a recovery bed has been secured for that patient. Adequate availability of recovery beds supports faster patient turnover in the operating room, thereby reducing both patients waiting time and operating room idle time. The contamination level of surgery is another critical factor that must be considered in operating room scheduling. Each type of surgical procedure carries a different level of contamination risk. If the sequence of surgeries is not arranged according to the principle of increasing contamination levels, additional time will be required for sterilization and cleaning before the operating room can be reused. Scheduling that fails to account for contamination levels may heighten the risk of cross-infection between patients.

The variability of surgery duration is a crucial factor in operating room scheduling. Developing a scheduling model that accounts for the uncertainty of surgery duration aims to create a more adaptive scheduling system that reflects actual operating conditions. Operating room schedules that are over or under estimated can lead to undesirable consequences such as idle time, overtime, or rescheduling of surgeries [8]. Considering the uncertainty in surgery duration allows the resulting schedule to better represent real-world conditions [9]. The duration of elective surgeries can be predicted based on hospital historical data analysis and through machine learning models that enable more accurate and efficient planning [10]. Several studies have highlighted the use of machine learning models for predicting surgery duration, which have been shown to reduce prediction errors and improve scheduling efficiency in operating rooms [11][12]. Effective operating room scheduling that incorporates surgery duration uncertainty can minimize the risk of surgical delays and enhance the utilization of hospital resources. Conversely, inaccurate prediction of surgery duration leads to inefficient scheduling, resulting in unexpected overlaps or patient waiting times. Therefore, selecting an appropriate predictive model is essential to ensure accurate estimation of surgery duration [13].

It is essential to consider individual patient needs and clinical priorities when developing an accurate scheduling model [14][15]. Several studies have developed operating room scheduling models that incorporate resource availability, including surgeons and nurses, into the scheduling framework [9][16][17]. Optimization of operating room scheduling highlights the importance of efficient resource utilization in reducing operating room idle time [18][19]. Excessive idle time can decrease productivity and increase overall operational costs. Nurse availability is one of the critical factors in operating room scheduling. Nurse overtime significantly affects performance levels, service quality, staff satisfaction, and the overall cost of overtime [17]. Excessive overtime can lead to fatigue, stress, and a decline in the quality of patient care. Surgical nurses have regulated working hour limits to prevent fatigue, which can impact both performance and patient safety. Overworking or excessive overtime negatively affects nurse well-being and job satisfaction among medical staff. Considering surgical nurse constraints in operating room scheduling can help reduce their workload [20]. Integrating nurse constraints into the scheduling process can result in a more balanced allocation of medical team resources, particularly nursing staff [21]. However, the number of surgical nurses available with the required qualifications for specific procedures at a given time is often limited [22].

The presence of surgeons during the critical phase of a surgical procedure is also an important constraint. The critical phase, which begins at the time out stage (a pre incision pause for verifying patient identity, procedure, and surgical site) and ends at the sign out stage (a post procedure check before wound closure), is part of the WHO Surgical Safety Checklist and plays a vital role in ensuring patient safety. Surgeon presence during this phase has a direct impact on patient safety, as it represents the stage of surgery with the highest risk of complications. Surgeons are required to be present during the critical phase. Scheduling must include constraints to prevent overlapping critical phases for a single surgeon, while non-critical phases may be handled by residents or fellows. Surgical fellows may participate during the pre-incision and post-incision phases [23]. In practice, however, surgeons are often unable to be fully present throughout the entire critical phase due to time limitations and heavy caseloads. This presents a significant challenge in developing realistic operating room schedules that remain compliant with patient safety standards. This study provides a more realistic operating room scheduling model than most existing operating room scheduling studies that assume full surgeon availability.

This study integrates multiple constraints, including surgeon availability, nurse availability, contamination level, recovery room capacity, and operating room availability, into a scheduling model that accounts for the uncertainty of surgery duration. The uncertainty in surgery duration is addressed through a predictive model with multiprocedure variables, where patients undergoing combined or multiple surgical procedures are represented through additional input variables in the duration prediction model. In addition to multiprocedure variables, the American Society of Anesthesiologists (ASA) classification is also included as an input variable in predicting surgery duration. Several previous studies have developed operating room scheduling models under the assumption of full surgeon availability [9][22] and integrated them with single procedure surgery duration prediction [22]. This study explicitly integrates machine learning based multi procedure duration prediction with a scheduling framework that enforces surgeon presence only during critical surgical phases. The combination of data driven duration estimation and critical phase based surgeon availability modeling constitutes a novel and clinically realistic contribution to the operating room scheduling literature. The operating room scheduling model developed in this study employs a lexicographic approach with three objectives: minimizing patient waiting time, nurse overtime, and operating room idle time. A Genetic Algorithm (GA) is utilized to determine the optimal solution, as operating room scheduling is an NP hard problem. This research not only extends previous studies but also proposes a novel framework to enhance the efficiency and effectiveness of operating room scheduling.

2. RESEARCH METHOD

This study adopts a quantitative approach by combining predictive modeling and optimization techniques to develop an operating room scheduling system. The research framework consists of two stages: predicting surgery duration using machine learning methods and optimizing the schedule using a Genetic Algorithm. Data collection and preparation involve obtaining data from the Central Surgical Installation of Hospital A, which serves as the research object for developing the operating room scheduling model. Primary data were collected from the hospital's Central Operating Room database, supported by direct observations, interviews with operating room scheduling staff, and operational system records, while secondary data were gathered from hospital documents, scientific literature, and relevant online sources.

2.2 Data Prepocessing

Data preprocessing plays a critical role in improving the generalization performance and accuracy of machine learning models [24]. Data preprocessing was carried out through several stages, namely data cleaning and data transformation. Data cleaning is the process of detecting and correcting data required for analysis and data processing. This step involves error detection methods to identify missing, redundant, and incorrect data [25]. In this study, data cleaning was performed by identifying and removing records with missing input values that could not be reliably imputed without introducing bias. In addition, non-standard feature entries, particularly inconsistent time formats used as the basis for surgery duration calculations, were standardized to ensure accurate duration measurements. Patient records associated with postponed or canceled procedures were also excluded, as these cases do not reflect actual surgical execution and may distort the representation of real operating room conditions. Records with implausible or extreme surgery duration values, such as unrealistically short or excessively long durations inconsistent with the corresponding procedure type, were carefully examined and removed to prevent skewed model training. A summary of the features for surgery duration prediction is presented in the following table.

Table 1. Summary of Features for Prediction Model

Feature	Type	Number of Categories
Age	Numerical	5
Gender	Categorical	2
ASA	Categorical	4
Specialization	Categorical	12
Anesthesia Type	Categorical	3
Class	Categorical	4
Contamination Level	Categorical	3

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Age and gender are variables representing patient profiles that reflect basic physical conditions. The relationship between age and the target variable (surgery duration) may not always be linear. Age classification allows the model to capture potential non linear relationships that may exist within age groups and the desired outcomes, which might not be detected when using raw numerical data. The age variable is categorized into several groups, as shown in the following table [26].

Table 2. Age Feature Classification

Age Range	**Category**
≤ 17	Category 1
18 - 39	Category 2
40 - 59	Category 3
60 - 74	Category 4
≥ 75	Category 5

The prediction of surgery duration also considers the ASA score and surgical variables associated with the complexity level of the procedure. The ASA score indicates the degree of anesthesia risk and the patient's overall health condition, serving as an important tool for predicting the risk of complications during and after surgery [27]. The risk of complications reflects the complexity of the surgical procedure undertaken by the patient, while surgical specialization, type of anesthesia, surgery class, and contamination level also represent the degree of procedural complexity. In many cases, a patient undergoes multiple procedures within a single operation, which may fall under the same or different specializations depending on the patient's diagnosis. Data transformation was performed using One Hot Encoding. One hot encoding is a method used in machine learning to transform categorical data into binary vector representations, enabling the handling of discrete data that cannot be directly processed by machine learning algorithms [28][29]. One hot encoding was applied to almost all algorithms except for the CatBoost algorithm.

2.3 Surgery Duration Prediction

Surgery duration prediction aims to estimate the time required for each surgical procedure based on patients' historical data and surgical procedure records. The prediction process considers historical operation duration data along with patient profile variables and surgical procedure parameters. The initial approach used in this study employs a set of surgical procedures as the baseline model for predicting surgery duration. This procedure set consists of surgical specialization, surgery class, anesthesia type, and contamination level. The prediction model was further developed by incorporating additional input variables such as the ASA score, as well as specialization and class for multiprocedure cases, to analyze their influence on the target variable surgery duration.

Feature scoring was conducted to identify which features had the most significant influence on the target variable. The Rank ReliefF method implemented in Orange software was used for feature scoring. Model performance was evaluated by comparing Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, which measure how well the model explains the variability of the target data. The dataset was split into training and testing sets with 80% of data used for model training and 20% of data used for model testing. The surgery duration prediction model was developed using several machine learning approaches available in Orange software, including XGBoost, CatBoost, Random Forest, Neural Network, and Ridge Regression. The following section describes the stages of the surgery duration prediction process.

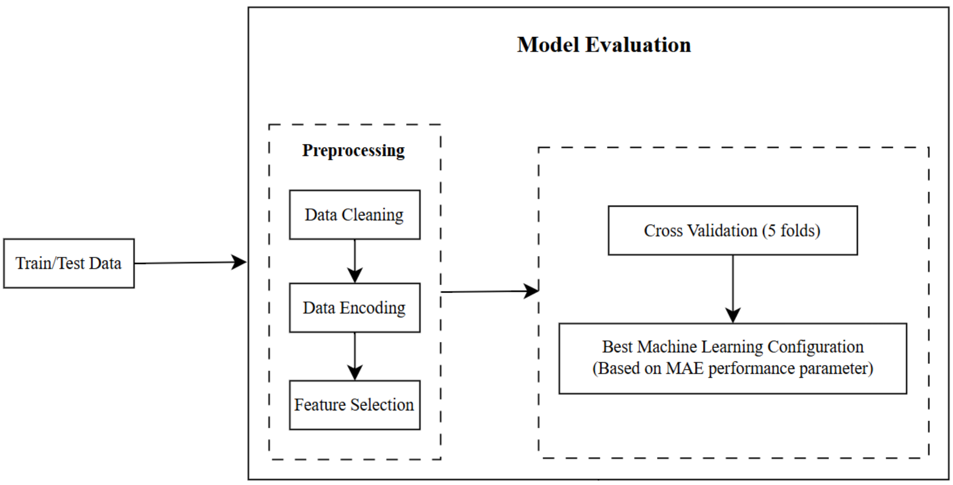

Figure 1. Model Evaluation

2.4 Optimization of Operating Room Scheduling Using a Genetic Algorithm

The scheduling model was developed by considering resource constraints, including the availability of surgeons, nurses, and operating rooms, as well as the sequence of surgical procedures based on contamination levels. The objective function of this model is to minimize the total surgery completion time, which includes patient waiting time, operating room idle time, and nurse overtime. Scheduling optimization was performed using the Genetic Algorithm (GA) due to the NP-hard and combinatorial nature of the operating room scheduling problem, which involves multiple interdependent constraints and discrete decision variables. As a population-based metaheuristic, GA maintains a set of candidate solutions that evolve simultaneously, enabling extensive exploration of the solution space and the identification of near-optimal scheduling configurations without being easily trapped in local optima. In addition, a random-immigrants strategy is incorporated by periodically introducing new randomly generated individuals into the population. The Genetic Algorithm consistently provides more optimal results in generating the best operating room scheduling solutions for the given problem. Moreover, GA offers an adaptive and efficient approach suited to the dynamic needs of modern hospitals [30]. Its evolutionary mechanisms selection, crossover, and mutation facilitate the generation of adaptive solutions that respond effectively to dynamic operational requirements in hospital settings.

In this study, a one-point crossover operator is applied to recombine parent solutions, while a flip mutation operator introduces controlled random changes to maintain population diversity. The crossover rate, mutation rate, and population size are systematically determined using a Taguchi-based Design of Experiments. The optimization process employs a binary chromosome representation that encodes the surgery start time, operating room allocation, and nursing team assignment. The lexicographic approach was applied to assign priority levels to the objective functions based on their relative importance. The first priority is minimizing patient waiting time. If multiple solutions yield the same minimum waiting time, the second priority is minimizing nurse overtime. If there are still multiple solutions with equal minimum overtime, the third priority minimizing operating room idle time is used. The following figure presents the flowchart of the Genetic Algorithm.

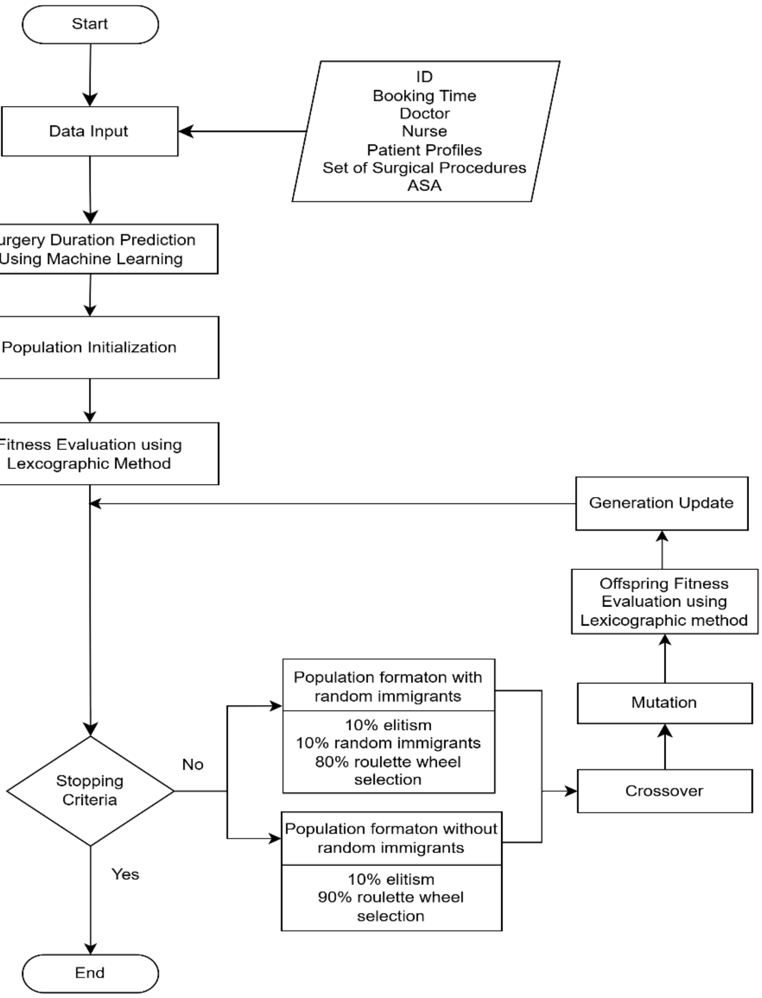

Figure 2. Flowchart of the Genetic Algorithm

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The lexicographic approach ensures that each objective function is optimized hierarchically. The optimized schedule serves as the basis for determining the number of recovery beds required for postoperative patients.

2.5 Model Verification and Validation

Model verification was carried out by examining the program and ensuring that the optimization output did not violate the defined constraints related to operating room availability, surgical nurses, or surgeons. Model validation, on the other hand, was conducted by comparing the optimized schedule with the actual schedule from the Central Surgical Installation (IBS) of Hospital A. The comparison indicators include patient waiting time, nurse overtime, operating room idle time, and the number of scheduling conflicts identified in the generated schedule.

2.6 Analysis Method

The analysis of the surgery duration prediction model was based on the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) obtained from each predictive approach. The analysis also considered the contribution of each variable in improving the accuracy of surgery duration predictions. Furthermore, optimization results were analyzed under various scenarios to evaluate model performance. The study compared the effectiveness of different approaches by introducing random immigrants into the genetic algorithm population. In addition, the analysis examined how the optimized schedule affected the number of recovery beds required. Expert validation was conducted to ensure that the assumptions, constraints, and model formulations used in the scheduling system were consistent with real hospital conditions.

3. RESULTS AND DISCUSSION

3.1 Surgery Duration Prediction

The input data used in the surgery duration prediction model were obtained from historical surgery duration records collected at the Central Surgical Installation (IBS) of Hospital A from November 2024 to March 2025. Based on the historical data, each surgical patient underwent between one and five combined procedures in a single operation. The number of procedures per patient varied depending on their condition and diagnosis. Feature scoring was conducted using the RReliefF approach, which selects attributes (features) based on their relevance to the target function. The results of the feature scoring using RReliefF are presented in the following table.

Table 3. RreliefF Scores

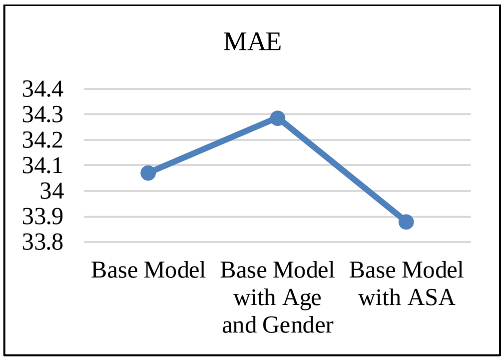
No	Feature	RReliefF Score
1	Procedure Classification 1	0.232
2	Age	0.212
3	Procedure Specialization 1	0.166
4	Procedure Classification 2	0.135
5	Procedure Specialization 2	0.128
6	Gender	0.087
7	ASA Score	0.073
8	Contamination Level	0.072
9	Anasthesia Type	0.063
10	Procedure Specialization 3	0.000
11	Procedure Classification 3	0.000
12	Procedure Classification 4	0.000
13	Procedure Classification 3	0.000
14	Procedure Specialization 4	0.000
15	Procedure Specialization 3	0.000

This study eliminated the specialization and classification features for the third, fourth, and fifth procedures, as they had a weight of 0, indicating that these features did not contribute to differentiating the data based on the target variable labels. The first research scheme involved testing the base model for surgery duration prediction, which included the variables specialization, classification, contamination level, and anesthesia type, where specialization and classification accounted for multi procedure cases. The surgery duration prediction results obtained from the base model were then compared with an extended model that incorporated basic patient profile variables, namely age, gender, and ASA score. The performance evaluation results of the surgery duration prediction models are presented as follows.

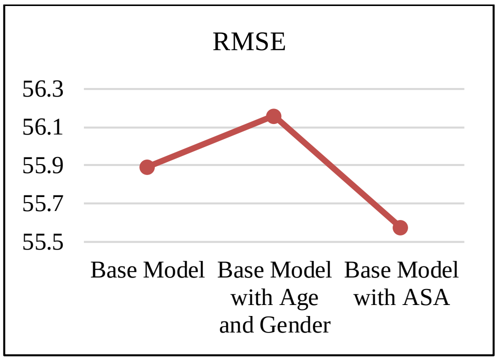
Table 4. Performance Evaluation Results of the Prediction Models

Algorithm	Base Model (*Multiprocedure*)		Base Model with Age and Gender		Base Model with ASA	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Baseline Predictor	49.738	72.130	49.738	72.130	49.738	72.130
XGBoost	34.155	56.008	34.188	56.252	34.037	55.951
CatBoost	34.073	55.890	34.288	56.160	33.880	55.575

Random Forest	35.175	57.337	35.030	57.253	35.154	57.270
Neural Network	34.917	57.306	36.548	59.091	35.003	57.253
Ridge Regression	37.716	58.992	37.696	58.924	37.738	58.996



MAE
(a)



RMSE
(b)

Figure 3. Comparison of Prediction Performance Based on (a) MAE and (b) RMSE

The CatBoost algorithm consistently produced the best results across all model schemes, outperforming other algorithms in both RMSE and MAE metrics. A baseline predictor (constant model) generates predictions using the mean surgery duration estimated from the training set. This demonstrates that CatBoost is more effective in minimizing large errors, as it applies stronger penalties to outliers or extreme prediction deviations, and better explains the variability in surgery duration based on the available features. CatBoost consistently outperformed the baseline model as well as other machine learning algorithms. This performance can be attributed to CatBoost's inherent ability to handle categorical features directly, thereby reducing the need for complex preprocessing or explicit encoding methods commonly required by other machine learning models [31][32][33].This advantage makes CatBoost particularly suitable for heterogeneous clinical data containing numerous categorical features, such as procedure type, surgical specialization, anesthesia type, and contamination level, enabling the model to capture complex nonlinear relationships that influence surgery duration. CatBoost has limitations in terms of higher computational complexity and reduced model interpretability compared to simpler tree-based models.

Patient profile features such as age and gender did not significantly improve model performance, indicating that these variables do not provide substantial predictive contributions in the context of multiprocedure surgeries. This finding is consistent with the study by Yuniartha et al. (2023), which reported that adding age and gender features did not enhance surgery duration prediction performance. In contrast, incorporating the ASA score into the base model improved prediction accuracy, reducing the MAE to 33.880 minutes and the RMSE to 55.575 minutes. This result highlights that the physical status (ASA), representing the patient's baseline health condition at diagnosis, is relevant and informative for predicting surgery duration. Patients with higher ASA classifications typically present greater comorbidity burdens, defined as the presence of multiple chronic medical conditions affecting a patient simultaneously [34][35], which can increase surgical complexity and lead to longer operation durations [36][37]. Moreover, higher ASA scores also indicate that patients have a greater risk of intraoperative and postoperative complications, thereby requiring more careful and rigorous monitoring as well as more meticulous surgical approaches during the procedure to minimize these risks [38].

The predicted surgery durations were subsequently used as input data for operating room scheduling optimization. The genetic algorithm utilizes deterministic surgery duration estimates predicted by the CatBoost model as fixed inputs for the scheduling optimization process. This deterministic assumption constitutes a limitation of the study. Future research should consider integrating stochastic scheduling methods to improve schedule robustness. Improvements in surgery duration prediction accuracy directly contribute to enhanced operating room scheduling outcomes. More accurate duration estimates reduce the risk of underestimation and overestimation, which are common causes of schedule disruptions such as operating room idle time, nurse overtime, and surgery delays. By providing more reliable duration inputs to the scheduling optimization model, the resulting schedules exhibit fewer overlaps, improved alignment with planned start times, and more balanced utilization of surgical resources. Accurate surgery duration prediction strengthens the effectiveness of the optimization process in minimizing patient waiting time, reducing operating room idle time, and limiting nurse overtime, thereby improving both operational efficiency and the quality of patient care.

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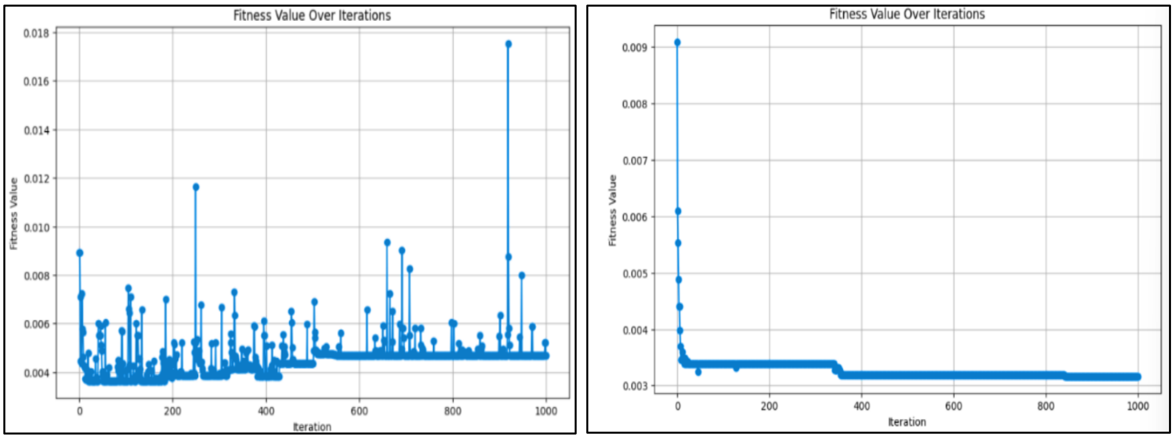
3.2 Operating Room Scheduling Optimization

The approach used in the Design of Experiment (DOE) was the Taguchi Design with an L9 orthogonal array, consisting of three factors, each tested at three levels. Each experiment was conducted with three replications, and the analyzed parameters included population size (p), crossover rate (c), and mutation rate (m). The observed response was the fitness value, which in this context represents the quality of the scheduling solution. The normality test results for the response design of experiment data showed a p-value of 0.930 (> 0.05), indicating that the data followed a normal distribution. The Plot for S/N Ratios illustrated the robustness of the system against factor variations, where a higher Signal to Noise (S/N) ratio indicates greater stability of the response quality against unwanted variations (noise). The Plot for Means depicted the average response values at each factor level. The S/N ratio analysis revealed that increasing the population size from 20 to 80 significantly improved the fitness value, with the optimal population size determined to be 80. A higher crossover rate was found to decrease solution quality, with the best crossover rate observed at 0.5. The mutation rate analysis indicated that the highest average fitness was achieved at 0.07, representing a moderate mutation level. The optimized parameters population size, crossover rate, and mutation rate produced the best results in terms of both performance and experimental stability.

Table 5. GA Parameters

Parameter	Symbol	Selected Value
Population size	p	80
Crossover rate	c	0.5
Mutation rate	m	0.07

Through a comparative analysis of scenarios with and without the incorporation of random immigrants. The normality test was conducted using the Shapiro Wilk method. The primary focus of the test was directed toward the patient waiting time variable, in line with the lexicographic approach for determining the optimal solution. The results indicated that the data in the With Random Immigrants group were normally distributed ($p = 0.212 > 0.05$), while the Without Random Immigrants group also exhibited a normal distribution ($p = 0.352 > 0.05$). Therefore, both groups satisfied the assumption of normality. Subsequently, a homogeneity test was conducted to examine the equality of variances between groups. The results showed a p-value ≤ 0.05, indicating that the group variances were not homogeneous. Consequently, the comparison of mean differences was carried out using the Welch t-test method. Based on the results of the Welch t-test, the obtained p-value was less than 0.05, indicating a statistically significant difference in patient waiting times between the With Random Immigrants and Without Random Immigrants scenarios. Descriptive analysis shows that the average patient waiting time in the With Random Immigrants scenario was 90.8 slots with a median of 91.5 slots, while in the Without Random Immigrants scenario, the average waiting time reached 111 slots with a median of 110 slots. The differences in both mean and median values indicate that the implementation of random immigrants contributes to improving the quality of operating room scheduling solutions.



Fitness Value with Random Immigrants (a)

Fitness Value without Random Immigrants (b)

Figure 4. Comparison of Fitness Value (a) With Random Immigrants and (b) Without Random Immigrants

The results of the genetic algorithm experiment reveal distinct convergence patterns between the With Random Immigrants and Without Random Immigrants scenarios. The convergence plot for the With Random Immigrants scenario exhibits more fluctuating fitness values, with notable improvements occurring at specific iterations. The introduction of random immigrants, accounting for 10% of the total population, effectively maintains solution diversity. This diversity enhances the exploration of the solution space and reduces the risk of being trapped in local optima. In contrast, the Without Random Immigrants scenario shows a rapid decline in fitness values during the early iterations, indicating that the algorithm tends to converge prematurely and is more prone to premature convergence. The inclusion of random immigrants in the genetic algorithm population maintains genetic diversity, which enables the algorithm to continuously adapt, while also enhancing its ability to dynamically track solutions in optimization problems [39].

Comparative analysis was conducted between the baseline schedule representing the hospital's current scheduling practice and the optimized schedule generated by the GA.

Table 6. Performance Comparison Between Baseline and GA-Optimized Schedules

Patient ID	Doctor	Actual Schedule					Optimized Schedule				
		Nurse	OK	WT	OT	IT	Nurse	OK	WT	OT	IT
3	1	1	4	952	55	893	8	1	745	35	1325
4	2	2	2				2	2			
5	3	3	1				6	4			
6	4	17	7				5	7			
7	5	4	6				1	5			
10	7	3	8				7	6			
12	8	1	4				4	1			
13	9	2	2				3	3			
14	10	5	5				9	2			
15	11	4	6				14	4			
17	13	4	6				18	5			
18	2	6	3				10	4			
19	3	10	2				8	7			
20	14	17	7				9	1			
21	5	1	4				17	2			
23	9	6	3				3	4			
24	14	18	1				13	7			
25	15	11	3				12	3			
26	15	12	4				11	2			
27	7	15	2				15	5			

As shown in Table X, the baseline schedule resulted in a waiting time (WT) of 952 minutes, overtime (OT) of 55 minutes, and idle time (IT) of 893 minutes. Under the schedule optimized using the Genetic Algorithm (GA), the waiting time was reduced to 745 minutes, representing a decrease of approximately 21.7%, while overtime was reduced to 35 minutes, corresponding to a reduction of about 36.4%. Although idle time increased from 893 minutes to 1,325 minutes (an increase of approximately 48.4%), this increase is a direct consequence of the lexicographic optimization strategy, where minimizing waiting time and overtime is prioritized before minimizing idle time. Consequently, the increase in idle time reflects a deliberate trade-off aimed at eliminating scheduling conflicts and improving clinical and operational feasibility. Overall, this comparison demonstrates that the proposed GA model effectively prioritizes patient flow and reduces staff workload while maintaining operational feasibility.

Although the operating room scheduling model can theoretically be formulated using exact methods, in practice, the problem's complexity is extremely high due to the numerous interdependent constraints involved, such as surgeon availability, nurse shift schedules, contamination-level sequencing of rooms, and operating room capacity. The experimental results showed that the Genetic Algorithm required approximately 16,000 seconds (around 4.44 hours) to compute the schedule for 37 patients, this computation time is still acceptable because the scheduling process is performed offline, typically conducted overnight to prepare schedules for the following day's surgical operations. This also implies that the use of exact methods would be far less efficient and may not produce feasible solutions within a practical timeframe. Nevertheless, the computation time remains a limitation of the current approach, and future work may focus on parallelizing GA operations or implementing hybrid acceleration strategies to further reduce computational latency. Subsequently, the optimized schedule was simulated to estimate recovery bed occupancy based on patients' recovery durations.

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Table 7. Simulation of Recovery Bed Utilization

No	Date	Number of Patients	Specialization	Surgeon	Number of Recovery Beds	No	Date	Number of Patients	Specialization	Surgeon	Number of Recovery Beds
1	1	20	7	13	4	12	30	14	6	9	4
2	2	20	5	7	4	13	31	4	3	3	1
3	3	30	9	15	5	14	22	25	10	17	4
4	7	21	10	15	4	15	28	28	10	17	5
5	9	18	3	4	3	16	5	33	12	19	4
6	15	19	11	13	3	17	6	36	10	17	5
7	16	16	5	8	4	18	8	29	9	18	4
8	19	25	9	14	3	19	10	38	13	20	3
9	20	27	13	17	5	20	12	35	15	22	5
10	23	16	6	7	4	21	24	24	11	14	4
11	29	12	7	8	2	22	28	23	9	14	5

The observation of the data indicates that the daily demand for recovery beds is significantly below the actual available capacity, with a maximum of five beds utilized compared to the hospital's total recovery room capacity of twelve beds. This finding suggests an excess capacity of more than twice the required amount. Operationally, the availability of surplus beds ensures that no bottlenecks occur during the patient recovery phase, allowing for a smooth transfer process from the operating room to the recovery room. The calculation of constraint conflicts was also conducted to determine whether the optimized schedule complies with the medical procedures and operational constraints applied in the operating room. The results of the constraint conflict analysis are presented as follows.

Table 8. Number of Constraint Conflicts

Patient ID	**Actual Schedule**			**Optimized Schedule**		
	Doctor Conflict	**OR Conflict**	**Nurse Conflict**	**Doctor Conflict**	**OR Conflict**	**Nurse Conflict**
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	1	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
10	0	0	1	0	0	0
12	0	0	0	0	0	0
13	1	0	0	0	0	0
14	0	0	0	0	0	0
15	0	1	1	0	0	0
17	0	1	1	0	0	0
18	0	0	0	0	0	0
19	0	0	0	0	0	0
20	0	0	0	0	0	0
21	0	0	0	0	0	0
23	1	0	0	0	0	0
24	0	0	0	0	0	0

Table 8. Number of Constraint Conflicts (Continued)

Patient ID	**Actual Schedule**			**Optimized Schedule**		
	Doctor Conflict	**OR Conflict**	**Nurse Conflict**	**Doctor Conflict**	**OR Conflict**	**Nurse Conflict**
25	1	0	0	0	0	0
26	1	0	0	0	0	0
27	0	0	0	0	0	0
Total	4	2	4	0	0	0

The comparison between the number of conflicts in the hospital's actual schedule and the optimized schedule shows that the actual schedule still contains four (4) surgeon conflicts, two (2) operating room conflicts, and four (4) nurse conflicts, whereas the optimized schedule is entirely free from such conflicts (0 conflicts). This finding indicates that the optimization model successfully satisfies the principle of clinical feasibility. This explicit reduction from multiple baseline conflicts to none demonstrates the effectiveness of the proposed GA based scheduling model in ensuring clinical feasibility while simultaneously improving operational efficiency and strict adherence to medical protocols. Expert validation was conducted to ensure that the assumptions, constraints, and scheduling formulations used in the model align with real hospital conditions. The validation process involved interviews with experts in surgical scheduling, during which the researcher presented the main constraints and the applied optimization approach, followed by confirmation regarding the model's compatibility with real world practices. This validation focused on the conceptual aspects of the model to strengthen both its theoretical foundation and practical relevance.

4. CONCLUSION

This study developed a two-stage approach to optimize operating room scheduling by considering constraints related to the availability of surgical teams, surgeons, contamination levels, as well as operating room and recovery bed capacity. The CatBoost algorithm demonstrated the best performance based on RMSE and MAE metrics. Patient age and gender variables did not contribute significantly to prediction accuracy, whereas the ASA (American Society of Anesthesiologists physical status) variable proved influential in improving model performance by reducing the MAE to 33.880 minutes and the RMSE to 55.575 minutes in multiprocedure cases. The operating room scheduling optimization model was successfully developed by incorporating both resource limitations and medical procedure constraints. The inclusion of 10% random immigrants in the genetic algorithm population effectively enhanced solution diversity and prevented premature convergence. However, the computation time of approximately 4.44 hours required to produce the final schedule represents a notable limitation of the current approach. This duration is still acceptable for offline scheduling performed overnight. Overall, the proposed model successfully generated clinically feasible schedules with optimal recovery bed utilization, reaching a maximum of five beds or less than 50% of the total available capacity. The proposed scheduling model provides practical benefits for hospital management by improving operating room utilization, reducing scheduling conflicts, and supporting more efficient coordination of critical resources. These improvements enhance healthcare efficiency by minimizing idle time and resource bottlenecks, while also improving patient care through more reliable schedules. These outcomes contribute to more efficient utilization of hospital resources while enhancing the overall quality of healthcare delivery. Future research should focus on parallelizing or accelerating the genetic algorithm to reduce computational latency, while also extending this study by incorporating the type of surgical procedure in multiprocedure cases and considering cost parameters and resource efficiency simultaneously to produce a more comprehensive prediction and optimization model.

CONFLICT OF INTEREST STATEMENT

The Authors state no conflict of interest.

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