Investigating Local Search Strategies in Variable Neighborhood Search for Patient Admission Scheduling Problem

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Abstract— **Efficient patient admission scheduling is a key challenge in hospital management, as it directly impacts resource utilization and the quality of care. The Patient Admission Scheduling Problem (PASP) involves assigning patients to hospital beds over a planning horizon while considering medical constraints and hospital capacity. Due to its complexity, heuristic and metaheuristic approaches are often used to find high-quality solutions within a reasonable time. In this work, we propose a Variable Neighborhood Search (VNS) metaheuristic to solve the PASP. VNS systematically explores different neighborhoods to escape local optima and improve solution quality. To assess the impact of local search strategies, we implement four versions of VNS, each using a different method for modifying patient assignments. The proposed approach is evaluated on benchmark instances, where we conduct parameter tuning and analyze computational performance. Experimental results demonstrate the effectiveness of the method, showing that the appropriate choice of local search strategies significantly impact the quality of the results.**
Keywords: Patient Admission Scheduling Problem, Variable Neighborhood Search, Local search, Hospitalization Management.

I. INTRODUCTION

Effective hospitalization management is crucial for ensuring optimal resource utilization, improving patient care, and reducing hospital congestion, making it a key challenge in modern healthcare systems, particularly in patient admission scheduling. The Patient Admission Scheduling Problem (PASP) consists of assigning patients to hospital beds over a given planning horizon while considering various constraints such as bed availability, medical requirements, and patient preferences. Poor scheduling can lead to overcrowding, inefficient resource utilization, and decreased quality of care. Addressing this problem is essential for optimizing hospital operations and improving patient outcomes.

PASP is a combinatorial optimization problem, where the goal is to find an optimal assignment of patients while satisfying all constraints [7]. Due to its complexity, exact methods become impractical for large-scale instances, making heuristic and metaheuristic approaches more suitable. Several methods, including Genetic Algorithms [13], Tabu Search [8] and Simulated Annealing [9], have been proposed to tackle PASP. However, existing approaches often struggle with solution quality, computational efficiency, or adaptability to different problem instances.

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To address these challenges, we propose a Variable Neighborhood Search (VNS) metaheuristic for PASP. VNS is an effective local search-based approach that systematically explores different neighborhoods to escape local optima and enhance solution quality. The method relies on the principle that different neighborhoods may lead to better solutions. It alternates between shaking, which diversifies the search by perturbing the current solution, and local search, which intensifies the search by refining the solution within a given neighborhood [14].

Our approach integrates different local search strategies to refine patient assignments, allowing a detailed analysis of their impact on performance. By applying VNS, we aim to improve the efficiency, stability, and adaptability of PASP solutions.

The rest of this paper is structured as follows: Section 2 provides a review of related work on PASP. Section 3 presents the problem formulation and constraints. Section 4 details the proposed VNS approach. Section 5 describes the experimental study. Section 6 concludes the paper with insights and future research directions.

II. LITERATURE REVIEW

The PASP is a hospitalization problem that is treated by an important number of papers. It consists in assigning patients to beds in a way to find the suitable bed for each patient, in other words, it aims to maximize the satisfaction of patients' needs and preferences.

A first introduction was elaborated by Deemester et al [8]. Then, the problem has been tackled by different researchers using different categories of methods. We can classify them into four classes: Exact methods, Heuristics, Metaheuristics, and Hyperheuristics.

- **Exact Approaches for solving PASP:**
  For this class of approaches, we find a work that used a Mixed Integer Program (MIP) to formulate the PASP [3]. As an exact method, this work has obtained the optimal results in 9 instances from 13 instances.
- **Heuristic Approaches for solving PASP:**
  Dealing with the problem using heuristics was the main objective of Borchani et al. [6] work, who investigated two versions of heuristics based on the Hungarian method. This method consists in transforming a cost matrix into a sequence of beds based on the constraints violation penalties. The first heuristic is applied to the problem while relaxing several constraints. However,

the second heuristic considers all the constraints. However, Turhan et al. [18] solve the PASP using a method based on heuristics named Fix-and-Relax (F&R) and Fix-and-Optimize (F&O). This paper obtained good results in less time than the compared papers.

- **Metaheuristic Approaches for solving PASP:**
The metaheuristics are the most used methods to treat the PASP. We find Ceshia et al. [7] who used the multi-neighborhood local search procedure based on two metaheuristics: Tabu Search and Simulated Annealing to obtain two competitive versions. A Biogeography-Based Optimization approach was proposed in [11]. This approach is inspired by the idea of species migration between different habitats . An improvement of the method was proposed in [12]. Moreover, Guido et al. [10] proposed a metaheuristic framework to solve the PASP. This method is inspired by the rescheduling approaches and is classified as cooperative between a metaheuristic and an exact method. In addition, late acceptance hill climbing algorithm was proposed as an iterative local search procedure that is inspired by the simple hill climbing optimization algorithm [5]. This method presents a new strategy that tries to escape from the local optimum until reaching a better candidate solution. Another paper proposed a Harmony search algorithm to solve the PASP [2]. The proposed approach is based on three operators to generate new solutions and a memory operator shared by all the operators in order to combine the features of the existing solutions in the population. A new metaheuristic was proposed by Abdelkareem et al. [1] based on the discrete flower pollination inspired by the flower pollination algorithm which is dedicated to continuous problems. The method is composed by a fundamental step called "discretization procedure" which consists in adapting the method to a discrete space to switch between continuous and combinatorial space. After the conversion, the algorithm applied two neighborhood operators according to a probability.

- **Hyperheuristic approaches for solving PASP:**
Reaching the hyperheuristic class, as this method is not much used, we find a less number of papers that used the hyperheuristics [4][15][16]. The first two papers are based on a hyperheuristic composed of three fundamental steps: heuristic selection strategy, mentoring and move acceptance phase. The only difference between the two works resides in the operators used to perform the three steps. For example, the first mentioned paper [4] used three operators as a heuristic selection strategy; the tournament selection for the mentoring and great deluge, Simulated Annealing, Improving or Equal, and Only Improving for the move acceptance phase. The mentioned second paper [15] used two versions of tournament selection for the mentoring step and he added the adaptive iteration limited list-based threshold accepting [17] for the move acceptance phase. The third paper used a hyperheuristic that simulates honey bee mating behavior to develop a strategy for selecting the most suitable heuristics to apply at each iteration. The proposed hyperheuristic is a hybridization of Genetic Algorithm and Simulated Annealing [16].
Given the significant role of metaheuristics in solving PASP and the continuous need for efficient approaches, our work contributes to this field by proposing a Variable Neighborhood Search (VNS)-based method, aiming to enhance solution quality and computational efficiency.

III. Problem Description

The PASP belongs to the hospitalization management domain that considers, for a given planning horizon, a set of patients that need to be assigned to a set of beds for each day of their stay. The static PASP is considered in this paper; in other words, the stay length between the date of entry and exit of each patient is contiguous, given from the beginning, and cannot be changed [7].
The PASP has the following basic features:

- The patient is characterized by age, gender, specialism needed, room preferences, and necessary and preferred properties.
- The hospital is composed of departments that are characterized by minimum and maximum age limits. Each department is composed of rooms that offer several specialisms with a level of expertise according to the department to which they belong. Each room is characterized by a gender policy: **M**: accepts only male patients, **F**: accepts only female patients, **D**: accepts both genders but in a day, it accepts only one gender, **N**: accepts both genders. Each room has different properties that the patients can need. The room is composed of beds that define its capacity, it can contain 1, 2, or 4 beds.

Several constraints are applied when processing the problem. We can find two types of constraints:

- Hard constraint: the violation of this constraint engenders an unfeasible solution which is represented, in this problem, by the capacity of the rooms.
- Soft constraints: the violation of these constraints generates a penalty in the objective function in a way that increases its value. The soft constraints are:
  - The gender of the patient should respect the gender policy of the room.
  - The age of a patient should not exceed the age limits of the department of the room where he is assigned.
  - The specialism that the patient needs should be offered with a high level of expertise by the department of the room where he is assigned.

* The needed and the preferred properties should exist in the room where he is assigned.
* The room capacity should be equal to or less than the room preferences of the patient.
* A patient should not be transferred from one room to another room during his stay period.

We note that specialisms, age limits, properties features of the room, and room preferences constraints are merged into one constraint called **PRC**, the gender constraint is called **RG**, and the transfer constraint is called **Tr**.
The objective is to minimize the patients' assignment cost by respecting the hard constraint and minimizing the total sum of soft-constraints violation penalties.

Mathematical formulation:
The mathematical model was proposed by [8], it includes the objective function (equation 1) and the constraints (equations 2, 3, 4, 5, 6 and 7). The definition of the terms is as follows:

- D: The set of days including Dp representing the set of days in which the patient p is present in the hospital.
- R: The set of rooms.
- P: The set of patients including P_F (the subset of female patients) and P_M (the subset of male patients).
- $C_{p,r}$: Penalty of assigning patient p to room r.
- Cap_r: Number of beds available in a room r.
- W_{RG}: Weight of a room gender policy constraint.
- W_{Tr}: Weight of transfer constraint.

Decision variables

- $x_{p,r,d}$: 1 if patient p is assigned to a bed in room r in day d, 0 otherwise.
- $t_{p,r,d}$: 1 if patient p is transferred from room r in day d, 0 otherwise.
- $m_{r,d}$: 1 if there is at least one male patient in room r in day d, 0 otherwise.
- $f_{r,d}$: 1 if there is at least one female patient in room r in day d, 0 otherwise.
- $b_{r,d}$: 1 if there are both male and female patients in room r in day d, 0 otherwise.

– **Objective function:**

$$Min \sum_{p\in P, r\in R, d\in D} C_{p,r} * x_{p,r,d} + \sum_{r\in R, d\in D} W_{RG} * b_{r,d} + \sum_{p\in P, r\in R, d\in D} W_{Tr} * t_{p,r,d} \quad (1)$$

The three components of the equation refer to PRC, RG and Tr.

– **Constraints:**

Hard Constraints:

* Each patient should be assigned to one room in the same day.

$$\sum_{r\in R} x_{p,r,d} = 1, \forall p \in P, d \in D_p \quad (2)$$

* The number of assigned patients to a room, in each day, should not exceed the number of beds available.

$$\sum_{p\in P} x_{p,r,d} <= Cap_r, \forall r \in R, d \in D \quad (3)$$

Soft Constraints:

* Every day, the gender of patients in a room should comply with the gender policy of the room.

$$x_{p,r,d} <= f_{r,d}, \forall p \in P_F, r \in R, d \in D \quad (4)$$

$$x_{p,r,d} <= m_{r,d}, \forall p \in P_M, r \in R, d \in D \quad (5)$$

$$f_{r,d} + m_{r,d} - 1 <= b_{r,d} \forall r \in R, d \in D \quad (6)$$

* Patients should be kept in the same room and not transferred to another one.

$$x_{p,r,d} - x_{p,r,d+1} <= t_{p,r,d}, \forall p \in P, r \in R, d \in D_p \quad (7)$$

IV. Variable neighborhood Search for Patient Admission Scheduling problem

A. *Variable neighborhood Search metaheuristic*

Variable Neighborhood Search (VNS) is a metaheuristic designed to solve combinatorial optimization problems. The basic idea behind VNS is to iteratively explore the solution space by changing the neighborhoods of the current solution. This is achieved by using a set of neighborhood operators that modify the current solution in various ways, followed by a local search to refine the solution.
The VNS algorithm is structured around two key concepts: neighborhood change and local search. The algorithm starts with an initial solution and then iteratively improves it by exploring a sequence of neighborhoods. At each iteration, the algorithm performs a local search within a chosen neighborhood. If a better solution is found, the algorithm continues the search in the same neighborhood. If no improvement is found, it moves to the next neighborhood operator [14].

B. *Solution representation*

In order to ensure feasible solutions when applying VNS to the PASP, we represent solutions using a matrix, where rows correspond to days in the planning horizon and columns represent hospital beds. Each cell in the matrix contains a patient assigned to a specific bed on a given day. The VNS algorithm explores different neighborhood structures by modifying patient assignments across beds and days to optimize the final scheduling. Figure 1 illustrates an example of a solution.

	Bed 1	Bed 2	Bed ...	Bed m
Day 1	Patient1	Patient6	...	Patient x
Day 2	Patient1	Patient7	...	Patient y
Day ...	Patient4	Patient7	...	Patient z
Day n	Patient3	Patient7	...	Patient z

Fig. 1. Example of a solution representation for the PASP

C. Generation of the initial solution

The quality of the initial solution in VNS plays a crucial role in exploring the search space effectively. Poor-quality initial solutions may lead to slow convergence or getting trapped in low-quality regions in the search space, while high-quality solution may limit the exploration. Therefore, it is essential to generate a solution with medium-quality to balance diversification and intensification, avoiding these issues. For this reason, we decide to generate a population of solutions instead of a single solution in order to more explore the space. The population of the solutions is composed by 20 solutions, and then it is reduced to five by keeping the best ones. In order to have a population with a medium quality, each solution is generated while respecting some soft constraints of the PAS problem and neglecting the others. Two important features we worked on to maintain them in the population: the first feature ensures that all the generated solutions are feasible ones, so they respect the hard constraints of the problem, and the second feature ensures that the generated solutions do not have the same features and they are well dispersed on the search space.

D. Proposed Approach

Our approach applies a Variable Neighborhood Search (VNS) metaheuristic to the Patient Admission Scheduling Problem (PASP). The process begins by generating an initial solution for the VNS. During each iteration, a neighborhood operator is chosen from a set of operators and applied to the current solution to generate a new candidate solution, promoting diversification by exploring different regions of the search space. A local search method is then applied to refine this candidate solution, ensuring intensification by improving solution quality within a specific region in the search space. In the next iteration, if the solution is improved, the algorithm retains the same neighborhood operator; otherwise, it selects a different one to enhance exploration. This cycle is repeated until a predefined number of iterations is reached. By combining multiple neighborhood explorations with local search, the proposed approach enhances the search process, leading to high-quality solutions. Figure 2 illustrates the details of the model process.

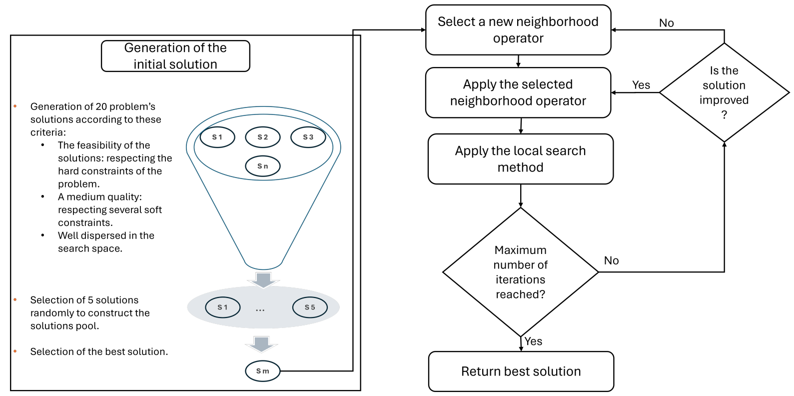

Fig. 2. The process of the proposed approach

TABLE I
NEIGHBORHOOD OPERATORS

Neighborhood operator	Description
N1	Select randomly two patients and swap their bed assignments.
N2	Swap all the bed assignments of two randomly selected rooms.
N3	Switch the bed assignments in pairs from three randomly selected rooms.
N4	Swap the bed assignments of a randomly selected patient to an empty bed.

E. Neighborhood operators

For the set of neighborhood operators, we used simple heuristics consisting in providing small changes in the solution. The set of these heuristics is detailed in the table I.

F. Local search method

The local search method in our VNS involves removing a subset of patients from the solution and reassigning them to optimize the schedule. This procedure begins by selecting a group of patients whose assignments are temporarily removed. The algorithm then reallocates these patients to available beds using different reassignment strategies. Several strategies for selecting patients to remove and determining their new bed assignments are considered, as illustrated in table II.

G. VNS algorithm

To explain our approach, we present the VNS algorithm in algorithm 1.

TABLE II
STRATEGIES FOR PATIENTS REMOVAL

Strategies for Patient Removal	Description
1	Random selection of patients.
2	Selection of patients assigned to the least suitable beds.

TABLE III

STRATEGIES FOR PATIENTS REASSIGNMENT

Strategies for Patient Reassignment	Description
1	Random selection of available beds.
2	Selection of the most suitable available beds.

Algorithm 1 Variable Neighborhood Search algorithm

```
Input: S: a set of initial solutions, N: a set of neighborhood operators, MI: max_iterations
Select a random subset of five initial solutions from S to form the solutions pool
Initial_solution = Select the best solution from the solutions pool
neighborhood_operator = choose a new neighborhood operator randomly from N
while iteration < MI do
    current_solution = initial_solution
    neighborhood_solution = apply the chosen neighborhood operator to the initial_solution
    new_solution = Apply the local search method (neighborhood_solution)
    if cost(new_solution) < cost(current_solution) then
        current_solution = new_solution
    else
        neighborhood_operator = choose a new neighborhood operator randomly from N
    end if
    if cost(current_solution) < cost(best_solution) then
        best_solution = current_solution
    end if
    iteration = iteration + 1
end while
return best_solution
```

V. EXPERIMENTAL STUDY

In this section, we evaluate the performance of our proposed VNS metaheuristic for the Patient Admission Scheduling Problem (PASP). First, we describe the benchmark instances used for testing, followed by the parameter tuning for our algorithm. Finally, we present and discuss the computational results obtained from our approach, highlighting the impact of the local search strategies on solution quality.

A. Benchmark

To validate our algorithm, we used the well-known Benchmark performed by Deemester et al. [8]. The dataset is composed of thirteen instances. In this work, we employed the first six instances. The characteristics of these instances vary according to the number of patients, rooms, and beds. Moreover, the planning horizon is between 1 and 14 days. Table IV shows the different features of the dataset.

TABLE IV

DESCRIPTION OF THE INSTANCES OF THE BENCHMARK

Instance	Patients	Beds	Rooms	Departments
1	286	652	98	4
2	465	755	151	6
3	395	708	131	5
4	471	746	155	6
5	325	587	102	4
6	313	685	104	4

B. Parameter Tuning

The parameter values used in the algorithm are summarized in Table V. These values, including the maximum number of iterations, and the percentage of patients modified in the local search method, are tuned using the Trial and error method in order to balance the efficiency and effectiveness of the search process.

TABLE V

PARAMETER TUNING VALUES

Parameter	Values
Maximum number of iterations	50
Percentage of patients modified in the local search method	15%

C. Computational results

In order to assess the impact of the local search method, we implemented four versions of our metaheuristic, each using a different local search strategy. As mentioned before, our local search method consists of removing a set of assigned patients and reassigning them. Each version follows a specific strategy for this process:

- **The first version:** consists in selecting a random set of patients and reassigns them randomly to available beds.
- **The second version:** consists in selecting a random set of patients and reassigns them to the most suitable available beds.
- **The third version:** consists in selecting patients assigned to the least adequate beds (those with the highest cost) and reassigns them randomly.
- **The fourth version:** consist in selecting patients assigned to the least adequate beds (i.e., those with the highest cost) and reassigns them to the most suitable available beds.

Table VI displays the total cost for each instance in the benchmark, provided by each versions. The mentioned results represent the minimum cost obtained after 11 runs. The values in bold indicate the best cost obtained among the four versions.

The results mentioned in table VI demonstrate the effectiveness of the fourth version (V4), which consistently achieves the lowest cost across all completed instances. This confirms that selecting patients assigned to the least adequate beds and reassigning them to the most suitable available beds significantly improves

TABLE VI
VNS: COMPUTATIONAL RESULTS FOR PASP

Instance	V1	V2	V3	V4
1	1947	1898,6	1902,6	**1816,4**
2	3624,8	3536,8	3628.79	**2790.2**
3	2905,2	2752	2942,8	**2112**
4	3722,8	3499,2	3685,4	**3069,4**
5	1468,2	1390,8	1487,2	**1137**
6	2188,2	2136,4	2225	**1943**

the solution quality. In contrast, the first version (V1), which consists in a random reassignment, performs the worst in most cases. The second version (V2), which incorporates a structured reassignment strategy, shows moderate improvements over V1 but does not reach the performance of V4. Moreover, the third version (V3), which selects poorly assigned patients but reassigns them randomly, often results in higher costs than V1, particularly in large instances. This indicates that diversification alone is insufficient without a proper intensification mechanism. In addition, for instance 2, V3 achieves a slightly better cost than V1 but still had lower performance compared to V2 and V4, reinforcing the importance of a guided reassignment process. The improvements achieved by V4 are more pronounced in larger instances, where the complexity of the problem increases with the number of patients, rooms, and departments. This confirms that the patients' reassignment is particularly crucial when handling large instances, as it allows better exploitation of the search space. The significant gap between V4 and the other versions highlights the importance of balancing intensification (focused reassignment) and diversification (exploring alternative solutions) to achieve high-quality solutions in the considered problem.

VI. CONCLUSION

In this work, we proposed a Variable Neighborhood Search (VNS) metaheuristic to solve the Patient Admission Scheduling Problem (PASP). Our approach efficiently explores different neighborhood structures to improve patient assignments while maintaining feasibility constraints. To analyze the impact of the local search component, we implemented four versions of the metaheuristic, each using a different patient reassignment strategy.

The experimental study demonstrated the effectiveness of the proposed method, highlighting the impact of local search strategies on solution quality. The results showed that the local search method combining targeted selection with guided reassignment, achieved the best performance, emphasizing the crucial role of structured exploration in improving the results.

For future work, several perspectives can be explored. First, incorporating adaptive mechanisms to dynamically select the most effective local search strategy could further enhance performance. Additionally, hybridizing VNS with machine learning techniques could help predict promising neighborhoods based on instance characteristics. Another direction is to extend the approach to more complex hospitalization problems, such as dynamic patient arrivals. Finally, applying the proposed methodology to other real-world scheduling problems could further validate its genericity and stability.

VII. ACKNOWLEDGMENT

This work was carried out within the framework of the TECSANTE project. The TECSANTE project is cofinanced by the Hauts-de-France Region and European Eco- nomic and Regional Development Fund (ERDF) of the EU.

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