A Novel Resilient Patient Admission Scheduling Conceptual Model

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Abstract. The advent of Industry 4.0 has revolutionized decision-making processes in production systems by leveraging real-time data provided by advanced information technologies. In service industries, effective planning and scheduling of resources have been shown to reduce waiting times, enhance user satisfaction, and improve organizational profitability. However, in the healthcare sector, where beds are among the most critical resources, optimal allocation of patients presents a complex challenge known as Patient Admission Scheduling (PAS). The dynamic nature of hospital environments, characterized by uncertainties and fluctuating occupancy rates of non-elective patients, demands periodic rescheduling. One key uncertainty lies in the availability of beds for elective patients, highlighting the importance of accurate prediction methods in the scheduling process. In this context, simulation-based optimization (SBO) techniques offer a promising solution due to their ability to handle stochastic behavior inherent in hospital systems. This paper proposes a conceptual resilient model for patient admission scheduling, integrating simulation-based optimization with machine learning-based forecasting models. By harnessing real-time data and predictive analytics, this model aims to address the challenges of patient admission scheduling in the era of Industry 4.0. Overall, this research contributes to the ongoing discussion on patient admission schedules by leveraging new technologies and advanced forecasting models to improve decision-making processes in healthcare management.

Keywords: Patient Admission Scheduling; Simulation-based Optimization; Short-term Forecast.

1 Introduction

The escalating healthcare costs underscore the urgent need for the development of efficient healthcare systems capable of meeting the growing demand for services while ensuring high-quality care. In response to these challenges, researchers are actively developing methodologies and solutions aimed at enhancing access to healthcare services and reducing expenses [1]. However, achieving these objectives requires the implementation of well-planned healthcare systems that maximize resource utilization and minimize costs across healthcare institutions [2].

The decision process of "when" and "in which bed" to allocate patients is known in the scope of hospital operations management as the Patient Admission Scheduling problem (PAS). This process consists of scheduling patients within a planning horizon in hospital beds to maximize management efficiency and patient comfort, as well as contributing to better treatment effectiveness [3]. Recently, dynamic business scenarios have imposed different needs on the decision-making processes, which must be supported by the discovery of information and knowledge [4]. Kazancoglu *et al.* [5] and Ogbuke *et al.*[6]encourage researchers to explore the potential of data-driven innovations in healthcare data management and practices. Emerging disruptive digital technologies such as blockchain, Industry 4.0 analytics models, robotics , IoT, and AI-driven methods are aimed at enhancing sustainability and resilience in healthcare systems.

In the hospital context, a series of uncertainties are present in the daily operations, such as the length of stay of the patient and the number of emergency patients who demand the services in a specific period [7]. A unique example of the variation in demand for beds is noticeable in the context of the COVID-19 pandemic, in which elective surgeries had to be suspended to provide structure to emergency patients affected by infections. Thus, as in other contagious diseases, new peaks of the disease are predicted over time [8], causing fluctuations in the demand for beds.

In response to the uncertain healthcare landscape, resilient health systems concepts have emerged, emphasizing adaptability to mitigate risks and ensure the continuous delivery of services to the population [9]. One possible strategy for addressing the challenges of admission scheduling is the forecast of non-elective patient admissions, which aids in determining the bed capacity available for elective patients [10]. Existing literature includes studies on hospital bed occupancy prediction, utilizing techniques such as machine learning to facilitate short-term resource management [11].

Moreover, the inherent variations in resource scheduling and planning parameters often necessitate the use of probability distributions to accurately represent uncertainty. For addressing complex stochastic, simulation approaches are widely recommended [12,13]. He *et al.* [14] suggest that hybrid approaches, which integrate optimization, simulation, and data-driven techniques, hold significant promise for advancing research in this field. By combining these methods, researchers can develop more robust solutions to optimize bed management processes. Nevertheless, the integration of these approaches in operational contexts remains uncommon [15].

Thus, this study aims to contribute by proposing a novel approach to patient admission scheduling. This approach involves integrating a demand forecasting model using machine learning and employing a hybrid method of simulation-based optimization to address the inherent uncertainty in the system. The paper will be organized as follows: Section 2 provides a literature review of the key topics informing the model; Section 3 details the proposed model and its functionality; Section 4 analyzes the model in terms of its characteristics and distinctions from existing research; finally, Section 5 presents conclusions and outline the next steps for its development.

2 Literature Review

2.1 Patient Admission Scheduling Problem

The problem of Patient Admission Scheduling and Planning (PAS) has attracted significant attention from researchers, as it represents both a scheduling challenge and a critical healthcare issue [16]. Considering the need to match patients to beds, Demeester *et al.* [3] developed the first formulation of PAS problem also known as Patient-to-bed assignment (PBA). This formulation is characterized by having admission dates already defined and known. Thus, the focus is the decision of the best allocation of patients to the beds, meeting the specificities and restrictions previously established between the parties (medical specialty, age, gender, mandatory equipment, preferred equipment, a set of preferred rooms, only one fixed admission date, and LOS). The objective of the model proposed by Demeester *et al.* [3] is to optimize the overall patient assignment, that is, to satisfy their preferences, respecting all the hard constraints of the problem. As in this case the admission and discharge dates have already been set, the PBA is considered a sub-problem of the PAS.

Ceschia and Schaerf [17] formulated a new and first completed version of PAS, also called PASU (U for uncertainty) that included various real-world aspects, such as the influx of urgency patients, uncertain lengths of stay, and potential delays in admissions. Ceschia and Schaerf [18] extended the problem by considering the operating room capacity as a hard constraint, while non-compliance with the allocation of workload per specialty in the operating room (surgical master plan) as soft constraint. Over the years, various studies have tackled PAS considering different optimization approaches to solve the different formulations of the problem, such as artificial bee colony algorithm [19] modified biogeography-based optimization algorithm [20] Discrete flower pollination algorithm [2] Harmony search algorithm [21] and mixed integer programming approach [22].

According to Abdalkareem [23], the literature has extensively examined elective patients, using historical data from the hospital and arranging the patients based on predetermined information (statically). Non-elective patients, on the other hand, encompass patients whose admission and discharge dates are unknown, such as emergency patients or those with uncertain conditions (dynamically). However, effectively scheduling uncertainty poses a challenge, and there is a scarcity of research on scheduling non-elective patients. It is important to acknowledge that the majority of studies focus on elective patients and disregard the issues that arise with non-elective patients.

2.2 Simulation-based Optimization in Hospital Context

The simulation-based optimization approach (SBO) consists of a feedback loop between the simulator and the optimizer to obtain robust results [24]. Its application is highly recommended in situations where there are uncertainties and stochastic data [25,26]. Ansari [27] emphasizes that hybrid modeling, such as SBO, may provide better results in situations with multiple sources of uncertainty, and can generate efficient projects with a higher degree of confidence.

The SBO approach has been used in production process scheduling problems. Nowadays, the healthcare industry demands a lot the use of simulation as a means to optimize systems in multiple aspects [28]. Chouba *et al.* [29] applied SBO to optimize the allocation of medical and para-medical human resources in an emergency department in a hospital. Durand and Bandoni [30] used the approach to generate an optimal schedule of elective surgery cases for a hospital surgery services unit considering surgical intensive care units (SICU). Granja *et al.* [32] applied SBO to optimize the healthcare providers' efficiency in a radiology workflow, increasing patient throughput.

The SBO approach shows promise for implementation within hospital settings, although it is currently more prevalent in other areas such as manufacturing [33,34] and logistics and supply chain management [13,35]. Given the various challenges that operational research can help address in hospitals, there is an opportunity to develop new models using this approach. In a study examining the use of simulation and optimization techniques in bed management, Mendes [15] pointed out that these methods are not widely used for short-term problems, despite their potential to help make decisions in real-time. This highlights the potential to use simulation and optimization models to address immediate bed management challenges by using real-time data.

2.3 Short-term Bed Occupation Time-series Forecast

Short-term forecasting models play a vital role in aiding operational decisions within hospitals, focusing on immediate needs rather than longer-term capacity issues within healthcare systems. In the context of bed occupation, time series analysis is a commonly employed method, offering various techniques and objectives to explore.

Numerous studies proposing methods for predicting occupancy using time series have emerged, particularly in extreme contexts such as pandemics. For instance, *Stasinos et al.* [36] developed an approach for predicting the occupancy of intensive care unit beds during the COVID-19 pandemic, employing three forecasting models, a combination of ARIMA and SARIMAX, ARTXP, and ARIMA, as well as Multivariate Regression. Similarly, Bouhamed [37] utilized three recurrent neural network methods to forecast bed occupancy at the national level. Additionally, Borges [38] applied the Prophet-LSTM (Long Short Term Memory) method to predict intensive care units (ICU) bed occupancy among COVID-19 patients in a Brazilian municipality.

Previous research has focused on developing methods for forecasting hospital admissions and bed occupancy under normal operating conditions. For example, Abraham *et al.* [11] utilized ARIMA to construct short-term forecasting models for admissions and bed occupancy. Meanwhile, Kutafina *et al.* [39] developed a model based on recursive neural networks, which incorporates historical admission and discharge data along with external factors like public and school holidays to forecast occupancy. Additionally, [10] used machine learning (ML) approach to forecasting emergency patients (artificial neural networks) to help with the patient-bed allocation problem.

Although hospital occupancy forecasts play a vital role in the process of scheduling patient admissions, no structured model has been identified in the literature that specifically incorporates forecasted data for non-elective patients into the scheduling of elective patient admissions, particularly within the framework of Patient Admission Scheduling (PAS). While Schafer's recent article addresses this issue within the context of Patient Bed Allocation (PBA), a sub-problem of PAS, the integration of forecasted data for emergency patients into elective patient admission scheduling remains largely unexplored within the broader PAS framework.

Based on the findings of the literature, our model addresses the following gaps: (i) Integrating an occupancy forecasting process for non-elective patients into the scheduling of elective patients; (ii) Implementing an adaptive optimization model based on simulation to address the PAS problem (iii) Identifying technologies as facilitators in PAS.

3 Proposed Conceptual Model

This section outlines a conceptual model for resilient patient admission scheduling, designed to enhance decision-making efficiency in the face of inherent uncertainties within healthcare systems. Firstly, the model integrates a non-elective patient occupancy forecast, enabling more accurate scheduling of elective patients based on bed availability. This holistic approach ensures that patient admissions are aligned with operational efficiency goals while prioritizing patient care. Furthermore, the model is designed to adapt to unexpected changes in the system, leveraging real-time data and decision-making technologies. This adaptability is an important aspect of effective scheduling, allowing the system to respond dynamically to evolving conditions.

Importantly, the proposed approach is underpinned by Industry 4.0 technologies, including real-time data analytics, machine learning, and digital twins. These technologies enable data-driven decision-making and enhance the accuracy and efficiency of the scheduling process. A conceptual representation of the model is provided in Figure 1, illustrating the three main processes: prediction of non-elective patient occupancy, initial admission scheduling, and admission rescheduling. Each of these is discussed in detail in the subsequent subsections.

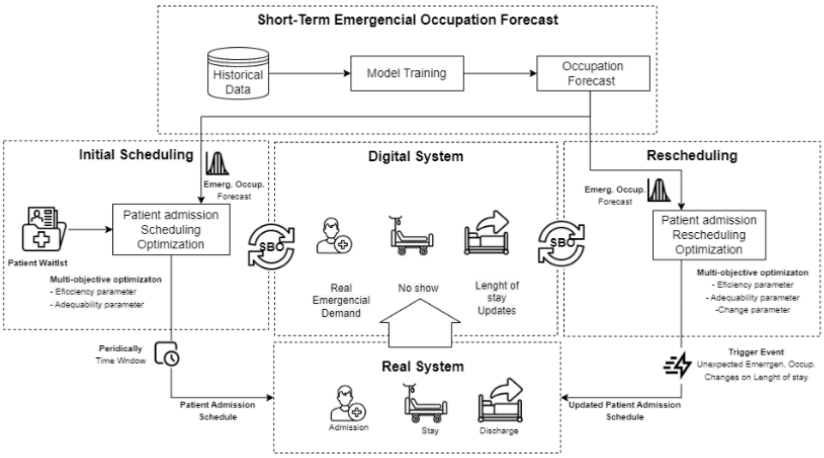

Fig. 1. Proposed conceptual model for Resilient Patient Admission Scheduling

3.1 Emergency Patient Bed Occupation Forecast

In hospitals, the demand for emergency patient care often fluctuates unpredictably, posing challenges in allocating beds and avoiding overcrowding. Predicting the occupancy of emergency beds is essential for optimizing resource utilization and guiding the scheduling of elective patients. Integrating emergency demand forecasting into the scheduling process enables hospital managers to efficiently allocate resources, prioritize cases, and manage patient flow, thereby improving operational efficiency.

Short-term forecasting models for emergency patients can significantly benefit the scheduling of elective patients. This approach allows for the establishment of robust overcrowding risk strategies using simulation models, enabling healthcare managers to proactively allocate resources and prioritize cases based on anticipated demand fluctuations. Machine learning approaches, such as long-short memory recurrent neural networks (RNN-LSTM), are capable of providing predictions by analyzing historical and recent occupancy data.

To predict emergency occupancy, we defined a forecasting model, as depicted in Figure 1. This model utilizes historical occupancy data to generate forecasts. Therefore, it is imperative to have a comprehensive database containing historical patient occupancy data. The focus of the forecast should primarily be on non-elective patient records, as the occupancy forecast for this patient profile serves as a key determinant for scheduling elective patients. Various features such as the day of the year, week, public holidays, festive dates, and an analysis of disease clusters' behavior can significantly enhance the accuracy of the model. As illustrated in Figure 1, the forecasting model functions as a sub-system within the broader framework, thereby complementing the initial scheduling and rescheduling stages.

3.2 Initial Patient Scheduling

The scheduling process begins with a list of patients eligible for scheduling within a specified time window (typically 7 to 14 days). Each patient is characterized by specific attributes, similar to initial PAS formulation. Concurrently, a pool of available beds, each with its own set of characteristics, is considered for patient allocation. The number of available beds may vary based on the outcome of the demand forecasting process, particularly influenced by the forecasted non-elective occupancy.

The scheduling process is driven by an SBO model that integrates with the hospital's simulation model to identify the most favorable configuration until predefined stopping criteria are met. Once these criteria are reached, the admission schedule for the designated time window is finalized and transmitted to the system. The initial scheduling proposal assumes that admission dates are not predefined. Utilizing simulation-based optimization, the scheduling algorithm determines the optimal allocation of patients to beds, taking into account factors such as the existence of a waiting list and the forecasted availability of beds due to non-elective occupancy.

The resulting patient admission schedules specify admission dates and bed assignments based on the objective function and defined constraints. This optimization objective, influenced is comprehensive, aiming to maximize resource utilization while considering patient room suitability. As such, the optimization algorithm must generate solutions that satisfy both efficiency and suitability criteria, ensuring the best sequencing of patient admissions to achieve optimal outcomes.

As illustrated in Figure 1, a digital system is depicted, representing the real hospital system by providing real-time information on resources and patients. The primary function of the digital model is to monitor the system's conditions and provide essential information for management. Additionally, it serves as a simulation model for generating new solutions for admission scheduling, effectively acting as a Digital Twin in the decision-making process. Figure 1 also highlights some of the key information that feeds into the digital system.

In real-world scenarios, unforeseen events often arise, requiring rescheduling. During the rescheduling process, patient assignments are adjusted for the following day within the initially scheduled time window. Once the scheduled period ends, a new initial schedule must be generated for the subsequent time window.

3.3 Patient Admission Rescheduling

In addition to forecasting the number of beds occupied by non-elective patients, unforeseen events such as sudden increases in emergency needs or changes in the length of patient stays can disrupt the initial elective admission schedule, requiring adjustments to be made. During the rescheduling process, a new forecast must be generated based on the updated context, while considering the existing schedule and patient expectations. The digital system plays a crucial role in facilitating this process by triggering the rescheduling process and serving as a simulation model to evaluate potential solutions.

The optimization process for rescheduling diverges from the initial scheduling process, aiming to minimize changes to existing appointment dates while ensuring high bed occupancy for elective patients. It is important to recognize that once a schedule is generated, resources are allocated, and patient expectations are established. Therefore, changes to admission dates are discouraged in the new optimization model, as they can disrupt resource allocation and impact the number of admissions. However, the optimization objective shifts from solely maximizing admissions to prioritizing the minimization of changes in admission dates compared to the previous schedule.

It's important to highlight that the rescheduling process is guided by updated forecasts from the machine learning model, especially when significant deviations from the forecast occur, prompting the need for adjustments. This iterative rescheduling process continues until the end of the initial window, at which point a new scheduling cycle begins. Moreover, during the rescheduling process, the primary objective is to ensure optimal patient allocation among the rooms while adhering to the admission dates defined in the initial schedule. Instances of delayed admission dates should only arise when allocation becomes infeasible due to overcrowding.

4 Discussion

Several publications in literature are related to the model proposed by Demeester *et al.*[3]. Over time, new derivations incorporating characteristics that bring the models closer to real systems and the use of different optimization methods to solve the problem have been presented in research, and the problem has been addressed in publications to this day.

In discussions regarding the future directions of Patient Admission Scheduling (PAS), Abera *et al.* [40] advocate for a more comprehensive adaptation to real hospital system data by employing simulation. Simulation offers the advantage of representing stochastic behavior, and when integrated with optimization, as in the Simulation-Based Optimization (SBO) approach proposed in this study, it combines the strengths of both techniques. Although simulation and optimization methods are commonly utilized in the operational level to address challenges at outpatient scheduling [41,42] and emergency management [43], Mendes *et al.* [15] state that, within the realm of bed management, the predominant focus has been on decision-making at the tactical level. However, there exists an opportunity to extend these applications to the operational level by leveraging real-time data in inpatient bed problems.

Incorporating a demand forecasting model into the admission scheduling process distinguishes this model. While some authors have attempted to address potential overstays for elective patients, the scheduling of non-elective patients has often been overlooked [23]. However, given recent experiences with pandemics disrupting elective admissions and the recurrent occurrence of local epidemics within health systems [8], this model proves valuable not only during periods of sudden demand changes but also in addressing the routine challenges of hospital operations. Schafer *et al.* [10] very recently considered the prediction of emergency patients for PBA, but still in the context of an exact approach.

Moreover, existing models addressing this problem have not integrated with the technologies available in the realm of data communication infrastructure, overlooking the contemporary context of Industry 4.0. Specifically, within the domain of Patient Admission Scheduling (PAS), such advancements have not been explored, with the literature predominantly focused on theoretical optimization problems. This study extends beyond the existing scope by elucidating the necessary technologies and data types essential for the functionality of the proposed model, and how it can be provided.

5 Conclusion

Industry 4.0 represents the current trend of automation technologies in the manufacturing industry and includes mainly enabling technologies. Due to these changes, manufacturing system environments and other areas have been changing [44]. These changes, driven by the adoption of enabling technologies, are reshaping manufacturing environments and service delivery methods alike. In service systems, there is a growing recognition of the potential benefits offered by Industry 4.0 approaches. In light of this, we propose a novel conceptual model for dynamic patient scheduling. This model leverages a simulation-based optimization approach, augmented by machine learning forecasts. By integrating these cutting-edge technologies, our model aims to enhance the efficiency and adaptability of patient scheduling processes, aligning them with the principles of Industry 4.0.

The proposed model facilitates dynamic patient admission scheduling by leveraging real-time data from the system. This feature is essential given the inherent uncertainties in such systems, including fluctuations in demand due to the arrival of emergency patients and variations in the length of stay of hospitalized patients. Furthermore, the integration of a non-elective patient occupancy prediction process enables more accurate scheduling, thereby mitigating the need for extensive rescheduling in case of disruptions and minimizing changes in human resource and facility scheduling.

We argue that the model introduces novel variables to the PAS framework and offers a new resolution approach, potentially yielding results that better align with the needs of real-world systems. Subsequent research endeavors will concentrate on developing the dynamic simulation and optimization model to operationalize the proposed conceptual framework, utilizing data from a service industry partner, and evaluating the efficacy of the model based on the obtained results.

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