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RESEARCH ARTICLE

Bed Allocation Optimization Based on Survival Analysis, Treatment Trajectory and Costs Estimations

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ABSTRACT The intensive care units are a key element of patient flow, but due to high demand and an alternating rate of arriving patients, these units are often challenged by insufficient capacity, very high expenses, and in some cases, an unfair distribution of resources. Proper allocation of resources to match demand is, therefore, a vital task for many wards in these units. The patient bed assignment problem consists of managing in the best possible way a set of beds with equipment to be assigned to a particular type of patient. However, in real-world scenarios, constraints like a possible treatment trajectory are violated in most cases. In this paper, we present a new approach for solving patient bed assignment problems constrained by targets on survival function estimation, cost estimation, and possible treatment trajectory estimation for patients with cardiovascular diseases. For survival function estimations, we used the nave estimator and Kaplan-Meier, and for treatment effect estimations, we used logistic regression and T-learning. Estimations of the three components are used as weights in a genetic algorithm. This technique allows for the consideration of various constraints, which, unlike other techniques, allows for the selection of dominant solutions as solutions that satisfy dominant constraints. In addition, we demonstrate the robustness of our approach by testing the algorithms with multiple classes of patients, testing multiple sets of parameters, and comparing our results with several similar research studies showing the added value of working on this management axis in hospitals using the new approach to bed allocation.

INDEX TERMS Bed allocation, costs, multi-objectives optimization, machine learning, intensive care units, survival analysis, treatment effect estimation.

I. INTRODUCTION

By far, the health care industry is one of the largest industries in the world, and it is number one in the United States with a total expenditure of 1553 billion dollars in 2002, while this amount reached 3.8 trillion dollars in 2019 according to the Centers for Medicare and Medicaid Services [1], [2]. In the United Kingdom, the total expenditure has been estimated at 269 billion pounds sterling [3]. In Germany, this amount rose to 410.8 billion euros in 2019, according to the German Federal Statistical Office [4]. In 2017, France spent 469 billion euros [5]. In terms of the Gross Domestic Product (GDP), in 2019, European countries devoted at least 10% of their GDP on health, with Germany (11.7%) and France (11.2%) having the highest shares. The lowest shares of GDP allocated to health care were in Luxembourg (5.4%), Romania (5.7%), Poland (6.2%), and Latvia (6.3%). Across Europe, Switzerland allocated the largest share (12.1%) of its GDP to health [6]. The tremendous growth of this industry is further demonstrated by the fact that this expenditure is double the size of health care's share of these countries' economies 30 years ago [6], [7]. These expenditures include personal health care (curative care, rehabilitative care, long-term care, ancillary services, and medical goods) and collective services

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(prevention and public health services, as well as health administration) [8]. On a more detailed level, the dynamics governing a hospital system and the flow of patients, and as a result, the health care expenditures, involve complexity, uncertainty, and variability. All these features point towards the need for sophisticated hospital capacity modeling that includes the necessary level of detail, incorporates the time-dependent demand profiles of hospitals, and uses meaningful statistical distributions to capture the inherent variability. Yet it must be accessible to stakeholders to support their understanding, planning, and management of hospital resources [9].

From a managerial perspective, understanding the inefficiencies in the hospital and improving them is crucial for making health care policy and budgeting decisions. These managerial insights can, in fact, improve expenditure to eliminate waste and improve medical care quality. Indeed, higher operational efficiency of the hospital has been demonstrated to help control the cost of medical services and, as a result, provide more affordable care and improved access to the public, not to mention high quality care [10], [11], [12].There is very extensive evidence for the importance of patient-centered care in the decision-making process to use medical resources more efficiently [13]. There are many other problems being encountered both by hospitals and patients. Longer waiting times for the inpatients to be admitted to the hospital, diversion from a unit as it reaches the underlined capacity, longer waiting lists and delays for elective patients, and higher operational costs due to inefficiencies are some of these challenges.

Studying and optimizing such variations that impact hospitals' performance requires, in a much-elaborated way, the use of multiple approaches. Such problems, with a double orientation, namely limitations in medical resources and high expectations regarding service quality, are generally multi-objective problems. Hence, multi-objective optimization deals with such problems by giving as solutions a set of non-dominated candidates based on two main approaches [14]. a generative approach and a preferences-based approach. Regarding the generating approach, the given set of solutions does not follow any preferences and covers the entire Pareto front. While the preferences-based approach requires predefined conditions and, in most cases, turns a multi-objective task into a single objective task [15], [16]. In hospital management systems, multi-objective optimization is almost always oriented toward capacity improvement, quality improvement, and other constrained medical issues. Furthermore, hospitals have faced and continue to face an increasing number of patients in recent years [17]. As a result of the increased demand in emergency departments (ED), most patient admissions are unexpected. The crucial point is that the growing demand for inpatient beds from the ED cannot be addressed at a strategic level by increasing bed capacity due to the persisting situation of public health budget cuts. The solution should instead be found at an operational and tactical level [18]. Many studies have been conducted on this subject; for example, in the United States, an occupancy rate of 89.7% was reported, with an average of 155 patient visits per day [19]. In the United Kingdom, in the period between the first quarter of 2010/11 and the first quarter of 2019/20, the total number of National Health Services (NHS) hospital beds decreased by 11%, from 144,455 to 128,943. But the number of occupied beds only decreased by 9%, from 122,551 to 111,321. Therefore, the bed occupancy rate increased slightly from 85% in the first quarter of 2010/11 to 86% in the first quarter of 2019/20 [20]. A holistic view of the whole patient process is therefore needed. Thus, hospital resource management is a complex and dynamic problem that requires a close study of state-of-the-art techniques.

To solve these issues, it has been demonstrated that early determination of severity scores, survival function, and predicting the trajectory of the treatment can help efficiently allocate or, in the case of reorganization, reallocate beds specifically in high intensity care units [21], [22], [23], [24]. We are adopting this evidence as a base for our research paper. In the following, we will be using the MIMIC III database, comprising thousands of recorded physiological signals, logistic transfers, and other patients' related data like their location, ethnicity, and so on. The core of the implementation will be divided into two main parts. We start by estimating the survival function and treatment effect of the drugs and therapy received by patients. Based on these results, we are using a weighted genetic algorithm to optimize the use of these beds in intensive care units (ICUs).

The rest of the paper will be as follows: in the second section, we will study the state of the art related to bed management and optimization techniques. The third section will contain the dynamics and implementation of our approach. In the fourth section, we present the results of our approach and a discussion of existing works. We finish the paper with a conclusion and perspective.

II. RELATED WORK

In the years between 2000 and 2020, healthcare resource usage has tripled according to the sustainable development goals of the World Health Organization [25], which has become problematic evidence against delivering high-quality healthcare services. Thus, it is declared that if the need for treatment resources exceeds availability and a safe transfer to another facility due to the patient's circumstances or an emergency, the resource triage team is responsible for allocating or re-allocating critical care resources. Decisions made regarding the allocation or reallocation of critical care resources in an extreme scenario should be evidence-based and applied uniformly and consistently, according to the US Department of Health Services' Resource Triage Team Implementation Protocol [26]. Such pressure decreases the quality and outcome of the medical care service. Indeed, many studies have addressed this issue of scarce resources from different perspectives.

A wide range of different techniques have been used. [27] used multi-objective comprehensive learning particle swarm optimization to solve the bed allocation problem based on binary search. Another study [28] introduced a multi-objective decision model based on queuing theory and goal programming to solve the same problem. Other studies used deterministic mathematical modeling, stochastic models with mixed exponential distributions, continuous-time Markov modes, and Bayesian belief networks to either minimize the overflow of patients in the emergency department, optimize stuff services, or efficiently allocate beds in high-priority departments [29], [30], [31], [32], [33].

Setting the threshold for medical need for ICU admission or continued ICU care depends on medical knowledge and professional judgment. Ideally, these judgments should be based on well-designed studies of outcomes comparing subsets of patients with differing degrees of medical need treated in ICUs compared with being treated in monitored non-ICU units [34]. Regarding the bed allocation problem, one can also focus on the relationship between the rate of usage of these resources and the epidemiology concerns to be considered [35].

From other perspectives, artificial intelligence (AI) has been used to discover many new roadmaps to optimize patient flow in hospitals. [36]. When a patient arrives at a hospital, AI models can stratify them based on their risk, allowing for more efficient resource allocation and significantly improved treatment outcomes and hospital stay. For example, in the emergency department, AI can provide an automatic diagnosis based on radiographs, thereby expediting the patient care plan [37], [38].At discharge, AI models can predict possible outcomes, most notably adverse events, and provide the patient with a personalized post-hospitalization plan [39], [40].Authors in [41] used an adaptive neural-fuzzy inference system, a feed-forward neural network, a recurrent neural network, AdaBoost, and genetic algorithms to decide the optimal way to allocate resources in the emergency department. In another study [42], the authors used heart-rate variability in the emergency department alongside other demographic information as input features to a support vector machine. This study is oriented to allow clinicians to predict resource utilization in the cardiac department. Other studies used logistic regression, gradient boosting, long short-term memory (LSTM), and natural language processing (NLP) approaches to predict and manage medical resources based either on demographic features or clinical features, or simply on a ''similar patterns, similar outcomes'' approach [43], [44], [45], [46].

Long Lengths of Stay (LOS) have been identified as one of the primary factors contributing to scarcity of resources, particularly bed availability [47], [48], [49]. Other studies found that longer LOS, which are highly proportional to a drop in the hospitals' accessibility and medical resource availability, especially in peak waves, are mostly recorded in ICUs [50], [51]. Critical illness is characterized by the presence or risk of developing life-threatening organ dysfunction. It is in this case that patients are treated in ICUs, which specialize in providing continuous monitoring and advanced therapeutic and diagnostic technologies [52]. Large amounts of data from many patients stored in electronic patient-data management systems are presented to ICU information systems, making it increasingly difficult to identify the most important information for care decisions [53], [54]. To improve efficiency and effectiveness in these ICUs, the patient flow needs to be focused, since it is central to an organization's capacity to provide specialized and very crucial healthcare services, while other operations provide support with the aim of creating conditions for an efficient and effective patient flow [55].

III. THE STRUCTURE OF THE PROPOSED APPROACH

Hospital managers and decision-makers faced significant challenges as the demand for healthcare increased. The challenges involve high costs, a limited budget, and limited resources, but more importantly, a decreased quality of care. The vision in the current paper is a patient-centered approach in which optimization of bed allocation efficiency will be a function of patient condition in intensive care units. Also, the approach considers costs related to the patient's stay in the ICUs.

The research in this article is divided into two parts. The first part is the statistics and analysis of the basic information of all patients in the MIMIC-III database, and the second part is the calculation of patients' related survival functions and treatment trajectories, followed, based on these parameters, by the optimization of bed allocation as well as related costs. A major part of this section includes a detailed study of the patient's treatment centered on drug therapy, as it is one of the most outcome-determining factors in the ICU. More specifically, the analysis includes drug therapy for patients with cardiovascular disorders: arrhythmias, heart failure, and congestive heart failure.

The emergency department admits a high proportion of patients with severe illness to ICUs. Once admitted, they will be dependent on a variety of different resources. Upon arrival, the patient is first triaged to determine the severity of their condition. A physician will then conduct an examination to determine whether more extensive treatment is required. Our objective is to contribute to the methodology related to balancing the ICU's capacity against service by considering the possible developments and changes in the admitted patients' treatment trajectory as well as their survival assessment. As waiting time has been shown to influence the patient's survival analysis as well as the final outcomes, the optimization model will be constrained by the waiting time target. Figure 1 describes the overall architecture of our proposed approach.

The ICU allocation model addresses the following situation: there are candidate patients for occupying available ICU beds, and the doctor must decide which patients need to be admitted to ICUs based on the survival function while also taking the treatment trajectory of patients already admitted to

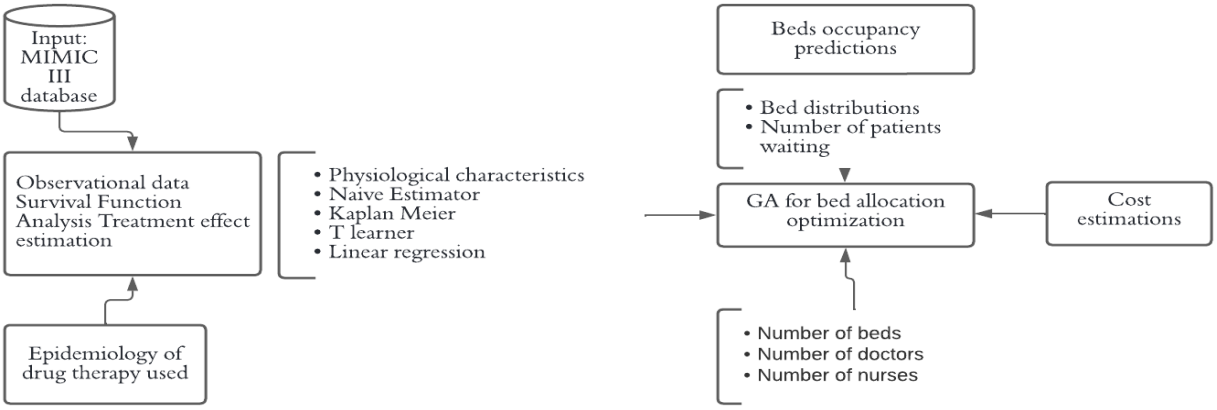


FIGURE 1. Architecture of our proposed approach.

ICUs into account. This includes their stay in ICUs or in low-care wards. For simplicity in addressing the actual problem, we consider the two following assumptions:

Assumption 1: Different types of patients arrive independently. Patients of the same type have the same distribution and arrival rate.

Assumption 2: The unit revenue is specific to patient types. We average revenues across all diseases, insurance policies, and lengths of stay within each patient type and take this as the revenue from serving one patient of that type..

A. DATA DESCRIPTION AND PROCESSING

Medical Information Mart for Intensive Care abbreviated MIMIC III is a large, single center database that contains deidentified, comprehensive clinical information related to patients admitted to ICUs at Beth Israel Deaconess Medical Center in Boston (BIDMC), Massachusetts. It includes measurements of patients' vital signs, laboratory tests, medications, procedures, diagnosis, length of stay and other information. This data is associated to more than 50000 admissions in the period between 2001 and 2012 shifted and deidentified in accordance with the Health Insurance Portability and Accountability Act (HIPAA) standards and grouped in 26 tables [56].

The ICU's department with the largest number of patients is the Medical Intensive Care Unit (MICU). The number of patients who died in the hospital and the number of survived patients within 90-day after discharge in the MICU are also much higher than those in other wards. This shows that patients with internal diseases have the largest number of patients and the highest mortality rate. In subsequent studies, we can study the survival function of patients and their treatment trajectory in MICU and use machine learning to predict the health of patients. Also, the number of patients admitted to Cardiac Surgery Intensive Care Unit (CSRU) was second only to MICU, but the number of deaths in hospital and the number of 90-day deaths after discharge is the lowest compared to other ICUs. We counted the mortality of patients admitted to each type of ICU wards, and we found that the highest mortality rate was 32.6% in MICU followed by the Cardiology Critical Care Unit (CCCU) with a mortality rate of 24%.

Figure 2 explains the observations we made on the patients with cardiovascular diseases in different wards. The main goal of such observations is to determine the number of time (in days) necessary for an event to happen.

The actual study will consider treatment complied to patients with cardiovascular disease. To follow the treatment effect, we will be considering a list of widely used drugs and track their effect on the records of patients transfer in the MIMIC III dataset. We categorize these drugs into five main categories: 1) anticoagulant drugs [57], antiplatelet drugs [58], [59], antiarrhythmic drugs [60], vasoactive drugs [62], and statins [64]. We followed condition of patients who received these drugs. The treatment effect is considered positive if the patient is discharged alive or if did not necessarily need to be discharged to a more intense care unit.

B. SURVIVAL FUNCTION, TREATMENT EFFECT AND COST ESTIMATION

1) SURVIVAL FUNCTION

Intensive Care Units take care of patients with the most severe and life-threatening illnesses and injuries, which require constant, close monitoring and support from special equipment and medication to maintain normal body functions. They are staffed by highly trained doctors and critical care nurses who specialize in caring for seriously ill patients. Critical care support with correct and accurate interventions prevents deaths. Factors that influence mortality need to be investigated to see the trend in our setup and how these factors can be improved. Researchers through the years have tried to use different techniques called ''survival function estimation'' to determine these factors [63]. Kaplan-Meier and its derivative nave estimator are reported to be the most used survival

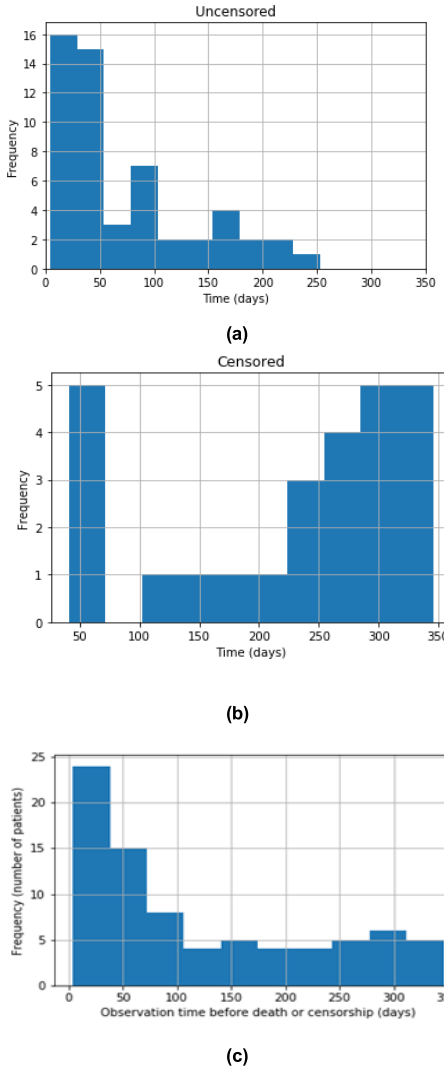


FIGURE 2. Binary counting of the duration survived before censorship or events related to a cardiac event. (a): frequency of patients not experiencing any event during the observation interval. (b): frequency of patients experiencing an event (change in their medical condition), (c): observation time before we notice any censored patients.

functions in the case of censored data [64]. These techniques are data-based and calculated using probabilistic calculus.

Kaplan Meier and naïve estimators were used to compare survival distribution of data dealing with differing survival times (times to death), especially when all the subjects do not continue in the study. The importance of deciding the survival estimation of patients is the ability to draw a treatment and availability trajectory.

a: Naïve ESTIMATOR

We'll start with a naive estimator of the above survival function. To estimate this quantity, we'll divide the number of people who we know lived past time t by the number of people who were not censored before t.

$$S\,(t) = P\,(T > t) \tag{1}$$

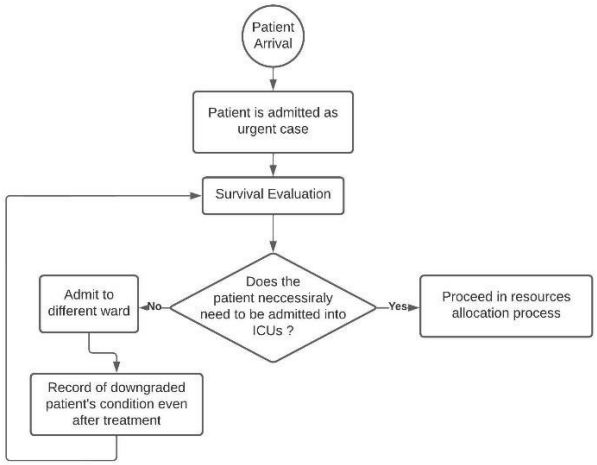


FIGURE 3. The role of survival to decide of patient's flow.

Formally, let i = 1, …, n be the cases, and let t_i be the time when i was censored or an event happened. Let $e_i = 1$ if an event was observed for i and 0 otherwise. Then let $X_t = \{i : T_i > t\}$, and let $M_t = \{i : e_i = 1 or T_i > t\}$. The estimator we will be computing will be:

$$\hat{S}\,(t) = \frac{|X_t|}{|M_t|} \tag{2}$$

b: KAPLAN MEIER

Next we are comparing Naïve estimate with the Kaplan Meier estimate. In the cell below, write a function that computes the Kaplan Meier estimate of S(t) at every distinct time in the dataset.

$$S\,(t) \prod_{t_i \le t} \left(1 - \frac{d_i}{n_i}\right) \tag{3}$$

where t_i are the events observed in the dataset and d_i is the number of deaths at time t_i and n_i is the number of people who we know have survived up to time t_i. Resulting estimations are represented in figure 4. The main conclusion

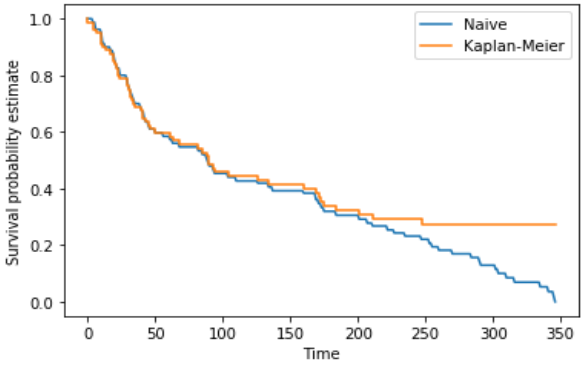


FIGURE 4. The survival probability estimation by Naïve and Kaplan Meier estimators in time (hours).

from the results shown in figure above is that using the naïve estimator shows continuously decreasing survival probability estimation while the Kaplan-Meier show stable situation after spending an average of 250 hours in ICUs.

2) TREATMENT EFFECT ESTIMATION

Patient data were considered as a multivariate timeseries defined by the times when patient events were recorded, the sequence of indexes mapped from each patient's discretized timeseries, and the set of outcomes for each patient episode.

To draw a patient's individual treatment trajectory, we started by counting every time every patient have been taken a dose of the specified drug.

Let the probability of dying for a patient who received the treatment be defined as:

$$P_{treatment,death} = n_{treatment,death} \Big/ n_{treatment} \tag{4}$$

where $n_{treatment,death}$ is the number of patients who received the treatment and died, while $n_{treatment}$ is the number of patients who received treatment.

The probability of dying for patients in the control group (who did not receive treatment):

$$P_{control,death} = n_{control,death} \Big/ n_{control} \tag{5}$$

where $n_{control,death}$ is the number of patients in the control group who died, while $n_{control}$ is the number of patients in the control group. The flowchart of the treatment trajectory is represented in figure 5.

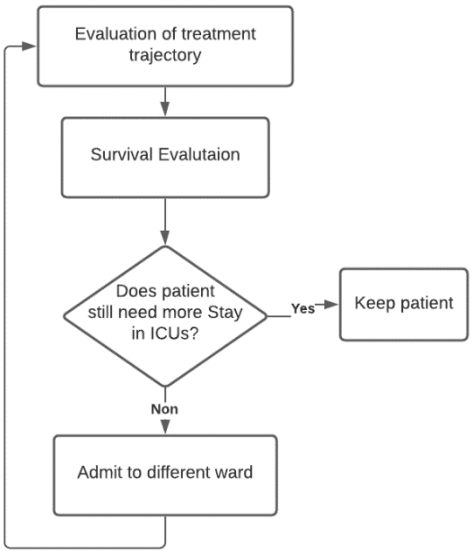


FIGURE 5. Treatment trajectory and its relationship with newly admitted patients to ICUs.

To estimate the outcome of a predetermined treatment we are using T-learner which uses logistic regression as the base learner. The T-learner is a meta-algorithm used for the estimation of heterogeneous treatment effects. It takes two steps: first, it uses the so-called base learners to estimate the conditional expectations of the outcomes separately for units under control (in this case we are considering 5 main units) and those under treatment. Second, it takes the difference between these estimates. This approach has been analyzed when the base learners are linear-regression [65] or tree-based methods [66].

Closely related to the T-learner is the idea of estimating the outcome by using all the features and the treatment indicator, without giving the treatment indicator a special role. The predicted average treatment effect for an individual unit is then the difference between the predicted values when the treatment-assignment indicator is changed from control to treatment, with all other features held fixed.

To apply the T-learner to our case, we first model the treatment effect using a standard logistic regression. Let $x^{(i)}$ be the input vector, based on this variable, we model the probability of death withing 5 years as:

$$\sigma\left(\theta^T x^{(i)}\right) = 1 \Big/ 1 + \exp(-\theta^T x^{(i)}) \tag{6}$$

where $\theta^T x^{(i)} = \sum_j \theta_j x_j^{(i)}$ is an inner product.

We also consider three main features, TRTMT (presented by drug therapy) by which we reflect the treatment received by patients in the ICUs mainly including drug therapy, age, and sex. As a result, we reformulated the probability of death:

$$\sigma\left(\theta^T x^{(i)}\right) = 1 \Big/ 1 + \exp(-\theta_{TRTMT} x_{TRTMT}^{(i)} - \theta_{AGE} x_{AGE}^{(i)} - \theta_{SEX} x_{SEX}^{(i)}) \tag{7}$$

Considering this equation, $x_{TRTMT}^{(i)}$ is the treatment variable. Therefore, θ_{TRTMT} tells us what the effect of the treatment is. If θ_{TRTMT} is negative, then having treatment reduces the log-odds of death, which means death is less likely than if treatment is not taken. Note that this assumes a constant relative treatment effect, since the impact of treatment does not depend on any other covariates.

We set $x_{TRTMT}^{(i)} = 1$ when a patient received treatment. If we calculating the odds related to a treated patient, it will take the following form:

$$\begin{aligned} \log(Odds_{treatment} &= \log\left(p_{treatment} \Big/ 1 - p_{treatment}\right) \\ &= \theta_{TRTMT} \times 1 + \theta_{AGE} x_{AGE}^{(i)} + \theta_{SEX} x_{SEX}^{(i)} \end{aligned} \tag{8}$$

By raising to the power of the exponential to take the inverse of the natural log, we will get:

$$Odds_{treatment} = e^{\theta_{TRTMT} \times 1 + \theta_{AGE} x_{AGE}^{(i)} + \theta_{SEX} x_{SEX}^{(i)}} \tag{9}$$

Similarly, when the patient has no treatment, this is denoted by $x_{TRTMT}^{(i)} = 0$. So, the log odds for the untreated patients can be expressed in the following way:

$$\begin{aligned} \log(Odds_{baseline} &= \log\left(Pbaseline \Big/ 1 - p_{baseline}\right) \\ &= \theta_{TRTMT} \times 0 + \theta_{AGE} x_{AGE}^{(i)} + \theta_{SEX} x_{SEX}^{(i)} \end{aligned} \tag{10}$$

and so:

$$Odds_{baseline} = e^{\theta_{AGE} x_{AGE}^{(i)} + \theta_{SEX} x_{SEX}^{(i)}} \quad (11)$$

We also define the Odds ratio as the subdivision of the $p_{baseline}$ and $p_{treatment}$:

$$OddsRatio = Odds_{treatment} / Odds_{baseline} = e^{\theta_{TRTMT}} \quad (12)$$

From the other side, we calculate the Absolute Risk Reduction (ARR)which reflects the risk when we do something protective, such as stop drinking alcohol. Otherwise, the ARR is a manifestation of how well goes a treatment received by a patient.

If we consider $p_{baseline}$ as the baseline probability of death after receiving the treatment and $p_{treatment}$ is the probability of death if treated, then $ARR = p_{baseline} - p_{treatment}$.

From other hand, we also define the empirical (actual) risk reduction. This variable measures how well the risk reduction calculated by the logistic regression model match actual values. This is complicated by the fact that for each patient, we only observe one outcome: treatment or no treatment.

Therefore, we will group patients into groups based on their baseline risk as predicted by the model, and then plot their empirical ARR within groups that have similar baseline risks. The empirical ARR is the death rate of the untreated patients in that group minus the death rate of the treated patients in that group.

The logistic regression model assumes that treatment has a constant effect in terms of odds ratio and is independent of other covariates. However, this does not mean that absolute risk reduction is necessarily constant for any baseline risk $p_{baseline}$. To illustrate this, we executed the previously mentioned calculus. Results are shown in figure 6.

Note that when viewed on an absolute scale, the treatment effect is not constant, even though we used a model with no interactions between the features. As shown in the plot, when the baseline risk is either very low (close to zero) or very high (close to one), absolute risk reduction from treatment is low. When the baseline risk is closer to 0.5 the ARR of treatment is higher (closer to 0.10).

In the plot of figure 6, the empirical absolute risk reduction is shown as circles, whereas the predicted risk reduction from the logistic regression model is given by the solid line. If ARR depended only on baseline risk, then if we plotted actual (empirical) ARR grouped by baseline risk, then it would follow the model's predictions closely (the dots would be near the line in most cases).

Our simulation study is designed to consider a range of situations. We include conditions under which the T-learner is likely to perform the best [67]. We consider cases where the treatment effect is zero for all units (and so pooling the treatment and control groups would be beneficial) and cases where the treatment and control response functions are completely different (and so pooling would be harmful). We consider cases of patients having

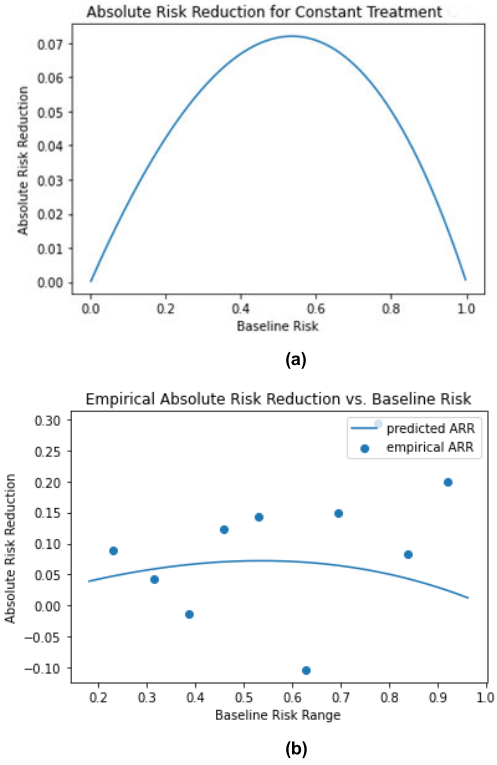


FIGURE 6. Absolute risk reduction compared with empirical absolute risk reduction.

interfering treatment and tuples of patient with no interfering treatments.

All simulations discussed in this section are based on synthetic data.

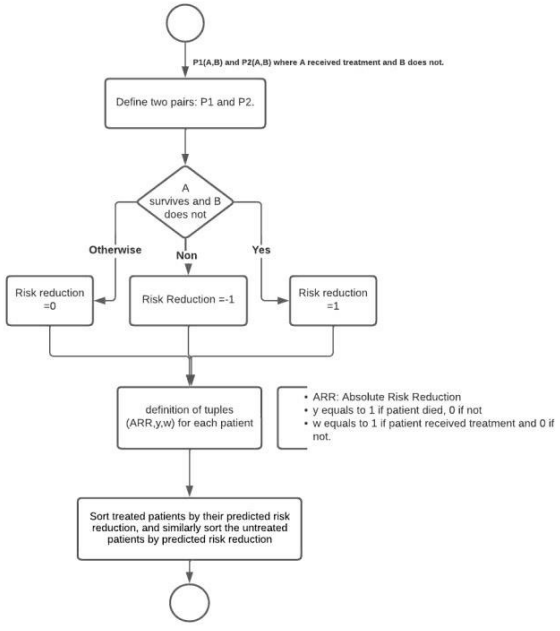
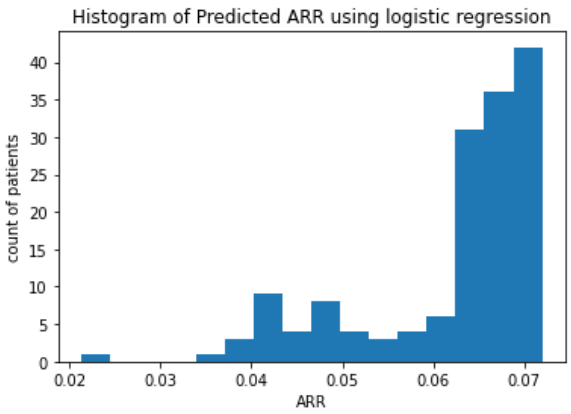
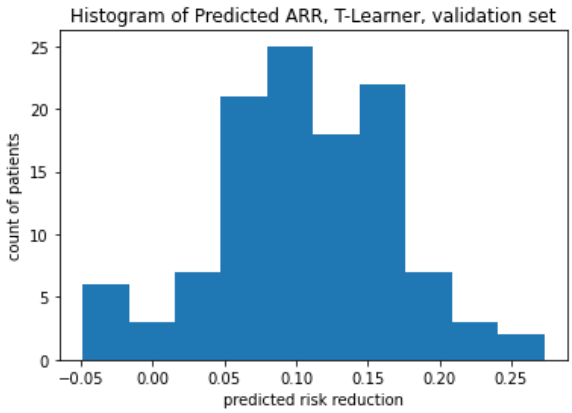


FIGURE 7. T-learner approach.

The T-learner, on the other hand, does not combine the treated and control groups. This can be a disadvantage when the treatment effect is simple because, by not pooling the data, it is more difficult for the T-learner to mimic a behavior that appears in both the control- and treatment-response functions. Therefore, the following figures represent the resulting treatment effect estimations both based on the logistic regression model alone or using the T-learner estimator.



(a)



(b)

FIGURE 8. (a): Regression and (b) T-learner prediction of Risk Reduction.

Note that although it predicts different absolute risk reduction, it never predicts that the treatment will adversely impact risk. This is because the odds ratio of treatment is less than 1, so the model always predicts a decrease in the baseline risk. We predicted a lower risk reduction for patients with actual lower risk reduction. Similarly, a higher risk reduction for patients with actual higher risk reduction.

3) COST ESTIMATION

Cost estimation of healthcare activities can be carried out using either micro-costing (bottom-up) [68] or macro-costing (top-down) [69] methods. In the bottom-up method, costs are derived for each element of intervention: staff time, supplies and medications, diagnostic and laboratory examinations, and so on. In the top-down view, there are no details available on the cost of every component of the inpatient's stay. The degree of aggregation used in this method is high. The type of cost information available usually determines the method that will be used in the analysis. In this case, estimation of the cost was performed using a top-down (macro-costing) approach, as shown in Figure 9, since data were retrospectively collected and patients' records did not provide analytical resource consumption. In all clinical affiliations of the Beth Israel Deaconess Medical Center (BIDMC), resource utilization was reported per hospital unit rather than per patient, and data were derived from their official website between 2001 and 2011 [70], [71]. All quarters were considered.

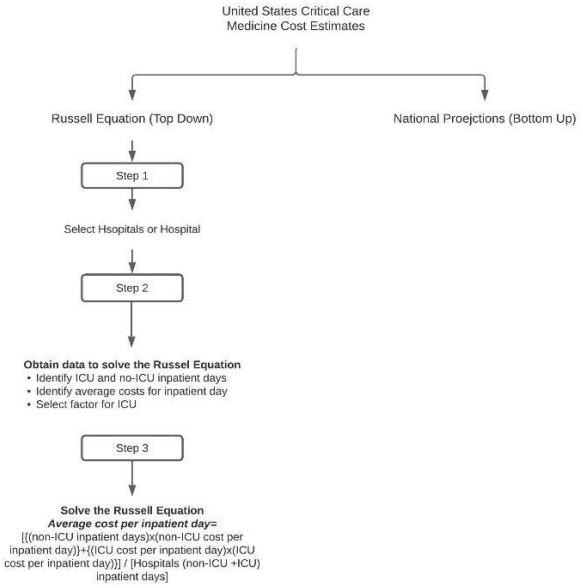


FIGURE 9. Critical care medicine costs estimation techniques.

Pharmaceutical costs included the cost of any drug used during the patient's overall stay in the ICU. In 2002 alone, approximately 705 pharmaceutical products were used, including anticoagulant drugs, statins, and antiarrhythmic drugs.The cost of angiotensin-converting enzyme (ACE) inhibitors, angiotensin-2 receptor blockers (ARBs), beta blockers, mineralocorticoid receptor antagonists, diuretics, ivabradine, hydralazine with nitrate, and digoxin used for heart failure treatment represented an important part of all hospitals' expenditures with a total amount of $30,482.00. This cost represents only pharmaceutical and variable costs (like hygienic needs, medicines, and others) and does not include fixed costs. Between 2000 and 2010, annual critical care medicine costs increased by 92%, from $56.6 billion to $108 billion. The 2010 costs represent 13.2% of all hospital costs, 4.1% of national health expenditures, and 0.754% of gross domestic product in the period between 2001 and 2011. Costs related to an intensive care unit per day in 2010 were

estimated to be $4300 per day, a 63.5% increase since the 2000 cost per day of $2649.

In this case, resource utilization in the considered affiliation of the BIDMC was not reported on a per patient basis, as previously mentioned, but per hospital unit, and data were derived from the 2012 budgetary control statements and balance sheets provided by the hospitals' finance department [72]. These were offered at a total cost. As such, the analysis included the annual cost of resource consumption (but not necessarily supplies, medication, laboratory, and medical tests), infrastructure and overhead costs (but not necessarily electricity, watering, heating, building maintenance, and repairs), and finally personnel costs (medical, nursing, administrative, paramedical, and auxiliary staff). The cost of the paramedical, administrative, and other staff was calculated according to the number of patients admitted to the hospital. Laboratory and diagnostic imaging costs were based on the aggregate annual records of the ICU and not on a per-patient basis. Only drug utilization was calculated per patient using data from the hospital pharmacy. The cost of oxygen and other consumables was obtained from the hospital supply department on an annual basis. Infrastructure and general overhead costs were allocated with respect to the area occupied (in square meters) by the ICU over the total area of the hospital. They were found in budgetary control statements provided by the hospital's finance department. Table 1 summarizes the results of the calculus we performed using the Russell formula.

TABLE 1. Macro-estimation related to the average ICU's patients stay.

Diagnosis	Pharmaceutical & Variable expenses (Per average stay-all patients)	Number of admitted patients
Atrial fibrillation	>$16,530.00	565
Long QT syndrome	>$10,301.00	287
Heart palpitations	>$15,229.00	815
Cardiac arrest	>$6,960.00	439
Supraventricular Tachycardia	>$12,396.00	412
Wolff Parkinson White syndrome	>$8,683.00	203
Atherosclerosis & Angina	>$11,514.00	764
Heart failure	>$30,482.00	917

IV. OPTIMIZATION OF BED'S ALLOCATION AND REALLOCATION

[73] presented a model of the patient flow using Non-Homogenous Discrete Time Markovian Chains and derive the time-dependent behavior of the bed's occupancy.

This approach yields a complex non-linear relation between assigning beds and the resulting patient waiting time.

In these 35 hospitals, the inpatient units can be broadly divided according to their varying nurse-to patient ratios and treatment and monitoring levels. Generally, the ICUs have a nurse-to-patient ratio of 1:1 to 1:2. There are two other kinds of inpatient units: general wards, with a ratio of 1:3.5 to 1:4, and intermediate care units, with a ratio of 1:2.5 to 1:3, though not all hospitals have intermediate care units. Although there is some differentiation within each level of care, the units are relatively fungible, so if the medical ICU is very full, a patient may be admitted to the surgical ICU instead. We focus on the ICU admission decision for patients who were admitted to a medical service at the hospital through the ED for the reasons discussed in the introduction. In our data set, about 55% of patients admitted to ICUs were admitted via the ED to a medical service. The admission process works as follows. If an ED physician believes that a patient is eligible for ICU admission, an intensivist will be called to the ED for consultation. Although the intensivist makes the ultimate decision about whether to admit the patient from the ED, the decision is typically based on a negotiation between the two physicians as to what the individual patient's needs are and what resources (e.g., ICU versus non-ICU beds) are available. The patient-level information in our data set includes patient age, gender, admitting diagnosis, hospital, and severity-of-illness function. In addition, we collect operational data that includes every unit that each patient visits, along with unit admission and discharge dates and times.

We present an approach to solve the problem of optimizing the way bed resources are allocated in ICUs. This is a constrained optimization problem. The constraints are mainly subject to the targets on the patient waiting times and by the patient's survival estimation, treatment effect and cost estimation.

We consider a set of beds in different ward types denoted $C = \{1,2,3,4,5\}$ in ICUs and $C = 6$ to be any ward other than ICUs, which is subject to a limited set of characteristics or patterns, J. The patient waiting time is a non-linear function of the available capacity in the ICUs. Given this, we define the following objective function:

$$\text{Minimize} \quad \sum_{c\in C}\sum_{j\in J} q_{cj} \tag{13}$$

$$\text{Subject to} : L_{ct}(z_{ct}) \le \tau \quad \forall t \in T, c \in C,$$

$$\text{where } z_{ct} = \sum\nolimits_{j\in J} a_{cjt} q_{cj} \tag{14}$$

$$\sum\nolimits_{j\in J} a_{cjt} q_{cj} \ge b_{ct} \quad \forall t \in T, c \in C \tag{15}$$

$$q_{cj} \in N_0 \quad \forall j \in J, c \in C \tag{16}$$

where q_{cj} is the number of beds of type $c \in C$ assigned to patients with patterns $j \in J$. The term "patterns" reflects the presence of the "actual" factors and characteristics for a patient to be assigned to a specific type of bed in ICUs. The equation (13) is then the total amount of beds allocated

"efficiently" to patients admitted to ICUs. And the equation:

$$L_{ct}(Z) = \sum_{i=0}^{w_c-1} f_{ci}(Z) + \sum_{k=w}^{M_c} f_{ck}(Z) \cdot \left(\left(1 + \sum_{j=0}^{k-1} (\mu_c w_c)^j \Big/ j! \right) * e^{-(\mu_c w_c)} \right) \quad (17)$$

is the fraction of patients waiting for a bed to be available of type $c \in C$ below a predefined time $t \in T$ where T is a discrete set of the hours in a week $T = \{1, 2, \ldots, 168\}$. This predefined time can vary depending on the day of the week or staff availability. Here, Z is a $|T| \times |C|$. While μ_c is defined to satisfy the following equation:

$$\log\left(a_{cjt}(u)\right) = \alpha + \beta u + \theta u^2 + \gamma_j + \delta_i + \phi_j u + \zeta_j u^2 + \psi_i u + \xi_i u^2 + \rho_{ij} + \eta_{ij} u + w_{ij} u^2 \quad (18)$$

where $a_{cjt}(u)$ is the expected number of arrivals on hour in a given day in the ICUs $\{u \in \mathbb{R} | 0 \leq u \leq 24\}$, on the day of the week $j \in \{Monday, Tuesday, \ldots, Saturday, Sunday\}$ for patients of triage priority $i \in \{1, 2, 3, 4, 5\}$. We used survival estimation Kaplan-Meier estimator to determine the priority and the way a certain treatment mainly drug therapy used for cardiovascular diseases patients admitted in ICUs. The variables $\{\beta, \theta, \gamma, \phi, \zeta, \psi, \xi, \eta, \omega\}$ represent the survival function estimations and service rates accordingly with this illness severity following our estimations. Each pathology is assigned to three variables to represent survival estimation, treatment effect and cost.

We also denote W as the waiting time at a queue with w beds, and k is the number of patients present at the queue at the time of arrival. Then $W = 0$ if $k \leq w - 1$. For exponential service times, means patients need more time to be treated, which means priority of 4 or 5, and $k \geq w$ we have $W = \sum_{i=w}^{k} Z_i$ where Z_i are the independent exponential random variables of rate w times the service rate of each server. The goal, then, is to derive the fraction of patients waiting below a specific target as function of time of the week:

$$Prob\{W_c(Z) \leq v_c\} = \sum_{i=0}^{w_c-1} f_{ci}(Z) + \sum_{k=w_c}^{M_c} f_{ck}(Z) .Prob\left(\sum_{i=1}^{k} z_i \leq v_c\right) \quad \forall c \in C \quad (19)$$

With $f_{ci}(Z) = \sum_{j \in J} Prob\{s = (.., k_c = i, \ldots)\}$ to define the marginal time-dependent state distribution obtained in [73] where $J = S|s = (.., k_c \neq i, \ldots)$ is the probability that queue c ∈ C is occupied by patients of type i. And v_c is the target waiting times. Defining readmission requires specifying a maximum elapsed time between consecutive hospital discharges and admissions. As this elapsed time increases, it becomes less likely that the complications were related to the care received during the initial hospitalization. Thus, based on research in literature, we define a relatively short time window for hospital readmission: within the first two weeks following hospital discharge. In the readmission analysis, "deceased" patients are not considered because they will not be readmitted to hospital.

In the following, we use constraint optimization based on the genetic algorithm [74], [75] to solve equation (13) whereas constraint (14), (15) and (16).

The computational study in this section has three objectives. First, to analyze and observe the convergence property of the integrated genetic algorithm as well as determining the termination condition and number of generations. Second, to study the performance and solution quality of the integrated genetic algorithm under various parameter combinations. Third, to identify the best parameter settings to generate the approximate optimal set of non-dominated resource allocation solutions. This objective is set because the performance of the genetic algorithm-based optimization strongly depends on the setting of various parameters.

In modelling the system behavior, we have limited our scope to the hospitalization of patients to the medical area of the hospital. More specifically, we focus on patient flow in MICU, SICU, CCCU, and CSRU. We present the data obtained from the case-hospital and test our homogeneous discrete-time Markov chain (CTMC) model [73] that predicts time dependent bed occupancy. Results are presented in figure 10.

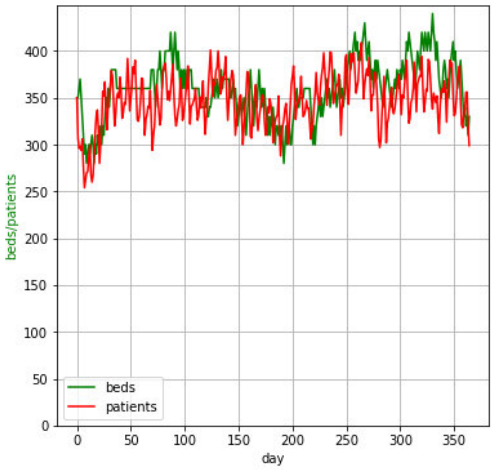


FIGURE 10. Forecasting of bed occupancy in ICUs wards and patients' admissions.

As shown in the figure above, it is very clear that bed occupancy distribution is very frequently estimated to exceed the demand related to newly admitted patients. As a result, we conducted a total of five different basic tests, where patient flow or available resources were changed. Tables 2-a and 2-b below represent the parameters that were subject to change in bold font. The results for each of tests from 1 to 5 are presented in table 3.

To avoid biased results, we have run our code, implemented on python 3.9, ten times which includes all configurations mentioned in tables 2-a and 2-b. In this step, it is necessary to compare specific conditions for algorithm termination in the different decision-making blocks. The first condition is to reach the maximum number of

TABLE 2. Parameters tuning for first and second round of experiments.

GA parameter	Test 1	Test 2	Test 3	Test 4	Test 5
Population size[(1)(2)]	150	200	250	300	350
Max number of iterations[(1)(2)]	10	15	20	25	50
Selection method[(1)(2)]	Roulette Wheel	Roulette Wheel	Roulette Wheel	Roulette Wheel	Roulette Wheel
Crossover method[(1)]	Double point crossover	Double point crossover	Double point crossover	Double point crossover	Double point crossover
Mutation method[(1)(2)]	Bit string mutation	Bit string mutation	Bit string mutation	Bit string mutation	Bit string mutation
Crossover method[(2)]	single-point crossover	single-point crossover	single-point crossover	single-point crossover	single-point crossover

[(1)(2)]: parameters for first and second round of experiments

[(1)]: parameters only for first round of experiments.

[(2)]: parameters only for second round of experiments.

TABLE 3. Results of fixed configurations.

		Test 1	Test 2	Test 3	Test 4	Test 5
Objective function	***Run 1***	1,826,250	**1,753,750**	1,975,000	2,205,047	2,150,884
	Run 2	1,889,375	1,787,500	**1,905,000**	2,293,938	2,068,203
	Run 3	1,841,250	1,770,000	1,921,250	2,174,356	2,236,219
	Run 4	1,875,000	1,773,750	1,926,250	2,209,866	**2,059,109**
	Run 5	1,893,750	1,796,254	1,936,250	2,036,578	2,096,508
	Run 6	**1,801,250**	1,778,750	**1,905,000**	**2,002,145**	2,286,277
	Run 7	2,241,621	2,014,884	2,120,279	2,007,581	2,031,828
	Run 8	2,032,472	1,965,956	2,067,359	1,923,141	2,032,667
	Run 9	2,091,044	2,188,592	2,140,407	2,030,595	1,983,330
	Run 10	2,216,239	2,126,761	2,169,123	2,034,200	2,133,150
Generation	***Run 1***	132	92	122	106	144
	Run 2	106	190	94	105	161
	Run 3	127	89	158	199	167
	Run 4	111	167	119	116	100
	Run 5	91	194	205	284	251
	Run 6	115	124	201	200	307
	Run 7	112	107	86	99	170
	Run 8	158	125	149	136	139
	Run 9	190	102	120	166	132
	Run 10	279	251	341	157	113

generations (iterations). The second condition is to reach or exceed the highest permissible fitness value or objective function. The third condition is to reach maximum solution time. The last condition is to exceed a set of iteration numbers without improving a reached solution. The last condition was integrated into the proposal to prevent extensive calculation time if the required or unachievable fitness function value is not set, and fitness function value is not improving. Therefore, there is an assumption that the extreme has been found in a group of solutions. When meeting any out of the stated conditions, the genetic algorithm is completed.

In case none of the finishing criteria was fulfilled, the algorithm continues by selection, in other words, by

selecting individuals who will crossbreed and eventually mutate between each other. For such a solution, the roulette wheel rule was selected. Probability selection was proportional to an individual's achieved suitability. This form was chosen based on a better possibility to search a complex set of solutions when later combining parents and their evaluation as well as their calculation speed.

To prevent a duplicate of identical bed transfers in crossover or omission of the same patient from the genetic chain, a mechanism of partially matched crossover was designed. We used single point crossover and double point crossover.

V. RESULTS AND DISCUSSION

According to the results of the experiments, functioning converges later with low probability mutation because it is primarily dependent on a randomly generated initial population and crossbreeding in all iterations. Only a small number of individuals are modified by mutation operators. With increasing mutation probability, the algorithm converges on average earlier with a higher quality solution, although it is accompanied by a higher generation dispersion of a found solution. This is caused by mutational randomness. The optimal mutation probability range was set between 0.05 and 0.15. As we want to avoid the algorithm going into a random search, we do not recommend higher probabilities for initial settings. One of the conditions of an algorithm's functioning termination is crossing the fixed number of iterations without improving the solution reached.

To verify this, the variable mutation was implemented in the algorithm. This variable mutation increases the probability of its application with an increasing number of interactions, without any improvement. In the basic setting, when functioning finishes after 100 interactions without any improvement, after 70 iterations, there is a mutation probability increased to 1.5 times the original value. After 80 iterations, it is a 1.75 multiple of the original value, and eventually, after 90 iterations, it is a total 2.04 multiple of the original value. Table 3 below recapitulates the results of the different runs:

Waiting time is the main index for measuring patient-reported quality of care with the feature of medical service quality in a specific situation of medical treatments and medical expenses. In our own experiments, we carried out three types of inputs: a survival function estimation system, treatment effect estimation, and cost estimation.

The main goal of our approach is not only to optimize the bed occupancy rate but also to make sure that these beds are allocated efficiently to patients that need to be admitted to ICUs. The authors of the article [73] provided a bed occupancy rate estimator based on Markov chains. In this paper, we present an optimization of estimation using other parameters that makes bed allocation personalized. Thus, bed allocation is a function of the patient's actual state, estimation of the treatment trajectory, and cost.

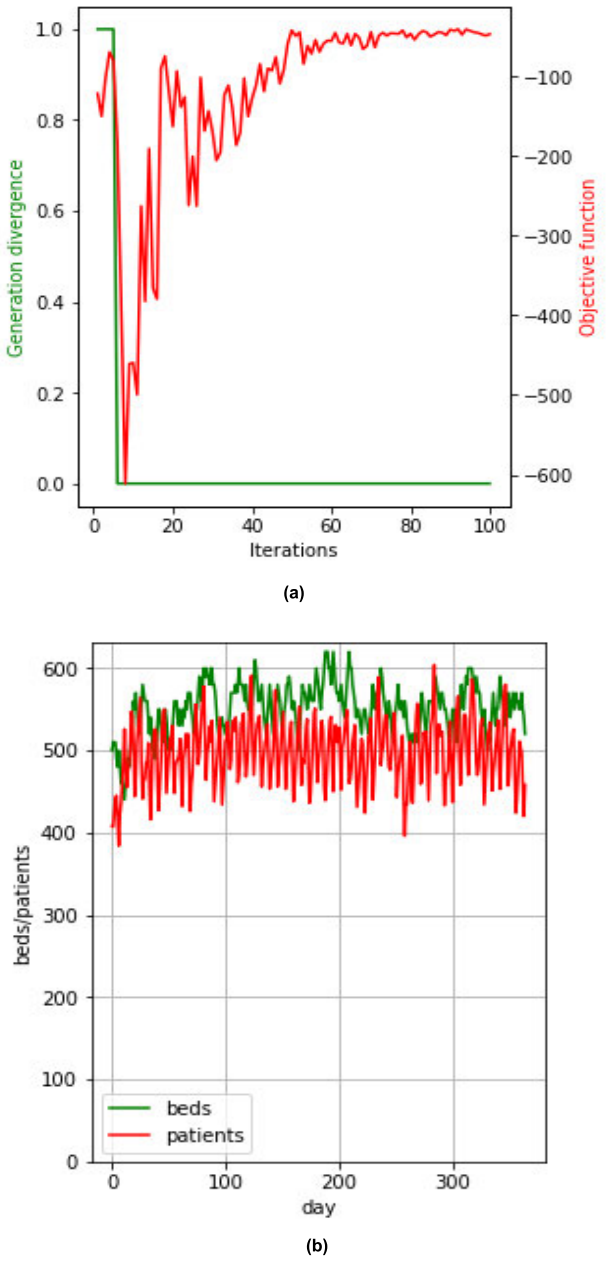


FIGURE 11. Minimized bed occupancy rate based on the patient's survival, treatment estimation and cost estimation.

It is not uncommon to experience a situation where the number of ICU beds available is less than the number required to attend to patients who require them: the availability of this scarce resource is highly impacted by patient demands and stochastic service times, in a way that makes managing such a resource a complex problem [77].

In figure 11 represent the new bed occupancy rate after adding all the constraints previously mentioned. The approach is introducing a new way to investigate the allocation of beds.

On the one hand, the ICU allocation problem has been investigated in the literature (as shown in table 4) for a long

TABLE 4. State of art works on optimization and medical resources scheduling.

Ref	Technique	Data source	Pathologies in consideration
[80]	Queuing system: flow of patients Compartmental model: feasible structure of the hospital department Evolutionary-based optimization: genetic algorithm to optimize the bed-occupancy	geriatric department of a hospital from London, UK	surgery, stroke, and mental illness
[81]	Hybrid simulated approach: simulated annealing for local search and genetic algorithm for a global search.	-	All types
[82]	Combinatorial optimization models for modeling and used metaheuristics as solving technique.	literature-based benchmark instances	All types (not defined)
[83]	Forecasting patient arrival: machine learning models compared to baseline models. Optimization: hyper-heuristic based on the pilot method and a specialized greedy look-ahead heuristic.	weather data, time and dates, important local and regional events, as well as current and historical occupancy levels.	Patients are categorized based whether they have infectious disease or not.
[84]	vapor-liquid equilibrium artificial bee algorithm, ant colony optimization, the bat method, cuckoo search, genetic algorithm, particle swarm optimization, and a random strategy.	30 benchmarks taken of Chilean health services	Different wards of the hospital.
[85]	discrete-event simulation model to evaluate different assignment strategies	data from Hospital Medicine (HM) services at the University of Chicago Medical Center.	7 types of diagnoses: liver transplant, renal transplant, lung transplant, oncology, general cardiology, general medicine, and patients who often have multiple major diagnoses and are enrolled in the Comprehensive Care Program
[86]	Discrete Event Simulation Most-Promising-Area Stochastic Search	large acute-care hospital (not specified)	Patients admitted to ICUs.
[87]	Analytic Hierarchy Process (AHP) Greedy Algorithm and Tabu Search (TS) to optimize the match between the patient's requirements and the characteristics of the assigned bed.	Hospital Universitario San Ignacio	Gynecology and Obstetrics Hospitalization Hospitalization (UADO) - Obstetric High Dependency Unit Hemato-oncology hospitalization Pediatric Hospitalization Pediatric High Dependency Unit
[88]	machine learning to estimate the required post-anesthesia care unit (PACU) time. integer programming models to schedule procedures in the operating rooms to minimize maximum PACU occupancy. discrete event simulation to compare our optimized schedule to the existing schedule	data from Lucile Packard Children's Hospital Stanford	Elective patients with surgical plans.
[89]	Mathematical modeling. Estimation of suitable capacity in the elective ICU using discrete event simulation. Optimization: fuzzy interactive method (TH)	The open-heart surgery unit (OHU) of Baghiatallah Hospital	Surgery types performed in the open-heart surgery unit in Intensive Care Unit (ICU).
Our work	**Analysis techniques: Survival function estimation using Kaplan-Meier and Naive estimator, treatment effect estimations using T learner and Linear regression, Russel formula for cost estimation.** **Optimization: weighted Genetic Algorithm**	**MIMIC III**	**ICUs; patients with cardiovascular diseases**

time since the resources for critical care are limited and very expensive.

Thus, some studies presented in the literature propose techniques or models to support the ICU allocation problem.

In [78], the authors presented a systematic literature review of research design and modeling techniques to support inpatient bed management. The authors recognized the complexity of this problem, which is affected by several factors, such as uncertainties about the patients' length of stay, fluctuations in demands, and unexpected admissions. They verified that simulation has been the main tool used in studies in this area. [79] discussed the use of big data and machine learning to improve the way the ICU allocation problem is handled.

Adding to this, [77] pointed out that most of the literature about the ICU allocation problem deals with the admission problem, but few studies tackles supporting the discharge decision problem. They investigated the ICU discharge problem: a univariate logistic regression model was proposed to assess the impact of the length of stay in the ICU, using data from two surgical ICUs of a large academic medical center. They observed that the absence of appropriate beds in the regular ward is the main cause of the delay in ICU discharge. They emphasized that this problem is of economic and ethical relevance since the resources of the ICU are scarce. [22] also focused on the ICU discharge problem: they present a review of the literature on patient discharge decisions and propose a simulation framework that enables the real-world processes for discharging patients to be modeled in a more realistic way. Some studies have addressed the ethical issues inherent to the ICU allocation problem: [90] conducted interviews with health professionals concerning ethical problems, such as how full ICU occupancy and treatment decisions are reached in terms of choosing what patients should benefit from them. Health professionals' attitudes were collected to provide insights to improve the management of intensive care resources. As a conclusion, the authors suggested that the collective responsibility and effort by health professionals (ICU professionals and different professionals in the wards) must be reinforced in a hospital routine to alleviate moral distress caused by the ethical dilemmas faced, since these two factors are mutually dependent on each other. Consequently, health professionals must work together for an optimal transfer of patients between hospital departments. [91] also discuss fairness and ethics in the ICU allocation problem, suggesting that an alliance of ethical and moral principles must be applied to obtain a moral, ethical, and common-sense approach to deal with this complex problem. This review demonstrates that the ICU allocation problem is not a trivial decision problem, first, because the scarcity of resources for intensive care cannot be overcome quickly because the cost of doing so is very high and there are shortages of appropriately qualified and experienced personnel and, secondly, because the no allocation of a place in an ICU in some cases is likely to increase the probability that the patient will die.

VI. CONCLUSION

The patient bed assignment problem is a complex combinatorial problem. In this paper, we have presented a genetic algorithm optimization model and shown the main differences in terms of parameters and stopping conditions. Our work focused on the implementation of a decision support system for bed assignment, considering the availability of suitable hospital beds. Decision support relies on estimations of survival function, treatment trajectory, and costs to provide the calculation of an optimal assignment plan for a given group of patients and its implementation in an intensive care unit. The admission planning and assignment problem was formally described in our previous work on bed occupancy calculation based on Markov chains. To solve the objective function, two types of cross-over techniques were used to assure population diversity and avoid premature convergence. Putting cost and waiting times as constraints of the objective function and not directly in the objective function helps achieve good results in a very short time.

Further research into the bed allocation problem is required as a follow-up to our work. To be a generic solution, the actual approach may require more datasets and contexts to be tested on. Such investigations may necessitate the use of parameters based on the dataset and applicable regulations.

REFERENCES

[1] *Historical | CMS|*. Accessed: Jun. 1, 2021. [Online]. Available: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthA

[2] A. B. Martin, M. Hartman, D. Lassman, and A. Catlin, "National health care spending in 2019: Steady growth for the fourth consecutive year," *Health Affairs*, vol. 40, no. 1, pp. 14–24, Jan. 2021, doi: 10.1377/hlthaff.2020.02022.

[3] *Healthcare Expenditure, UK Health Accounts Provisional Estimates—Office for National Statistics*. Accessed: Jun. 1, 2020. [Online]. Available: https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthcaresystem/bulletins/healthcareexpenditureukhealthaccountsprovisionalestimates/2020#:~:text=Total%20current%20healthcare%20expenditure%20in,%2C%20from%2010.2%25%20in%202019

[4] *Health Expenditure—German Federal Statistical Office*. Accessed: Jun. 3, 2021. [Online]. Available: https://www.destatis.de/EN/Themes/Society-Environment/Health/Health-Expenditure/_node.html

[5] *France Healthcare Spending 2000–2021 | Macro-Trends*. Accessed: Jun. 3, 2021. [Online]. Available: https://www.macrotrends.net/countries/FRA/france/healthcare-spending

[6] D. Morgan and R. Astolfi, "Health spending continues to stagnate in many OECD countries," OECD Publishing, Paris, France, OECD Health Work. Papers 68, 2014, doi: 10.1787/5jz5sq5qnwf5-en.

[7] OECD iLibrary. *Health Expenditure in Relation to GDP | Health at a Glance: Europe 2020: State of Health in the EU Cycle*. Accessed: Jun. 3, 2021. [Online]. Available: https://www.oecd-ilibrary.org/sites/860615c9-en/index.html?itemId=/content/component/860615c9-en

[8] L. Zhou, S. Ampon-Wireko, H. Asante Antwi, X. Xu, M. Salman, M. O. Antwi, and T. M. N. Afua, "An empirical study on the determinants of health care expenses in emerging economies," *BMC Health Services Res.*, vol. 20, no. 1, pp. 1–15, Dec. 2020, doi: 10.1186/s12913-020-05414-z.

[9] V. Raghupathi and W. Raghupathi, "Healthcare expenditure and economic performance: Insights from the United States data," *Frontiers Public Health*, vol. 8, p. 156, May 2020, doi: 10.3389/fpubh.2020.00156.

[10] J. Bhatt and P. Bathija, "Ensuring access to quality health care in vulnerable communities," *Academic Med.*, vol. 93, no. 9, pp. 1271–1275, Sep. 2018, doi: 10.1097/ACM.0000000000002254.

[11] F. El-Jardali and R. Fadlallah, "A review of national policies and strategies to improve quality of health care and patient safety: A case study from Lebanon and Jordan," *BMC Health Services Res.*, vol. 17, no. 1, p. 568, Dec. 2017, doi: 10.1186/s12913-017-2528-1.

[12] K. E. J. Maddox, H. Bauchner, and P. B. Fontanarosa, "US health policy—2020 and beyond: Introducing a new JAMA series," *JAMA*, vol. 321, no. 17, pp. 1670–1672, 2019, doi: 10.1001/jama.2019.3451.

[13] R. M. Epstein, K. Fiscella, C. S. Lesser, and K. C. Stange, "Why the nation needs a policy push on patient-centered health care," *Health Affairs*, vol. 29, no. 8, pp. 1489–1495, Aug. 2010.

[14] J. L. Cohon and D. H. Marks, "A review and evaluation of multiobjective programing techniques," *Water Resour. Res.*, vol. 11, no. 2, pp. 208–220, Apr. 1975, doi: 10.1029/wr011i002p00208.

[15] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multiobjective evolutionary algorithms: Empirical results," *Evol. Comput.*, vol. 8, no. 2, pp. 173–195, Jun. 2000.

[16] K. Miettinen, *Nonlinear Multiobjective Optimization*. Norwell, MA, USA: Kluwer, 1999.

[17] L. Zhou, N. Geng, Z. Jiang, and X. Wang, "Multi-objective capacity allocation of hospital wards combining revenue and equity," *Omega*, vol. 81, pp. 220–233, Dec. 2018, doi: 10.1016/j.omega.2017.11.005.

[18] T. Gal, "Multiple objective decision making—Methods and applications: A state-of–the art survey," *Eur. J. Oper. Res.*, vol. 4, no. 4, pp. 287–288, Apr. 1980.

[19] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.

[20] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the performance of the strength Pareto evolutionary algorithm," Comput. Eng. Commun. Netw. Lab (TIK), Swiss Federal Inst. Technol. (ETH), Zürich, Switzerland, Tech. Rep., 103, 2001.

[21] J. Ruyssinck, J. van der Herten, R. Houthooft, F. Ongenae, I. Couckuyt, B. Gadeyne, K. Colpaert, J. Decruyenaere, F. De Turck, and T. Dhaene, "Random survival forests for predicting the bed occupancy in the intensive care unit," *Comput. Math. Methods Med.*, vol. 2016, pp. 1–7, Jan. 2016, doi: 10.1155/2016/7087053.

[22] C. Azcarate, L. Esparza, and F. Mallor, "The problem of the last bed: Contextualization and a new simulation framework for analyzing physician decisions," *Omega*, vol. 96, Oct. 2020, Art. no. 102120, doi: 10.1016/j.omega.2019.102120.

[23] Q. J. Leclerc, N. M. Fuller, R. H. Keogh, K. Diaz-Ordaz, R. Sekula, M. G. Semple, K. E. Atkins, S. R. Procter, and G. M. Knigh, "Importance of patient bed pathways and length of stay differences in predicting COVID-19 hospital bed occupancy in England," *BMC Health Services Res.*, vol. 21, no. 1, p. 566, Dec. 2021, doi: 10.1186/s12913-021-06509-x.

[24] D. A. Marshall, L. Burgos-Liz, M. J. IJzerman, W. Crown, W. V. Padula, P. K. Wong, K. S. Pasupathy, M. K. Higashi, and N. D. Osgood, "Selecting a dynamic simulation modeling method for health care delivery research—Part 2: Report of the ISPOR dynamic simulation modeling emerging good practices task force," *Value Health*, vol. 18, no. 2, pp. 147–160, Mar. 2015.

[25] *Monitoring Health for the SDGs, Sustainable Development Goals*, World Health Statistics, Geneva, Switzerland, 2020.

[26] WADOH. (Jun. 2019). *Washington State Crisis Standards of Care Community Engagement Report*. [Online]. Available: https://www.qualityhealth.org/wp-content/uploads/2020/03/Scarce-Resource-Triage-Team-Guidelines.pdf

[27] Y.-J. Gong, J. Zhang, and Z. Fan, "A multi-objective comprehensive learning particle swarm optimization with a binary search-based representation scheme for bed allocation problem in general hospital," in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, Istanbul, Turkey, Oct. 2010, pp. 1083–1088.

[28] X. Li, P. Beullens, D. Jones, and M. Tamiz, "An integrated queuing and multi-objective bed allocation model with application to a hospital in China," *J. Oper. Res. Soc.*, vol. 60, no. 3, pp. 330–338, Mar. 2009.

[29] G. W. Harrison and P. H. Millard, "Balancing acute and long-term care: The mathematics of throughput in departments of geriatric medicine," *Methods Inf. Med.*, vol. 30, no. 3, pp. 221–228, 1991.

[30] S. I. McClean and P. H. Millard, "Patterns of length of stay after admission in geriatric medicine: An event history approach," *Statistician*, vol. 42, pp. 263–274, Aug. 1993.

[31] G. Taylor, S. McClean, and P. Millard, "Continuous-time Markov models for geriatric patient behaviour," *Appl. Stochastic Models Data Anal.*, vol. 13, nos. 3–4, pp. 315–323, Sep. 1997.

[32] A. H. Marshall, S. I. McClean, and C. M. Shapcott, "Developing a Bayesian belief network for the management of geriatric hospital care," *Health Care Manage. Sci.*, vol. 4, pp. 23–30, Feb. 2001.

[33] M. J. Faddy and S. I. McClean, "Using a multi-state model to enhance understanding of geriatric patient care," *Austral. Health Rev.*, vol. 31, no. 1, pp. 91–97, 2007.

[34] Fair Allocation of Intensive Care Unit Resources, "Fair allocation of intensive care unit resources," *Amer. J. Respiratory Crit. Care Med.*, vol. 156, no. 4, pp. 1282–1301, 1997, doi: 10.1164/ajrccm.156.4.ats7-97.

[35] E. R. M. Sydnor and T. M. Perl, "Hospital epidemiology and infection control in acute-care settings," *Clin. Microbiol. Rev.*, vol. 24, no. 1, pp. 141–173, Jan. 2011, doi: 10.1128/CMR.00027-10.

[36] M. Klumpp, M. Hintze, M. Immonen, F. Ródenas-Rigla, F. Pilati, F. Aparicio-Martínez, D. Çelebi, T. Liebig, M. Jirstrand, O. Urbann, M. Hedman, J. A. Lipponen, S. Bicciato, A.-P. Radan, B. Valdivieso, W. Thronicke, D. Gunopulos, and R. Delgado-Gonzalo, "Artificial intelligence for hospital health care: Application cases and answers to challenges in European hospitals," *Healthcare*, vol. 9, no. 8, p. 961, Jul. 2021, doi: 10.3390/healthcare9080961.

[37] M. M. Saraiva, T. Ribeiro, J. P. S. Ferreira, F. V. Boas, J. Afonso, A. L. Santos, M. P. L. Parente, R. N. Jorge, P. Pereira, and G. Macedo, "Artificial intelligence for automatic diagnosis of biliary stricture malignancy status in single-operator cholangioscopy: A pilot study," *Gastrointestinal Endoscopy*, vol. 95, no. 2, pp. 339–348, Feb. 2022, doi: 10.1016/j.gie.2021.08.027.

[38] Y. Kumar, A. Koul, R. Singla, and M. F. Ijaz, "Artificial intelligence in disease diagnosis: A systematic literature review, synthesizing framework and future research agenda," *J. Ambient Intell. Humanized Comput.*, vol. 2022, pp. 1–28, Jan. 2022, doi: 10.1007/s12652-021-03612-z.

[39] D. Cordova, G. Medwig, A. Variathu Roy, and S. Karmakar, "Artificial intelligence (AI) to study self-discharge batteries," in *Proc. IEEE 12th Annu. Ubiquitous Comput., Electron. Mobile Commun. Conf. (UEMCON)*, Dec. 2021, pp. 298–302, doi: 10.1109/UEMCON53757.2021.9666507.

[40] Y. Berlyand, A. S. Raja, S. C. Dorner, A. M. Prabhakar, J. D. Sonis, R. V. Gottumukkala, M. D. Succi, and B. J. Yun, "How artificial intelligence could transform emergency department operations," *Amer. J. Emergency Med.*, vol. 36, no. 8, pp. 1515–1517, Aug. 2018.

[41] M. Yousefi, M. Yousefi, R. P. M. Ferreira, J. H. Kim, and F. S. Fogliatto, "Chaotic genetic algorithm and AdaBoost ensemble metamodeling approach for optimum resource planning in emergency departments," *Artif. Intell. Med.*, vol. 84, pp. 23–33, Jan. 2018.

[42] M. E. H. Ong, C. H. L. Ng, K. Goh, N. Liu, Z. Koh, N. Shahidah, T. Zhang, S. Fook-Chong, and Z. Lin, "Prediction of cardiac arrest in critically ill patients presenting to the emergency department using a machine learning score incorporating heart rate variability compared with the modified early warning score," *Crit. Care*, vol. 16, no. 3, p. R108, 2012.

[43] P. C. Pendharkar and H. Khurana, "Machine learning techniques for predicting hospital length of stay in Pennsylvania federal and specialty hospitals," *Int. J. Comput. Sci. Appl.*, vol. 11, no. 3, pp. 45–56, 2014.

[44] S. Srinivas and A. R. Ravindran, "Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: A prescriptive analytics framework," *Expert Syst. Appl.*, vol. 102, pp. 245–261, Jul. 2018.

[45] D. A. Thompson, P. R. Yarnold, D. R. Williams, and S. L. Adams, "Effects of actual waiting time, perceived waiting time, information delivery, and expressive quality on patient satisfaction in the emergency department," *Ann. Emergency Med.*, vol. 28, no. 6, pp. 657–665, Dec. 1996.

[46] J. Yoon, A. Alaa, S. Hu, and M. Schaar, "ForecastICU: A prognostic decision support system for timely prediction of intensive care unit admission," in *Proc. Int. Conf. Mach. Learn.*, 2016, pp. 1680–1689.

[47] J. Ma, D. K. K. Lee, M. E. Perkins, M. A. Pisani, and E. Pinker, "Using the shapes of clinical data trajectories to predict mortality in ICUs," *Crit. Care Explor.*, vol. 1, no. 4, p. e0010, Apr. 2019, doi: 10.1097/CCE.0000000000000010.

[48] Z. J. Eapen, S. D. Reed, L. Yanhong, R. D. Kociol, P. Armstrong, R. C. Starling, and A. F. Hernandez, "Do countries or hospitals with longer hospital stays for acute heart failure have lower readmission rates? Findings from ASCEND-HF," *Circulat., Heart Failure*, vol. 6, no. 4, pp. 727–732, 2013, doi: 10.1161/CIRCHEARTFAILURE.112.000265.

[49] H. F. Lingsma, A. Bottle, S. Middleton, J. Kievit, E. W. Steyerberg, and P. J. Marang-van de Mheen, "Evaluation of hospital outcomes: The relation between length-of-stay, readmission, and mortality in a large international administrative database," *BMC Health Services Res.*, vol. 18, no. 1, pp. 1–10, Dec. 2018, doi: 10.1186/s12913-018-2916-1.

[50] H. Baek, M. Cho, S. Kim, H. Hwang, M. Song, and S. Yoo, "Analysis of length of hospital stay using electronic health records: A statistical and data mining approach," *PLoS ONE*, vol. 13, no. 4, Apr. 2018, Art. no. e0195901, doi: 10.1371/journal.pone.0195901.

[51] T. A. Williams, K. M. Ho, G. J. Dobb, J. C. Finn, M. Knuiman, and S. A. R. Webb, "Effect of length of stay in intensive care unit on hospital and long-term mortality of critically ill adult patients," *Brit. J. Anaesthesia*, vol. 104, no. 4, pp. 459–464, Apr. 2010, doi: 10.1093/bja/aeq025.

[52] M. O. Harhay, S. J. Ratcliffe, D. S. Small, L. H. Suttner, M. J. Crowther, and S. D. Halpern, "Measuring and analyzing length of stay in critical care trials," *Med. Care*, vol. 57, no. 9, pp. e53–e59, Sep. 2019, doi: 10.1097/MLR.0000000000001059.

[53] S. L. Kane-Gill, J. F. Dasta, M. S. Buckley, S. Devabhakthuni, M. Liu, H. Cohen, E. L. George, A. S. Pohlman, S. Agarwal, E. A. Henneman, S. M. Bejian, S. M. Berenholtz, J. L. Pepin, M. C. Scanlon, and B. S. Smith, "Executive summary," *Crit. Care Med.*, vol. 45, no. 9, pp. 1546–1551, Sep. 2017, doi: 10.1097/CCM.0000000000002519.

[54] N. Smith, C. Mitton, W. Hall, S. Bryan, C. Donaldson, S. Peacock, J. L. Gibson, and B. Urquhart, "High performance in healthcare priority setting and resource allocation: A literature- and case study-based framework in the Canadian context," *Social Sci. Med.*, vol. 162, pp. 185–192, Aug. 2016.

[55] L. H. Lee, G. Pedrielli, C.-H. Chen, and H. Li, "Constrained optimizaton for hospital bed allocation via discrete event simulation with nested partitions," in *Proc. IEEE Winter Simulation Conf. (WSC)*, Washington, DC, USA, Dec. 2016, pp. 1916-1925, doi: 10.1109/WSC.2016.7822237.

[56] A. Johnson, T. Pollard, and R. Mark, "MIMIC-III clinical database (version 1.4)," PhysioNet, 2016, doi: 10.13026/C2XW26.

[57] A. Badjatiya and S. V. Rao, "Advances in antiplatelet and anticoagulant therapies for NSTE-ACS," *Current Cardiol. Rep.*, vol. 21, no. 1, p. 3, Jan. 2019.

[58] J.-R. Zhang, D.-Q. Wang, J. Du, G.-S. Qu, J.-L. Du, S.-B. Deng, Y.-J. Liu, J.-X. Cai, and Q. She, "Efficacy of clopidogrel and clinical outcome when clopidogrel is coadministered with atorvastatin and lansoprazole: A prospective, randomized, controlled trial," *Medicine*, vol. 94, no. 50, p. e2262, Dec. 2015, doi: 10.1097/MD.0000000000002262.

[59] *Plavix (Clopidogrel) Dosing, Indications, Interactions, Adverse Effects, and More*. Accessed: Jun. 18, 2021. [Online]. Available: https://reference.medscape.com/drug/plavix-clopidogrel-342141

[60] H. Fröhlich, J. Zhao, T. Täger, R. Cebola, D. Schellberg, H. A. Katus, M. Grundtvig, T. Hole, D. Atar, S. Agewall, and L. Frankenstein, "Carvedilol compared with metoprolol succinate in the treatment and prognosis of patients with stable chronic heart failure: Carvedilol or metoprolol evaluation study," *Circulat., Heart Failure*, vol. 8, no. 5, pp. 887–896, Sep. 2015.

[61] G. Levine, E. Bates, J. Bittl, R. Brindis, S. Fihn, L. Fleisher, and C. B. Granger, "A report of the American college of cardiology/American heart association task force on clinical practice guidelines," *Circulation*, vol. 136, no. 6, pp. e137–e161, Aug. 2017.

[62] E. N. Shen, "Propafenone: A promising new antiarrhythmic agent," *Chest*, vol. 98, no. 2, pp. 434–441, Aug. 1990, doi: 10.1378/chest.98.2.434.

[63] S. Lee and H. Lim, "Review of statistical methods for survival analysis using genomic data," *Genomics Informat.*, vol. 17, no. 4, p. e41, Dec. 2019, doi: 10.5808/GI.2019.17.4.e41.

[64] P. Boracchi, P. Roccabianca, G. Avallone, and G. Marano, "Kaplan-Meier curves, Cox model, and P-values are not enough for the prognostic evaluation of tumor markers: Statistical suggestions for a more comprehensive approach," *Vet. Pathol.*, vol. 58, no. 5, pp. 795–808, Sep. 2021.

[65] L. M. Vaughn, R. C. Baker, and T. G. DeWitt, "The problem learner," *Teach. Learn. Med.*, vol. 10, no. 4, pp. 217–222, Oct. 1998, doi: 10.1207/S15328015TLM1004_4.

[66] S. R. Künzel, J. S. Sekhon, P. J. Bickel, and B. Yu, "Metalearners for estimating heterogeneous treatment effects using machine learning," *Proc. Nat. Acad. Sci. USA*, vol. 116, no. 10, pp. 4156–4165, Mar. 2019, doi: 10.1073/pnas.1804597116.

[67] S. Wager, S. Athey, S. Wager, and S. Athey, "Estimation and inference of heterogeneous treatment effects using random forests," *J. Amer. Stat. Assoc.*, vol. 113, no. 523, pp. 1228–1242, Jul. 2018.

[68] S. S. Tan, J. Bakker, M. E. Hoogendoorn, A. Kapila, J. Martin, A. Pezzi, G. Pittoni, P. E. Spronk, R. Welte, and L. Hakkaart-van Roijen, "Direct cost analysis of intensive care unit stay in four European countries: Applying a standardized costing methodology," *Value Health*, vol. 15, no. 1, pp. 81–86, Jan. 2012, doi: 10.1016/j.jval.2011.09.007.

[69] M. Geitona, L. Androutsou, and D. Theodoratou, "Cost estimation of patients admitted to the intensive care unit: A case study of the teaching university hospital of Thessaly," *J. Med. Econ.*, vol. 13, no. 2, pp. 179–184, Jul. 2010, doi: 10.3111/13696991003684092.

[70] *Hospital Cost Compare | Inpatient Diagnosis and Surgery Procedure List*. Accessed: Jun. 5, 2021. [Online]. Available: https://www.hospitalcostcompare.com/drgs/

[71] *MIMIC III*. Accessed: Jun. 7, 2021. [Online]. Available: https://mit-lcp.github.io/mimic-schema-spy/tables/admissions.html

[72] *BIDMC Financial Assistance Policy*. Accessed: Jun. 29, 2021. [Online]. Available: https://www.bidmc.org/-/media/files/beth-israel-org/patient-and-visitor-information/patient-information/bidmc-fap-english.pdf

[73] K. Karboub, M. Tabaa, S. Dellagi, F. Monteiro, A. Dandache, and F. Moutaouakkil, "Modeling and validation of the hospital's ambulatory and inpatients operations using a non-homogenous discrete time Markovian chains," *IEEE Access*, vol. 9, pp. 103044–103055, 2021, doi: 10.1109/ACCESS.2021.3098715.

[74] J. McCall, "Genetic algorithms for modelling and optimisation," *J. Comput. Appl. Math.*, vol. 184, no. 1, pp. 205–222, Dec. 2005, doi: 10.1016/j.cam.2004.07.034.

[75] K. De Jong, "Evolutionary computation: A unified approach," in *Proc. Genetic Evol. Comput. Conf. Companion*, Jul. 2018, pp. 185–199.

[76] K. Karboub and M. Tabaa, "A machine learning based discharge prediction of cardiovascular diseases patients in intensive care units," *Healthcare*, vol. 10, no. 6, p. 966, May 2022, doi: 10.3390/healthcare10060966.

[77] G. Edenharter, D. Gartner, M. Heim, J. Martin, U. Pfeiffer, F. Vogt, K. Braun, and D. Pförringer, "Delay of transfer from the intensive care unit: A prospective observational analysis on economic effects of delayed in-house transfer," *Eur. J. Med. Res.*, vol. 24, no. 1, pp. 1–5, Dec. 2019.

[78] L. He, S. C. Madathil, A. Oberoi, G. Servis, and M. T. Khasawneh, "A systematic review of research design and modeling techniques in inpatient bed management," *Comput. Ind. Eng.*, vol. 127, pp. 451–466, Jan. 2019.

[79] A. N. Reiz, "Big data and machine learning in critical care: Opportunities for collaborative research," *Medicina Intensiva*, vol. 43, no. 1, pp. 52–57, Jan. 2019.

[80] S. Belciug and F. Gorunescu, "Improving hospital bed occupancy and resource utilization through queuing modeling and evolutionary computation," *J. Biomed. Informat.*, vol. 53, pp. 261–269, Feb. 2015.

[81] K. Dorgham, I. Nouaouri, H. Ben-Romdhane, and S. Krichen, "A hybrid simulated annealing approach for the patient bed assignment problem," *Proc. Comput. Sci.*, vol. 159, pp. 408–417, Jan. 2019, doi: 10.1016/j.procs.2019.09.195.

[82] R. Guido, M. C. Groccia, and D. Conforti, "An efficient matheuristic for offline patient-to-bed assignment problems," *Eur. J. Oper. Res.*, vol. 268, no. 2, pp. 486–503, Jul. 2018, doi: 10.1016/j.ejor.2018.02.007.

[83] F. Schäfer, M. Walther, D. G. Grimm, and A. Hübner, "Combining machine learning and optimization for the operational patient-bed assignment problem," *SSRN Electron. J.*, vol. 2021, pp. 1–12, Sep. 2021.

[84] C. Taramasco, B. Crawford, R. Soto, E. M. Cortés-Toro, and R. Olivares, "A new metaheuristic based on vapor-liquid equilibrium for solving a new patient bed assignment problem," *Expert Syst. Appl.*, vol. 158, Nov. 2020, Art. no. 113506, doi: 10.1016/j.eswa.2020.113506.

[85] H. Zhang, T. J. Best, A. Chivu, and D. O. Meltzer, "Simulation-based optimization to improve hospital patient assignment to physicians and clinical units," *Health Care Manage. Sci.*, vol. 23, no. 1, pp. 117–141, Mar. 2020, doi: 10.1007/s10729-019-09483-3.

[86] Y. Wang, L. H. Lee, E. P. Chew, S. S. W. Lam, S. K. Low, and H. Li, "Multi-objective optimization for a hospital inpatient flow process via discrete event simulation," in *Proc. Winter Simulation Conf. (WSC)*, Huntington Beach, CA, USA, Dec. 2015, pp. 3622–3631, doi: 10.1109/WSC.2015.7408521.

[87] A. C. Arguello-Monroya, V. Castellanos-Ramírez, E. M. González-Neira, R. F. Otero-Caicedo, and V. P. Delgadillo-Sánchez, "A greedy-tabu approach to the patient bed assignment problem in the hospital Universitario San Ignacio," *Decis. Sci. Lett.*, vol. 10, pp. 21–38, Jan. 2021, doi: 10.5267/j.dsl.2020.10.006.

[88] M. Fairley, D. Scheinker, and M. L. Brandeau, "Improving the efficiency of the operating room environment with an optimization and machine learning model," *Health Care Manage. Sci.*, vol. 22, no. 4, pp. 756–767, Dec. 2019, doi: 10.1007/s10729-018-9457-3.

[89] M. Hamid, M. Hamid, M. Musavi, and A. Azadeh, "Scheduling elective patients based on sequence-dependent setup times in an open-heart surgical department using an optimization and simulation approach," *Simulation*, vol. 95, no. 12, pp. 1141–1164, Dec. 2019, doi: 10.1177/0037549718811591.

[90] A. J. Oerlemans, N. van Sluisveld, E. S. van Leeuwen, H. Wollersheim, W. J. Dekkers, and M. Zegers, "Ethical problems in intensive care unit admission and discharge decisions: A qualitative study among physicians and nurses in The Netherlands," *BMC Med. Ethics*, vol. 16, no. 1, pp. 1–15, Dec. 2015.

[91] A. McGuire and P. C. McConnell, "Resource allocation in ICU," *Current Opinion Anaesthesiol.*, vol. 32, no. 2, pp. 190–194, 2019.

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