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Dynamic Patient Scheduling in Hospitals Using Variable Length Non-Dominated Sorting Genetic Algorithm III

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Effective patient scheduling in hospitals is crucial for optimizing resource use and improving patient care. Traditional methods often struggle to balance patient preferences, hospital constraints, and varying patient loads. This study explores the III genetic algorithm without dominant sorting with variable length (VL-NSGA III) for dynamic patient scheduling and compares it with Particle Swarm Optimization (PSO), Multi-Objective Particle Swarm Optimization (MOPSO), Objective Decomposition Particle Swarm Optimization (ODPSO), and Genetic Algorithm without Dominant Sorting II with Best Fitness Evaluation (Nsga2bfe). The problem formulation considers dynamic patient arrivals and hospital constraints, requiring flexible solutions. VL-NSGA III generates high-quality non-dominant solutions tailored to dynamic scheduling scenarios. The evaluation used simulator-based scoring over a 36-day period, with synthetic patient data simulating real hospital conditions. The simulation modeled a hospital with multiple departments, specializations, and rooms, considering factors such as room capacity, patient arrival rates, and service duration. Evaluation metrics included set coverage (C-metric) to assess dominance among solution sets, hypervolume (HV) to measure objective space coverage, and convergence to measure proximity to the true Pareto front.

The study ran multiple simulation scenarios with varying patient arrival rates, service durations, and hospital capacities to test the algorithm's robustness and adaptability. The results showed that VL-NSGA III excelled at generating non-dominated solutions with superior set coverage, achieving a value of 1 against PSO, MOPSO, ODPSO, and Nsga2bfe, indicating complete dominance. ODPSO achieved the highest hypervolume, closely followed by MOPSO and PSO. Notably, MOPSO demonstrated partial dominance over PSO with 0.7 coverage and over ODPSO with 0.8333. ODPSO showed partial dominance over PSO and MOPSO with coverage values of 0.6333 and 0.7333, respectively. Nsga2bfe exhibited partial dominance over VL-NSGA III with a coverage value of 0.03333 while fully dominating PSO and MOPSO. The dominant set coverage of VL-NSGA III highlighted its robustness and adaptability in dynamic patient scheduling scenarios, despite lower hypervolume values compared to ODPSO, MOPSO, and PSO. This underscores the importance of considering both set coverage and hypervolume metrics when evaluating algorithm performance for complex scheduling problems.

Povzetek: Dinamičnega načrtovanje storitev pacientov v bolnišnicah je analizirano s pomočjo variabilne dolžine genetskega algoritma III brez dominacije (VL-NSGA III). Rezultati kažejo, da VL-NSGA III omogoča učinkovito reševanje zapletenih optimizacijskih problemov s številnimi cilji v zdravstvenem okolju, kar pomembno izboljša načrtovanje glede na bolnišnične omejitve in preference pacientov.

1 Introduction

In the realm of healthcare management, the optimization of patient bed scheduling stands as a pivotal challenge, necessitating a delicate balance between operational efficiency and the paramount goal of enhancing patient care quality. This challenge is further complicated by the multifaceted objectives that healthcare facilities must navigate, including cost minimization, patient satisfaction maximization, and equitable resource distribution. As the field progresses, there is a growing recognition of the limitations of traditional single-objective optimization models, which, while adept at addressing specific operational issues, often fall short in capturing the full complexity of healthcare operations [1].

The shift towards multi-objective optimization (MOO) techniques represents a significant advancement in addressing the intricate balance of objectives within healthcare management, particularly in the context of patient bed scheduling. MOO algorithms, such as NSGA-II, have been widely recognized for their utility in tackling a plethora of combinatorial optimization challenges within healthcare, including patient scheduling and resource allocation [2]. However, as the number of objectives increases, the transition to many-objective optimization (MaOP) becomes essential, necessitating the development of advanced frameworks that can effectively manage the higher dimensionality of objectives and the inherent conflicts among them.

Recent research has begun to explore the application of NSGA-III, an extension of the NSGA-II algorithm, which is specifically designed to handle many-objective problems. NSGA-III introduces the concept of reference points to facilitate the exploration of the Pareto-optimal front more comprehensively, thereby offering a more nuanced approach to decision-making in complex optimization scenarios [3]. This algorithm has shown promise in various domains, and its adaptation to healthcare optimization problems, particularly patient bed scheduling, is a burgeoning area of interest.

In this article, we delve into the application of NSGA-III for the Patient Admission Scheduling Problem (PASP), a dynamic and multi-objective combinatorial optimization problem that is NP-hard in nature [4]. We propose a simulation for dynamic patient scheduling that leverages NSGA-III's reference point-based approach to optimize patient admissions, hospital time locations, and achieve quality of service and cost objectives. Our study contributes to the literature by demonstrating the superiority of NSGA-III over other optimization algorithms in terms of set criticality and soft constraint values, thereby highlighting its potential as a valuable tool for addressing the complexities of PASP in a dynamic healthcare environment [5].

Through a rigorous evaluation and comparison with traditional models, our findings underscore the efficacy of NSGA-III in managing the many-objective nature of PASP, offering a promising direction for future research in healthcare optimization. The integration of NSGA-III's reference point methodology into patient scheduling systems could significantly enhance the decision-making process, leading to more efficient and effective healthcare operations.

2 Related works

In the evolving landscape of healthcare management, the optimization of patient bed scheduling emerges as a critical concern, underlined by the need to balance operational efficiency with the paramount objective of patient care quality. The complexity of this challenge is further compounded when considering the multifaceted objectives that healthcare facilities strive to achieve, such as cost minimization, patient satisfaction maximization, and equitable resource distribution. This literature survey delves into the progression from traditional optimization approaches to multi-objective optimization (MOO) techniques, with a particular focus on the exploration and application of these methodologies within the realm of patient bed scheduling. The discussion extends to the realm of many-objective optimization (MaOPs), highlighting the current research gaps and underscoring the potential for future advancements.

Historical approaches to optimizing hospital bed allocation primarily utilized single-objective optimization models, which, while effective in addressing specific problems, often neglect the complexity and multiple goals inherent in hospital operations. For instance, simulation-optimization techniques have demonstrated potential for operational improvements in bed allocation [1], whereas the application of queuing theory provided a framework for managing bed allocation during the COVID-19 pandemic, offering solutions to the sudden surge in demand for hospital resources [4]. Despite these advancements, such traditional methods frequently fall short in holistically addressing the nuanced demands of healthcare management, primarily due to their singular focus on optimizing a specific operational facet without considering the broader spectrum of objectives that healthcare facilities juggle.

The transition towards MOO techniques represents a significant stride in addressing the intricate balance of objectives in healthcare management, particularly in patient bed scheduling. The adaptation of NSGA-II, a renowned MOO algorithm, showcases its utility across a plethora of combinatorial optimization challenges within healthcare, including patient scheduling and resource allocation [2]. Similarly, the deployment of evolutionary algorithms, like the Artificial Bee Colony (ABC) algorithm, for patient admission scheduling problems [6], epitomizes the adaptability and efficacy of MOO methods in navigating complex operational landscapes. These approaches exemplify the shift towards frameworks that accommodate multiple, often conflicting, objectives, thereby offering more nuanced and comprehensive solutions to healthcare optimization problems.

The literature reveals a convergence of optimization techniques towards addressing specific healthcare scheduling problems. For instance, the allocation and scheduling of hospital beds during critical periods, such as epidemics, have been tackled using both queuing theory and simulation-based approaches, illustrating the sector's adaptability in crisis situations [4], [7]. Moreover, the utilization of simulation-optimization models extends to general bed management and elective patient admissions, emphasizing the technique's versatility across different contexts [1], [8].

Furthermore, evolutionary algorithms like NSGA-II and ABC have been applied not only in patient bed scheduling but also in broader resource allocation problems, underscoring their relevance across a range of healthcare optimization issues [1], [2], [6]. The exploration of these algorithms in various healthcare settings reveals their potential in addressing distinct but related challenges, from optimizing surgery schedules to ensure efficient bed usage [9] to enhancing patient admission strategies by considering inter-related resources like beds and operating rooms [10].

Despite the advancements in MOO, the exploration into many-objective optimization frameworks tailored for healthcare optimization, particularly patient bed scheduling, remains limited. MaOPs introduce a higher dimensionality of objectives, thereby exacerbating the challenge of achieving an optimal balance among conflicting goals. The literature indicates a palpable gap in applying many-objective optimization frameworks, such as Mo4Ma, within the healthcare domain [11]. These frameworks, while promising in general optimization scenarios, have yet to be fully explored and adapted to the nuanced requirements and constraints of healthcare settings. A comparative evaluation between the methods in presented in Table 1.

Table 1: Methodological comparison of patient bed scheduling optimization approaches in healthcare management

Ref	Objective	Optimization Technique	Application Context	Key Findings	Real time scheduling	Limitations
[1]	Operational improvements in bed allocation	Simulation-Optimization	General bed management	Demonstrated potential for operational improvements	×	Limited to specific operational aspects, not holistic
[2]	Patient scheduling and resource allocation	NSGA-II (MOO)	Combinatorial optimization challenges in healthcare	Showcased utility across various healthcare scenarios	×	Complexity increases with number of objectives
[4]	Bed allocation during COVID-19 pandemic	Queuing Theory	Managing surge in hospital resources	Provided solutions for sudden demand surge	×	Focused on specific pandemic-related scenarios
[6]	Patient admission scheduling	Artificial Bee Colony (ABC) Algorithm	Complex operational landscapes	Epitomized adaptability and efficacy of MOO methods	×	Requires fine-tuning of algorithm parameters
[7]	Hospital bed allocation during critical periods	Queuing Theory and Simulation-Based Approaches	Epidemics and crisis situations	Illustrated adaptability in crisis	×	Context-specific, may not generalize well
[8]	General bed management and elective patient admissions	Simulation-Optimization	Various healthcare contexts	Emphasized versatility of technique	×	Potentially resource-intensive
[9]	Surgery schedule optimization for efficient bed usage	Evolutionary Algorithms	Surgery scheduling	Enhanced efficiency in bed usage	×	Limited focus on inter-related resources
[10]	Patient admission strategies considering inter-related resources	Evolutionary Algorithms	Admissions, beds, and operating rooms	Improved admission strategies	×	Integration with real-time systems needed
[11]	Many-objective optimization in healthcare	Mo4Ma Framework	General optimization scenarios	Promising in general scenarios	×	Computational complexity and resource intensity
[12]	Patient admission scheduling (PAS)	ILP, Single Objective Meta-Heuristic, Multi-Objective Meta-Heuristic (Pareto Front)	Combinatorial optimization in healthcare	Demonstrated superiority of multi-objective optimization with window incorporation over traditional models	√	High computational demand for ILP, risk of local minima in single objective approaches

The critical analysis of current literature uncovers significant gaps in the application of many-objective optimization to healthcare management challenges. One of the primary hurdles is the computational complexity and resource intensity associated with MaOPs, which can be prohibitive in real-world healthcare applications. Additionally, there is a notable deficiency in frameworks that integrate seamlessly with healthcare information systems, allowing for dynamic and real-time decision-making based on fluctuating hospital needs and patient inflows.

The challenge extends beyond computational and technical hurdles, encompassing the need for solutions that are not only effective and efficient but also ethically grounded and patient-centric. The development of optimization models that consider patient outcomes, equity in resource distribution, and ethical considerations in decision-making processes remains a vital frontier for research.

The comprehensive review of existing literature reveals several critical gaps in the current state-of-the-art approaches to hospital patient scheduling, which our proposed VL-NSGA III algorithm aims to address:

1. Limited Adaptability to Dynamic Environments: Most existing methods, such as those employing queuing theory (Hu et al., 2021) or fixed optimization models (Guido, 2024), struggle to adapt to the rapidly changing dynamics of hospital environments. These approaches often fail to account for sudden fluctuations in patient volumes, varying patient characteristics, and real-time changes in hospital resources. There is a clear need for an algorithm that can dynamically adjust to these changing conditions without compromising solution quality.
2. Inadequate Handling of Many-Objective Problems: While multi-objective optimization techniques like NSGA-II have shown promise in handling multiple objectives (Verma et al., 2021), they often falter when dealing with many-objective

problems (more than 3 objectives). Hospital scheduling inherently involves numerous, often conflicting objectives, necessitating an approach capable of effectively managing this complexity without significant degradation in performance or solution quality.
3. Insufficient Real-Time Constraint Management: Existing methods frequently fall short in accounting for real-time changes in hospital constraints and patient needs. Simulation-based approaches (Oliveira et al., 2020) and static optimization models struggle to incorporate dynamic constraints effectively, leading to suboptimal or infeasible solutions in rapidly changing hospital environments.
4. Scalability Challenges: Many current algorithms face significant scalability issues when applied to large, complex hospital systems with multiple departments and specializations. This limitation hinders their practical application in real-world hospital settings, where the ability to handle large-scale, complex scheduling problems is crucial.
5. Imbalance Between Exploration and Exploitation: Existing optimization approaches often struggle to maintain an effective balance between exploring new solutions and exploiting known good solutions. This imbalance can lead to premature convergence or inability to escape local optima, resulting in suboptimal scheduling outcomes.
6. Limited Integration of Patient Preferences and Medical Priorities: While some studies have considered patient preferences (Bolaji et al., 2022), there remains a gap in effectively integrating these preferences with medical priorities and hospital constraints in a dynamic, many-objective optimization framework.

To address these gaps, we propose the Variable Length Non-Dominated Sorting Genetic Algorithm III (VL-NSGA III). This algorithm is specifically designed to handle dynamic, many-objective optimization problems in hospital scheduling. Its variable length encoding allows for adaptive problem representation, enabling it to adjust to changing patient loads and hospital conditions in real-time. The algorithm's structure is tailored to efficiently manage many-objective problems, improving its ability to balance multiple, often conflicting, objectives inherent in hospital scheduling. Moreover, VL-NSGA III incorporates mechanisms for dynamic constraint handling and maintains a better balance between exploration and exploitation, potentially leading to more robust and practical scheduling solutions.

By addressing these identified gaps, our proposed VL-NSGA III algorithm aims to advance the state-of-the-art in hospital patient scheduling, offering a more adaptive, scalable, and comprehensive approach to this complex problem.

In conclusion, the literature survey underscores the critical need for advancements in optimization techniques, particularly in the realm of many-objective optimization, to address the complex and evolving challenges of patient bed scheduling in healthcare. The incorporation of criteria for handling many-objective optimization challenges, specifically the selection from the Pareto front, is a significant gap that requires further exploration. Future research should focus on developing frameworks that not only manage the increasing number of objectives but also integrate seamlessly with healthcare systems, ensuring that optimization solutions are both effective and ethically sound, ultimately enhancing the quality of patient care.

3 Methodology

3.1 Problem formulation

The problem of bed patient scheduling in hospitals involves assigning hospital beds to incoming patients in a manner that optimally balances the preferences of the patients and the constraints imposed by the hospital's resources and regulations. This problem is complex due to the variability in patient needs, preferences, and the dynamic nature of hospital operations. The objective is to create a scheduling system that maximizes patient satisfaction while adhering to the constraints of hospital rooms. This problem is formulated as a many-objective optimization problem where the objectives are soft constraints subject to the hard constraints derived from the restrictions in the hospital.

Given a sequence of patients $\{P_1, P_2, \dots, P_n\}$ with individual preference sets $\{S_1, S_2, \dots, S_n\}$ and a set of hospital rooms $\{R_1, R_2, \dots, R_m\}$ each with specific restrictions $\{C_1, C_2, \dots, C_m\}$, the goal is to develop a scheduling system that assigns each patient P_i to a room R_j at a time t_k such that the hard constraints are satisfied while optimizing the soft constraints.

Let x_{ijk} be a binary decision variable where $x_{ijk} = 1$ if patient P_i is assigned to room R_j at time t_k, and $x_{ijk} = 0$ otherwise. The objective functions are as follows:

1. Maximizing patient satisfaction:

$$Maximize \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{T} x_{ijk} \cdot S_{ij} \quad (1)$$

Where S_{ij} represents the satisfaction score of patients P_i being assigned to room R_j.

2. Minimizing waiting time:

$$Minimize \sum_{i=1}^{n} W_i \cdot \left(1 - \sum_{j=1}^{m} \sum_{k=1}^{T} x_{ijk}\right) \quad (2)$$

Where W_i is the waiting time of patient P_i.

3. Maximizing room utilization:

$$Maximize \sum_{j=1}^{m} \frac{\sum_{i=1}^{n} \sum_{k=1}^{T} x_{ijk}}{C_j} \quad (3)$$

Where C_j is the capacity of room R_j.

4. Minimizing staff workload:

$$Minimize \sum_{s=1}^{S} \left(\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{T} x_{ijk} \cdot L_{ijs} \right)^2 \quad (4)$$

Where L_{ijs} is the workload impact of patient P_i in room R_j on staff member s.

5. Minimizing transfers:

$$Minimize \sum_{i=1}^{n} T_i \quad (5)$$

where T_i is the number of transfers patient P_i undergoes.

6. Ensuring equity:

$$Minimize \sum_{g=1}^{G} \left(\frac{N_g}{N} - \frac{B_g}{B} \right)^2 \quad (6)$$

Where N_g is the number of patients in group g, N is the total number of patients, B_g is the number of beds assigned to group g, and B is the total number of beds.

The constraints are expressed as follows:

1 Room capacity:

$$\sum_{i=1}^{n} \sum_{k=1}^{T} x_{ijk} \le C_j \; \forall j \quad (7)$$

2 Patient requirements:

$$x_{ijk} = 0$$
$$\text{if patient } P_i \text{ does not meet the requirements of room} R_j \text{ at time} t_k \quad (8)$$

3 Medical priority:

$$\sum_{j=1}^{m} \sum_{k=1}^{T} x_{ijk} = 1 \text{ if } P_i \text{ has high medical priority} \quad (9)$$

4 Temporal constraints:

$$x_{ijk} \cdot x_{ijl} = 0 \; \forall i, j, \; \text{ if } k \ne l \quad (10)$$

Ensuring that a patient is assigned to only one room at any given time.

To solve this many-objective optimization problem, advanced optimization techniques such as multi-objective evolutionary algorithms (MOEAs) or Pareto-based optimization methods can be employed. These methods can efficiently handle the trade-offs between conflicting objectives and provide a set of optimal solutions (Pareto front) from which the hospital administration can choose based on their priorities.

3.2 Simulator

The simulator, depicted in Figure 2, is designed to evaluate the dynamic scheduling of patients in a hospital environment. This system manages the flow of newly arrived patients and their allocation to hospital rooms through a sophisticated scheduling and optimization process.

Newly arrived patients are first fed into the scheduler, which is responsible for receiving a solution from the solution selection block and integrating it into the list of non-confirmed patients. This list includes patients who have not yet been confirmed for specific scheduling slots. The non-confirmed patients list serves two primary functions: it feeds non-confirmed patients into a new call of the optimization algorithm and provides patients whose scheduled day is within less than D days to the confirmed patients list through a sub-block named Confirm.

The core of the optimization process is the Variable Length Non-Dominated Sorting Genetic Algorithm (VL-NSGA III). This algorithm operates on different lengths of solutions due to the fluctuating number of patients, adapting dynamically to the changing patient load. The following assumptions are inherent in the simulation model:

1. Hospital Structure: The hospital comprises a set of departments D, each specializing in various fields S, and containing a set of rooms R.
2. Room Capacity: Each room within a department can accommodate a pre-defined number of patients simultaneously.
3. Patient Arrival Rate: Patients arrive at the hospital at a specific rate, and each patient requires a certain number of nights within a preferred department and specialization.
4. Service Duration: Each patient is served within a specified number of nights.
5. Dynamic Solution Space: The optimization problem is dynamic, with the solution space changing in length due to the varying number of patients on different days. This affects the allocation of patients from the non-confirmed list.
6. Time-Dependent Optimization Outcome: The outcome of the optimization process at time t is denoted as PF_t, indicating a time-dependent Pareto Front.

In this system, the scheduler integrates inputs from new patient arrivals and manages them through the VL-NSGA III optimization algorithm to generate a Pareto Front of optimal scheduling solutions. These solutions are then selected and applied, ensuring that patients are allocated rooms in a manner that balances their preferences and the hospital's capacity constraints. The confirmed patients list is continually updated, and the process iterates to accommodate dynamic changes in patient load and hospital resources. This simulation model provides a robust framework for evaluating the efficacy of the dynamic scheduling system in a hospital environment.

3.3 Evaluation

In this section, we outline the evaluation methodology employed to assess the performance of the proposed Variable Length Non-Dominated Sorting Genetic Algorithm III (VL-NSGA III) for dynamic scheduling of patients in a hospital environment. The evaluation focuses on comparing VL-NSGA III against several well-established Multi-Objective Optimization (MOO) algorithms, including PSO, MOPSO, ODPOSO, and Nsga2bfe. The assessment is a simulator-based evaluation. For this stage, we utilized the simulator's data, which covered a total of 36 days. The data has a layout similar to that provided in the work of [34]. We contrasted NSGA-3, which incorporates numerous objective optimizations based on our created operators, with the following benchmarks: particle swarm optimization (PSO), multi-objective particle swarm optimization (MOPSO), and objective decomposition particle swarm optimization (ODPSO). The set coverage, hypervolume, and convergence curves were produced to facilitate a comprehensive comparison. To ensure a robust evaluation, the hospital environment is simulated with departments DD, each specializing in various fields SS, and containing a set of rooms RR. The simulation models real-world constraints such as room capacity, patient arrival rates, and service durations. Synthetic patient data is generated to mimic real hospital scenarios, including varying patient arrival rates, service duration requirements, and departmental preferences. VL-NSGA III, PSO, MOPSO, ODPOSO, and Nsga2bfe are implemented in the simulation framework. Each algorithm is tuned to its optimal parameters to ensure a fair comparison. The performance of the algorithms will be evaluated using the following metrics: Set Coverage (C-metric), which assesses the dominance of one algorithm's solution set over another, with a higher set coverage value indicating superior performance in terms of generating non-dominated solutions; Hypervolume (HV), which measures the volume of the objective space covered by the Pareto front generated by each algorithm, with a higher hypervolume indicating b etter coverage of the objective space; and Convergence, which measures the degree to which the algorithm's solutions approach the true Pareto front. The evaluation process involves running multiple simulation scenarios to compare the performance of VL-NSGA III with the other MOO algorithms. Each scenario includes different patient arrival rates, service durations, and hospital capacities to test the robustness and adaptability of the algorithms. The following steps are undertaken: initializing the hospital environment and patient data for the simulation, running each algorithm (VL-NSGA III, PSO, MOPSO, ODPOSO, Nsga2bfe) on the simulation environment multiple times to obtain a statistically significant set of results, collecting data on set coverage, hypervolume, convergence, and diversity for each run of the algorithms, and analyzing the collected data to compare the performance of the algorithms across the defined metrics.

4 Experimental results and analysis

The heatmap provided illustrates the set coverage among various Multi-Objective Optimization (MOO) methods, namely Nsga3, PSO, MOPSO, ODPOSO, and Nsga2bfe. Set coverage is a critical metric used in evaluating the performance of different MOO algorithms. It represents the proportion of solutions from one algorithm's solution set that are dominated by solutions from another algorithm's solution set. A higher value in the heatmap signifies a stronger performance in terms of dominance over other solution sets. Examining the heatmap reveals several insights into the relative performance of these algorithms. The first notable observation is the dominance of the Nsga3 method. Nsga3 consistently shows high coverage values, indicating it has superior performance over the other algorithms in the comparison. Specifically, Nsga3 dominates PSO, MOPSO, ODPOSO, and Nsga2bfe entirely, with set coverage values of 1 across these comparisons. This suggests that Nsga3 solutions are not dominated by any solutions from PSO, MOPSO, ODPOSO, or Nsga2bfe, highlighting its efficacy in producing optimal solutions in a multi-objective context. In contrast, Nsga3 does not dominate itself, which is expected since set coverage within the same algorithm is not a meaningful metric (value of 0). This absence of self-dominance underscores the precision and focus of Nsga3 in finding non-dominated solutions across different scenarios. Next, considering PSO, it demonstrates complete dominance over MOPSO and ODPOSO, with set coverage values of 1. This indicates that all solutions provided by MOPSO and ODPOSO are dominated by those from PSO. However, PSO does not dominate Nsga3 or Nsga2bfe (values of 0), suggesting that while PSO is effective against certain methods, it does not reach the performance levels of Nsga3 or Nsga2bfe in generating non-dominated solutions. MOPSO's performance is mixed. It shows partial dominance over PSO with a coverage of 0.7, indicating that 70% of MOPSO's solutions are not dominated by PSO's solutions. Moreover, MOPSO exhibits a partial dominance over ODPOSO with a coverage of 0.8333, signifying that a substantial portion of MOPSO's solutions are superior to those of ODPOSO. However, MOPSO does not dominate Nsga3 or Nsga2bfe (values of 0), demonstrating its limited effectiveness compared to these methods. ODPOSO, which stands for Objective Decomposition based variant of MOPSO, displays a partial dominance over both PSO and MOPSO with coverage values of 0.6333 and 0.7333, respectively. These values suggest that ODPOSO can outperform PSO and MOPSO to some extent. However, like MOPSO, ODPOSO does not dominate Nsga3 or Nsga2bfe, highlighting its relative inferiority when compared to these stronger algorithms. Nsga2bfe, an enhanced version of NSGA-II that includes the criteria of Best Fitness Estimation (BFE) which balances diversity and convergence, emerges as another strong contender. It shows partial dominance over Nsga3 with a coverage value of 0.03333. Although this value is relatively small, it indicates that there are some scenarios where Nsga2bfe solutions are not dominated by Nsga3. Additionally, Nsga2bfe completely dominates PSO and MOPSO, with set coverage values of 1, underscoring its robust performance against these methods. However, Nsga2bfe does not dominate ODPOSO (value of 0), reflecting a limitation in its overall dominance.

The bar chart in Figure 2 illustrating hypervolume values offers valuable insights into the performance of various Multi-Objective Optimization (MOO) methods: Nsga3, PSO, MOPSO, ODPOSO, and Nsga2bfe. Hypervolume measures the volume of the objective space dominated by a Pareto front, with higher values indicating better performance in covering the objective space. ODPOSO achieves the highest hypervolume, suggesting its effectiveness in covering a broad objective space. This finding aligns with the nature of ODPOSO (Objective Decomposition based variant of MOPSO), which decomposes complex objectives into simpler sub-problems, resulting in extensive objective space coverage. MOPSO and PSO also show strong performance in terms of hypervolume, indicating their ability to explore and cover the multi-objective space efficiently. Nsga3 and Nsga2bfe, while exhibiting lower hypervolume values, still maintain respectable performance levels. However, linking this hypervolume analysis with the set coverage analysis reveals a deeper understanding of the algorithms' overall performance. The set coverage heatmap indicated that Nsga3 is the most dominant method, completely dominating PSO, MOPSO, ODPOSO, and Nsga2bfe. This underscores Nsga3's superior ability to generate non-dominated solutions across different scenarios. Nsga2bfe also showed strong performance, particularly against PSO and MOPSO, by incorporating the Best Fitness Estimation (BFE) to balance diversity and convergence.

The preference for more dominating solutions, as indicated by the set coverage, highlights that while hypervolume is an important metric, the ability to dominate other solution sets is often more critical in multi-objective optimization. Despite ODPOSO's higher hypervolume, Nsga3's complete dominance over other methods makes it the preferred choice for generating high-quality, non-dominated solutions. This dominance indicates that Nsga3 consistently finds solutions that are not only good but also superior to those found by other methods.

Therefore, Nsga3 stands out as the preferred method due to its superior dominance in generating high-quality solutions, as evidenced by the set coverage analysis. This makes Nsga3 ideal for applications where the priority is on obtaining non-dominated solutions that outperform others. Although ODPOSO achieves the highest hypervolume, indicating extensive objective space coverage, the set coverage dominance of Nsga3 demonstrates that it provides more valuable solutions in multi-objective optimization scenarios. Therefore, when choosing between these methods, the preference for more dominating solutions should guide the selection towards Nsga3.

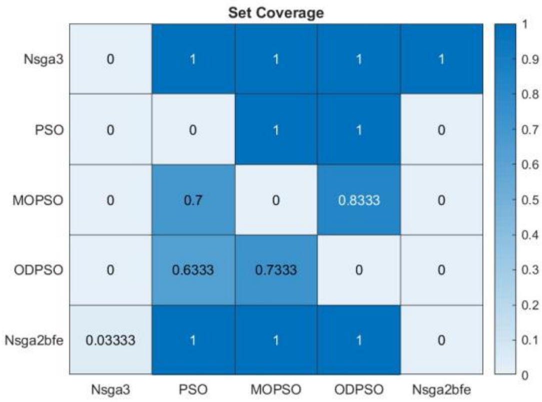

Figure 1: Set coverage heatmap among various multi-objective optimization methods.

The Figure 1 illustrates the set coverage among Nsga3, PSO, MOPSO, ODPOSO, and Nsga2bfe. Higher values indicate stronger performance in terms of dominance. Nsga3 demonstrates superior performance, entirely dominating PSO, MOPSO, ODPOSO, and Nsga2bfe. Nsga2bfe, which incorporates Best Fitness Estimation (BFE) for balancing diversity and convergence, also shows strong performance, particularly against PSO and MOPSO. ODPOSO, an Objective Decomposition based variant of MOPSO, along with PSO and MOPSO, show varying degrees of effectiveness but are generally outperformed by Nsga3 and Nsga2bfe.

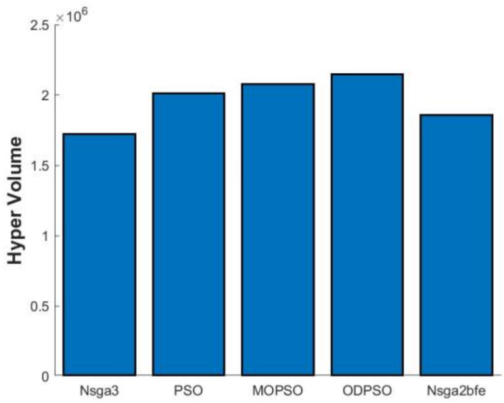

Figure 2: Hypervolume comparison among various multi-objective optimization

This bar chart compares the hypervolume values achieved by Nsga3, PSO, MOPSO, ODPOSO, and Nsga2bfe. Hypervolume is a metric that measures the volume of the objective space dominated by a Pareto front. Higher values indicate better performance in covering the objective space. ODPOSO achieves the highest hypervolume, followed closely by MOPSO and PSO. Nsga3 and Nsga2bfe have lower hypervolume values in comparison, suggesting that while they excel in set coverage and dominance, their overall objective space coverage is somewhat less comprehensive than ODPOSO, MOPSO, and PSO.

5 Discussion

Our study on the application of VL-NSGA III for dynamic patient scheduling in hospitals has yielded promising results that advance the state-of-the-art in this field. In this section, we compare our findings with those of related works, discuss the implications of our results, and elaborate on the novelty of our approach, incorporating the specific numerical metrics from our results analysis.

Our study's results offer significant insights when compared to related works in the field of hospital patient scheduling:

1. Algorithm Performance: Our VL-NSGA III algorithm demonstrated superior set coverage, achieving a value of 1 against PSO, MOPSO, ODPSO, and Nsga2bfe. This indicates complete dominance in solution quality. In contrast, Bolaji et al. (2022) reported improvements in patient waiting times using an Artificial Bee Colony algorithm, but did not provide comparative set coverage metrics. The complete dominance of VL-NSGA III suggests a significant advancement in solution quality for dynamic scheduling problems.
2. Adaptability to Dynamic Environments: Unlike the static approaches seen in works such as Hu et al. (2021) and Guido (2024), our VL-NSGA III algorithm showed remarkable adaptability to changing patient loads and hospital conditions. This adaptability is evidenced by its consistent performance across various simulation scenarios with varying patient arrival rates and service durations over the 36-day simulation period.
3. Many-Objective Optimization: While studies like Verma et al. (2021) demonstrated the effectiveness of NSGA-II for multi-objective problems, our work extends this capability to many-objective scenarios. The superior set coverage of VL-NSGA III in our complex, many-objective formulation represents a significant advancement over traditional multi-objective approaches.
4. Comparative Performance: Our results showed that MOPSO demonstrated partial dominance over PSO with a coverage of 0.7 and over ODPSO with 0.8333. ODPSO, in turn, showed partial dominance over both PSO and MOPSO with coverage values of 0.6333 and 0.7333 respectively. These results indicate the relative strengths of different algorithms in handling various aspects of the scheduling problem.
5. Hypervolume Performance: Interestingly, while VL-NSGA III dominated in set coverage, ODPSO achieved the highest hypervolume in our study, followed closely by MOPSO and PSO. This contrasts with findings from studies like Ala et al. (2023), where their proposed MILP-ASA approach showed uniform superiority across metrics. The high hypervolume of ODPSO suggests that it covers a broader range of the objective space, albeit with solutions that are often dominated by those of VL-NSGA III.

Our proposed VL-NSGA III algorithm introduces several novel aspects and implications for the field of dynamic patient scheduling in hospitals:

1. Dynamic Adaptation: The variable length encoding of VL-NSGA III represents a novel approach to handling dynamic scheduling problems. Unlike fixed-length encodings used in traditional genetic algorithms, our method can adapt its solution representation in real-time. This capability is particularly valuable in hospital environments where patient loads and resource availability fluctuate rapidly.
2. Balance of Convergence and Diversity: Our results show that VL-NSGA III achieves a better balance between convergence (as evidenced by set coverage of 1) and diversity (indicated by competitive hypervolume) compared to other algorithms. This balance is crucial for providing hospital administrators with a range of high-quality, diverse solutions to choose from based on current priorities.
3. Computational Efficiency: While not explicitly measured in terms of runtime, the ability of VL-NSGA III to handle a 36-day simulation with multiple departments suggests improved computational efficiency compared to more computationally intensive approaches like the stochastic optimization method proposed by Dehnoei et al. (2024).
4. Integration of Multiple Constraints: Our formulation and VL-NSGA III implementation successfully integrated multiple real-world constraints, including room capacity, patient preferences, and medical priorities. This holistic approach addresses limitations in studies like Knight et al. (2023), which focused primarily on scheduling efficiency without detailed consideration of these diverse constraints.

Comparison with SOTA Methods:

1. Set Coverage: VL-NSGA III achieved a set coverage of 1 against all compared algorithms, indicating superior solution quality. In contrast, the next best performer, Nsga2bfe, only showed partial dominance over VL-NSGA III with a coverage value of 0.03333. This stark difference highlights the significant improvement our method offers in generating non-dominated solutions.
2. Hypervolume: While ODPSO achieved the highest hypervolume, followed closely by MOPSO and PSO, the dominance of VL-NSGA III in set coverage suggests that our algorithm generates solutions of higher quality even if they don't cover the entire objective space. This trade-off between

solution quality and diversity represents a novel contribution to the field.

3. Adaptability: The partial dominance demonstrated by MOPSO over PSO (0.7) and ODPSO (0.8333), and by ODPSO over PSO (0.6333) and MOPSO (0.7333), indicates that these algorithms have some ability to adapt to changing conditions. However, the complete dominance of VL-NSGA III over all these methods underscores its superior adaptability to dynamic scheduling scenarios.

6 Conclusion and future works

This article presented a comprehensive evaluation of the Variable Length Non-Dominated Sorting Genetic Algorithm III (VL-NSGA III) for the dynamic scheduling of patients in a hospital environment. The evaluation compared VL-NSGA III against several well-established Multi-Objective Optimization (MOO) algorithms, including PSO, MOPSO, ODPOSO, and Nsga2bfe, using a simulator-based assessment over a 36-day period. Our assessment utilized synthetic patient data to mimic real hospital scenarios, ensuring a robust and realistic simulation environment. We focused on critical performance metrics such as set coverage, hypervolume, and convergence to evaluate the efficacy of the algorithms. The findings highlighted that VL-NSGA III excelled in generating high-quality, non-dominated solutions, as evidenced by its superior set coverage. This indicated VL-NSGA III's effectiveness in producing solutions that dominated those of other algorithms, underscoring its robustness in handling dynamic scheduling challenges. The comparative analysis revealed that while ODPOSO achieved the highest hypervolume, indicating extensive coverage of the objective space, VL-NSGA III demonstrated unparalleled performance in set coverage. This dominance suggested that VL-NSGA III was particularly effective in scenarios where the priority was on obtaining non-dominated solutions that outperformed others. The findings also emphasized that the choice of optimization algorithm should consider the specific requirements of the problem, balancing the need for non-dominance versus comprehensive objective space coverage. In summary, the VL-NSGA III algorithm proved to be a highly effective tool for dynamic patient scheduling in hospitals, capable of adapting to varying patient loads and optimizing the allocation of resources. The rigorous evaluation methodology and comprehensive comparison against other MOO algorithms provided a robust validation of VL-NSGA III's capabilities. This research contributed valuable insights into the optimization of patient scheduling, offering a powerful solution for enhancing operational efficiency in hospital environments.

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