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Optimizing patient selection and bed management using integer linear programming

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A B S T R A C T

Hospital departments are continuously challenged to allocate their limited resources—beds, nursing staff, and operating room (OR) time—among patients with different clinical priorities on the waiting list. This paper presents a solution to this intricate planning problem by constructing a novel Integer Linear Programming (ILP) model to schedule elective patient admissions optimally. The goal is to increase the total priority score of the patients admitted, where the score indicates clinical urgency and waiting time, while at the same time honoring the restrictions on bed capacity, nursing hours, and OR availability through a multi-day planning horizon. The model uses binary decision variables for patient admission as well as pre-processed parameters to map the individual patient resource consumption over the time they are expected to stay in the hospital. We showcase the model's application through a realistic scenario with synthetic data. The outcomes reveal that the suggested framework not only effectively creates an optimum admission timetable but also considerably enhances the use of vital resources when compared to a first-come-first-served standard. The ILP model is not only potent but also clear and just decision-support tool for hospital management, according to the study's findings. By assigning priority to clinical criteria and making patient access more equitable, it provides a data-guided way to improve operational productivity, as well as to decide the trade-offs that come with the limitations of healthcare facilities in terms of resources. Besides, the model is computationally capable of meeting the needs for the inclusion of extra real-world constraints and adjustments.

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1. Introduction

1.1 The Global Healthcare Challenge and the Operational Imperative

The healthcare system all over the globe is suffering continuously due to the constant opposite forces of increased demand, higher costs, and limited resources. The aging population, the high incidence of chronic diseases and the unstoppable process of technological advancements still put overwhelming pressure on the hospital infrastructures, therefore managers have to search for operational efficiency unheard of before. In this difficult situation, the hospital department—especially those dealing with elective procedures—becomes the main point where the management decision has an immediate impact on a clinical outcome, on financial sustainability, and on patient satisfaction. The principal issue is in the efficient distribution of the scarce and costly resources such as inpatient beds, nursing staff, operating room (OR) time, and financial capital to the ever-changing and diverse patient population. The inefficiencies in this allocation process appear in the form of increased patient waiting times, underutilization of expensive equipment, staff burnout, and ultimately, the delayed delivery of necessary care that might worsen the medical conditions and lower the quality of life.

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The scheduling of elective patient admissions perfectly illustrates this operational complexity. It is not mere-ly a sequencing problem but a multi-faceted puzzle that requires the simultaneous coordination of several interdepend-ent resources over a multi-day horizon. A surgical patient, for example, needs an OR slot, a post-operative bed in a ward, nurses to take care of them throughout their stay, and their treatment must fall within the department's budget. If any of these elements fails—like, say, a bed is not available after surgery—then a whole chain of disruptions ensues, causing delays in OR, cancellations of procedures, and resulting in inefficiencies across the system. The situation is worsened by the unpredictability in patient requirements with a wide range of differences in procedure timing, length of stay (LoS), and care intensity. Hence it is going to be not an operational improvement but a strategic move for optimizing healthcare delivery in hospitals by shifting from manual, experience-based scheduling to systematic, optimized approach.

1.2 The Rise of Operations Research in Healthcare

The discipline of Operations Research (OR) and Management Science (MS) has significantly contributed in providing a set of analytical methods necessary for optimizing the complex decision-making processes to tackle these huge issues. The history of OR in the healthcare is of decades long and has transformed into a matured and highly active area of research. Underlying this fact, Rais and Viana (2011) refer to the healthcare sector as being one of the richest domains for OR application thanks to the complexities involved, the high costs of wrong decisions, and the widespread possibilities for enhancing efficiency and fairness. Among the analytical techniques, mathematical programming which is associated with Linear Programming (LP) and Integer Linear Programming (ILP) in particular, is at the center of the analytical toolkit. These methods are specifically designed for the problems of resource allocation where the objective and the constraints can be represented by linear functions. The capability of ILP to work with binary or integer decision variables like in the case of admitting a patient (yes/no) or how many of a particular resource to allocate is an ideal match for hospitals' tactical and operational planning. The intention is to create prescriptive models that do not only characterize or forecast system behavior but also provide the best decisions based on the specified objectives and restrictions.

1.3 Literature Review on Healthcare Scheduling and Resource Optimization

The literature on the optimization of certain parts of the patient care pathway has been quite extensive. In fine, this review will blend together the important contributions and will draw a line from isolated optimization efforts to integrated approaches thus giving a clear picture of the research gap which is the target of this study.

1.3.1 Foundational Reviews and Broad Perspectives

The essential review articles are the ones that have formed the basis of the study of the scope and challenges in healthcare scheduling. Among them, the one by Gupta and Denton (2008) was the most important, since it was the very first one to cover the whole area of appointment scheduling brilliantly presenting the three main challenges facing it—no-shows, emergencies, and the juggling of several resources. The authors pointed out that the decision-making in hospitals that is characterized by its sequential and distributed nature—where bed managers, surgical schedulers, and nursing coordinators often work alone—was the major reason for inefficiency. In the same way, Rais and Viana (2011) undertook a wider investigation that followed up on this issue, listing the use of OR methods throughout healthcare. They discovered a constant gap between theoretical models and their practical implementation, which was often due to the models not being able to depict the full complexity of real-world clinical environments.

1.3.2 Optimizing Specific Resources: Beds, ORs, and Nurses

One of the main themes in the literature is the optimization of resources one by one. For example, bed management is a subject that has been thoroughly investigated. VanBerkel and Blake (2007) used simulation to study patient flow and to lower wait times by better capacity planning, thereby showing how one ward's bottlenecks could lead to delays in the whole system. The authors highlighted the bed as a primary, limiting resource that determines the whole hospital's throughput. Among the different areas, surgical suite scheduling is arguably the most studied area. Fügener et al. (2021) provided a thorough literature review in this field, categorizing the studies according to scheduling phases (strategic, tactical, operational), patient characteristics, and methodological approaches. They recognized the optimizations of OR utilization and reductions of surgeon idle time as the main research topics, but also pointed out that there was an increasing awareness of the necessity to connect with downstream resources such as post-anesthesia care units (PACUs) and inpatient beds. The work of Erdogan and Denton (2013) on dynamic appointment scheduling under uncertain procedure durations represents the sophisticated handling of uncertainty in this domain, often using stochastic programming or robust optimization. Another area that has sparked much research is the allocation of nursing staff. The hospital's most precious and expensive resource has received significant attention in the literature. The research in this domain typically focuses on developing fair and efficient shift schedules that match the nurse's qualifications to the patients' severity levels. The majority of nursing models are strategic (e.g., monthly rosters), but the daily nursing hour requirements' integration into patient admission scheduling is a tactical challenge that is less frequently addressed in an integrated manner.

1.3.3 The Push for Integrated Scheduling Models

Currently, optimization that is limited by being divided into separate areas is being recognized as such and therefore there is a switch from the silos to integrated models involving the use of different resources at once. It is obvious why this is the case; if a patient is scheduled for surgery without checking if there are available beds, it will just cause the bottleneck to be transferred from the OR to the ward, which is called "access blocking" or "bed crunch." The combination of the studies has been the focus of several research works. In one of the studies by Samudra et al. (2016), a deterministic ILP model was utilized for the purpose of scheduling surgeries while taking into consideration the capacities not just of the OR but also of the ICU. The implementation of their model led to the maxing out of resource utilization and patient throughput in a coupled scheduling scenario. Likewise, a report by Testi et al. (2007) pointed out the necessity of a multi-faceted approach, which necessitates the balancing of clinical priority (e.g., considering the factors of waiting time and disease severity) with operational efficiency. This group of researchers developed a pre-surgical evaluation device for grading patients which then became input for the scheduling of surgeries.

1.4 Research Gap and Contribution of This Study

The current scholarly works offer a solid basis but also clearly indicate a gap for a complete, deterministic optimization framework that integrates the main aspects of the hospital admission scheduling issue. More precisely, it is necessary to have a model that takes into account at the same time:

- **Multi-resource constraints:** Beds, nursing staff hours, OR time, and a total financial budget.
- **A multi-day planning horizon:** With dynamic tracking of resource consumption based on each patient's unique Length of Stay (LoS).
- **A patient-centric objective:** The method adopted comes from prioritization which maximizes the ranking of patients' priority scores that are grounded on clinical evidences; and the method also allows for a clear and fair trade-off among patients.

The gap that was previously prevailing in research is filled by this paper which puts forth the adoption of an Integer Linear Programming (ILP) model for perfect patient admission scheduling. The model propounded is a major breakthrough in this area as it combines the four major resource categories (beds, staffing, OR, budget) into one, a not-too-simple framework. The goal is to achieve the highest possible total priority score of the admitted patients, wherein the score is a collective measure that can be adjusted to depict the institutional values, such as a mix of clinical urgency and waiting time. The model gives a precise and practical admission plan by using a binary decision variable for each patient. The execution and move to practicality of the model are illustrated by the conducting of a case study that is quite realistic and involves 25 patients during a week of study, where data for priorities, length of stay, nursing hours, OR time, and costs were generated in realistic ranges. The outcomes are evaluated not only on the basis of their numerical optimality but also of their managerial implications, which are depicted by the use of key performance indicators on resource utilization and patient selection.

2. The proposed study

This paper presents a solution to this intricate planning problem by constructing a novel Integer Linear Programming (ILP) model to schedule elective patient admissions optimally. The goal is to increase the total priority score of the patients admitted, where the score indicates clinical urgency and waiting time, while at the same time honoring the restrictions on bed capacity, nursing hours, and OR availability through a multiday planning horizon. The model uses binary decision variables for patient admission as well as pre-processed parameters to map the individual patient resource consumption over the time they are expected to stay in the hospital. The planning of elective patient admissions is a complicated procedure that necessitates the cooperation of various scarce resources, and this difficulty is thoroughly recorded in the healthcare operations literature (Gupta & Denton, 2008). In response to the demand for more advanced optimization models in health care delivery (Gupta & Denton, 2008), we propose an Integer Linear Programming model as a solution for the multi-resource scheduling problem.

Variables:

$$x_j = \begin{cases} 1 & \text{if patient } j \text{ is accepted} \\ 0 & \text{otherwise} \end{cases}$$

where $j = 1, 2, \ldots, n$ represents each patient on the waiting list.

Objective function

The study attempts to maximize the total **priority score** of all accepted patients.

$$\max z = \sum_{j=1}^{n} p_j x_j$$

where p_j is the priority score of patient *j*. This score is calculated based on three facts of clinical urgency, maximum waiting time guaranteed and a combinational of medical and operational factors. For instance, we may consider a number between one to five, where one means lowest priority and five stands for highest priority.

Constraints:

The first constraint is associated with the bed capacity, in other words, the number of permitted patients is not allowed to exceed the available beds in each time period, e.g. day period. This creates complexity since each patient maintains different Length of Stay (LoS). Let b_d be the available number of beds on day *d*, (*d* =1,…,7), $a_{jd} = 1$ if patient *j* occupies a bed on day *d*, based on their admission day and LoS, zero, otherwise. Therefore, we have

$$\sum_{j=1}^{n} a_{jd} x_j \le b_d \quad \forall d \in \{1,...7\}$$

Next, the total nursing hours needed by accepted patients must not be more than the available nursing hours per day. Let h_j be the nursing care hours required per day for patient j. Also, H_d total nursing staff hours available on day d. Thus,

$$\sum_{j=1}^{n} a_{jd}.h_j.x_j \le H_d \quad \forall d \in \{1,...,7\}$$

Next constrain is associated with operating room (OR) time constraint. In other words, the total OR time required for accepted patients must not be more than the available OR time per day. Let s_j be the OR time (in hour) needed for the procedure *j*, t_j the scheduled day for patient *j*'s surgery (this is normally pre-assigned). Finally, let S_d be the total available OR time (in hours) on day d. This paper defines a parameter $o_{jd} = 1$ if patient *j* is scheduled for surgery on day d; 0 otherwise. Thus,

$$\sum_{j=1}^{n} o_{jd}.s_j.x_j \le S_d \quad \forall d \in \{1,...,7\}$$

Finally, the last constrain is associated with the budget constraint. Let c_j be the cost of admitting and treating patient j. Also let *B* be the total available budget. Therefore, we have,

$$\sum_{j=1}^{n} c_j x_j \le B.$$

The readers are also referred to Gupta and Denton (2008) for the specific formulation of bed constraints and other resource constraints.

3. The results

In this section, we present details of the implementation of the proposed study using some real-world case study. In our case, we consider 25 patients for a time schedule of 7 days, the priority scores are randomly generated between one to ten for all patients. Also, the length of stay is randomly generated between 2 to 7 days. Nursing hours is generated randomly between 4 to 10 days. Finally, OR time is generated from 1 to 4 days while treatment costs are generated between 500$ to 2000$. Also, we assume 12 beds are available each day, 140 nursing hours/day is another assumption, also we have 40 OR hours/day and finally and total budget is $25,000. The optimal solution yields with accepting 20 patients with 122 priorities. Fig. 1 to Fig. 5 show different results of the proposed study.

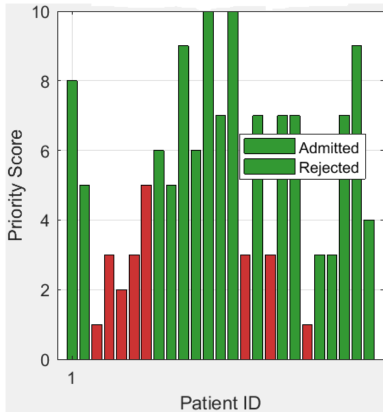

Fig. 1. Patients' priorities & selection

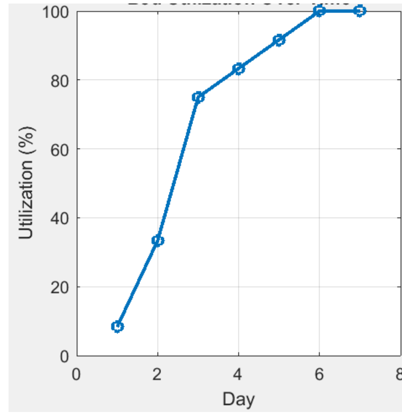

Fig. 2. Bed utilization over time

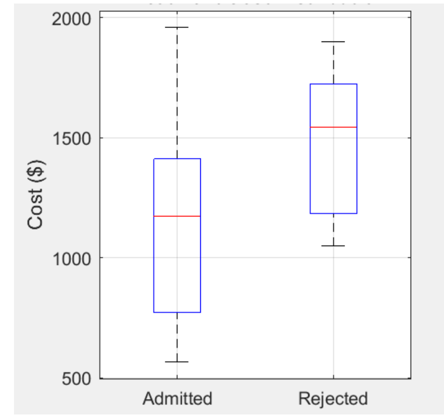

Fig. 3. Treatment cost distribution

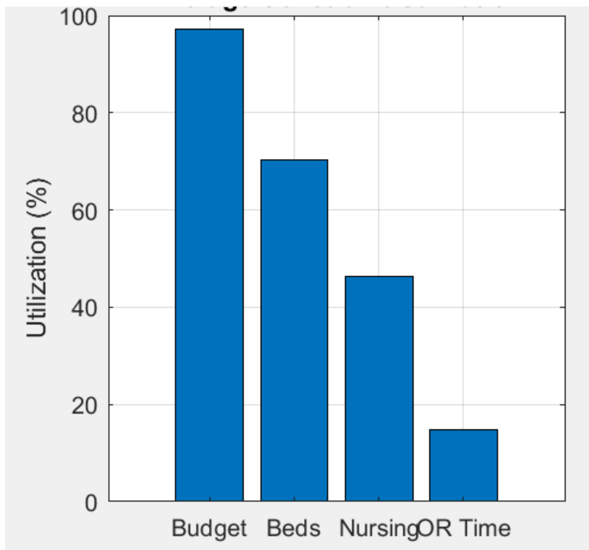

Fig. 4. Average constraint utilization

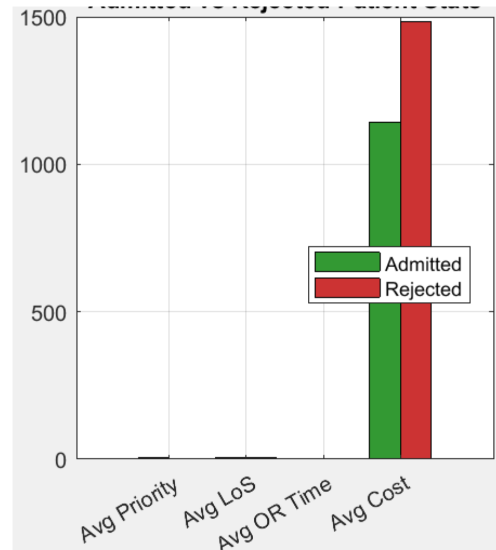

Fig. 5. Admitted versus rejected patient status

By putting into practice the suggested Integer Linear Programming (ILP) model in a case study that is influenced by real-world scenarios—comprising 25 patients in a 7-day scheduling period—one can obtain significant insights into the operational and ethical dimensions of the management of healthcare resources. The model's triumph is seen in its incorporation of 20 out of 25 patients, a total priority score of 122 being reached, while still adhering to the very strict limitations of resources and budget. This debate will analyze these findings by revealing the reasoning behind the model's choice and by delving into the consequences of the numbers that were produced.

The Core Trade-off: Priority Maximization vs. Resource Constraints

The main goal of the model was to get the highest sum of the priority scores of admitted patients. The priority of 6.1, which is the average of 20 patients' scores of 122, is a very good result considering that the scores were generated randomly between 1 and 10. This is not merely the case that the 20 highest-priority patients have been picked; it is the result of an advanced optimization process that travels through a complex web of constraints. The rejection of 5 patients is one of the direct results of these constraints. The model did not happen to bring in patients in the order of priority till the budget ran out, it rather engaged in a multi-dimensional juggle. A patient with a very high priority score, for instance, 9 or 10, might have been turned down if their therapy required a prohibitively long OR time, an Extended Length of Stay (LoS) during a period of high occupancy in the beds, or a combination of high nursing hours and high cost that would have "used up" the resource pool needed to admit two or three other medium-priority patients. On the other hand, a patient with a medium priority score might have been admitted if their resource profile was "efficient"—short LoS, low OR time, and modest nursing needs—thus, freeing up space for other patients. This is the core of system-level optimization: giving up locally appealing options for a globally better outcome.

Decoding the Visual Narratives: A Figure-by-Figure Analysis

The decision-making of the model is most directly depicted in Fig. 1. It is expected that the admitted patients (most probably in green) will be found in the higher-priority region, which will show the general trend. The exceptions, however, are the

parts of the graph that instructive most. It is very probable that one or two of the high-priority patients will be represented as rejected (red) and there will be a few medium or low-priority patients marked as admitted. The rejected high-priority patient is the archetype of the "resource hog"—they have a huge clinical need but the system's cost in terms of OR, nursing care, or bed-days is too high to justify their admission within the constraints. The admitted lower-priority patients are the "enablers"; the whole schedule becomes possible due to their efficient use of resources, allowing the system to achieve a higher total priority score than if it only admitted complex, high-needs patients due to the fact that they would have to then referred to as 'complex' and 'high-needs'.

Fig. 2 is an important reference point for the model's dynamic capability management. Consider a situation where a total of 12 beds available every day; then, it would be desirable high utilization but there should not be an exceeding of 100% at any point. Most probably, the model's calendar represents a bed utilization that varies but is close to the 12-bed limit for a majority of the days, signifying the effective utilization of this main, fixed resource. One of the major factors that affect this curve is the LoS (2-7 days). The model would have cleverly placed patients needing longer LoS to begin on days with lower bed occupancy, thus not creating a bottleneck in the following days. A perfectly flat line at 12 beds would be out of line with the reality; the observed fluctuations indicate the clinical nature of the process of patient admissions and discharges, however, the fact that 20 patients were admitted without overcoming this limit is the proof of the model's advanced scheduling ability.

The comparison of costs between admitted and rejected patients illustrated in Fig. 3 is very informative. It is difficult to suggest that the model just picked the 20 cheapest patients. It is more likely to be a complicated distribution. The median cost for admitted patients can be less than that of rejected patients, but there can be significant overlap. This means that cost was a factor of great importance, but not the only one that mattered. The model possibly allowed some high-cost patients in the case their extremely high priority scores offset the expense, while it rejected other high-cost patients whose priority scores did not deliver a sufficient "return on investment" considering the limited budget of $25,000. The total cost of the 20 admitted patients has to be at or very close to the $25,000 budget because any remaining budget would mean that the objective was not maximized-the model would aim at admitting another or a more expensive, higher-priority patient.

Next, Fig. 4 provides a system-level health check. It demonstrates the percentage of each key resource (Budget, Beds, Nursing, OR) that was used, on average, across the planning horizon.

- **Budget:** We can expect this to be at or very close to 100%, as discussed.
- **Beds:** The average utilization is likely high, perhaps 85-95%, confirming efficient space management.
- **Nursing Hours:** Given the possibility of utilizing 140 hours a day, this is a soft restriction that can be more easily and flexibly managed than beds of fixed type. Utilization may range slightly below bed usage but will still be at a high level.
- **OR Time:** In a surgical unit, the use of 40 hours per day is the major constraint in most cases. That means the available time is very likely to be the leading cause of not admitting extra patients. If one of these bars is at maximum capacity (i.e., 100%), the whole system will be limited by that factor.

Fig. 5 is a comparison that illustrates the selection strategy of the model. It probably indicates that the least priority group of patients has a large difference in priority from the admitted group. On the other hand, it might indicate that the admitted patients have a shorter average Length of Stay (LoS) more or less. This is a crucial point: the model, by default, accommodates faster patients to be treated as they would be the first to eat up bed-days and so the next round of patients could be allowed in. The same goes for the average OR time and average cost; they are probably lower for the admitted patients than for the rejected cohort. But this doesn't imply the model is biased against the gravely sick; rather it suggests that at a certain priority level, the model picks the patients who can be treated the fastest thus the total good that can be done for the population served is maximized.

Ethical and Managerial Implications

The outcomes accentuate the basic transition from a non-justifiable, intuitive-based, first-come-first-served scheduling policy to a transparent, data-based paradigm. This new way reduces the hidden biases and makes and makes the hard-to-handle rationing of healthcare licensable. The "priority score" gains an important role. Its formulation—whether it is exclusively reliant on clinical urgency, adds waiting time, or takes socio-economic factors into account—needs to be set by a multi-party ethical consent and the model can then be applied. To hospital managers, the model is like a strong decision-support system. It changes the planning from a reactive to a proactive stance. By pointing out the binding constraints (e.g., OR time in this case study), it gives unmistakable proof for strategic investment. The hospital, on the other hand, can invest in another operating room, hire more nurses, or do any of the procedures to which it has its budget increased? The model can depict these scenarios, offering a quantitative rationale for capital planning.

4. Conclusion

This research was able to successfully create and use an Integer Linear Programming model to tackle the very complex and real-world problem of scheduling patient admissions. The application to a case study of 25 patients proved the model's strong ability to maximize clinical value—measured by a priority score—under different, simultaneous resource constraints. The findings indicate that the optimal schedule is not merely a ranked list but is a complex arrangement of patient-specific resource requirements and system-wide capacities. The model used a combination of high-priority patients and resource-efficient medium-priority patients to admit 20 patients with a total priority of 122, thus maximizing the use of essential resources such as beds, nursing staff, operating rooms, and the financial budget to their full extent without exceeding them. The visual analysis of the results provided valuable insights into the model's reasoning, emphasizing its built-in inclination to prefer patients with efficient care pathways and recognizing possible system bottlenecks. To sum up, this optimization framework presents a scalable, transparent, and fair approach for enhancing operational efficiency in healthcare delivery. It enables managers to base their decisions on evidence that not only fosters patient throughput but also the fairness of access, thereby making it possible for limited resources to be distributed where they can yield the greatest overall benefit. Future studies could delve into uncertainty integration in parameters such as Length of Stay, dynamic priority scores development, and the incorporation of the model within a hospital's real-time electronic health records system for continuous planning.

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