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Optimizing Operating Room Scheduling Using Bat Algorithm

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Abstract: Operating room (OR) scheduling is a difficult combinatorial optimization problem and has an importance in hospital resource management. Effective scheduling is critical to utilizing operating rooms effectively and avoiding long waiting times, as well as minimizing costs. Due to the high computational complexity of the Mixed Integer Programming (MIP) in large scale instances, meta heuristics such as Bat algorithm (BA) can provide strong alternatives to solve this problem. In this study, a new model for optimization of surgical scheduling with considering performance measures such as makespan, waiting time and scheduling cost via BA is introduced. Stochastic elements are introduced in the schedule generator, using Pearson III and normal distributions to generate surgery times according to real-life situations. Experiments show that heuristic approaches based on computational efficiency, especially in larger instances when exact solvers are unfeasible. It is the better performance of swarm-intelligence-based algorithms over traditional methods in generating high-quality schedule solutions with the lowest possible execution time. The results of this study are practical for intelligent decision support systems for hospital scheduling optimization.

Keywords: Operating room scheduling, Swarm intelligence, Bat algorithm, Metaheuristics, Healthcare optimization, Makespan minimization.

Introduction

Operating room scheduling is a fundamental optimization challenge in healthcare systems, where the goal is to allocate a set of surgeries S = {s1, s2, . . . , sn} to a set of operating rooms R ={r1, r2, . . . , rm} while considering constraints related to surgeon availability, surgery durations, and hospital operational limits. The complexity of this problem arises from the need to minimize key performance indicators such as total waiting time W, makespan M, and while ensuring that each surgery s_i is scheduled within its feasible time window [T_i^{start}, T_i^{end}]. The presence of stochastic factors, such as variations in surgery durations and unexpected delays, further complicates the optimization process. Traditional scheduling approaches rely on deterministic models that attempt to minimize an objective function by exhaustively searching the solution space (Al Amin et al., 2025). But, because the problem is combinatorial and for a large time table, possible schedules grow exponentially as O(mn), an exact mechanisms such as MIP prove to be computationally infeasible for practical timetable size. Therefore, metaheuristic algorithms, in particular swarm intelligence techniques have drawn considerable attention as they are capable of effectively exploring complex search spaces and finding near-optimal solutions within a reasonable time period. Swarm intelligence-based algorithms, such as the Bat Algorithm (BA), are inspired by natural behaviors and offer adaptive mechanisms to explore and exploit the solution space dynamically. The Bat Algorithm is inspired by the echolocation mechanism of the bats, in which where the frequency f, velocity v, and pulse rate p of all bats vary dynamically in search of improving their solutions quality. Through the adaptation of their frequency modulation, each bat explores the solution space, which corresponds to a schedule configuration (Lee et al., 2019). By adjusting the intensity of the emitted pulses, a local search is performed, or the algorithm will be released for continued global search. This will then have a new solution based on both the best-known schedule S^* and a random variation S', where S' is Min$(1, S + \epsilon)$, with ϵ a uniform random variable, and iteratively improves the solution (Esra et al., 2024; Zhu et al., 2018). This adaptive mechanism enables the Bat Algorithm to avoid local optima and converge toward a global optimum. The problem formulation also takes into consideration the variations in durations of the surgeries and the uncertainty of scheduling them, by way of probability distributions the Pearson III, Normal, and the Gaussian distributions. In particular, in the classfindlibrary command, we apply the density function of a Pearson III distribution with skewness parameter γ mean μ and stan- dard deviation σ which is useful for the modeling applications for asymmetric distributions of the durations of surgery (Samudra, 2016; Zhu, 2018). Because there are many types of probability distributions, the one selected directly influences the robustness of the scheduling model (through the expected completion time $E(T_c)$ and variance $V(T_c)$ of the same scheduled surgeries). Scheduling performance can be evaluated with the total waiting time $W = \sum_{i=1}^{n} (T_i^{scheduled} - T_i^{ready})$, makespan $M = \max(T_i^{completion})$ or total cost C, in which the idle time and penalty for overtime is weighted sum between individual cost (Cardoen et al, 2010). The optimization strives to minimize these objectives concurrently while adhering to operational constraints like surgeon availability, room capacity limits, and precedence relationships between surgeries. This paper performs an analysis of Bat Algorithms when used for optimizing operating room scheduling Algorithms (Cardoen et al., 2010, Floudas, 2005). We review their speed of convergence, quality of the solution and computational complexity. We also compare the effect of various probability distributions on scheduling robustness (Fahmy, 2016; Abdalkareem et al., 2021). The results of the present article contribute to an understanding of how swarm intelligence techniques may be deployed to solve hard scheduling problems and, as such, they assist in building sound decision-support systems for hospital resources management. The rest of this paper is organized as follows: Section 2 describes a brief literature review about operating Room Scheduling; Section 3 describes the proposed methodology, the experimental results are given in section 4 and concludes with section 5.

Related Works

Operating room (OR) planning and scheduling are very important issues in healthcare management for two reasons. First, an organized program accelerates patient care through prompt medical work-up. Second, hospital managers focus on the utilization of operating room resources and facilities, as it is expensive equipment that can be used to enhance productivity and reduce costs. The number of old people has significantly increased because of the prolonged life expectancy in developed countries and because of that, demand for medical treatments, especially surgery, has increased (Fathollahi & Rahvar, 2017). Therefore, OR design provides a cost-effective measure to enhance productivity that supports the mission of health care institutions. This planning is generally classified by long-, medium- and short-term perspectives (strategic, tactical or operational). Strategic decisions are the one that are made for long-term time horizon and as a part of strategic planning (which is eradicated probably once in a single year (Bouguerra et al., 2015). To maintain an equitable use of resources, medium term planning is the area addressed by Master Surgical Scheduling (MSS). Meanwhile, OLPP concentrates on short-term scheduling which usually involves daily and weekly assignments. Decisions are made at a daily scheduling level of allocating surgeries that must be scheduled in each operating room. This stage exists under the influence of surgeon decisions alongside resource availability, admission capacity, operating room operation effectiveness, and minimizing overtime work hours, as described in (Nasiri, 2015). Operating room scheduling emerged in 1935 before scientists started developing academic studies about this domain in the 1960s (Kamran et al., 2018). The 1970s maintained this rising pattern of research work, which resulted in improved planning methodologies (Tegos et al., 2022). The author of (Zhou & Yue, 2021) suggested a sophisticated operating room scheduling strategy to maximize room use, minimize overtime, and minimize overall operating expenses. An updated mathematical model that can provide optimal solutions for up to 110 surgical situations was introduced in their study. Two modified heuristics based on the earliest due date (EDD) and longest processing time (LPT) norms were also created to produce workable scheduling solutions efficiently. An artificial bee colony (ABC) algorithm was implemented to improve performance further, combining elitism, local search methods, recovery schemes, and starting solutions. When applied to more than 110 schedule procedures, the ABC algorithm generated better results compared with heuristic methods; all-optimal solutions were obtained for surgeries of different sizes ranging from 40 to 100 patients. Their study presented the results, illustrated in a refined mathematical model which can optimally solve up to 110 surgical scenarios. In addition, two pairwise sequencing heuristics incorporating the EDD and LPT guidelines were generated to efficiently retrieve workable scheduling solutions. Sun et al. (2021) considered the optimization of scheduling emergency hospital appointments, with simulation being used to test and refine the schedules that were proposed. Their results showed a TTP improvement of 11.6% using block scheduling methods. Through the use of multi-objective mathematical models, medical centres may adjust and refine their scheduling policies to better reflect operational conditions, and to achieve improved resource utilisation. We will enhance your experience in the healthcare sector by offering you quality service and solutions for your business. Zhou and Yue (2021) addressed the scheduling problem in multidimensional service system with unpredicted service durations, possible customer abandonment. Their model sought to minimise patient wait times and idle time for healthcare providers through a two-stage stochastic optimisation program, supplemented by a Benders decomposition algorithm, which improved efficiency by 6%.

Proposed Methodology

Bat Algorithms (BA) use swarm intelligence approaches to address scheduling problems in operating rooms. The selected metaheuristic techniques demonstrate superior performance in discovering broad solution regions by efficiently exploring the balance between exploration and exploitation. As part of the operating room allocation process, several surgical procedures must be distributed, including $S = \{s_1, s_2, . . ., s_n\}$ across $R = \{r_1, r_2, . . ., r_m\}$ operating facilities subject to medical staff availability and procedural length and hospital administrative standards. Reducing total waiting periods W and makespan M and overall operational expenses C represent the main goals. Optimization involves repetitive solution refinement, enabling algorithms to find optimal schedules by adjusting resource use, time scheduling, and resource assignment methods. The Bat Algorithm uses echolocation-based search through dynamic bat adjustments of frequency velocity and pulse rate to find optimal solutions. The methodology enhances reliability by implementing Pearson III and Normal and Gaussian probability distributions to handle surgery duration uncertainties. Performance metrics evaluate the final scheduling solutions to determine their cost efficiency, scheduling feasibility, and convergence speed for optimal hospital procedure allocation.

Dataset Simulation

The dataset simulation process effectively represents all operating room constraints and available resources required for scheduling. The scheduling framework uses a five-day planning horizon designated as H = 5, which spans an ordinary workweek. Multiple operating rooms in the set R = {r1, r2, . . . , rm} are ready for use during normal working times and can add supplementary work time as needed. The regular working minutes for operating room r during day d are stored in matrix Rreg through element Rreg(d, r). The overtime capacity information is provided through matrix Rot, which describes the supplementary minutes beyond standard working hours. Each operating room's scheduled operations must stay within the sum of its regular times and overtime schedule allocations. Beyond operating room limitations, the dataset includes information about the surgeon's- ability and capacity. A group of surgeons S = {s1, s2, . . . , sk} exists which each has their daily availability expressed through the matrices Ts(d) indicating the number of working minutes for surgeon s on day d. The dataset accurately displays surgeon scheduling limitations because surgeons have different daily availability schedules (Demeulemeester et al, 2013). The allocation balance re-choirs an overtime penalty factor α = 1.5, raising the expense of utilising overtime resources. The scheduling cost calculation contains two parameters for idle and overworked time utilisation, which enable balanced operational efficiency and cost-saving performance. The set of constraints for surgical allocation requires the fulfilment of the following conditions:

$$T_j^{used} \leq \mathrm{T}_{\mathrm{j}}^{\mathrm{reg}} + T_j^{ot} \ , \ \forall\, \mathrm{j} \in \mathrm{R} \tag{1}$$

With T representing the entire time spent in room j over a day, this simulation framework helps evaluate the performance metrics of optimization algorithms used to solve challenging hospital scheduling problems while producing a realistic dataset (Al Amin et al, 2024).

Data Generation: Multiple Distributions

When developing realistic simulation models for operating room scheduling, calculating surgical duration is critical. The dataset contains different probability distributions because surgical times vary greatly in nature. Because the variable skewness coefficient improves comparison to real-world distributions, Pearson III is the primary tool used by the distribution system to produce realistic patterns of surgical length. The two parameters γ and β determine the spread of distribution outcomes, so simulated durations match real surgery durations prominently. The Pear-III distribution offers excellent results when modelling asymmetric distribution patterns that exhibit infrequent and possibly longer procedures. A realistic range from 40 to 150 minutes bounds the generated surgical durations to keep the scheduling rules practical (Al Amin et al., 2024). The normal distribution is the alternative option when Pearson III distribution cannot be accessed. The normal distribution requires two parameters to specify the mean μ and standard deviation σ, but both values must fall within the defined duration boundaries. The di value receives a randomly selected due date, representing the last day surgery execution can occur during the planning horizon. Randomly selecting surgeon Sj from active candidates allows uniform distribution throughout the staff during task assignments. The simulation produces realistic surgery assignments that combine controlled nurse-to-operation assessments with naturally occurring surgical time adjustments. Each procedure receives its surgery duration according to the established limitation (Al Amin et al, 2024).

$$40 \le d_i \le 150, \qquad d_i \sim P(\gamma, \beta) \text{ or } N(\mu, \sigma^2) \tag{2}$$

Where P (γ, β) is the Pearson III and N (μ, σ2) is the normal. Dynamically engaging uncertainty promotes diversity in the generated workloads, creating a well-rounded dataset. It also enables assessing different scheduling algorithms in varying degrees of uncertainty (Yang & He, 2013).

Heuristics: MEDD & MLPT & BAT Algorithm

Heuristic methods are frequently used to provide good solutions to complicated scheduling problems for which exact methods would be too computationally intensive. The Minimum Earliest Due Date (MEDD) and the Maximum Longest Processing Time (MLPT) heuristics are two rule-based scheduling methods proposed to assign surgeries with minimal make-ups and waiting time in a given schedule. These heuristics vary in terms of sorting methods and priorities, which affect how well they are able to queue up operating room human resources. The MEDD heuristic schedules the surgeriees according to their due date in non-decreasing order, and further break ties by selecting the longer surgeries first (Agarwal & Kumar, 2021). This ensures surgeries with earlier deadlines are scheduled effectively in the earliest positions.

The Bat Algorithm (BA) is a bio-inspired algorithm based on the echolocation bats use to find their prey. An Exploration-exploitation Algorithm was deployed for updating frequency, velocity and loudness simultaneously in order to promote a refinement of the optimal solution iteratively. Every bat in the population is a potential schedule solution, and its motion in the search space is determined by a frequency (fi), velocity (vi) and position (xi) associated to a feasible scheduling solution (Dao et al., 2024). The frequency update mechanism allows bats to explore different regions of the search space, preventing premature convergence. The frequency for each bat is updated as follows:

$$f_i = f_{min} + (f_{max} - f_{min}) \,.\text{rand}() , \tag{3}$$

Where β is a random number drawn from a uniform distribution U(0, 1). The velocity and new position of the bat are updated as follows:

$$v_i^{t+1} = v_i + (x_i - x^*).f_i , \tag{4}$$

$$x_i^{t+1} = x_i + v_i^{t+1} \tag{5}$$

Where x∗ is the best global solution found so far, if a bat generates a new solution that improves upon its current one, it updates its position and reduces its loudness Ai and pulse rate ri, using the rules:

$$A_i^{t+1} = \alpha A_i^t , \; r_i^t = r_i^0 \, [1 - \exp(-\gamma \tau)] \tag{6}$$

Where α and γ are predefined constants controlling the rate of adaptation.

Experimental Results

We compare the efficiency of the proposition algorithm through a series of experiments on optimization scheduling for operating rooms. Furthermore, Pearson III and normal distributions were utilized as a basis for the dataset, to ensure that realistic surgery times are presented. In the experiment, the problem size **Ω** was randomly changed from 40 to 130 and multiple random seeds per instance were used for statistical reliability. The algorithms being pitted against each other are Minimum Earliest Due Date (MEDD), 1) Minimum Largest Processing Time (MLPT) and Bat Algorithm 2) (BA). It was also tested considering key scheduling performance measures, such as makespan, waiting time and execution time. The procedure flow for the experiment consisted of First Generate n number of surgery request s with di ~ P(90, 15) where P is Pearson III distribution, second Allocate surgeries to all time slots using MEDD and MLPT heuristic, third fine tuning the schedule usin g BA in order to r un the optimization for multiple iterations and keepi ng track of pe rformance metrics. The latest end processing time over all the scheduled surgeries is called makespan:

$$\text{Makespan} = \max(T_{\text{finish},i}) \tag{7}$$

The waiting time is calculated as:

$$W_{\text{total}} = \max(0, T_{\text{start},i} - T_{\text{earliest},i}) \tag{8}$$

Table 1. Makespan, waiting time, and cost across different problem sizes

Ω (Surgeries)	Method	Makespan	Waiting	Cost
40	MEDD	2.97	1.08	121.17
40	MLPT	59.55	0.00	77.33
40	BA	4.46	1.17	84.75
50	MEDD	2.97	1.50	110.01
50	MLPT	74.42	0.00	99.62
50	BA	6.05	1.37	88.88
60	MEDD	3.07	2.00	95.15
60	MLPT	89.28	0.00	121.92
60	BA	6.05	1.83	78.01
70	MEDD	4.46	2.20	85.15
70	MLPT	104.14	0.00	144.21
70	BA	5.94	2.18	83.80
80	MEDD	4.46	2.67	72.58

Table 1 presents the key performance metrics makespan, waiting time, and operating-room cost (all in hours) for the three heuristics (MEDD, MLPT, BA) across increasing problem sizes. From these results, several precise observations emerge:

- MEDD achieves the lowest average makespan (2.97– 4.46), indicating highly efficient total completion times. Although it incurs non-zero waiting (1.08–2.67) due to front-loading of cases, its overall cost declines from 121.17 at Ω=40 to 72.58 at Ω=80, reflecting improved room utilization as volume grows.
- MLPT eliminates waiting altogether (0 h) but at the expense of excessive makespans (59.55–119.00) and sharply increasing cost penalties (77.33–166.50), making it unsuitable when rapid throughput is required.
- BA strikes a balance: makespans remain moderate (4.46–8.92), waiting times are limited (1.17–2.43), and costs stabilize around 78–84 , demonstrating robust performance under randomized slot selection with capacity constraints.

if the primary objective is to minimize overall completion time, MEDD is unequivocally the best-performing heuristic. Its slight waiting and moderate cost overhead are outweighed by its superior makespan reduction. Conversely, MLPT may be chosen only if zero waiting is critical and longer makespans are acceptable. For a more balanced trade-off among all three objectives, the BA approach is recommended.

Conclusions

This paper analysis demonstrates that a planning horizon of Ω=40 surgeries achieves the optimal trade off among the three primary objectives total completion time makespan patient waiting and operating room cost By synthesizing surgery durations from a Pearson Type III distribution to accurately model right skewed procedural times and applying a capacity aware randomized Bat Algorithm for slot assignment the proposed framework yields minimized makespan by front loading high priority cases under capacity constraints compressed overall schedule horizon controlled waiting by randomized yet capacity aware placement without excessive delays and reduced idle overtime cost by balanced utilization of regular and overtime hours This configuration comprising Ω=40 surgeries per planning period Pearson Type III duration model and capacity aware randomized Bat

Algorithm offers a robust grounded solution for operating room scheduling under high variability and competing objectives.

Scientific Ethics Declaration

* The authors declare that the scientific, ethical, and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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