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Metaheuristic Optimization for Hospital Sterilisation and Decontamination Services

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Abstract. Hospital Sterilization and Decontamination Units (HSDUs) play a critical role in ensuring the safe and efficient decontamination of surgical instruments to prevent healthcare-associated infections. This paper presents a mathematical modeling approach using Discrete Event Simulation (DES) to optimize staffing schedules within HSDUs at a district general hospital using Metaheuristic Optimization. The objective is to identify the optimal number of staff required to meet service demands while maintaining operational efficiency. A Greedy Heuristic and Tabu Search are employed to determine staffing levels that meet specific performance targets, including decontaminating at least 99% of items within the target time. Results showed that the Tabu Search algorithm significantly outperforms the Greedy Heuristic while maintaining 99% of items decontaminated within the required time. Our findings suggest that Tabu Search provides a more reliable and efficient method for optimizing staffing in HSDUs. Further work is recommended to explore cost implications of staffing decisions.

Keywords. Discrete-Event Simulation, Quality Improvement in Healthcare, Optimization, Mathematical Modelling

1. Introduction

Hospital Sterilisation and Decontamination Units (HSDUs) are integral to the decontamination of surgical instruments in hospitals, ensuring that items are safe for reuse in medical procedures. The efficiency and capacity of the decontamination process within these units are critical to reducing the risk of healthcare-associated infections (HAIs), a significant concern in healthcare settings. Maximising efficiency while maintaining a high standard of safety is essential, as the timely decontamination of instruments impacts both patient safety and operational effectiveness.

In addition to speed, another key factor influencing HSDU efficiency is the staffing schedule. The optimal shift pattern for staff operating the decontamination machines plays a significant role in ensuring smooth operations, reducing staff and operational costs, and maximising overall efficiency. HSDUs employ a combination of automated processes and manual tasks, all overseen by a team working in shifts. This integrated

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approach is vital for maintaining high standards of sterilization and decontamination. The process within an HSDU typically follows a defined pathway, as illustrated in Figure 1.

Figure 1. Process map of an HSDU [1].

The figure reveals that, initially, items undergo pre-processing, where they are checked for damage and sorted based on priority. After pre-processing, the items enter the washing phase, performed by automated machines for more than one hour. Items are then manually inspected for any contamination, with contaminated items sent back to the start of the process. Those that pass inspection are moved to autoclaves for sterilisation, where they undergo a 45-minute cycle before being ready for reuse.

In this research, we build on the work of England et al. (2025) [2], who developed an initial Discrete-Event Simulation (DES) model to determine staffing levels at a Hospital Decontamination and Sterilization Unit (HDSU). We extend their research by developing an open-source DES model paired with a metaheuristic simulation optimization strategy to address the combinatorial complexity and stochastic variation in the service. The goal is to improve operational efficiency while ensuring that the HDSU can meet the demand for surgical instruments to be sterilized, all while maintaining patient safety standards.

2. Methods

2.1. Discrete Event Simulation (DES)

To addresses the stochastic nature of the problem, which can be solved either through queuing theory (providing an analytical model) or by using Discrete Event Simulation (DES). We opted for DES due to its common use in healthcare settings and its ability to model dynamic and complex systems [3,4]. DES allows for the exploration of different staffing schedule scenarios and enables us to observe the system's behavior under various conditions. Specifically, the model predicts whether changes in staffing levels result in increased backlogs or improved flow through the system. The goal is to find a balance that minimizes staffing levels while maintaining quick turnaround times of items. We constructed a DES model to simulate the HSDU process and gain insights into potential bottlenecks, as well as to optimize staffing schedules. The model was built using the open-source Python library, *Ciw* [6]. Python was chosen over other simulation software (e.g., Simul8) due to its faster execution speed, particularly when running multiple iterations.

The model follows the process described in Figure 1 and operates on a first-in-first-out (FIFO) basis. However, prioritization is applied, where high-priority items are processed before low-priority ones. For nodes 2 and 4 (washing machines and autoclaves), we used a deterministic distribution to set the processing times, while nodes 1 and 3 (staff task completion) used a uniform distribution for task durations. For the two-site scenario, the same distributions were mirrored for the additional nodes. The model calculates the time each item spends in the system based on its arrival and exit times and evaluates whether items meet the target times. High-priority items are expected to be serviced within 5 hours, while low-priority items have a target time of 24 hours. The DES simulation ran for three weeks of operation, with results from week two used for analysis to allow for a warm-up and cooldown period, reflecting a more realistic scenario where the HSDU does not start with an empty queue.

2.2. A Greedy Heuristic

A greedy heuristic algorithm was employed to minimize staffing numbers while ensuring that 99% of items were serviced within the target time [5]. We began with an initial staffing schedule that included a surplus of staff, ensuring 100% of items were processed within the target time. From this initial setup, we randomly reduced the number of staff on each shift by one at a time and reran the HSDU simulation to check if the new staffing schedule remained feasible (i.e., still meeting the 99% target). The process continued until a point where further reduction in staff led to infeasible results, at which point the last feasible staffing schedule was considered optimal.

2.3. A Tabu Search

To avoid the issue of local optimal solutions encountered with the greedy heuristic, a Tabu search algorithm was implemented [7]. The Tabu search is a meta-heuristic approach that uses multiple algorithms in tandem to improve the solution iteratively. In our case, Tabu operators were employed to modify the staffing schedule, and the best feasible solutions were stored in a Tabu list. The algorithm starts with an initial solution that includes a staffing surplus (ensuring 100% of items were processed within the target time). The Tabu search aims now to reduce staffing levels while maintaining at least 99% of items processed within target times. Any schedules that did not meet this criterion were rejected.

2.3.1. Tabu Operators

The Tabu search used four operators ($\tau := \{0,1,2,3\}$), which were divided into two categories: intensification and diversification strategies [7]. The intensification strategies include the Addition Operator ($\tau = 0$), where a random integer between 0 and 7 selects a shift and adds one member of staff, and the Removal Operator ($\tau = 1$), where a random integer between 0 and 7 selects a shift and removes one member of staff. The diversification strategies consist of the Swap Within Operator ($\tau = 2$), where a random integer selects shifts 0–3 or 4–7, and the number of staff between two shifts.

2.3.2. Tabu List

The Tabu List stores the best feasible solutions encountered during the search process. At the end of the algorithm, the best solution in the Tabu List was chosen as the optimal solution. Iterating multiple times allowed for progressively better solutions, approaching the true optimal staffing schedule.

2.3.3. Tabu Search Algorithm

The algorithm begins by initializing the Tabu list and identifying an initial solution (starting from a staffing schedule that ensures 100% of items are serviced within the target time). The constraints of the problem were defined, and the objective was to minimize staffing levels. Each iteration involves applying a Tabu operator, running the HSDU simulation, and storing the best feasible solution in the Tabu list.

3. Results

The initial staffing levels were set with an excess of staff to ensure 100% of items were decontaminated within the target time. These initial staffing levels are shown in Table 1.

	Initial Number of Staff	Improved Number of Staff After 20 TS Iterations
12pm -6am	5	0
6am - 2pm	5	4
8am - 4pm	5	2
4pm - 12am	5	2

Table 1: Initial Staffing Levels and Improved Staffing Levels after Tabu Search (TS).

The discrete event simulation (DES) confirmed that with the initial staffing schedule (5 members of staff per shift), 100% of items were successfully decontaminated within the required time. The Tabu search algorithm was then used for twenty iterations, with the results indicating a reduction in staffing levels, while still maintaining a high level of performance. As shown in **Table 1**, the best staffing levels after 20 iterations were [0, 4, 2, 2], requiring a total of eight staff members to decontaminate 99% of items within the target time.

To explore the trade-off between staffing and decontamination performance, the Tabu search algorithm was rerun with the constraint reduced to ensure that 90% of items were decontaminated within the required time. The results showed that the optimal staffing schedule for this constraint was [1, 3, 2, 1], requiring only seven staff members. This illustrates that staffing can be reduced to seven while still achieving a high decontamination rate, though at the expense of processing a smaller percentage of items within the target time. **Figure 2** shows how the staffing levels evolved over the course of twenty iterations under different constraints.

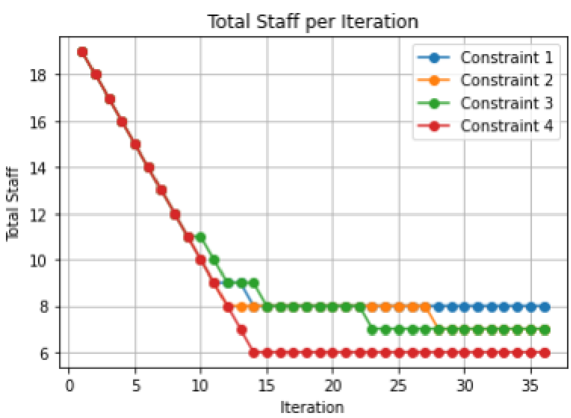

Figure 2: Graph showing how the number of staff in optimal solution changes for number of iterations of algorithm, where Constraint 1 = 99% of items in required time, Constraint 2 = 90% of items in required time, Constraint 3 =85% of items in required time, and Constraint 4 = 80% of items in required time.

4. Discussion and Conclusion

In this research, our goal was to identify the optimal staffing levels for a Hospital Sterilisation and Decontamination Unit (HSDU). We built an Open-Source Discrete Event Simulation (DES) model using the Python package *Ciw* [6], and then applied two optimization algorithms, the Greedy Heuristic and the Tabu Search, to determine staffing requirements that would meet service demand while maintaining efficiency.

The results demonstrated that the Tabu Search algorithm outperforms the Greedy Heuristic in finding optimal staffing solutions. Specifically, under the constraint of decontaminating 99% of items within the target time, the Tabu Search algorithm reduced the staffing requirement for two sites from an initial forty staff members to just twenty-one. In comparison, the Greedy Heuristic averaged a staffing requirement of twenty-seven staff members after 34 iterations. While the Greedy Heuristic occasionally reached the same solution as the Tabu Search, it frequently found other local optimal solutions, making it less dependable for this problem. These findings suggest that the Tabu Search is the superior approach for optimizing staffing levels in HSDUs, as it provides more consistent results and better efficiency.

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