A HYBRID SYSTEMS MODEL FOR EMERGENCY DEPARTMENT BOARDING MANAGEMENT

by

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ABSTRACT

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The purpose of this research is to examine methods for minimizing the influence of boarding on emergency department (ED) crowding outcomes. To accomplish this purpose, this research uses a hybrid systems model framework by combining agent-based simulation, predictive and optimization models to improve ED outcomes such as length-of-stay and left-without-being-seen rates. For the research, different types of simulation models were examined (discrete event and agent-based/discrete event combination) to identify the most parsimonious for studying ED boarding. Predictive models using simulation output were developed to understand the factors that influence future boarding levels as well as generate predictions. Research has previously highlighted how valuable bed assignment/management strategies can be in ensuring minimal length-of-stays in healthcare systems. Such research is limited for EDs specifically, however. This research contributes by directly leveraging the predictions of future boarding levels to develop a bed assignment strategy that can optimize fast track bed capacity to ensure improved ED outcomes.

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DEDICATION

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CHAPTER 1: INTRODUCTION

Demand for all areas of healthcare, including emergency medicine, is growing globally. Different environmental and societal factors are driving this increased demand. These factors include an aging population combined with longer life spans, advancement in medicine which creates net new needs, a changing climate that is paving the way for pandemics via worsening air quality, and the widely reported increasing strain of mental health problems. Although healthcare demand is growing, the availability of human and material resources required to address this demand is not growing correspondingly, leading to an ineffectual healthcare system. This research focuses specifically on improving the operations of emergency departments, which are a critical artery of the healthcare system. In this chapter, we will introduce the emergency department (ED) and its place in the United States hospital system. Additionally, we will provide motivation for this research, introducing the key problems EDs face and the factors responsible for said problems.

1.1 ED Process – A Brief Introduction

Patients who require immediate medical attention access medical services where they can receive treatments without appointments. These services can be accessed at EDs within a hospital system or in primary care settings via urgent care clinics. This research focuses on the processes used by emergency departments in hospital systems where the relationship between the hospital and its ED provide complexity that result in poor patient experience and less-than-stellar operational performance.

Patients originate from outside the hospital via an ambulance or personal transportation (walk, bus, car, etc.). Once in the hospital, these patients either directly access the ER or are referred. At the ED, nurses assess the patient's medical needs using a process called "triage." The triage process aims to prioritize patient care based on illness/injury, severity, prognosis, and resource availability so that diagnostic/therapeutic measures can be initiated as appropriate [1]. In the US, the emergency severity index (ESI) is the algorithm used. ESI is a clinically relevant five-level stratification system that classifies patients into five groups from 1 (most urgent) to 5 (least urgent), based on acuity and resource needs [2].

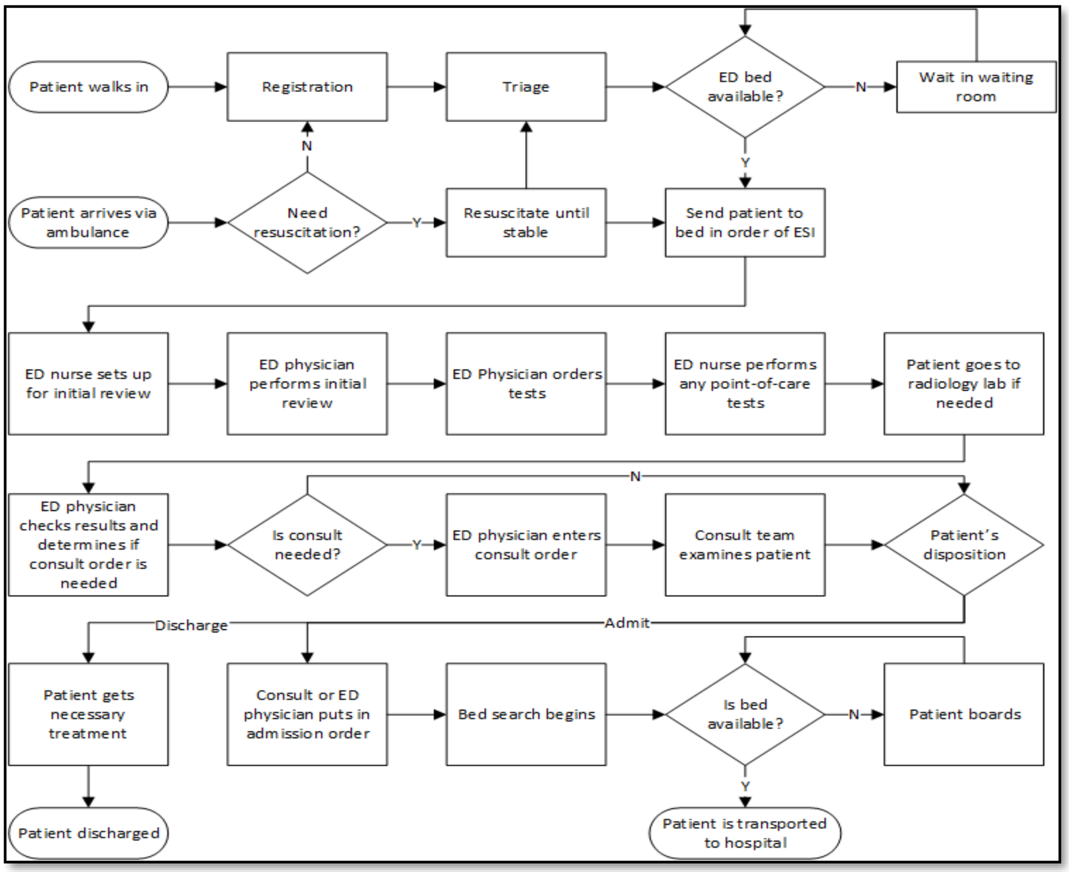

Figure 1-1: Typical ED Patient Pathway

Patients wait their turn for medical care according to their ESI. After medical care from physicians, there are different pathways for the patient. The patient can be discharged home with care instructions. Further treatment may be needed either requiring admission to the ED's attached hospital or transfer to a different hospital. For non-transfer cases, patients will wait until the hospital has a bed available, at which point the patient officially exits the ED to the main hospital. This waiting period is known as boarding and depending on the hospital's process, patients may be boarded in the ED or in the main hospital. If they are boarded in the ED, the ED typically bears responsibility for these patients, providing continuous care until they are admitted to the hospital. Figure 1-1 above provides a visualization of the ED patient pathway.

1.2 Motivation for improving ED boarding management

The basic structure of the process described in the previous section is similar to general queue-based systems: customers arrive, wait for service, receive service based on some pre-determined criteria and then exit the system. As with most queuing systems (e.g., banks, shops, etc.), the ED system is a victim of crowding and long wait times. ED crowding occurs when the number of resources in the ED or hospital is insufficient for coping with patient volume/demand [3]. The most common characterization of ED crowding is long patient length of stay (LOS) [4] [5]. The ED-LOS is the total time from the patient's arrival time to the ED to the time the patient is discharged from the ED, whether to their home or a hospital. In the US, as of September 2019, for patients discharged home, median ED-LOS ranged from 1.5hours in North Dakota (ND) to 3.5hours in Maryland (MD). For those admitted to the hospital, the median ED-LOS ranged from 2.2hours in ND to 6.5hours in MD [6].

The most obvious consequence of high levels of ED crowding is overall reduced patient satisfaction driven by long wait times [7]. According to the National Center for Health Statistics, 27% of US ED visits in 2017 required a wait of at least 1hour to see a physician [8]. But ED crowding has more harmful effects. ED crowding is associated with a high number of patients leaving the ED without being seen (LWBS) or completing their medical treatment [9]. Aside from clinical implications, this LWBS phenomenon has direct financial implications, leading to $500 lost per patient in revenue for the hospital [10]. Further, ED crowding is associated with larger exposure to clinical errors [11] and higher risk of mortality; with one study estimating an additional 3% mortality risk for every 10% increase in ED bed occupancy [12]. There are also operational concerns like higher ambulance diversion rates. It is estimated that each ambulance diversion hour results in >$5,000 in lost revenue for teaching hospitals in urban areas [13]. ED crowding also has harmful effects on ED staff including increased stress [14], higher risk of being assaulted [15] and lower rates of adherence to clinical guidelines [16].

There are various influencing factors associated with ED crowding. These factors can be classified into major components using the input-throughput-output model proposed by Asplin et al [17]. Input factors describe those that contribute to the demand for ED services. For instance, researchers in different countries have identified older patients seeking care [18] [19] [20] as a determinant for longer ED-LOS. Throughput factors are those related to the ED's care processes and impact both efficiency and efficacy. For example, evaluation by more junior physicians (e.g. medical students, non-trainee residents) is associated with longer ED-LOS [21]. When combined with patient-specific characteristics, some of these factors lead to longer LOS, like delays with laboratory or radiology testing or treatments by additional consultants [19] [22] [23] [24].

The output component of Asplin's model focuses on inefficient removal of patients from the ED after service is completed. There is anear-universal agreement that the inability to move admitted patients to hospital beds is the biggest contributor to long ED-LOS [17] [25] [26] and that improving this movement is the most impactful to overall ED-LOS [27] [28]. These unmoved patients experience **boarding** and thus continue consuming ED resources (beds, nurses, doctors), which results in the delay of new patient evaluation. This delay has consequences. A 2016 study [29] showed that 37% of total ED-LOS is boarding time; it also showed that every additional 2hours boarding results in 50% higher LWBS patients. Boarding has also been directly linked to the other aforementioned consequences [30]. Boarding is a product of factors impacting the ED-hospital system. Factors such as hospital beds [31] and nurses [17] availability as well as communication breakdown between ED and the hospital [32] are also cited as reasons for boarding.

This research focuses on reducing harmful effects of ED crowding, particularly the impact of boarding by applying simulation-based operational research techniques. In the next chapter, we will review existing work focused on ED crowding leveraging similar techniques. We will also highlight the specific contribution that this research will provide to this field of study.

CHAPTER 2: LITERATURE REVIEW

The problem of ED crowding is a famous area of study in literature. Understanding the factors that lead to ED crowding as well as identifying solutions to alleviate the problem has been actively researched by clinical and non-clinical researchers for the last four decades. In this section, we will focus on application of operations research (OR) in this field. For a detailed review of OR applications in ED research, please refer to Saghafin et al [33]. There are two broad categories of OR techniques used in ED operations analysis: descriptive and prescriptive modelling, according to Sinreich and Marmor [34]. The descriptive techniques are used to model and analyze ED operations, while prescriptive techniques focus on optimizing ED performance. In the following sub-sections, we will review literature related to these techniques, highlighting applications to this research focus of boarding. We will also review the use of predictive models, a key component of this research and an emerging force in this field given the recent advancements in data science.

2.1 Descriptive Models for ED Crowding

Descriptive models come in various forms: empirical, analytical and simulation. All these forms of models have been applied in modeling ED operations to improve crowding outcomes.

2.1.1 Empirical/Statistical Models

Empirical models are mathematical models that are generated through observations from a general population and experiments. These models tend to be used in analyzing the relationship between the performance-related factors and influencing variables related to patient flows [35]. The mostcommon application for this model type is in forecasting ED crowding and patient flows. Patient flow studies are focused on understanding patient pathways through the ED by making physical or process adjustments to this pathway, with the aim of reducing patient wait times including boarding times. Empirical techniques used in ED patient flow modelling come in various forms: formula-based methods [36] [37] [38], regression-based methods [39] [40] and time-series analysis [41] [42] [43] [44]. Well-known empirical models for forecasting ED crowding include EDWIN and NEDOCS. EDWIN is a formula-based index that measures the crowding level of the ED by considering the number of patients per ESI class, the ED resources available and the number of boarding patients already in the ED. This index/measure (from 1 to 5, in ascending order of serious crowding) is typically taken at the point of a new patient's arrival. In it's introductory paper, Bernstein et al [36] define the aim of EDWIN as an alert mechanism for ED personnel to respond appropriately when the ED is approaching crisis. Comparing to physician and nurse assessment of ED crowding, the authors showed that EDWIN was a reasonable measure of ED crowding since it was strongly associated with clinician assessment. Similarly, to forecast ED crowding and provide an early warning signal for ED personnel, Weiss et al [39] introduced the NEDOCS measure using regression methods. A mixed-effect linear regression model using information from eight US academic EDs was to predict crowding using variables referencing patient counts and wait times as well as available beds. The model was also shown to be a reasonable predictor of ED crowding when compared to clinician assessment of crowding. While these forecasting measures are very useful and accessible to ED personnel given their ability to easily tie performance outcomes to contributing factors, they are not perfect. Formula-based models are not true predictors as they are static models that mostly reflect current state. Conversely, regression-based models do provide predictions and are able to accommodate more input variables. Due to the unique patient arrival pattern and its impact on downstream processing however, these models fall short in accurately forecasting ED crowding. As a result, researchers have been working on time-series analysis and forecasting as an alternative, more accurate modeling technique. Eiset et al [40] recently developed a transition regression model to predict the number of departures and expected wait time at each step in an ED. The researchers use binominal regression models to predict the probability of departure in the next time step based on input variables shown to be related to ED crowding. Results showed that number of arrivals and number of people waiting already have the largest impact to wait times. Note that forecasting models are also classed as predictive models which are discussed further in section 2.3. In general, these empirical model types are very helpful for extracting information from observational ED data to better understand ED patient flows which can then be used in other models. Due to some of the aforementionedgaps in empirical modeling, including the use of data that can differ due to collection methods or timing or collection sites, these models are not well suited for creating process improvement models.

2.1.2 Analytical Models

Similar to empirical models, analytical models also represent the system in terms of mathematical equations. In contrast, their representation specifies parametric relationships and associated parameter values as a function of time, space, and/or other system parameters. The most common analytical modelling technique used in this field of study is queueing. A queueing model is a mathematical description of a queuing system which makes some specific assumptions about the probabilistic nature of the customer arrivals and service processes, the number and type of servers, as well as the queue discipline and organization. Queuing models have been applied to improve ED operations in a variety of ways: understanding the complexities of patient arrivals [45] [46],managing patient flow through the implementation of different priority-based queue disciplines (i.e. service rules) [47] [48], and improving resource (human and bed) management [49] [50]. Queueing models have also been applied in understanding boarding and its effects on ED performance by studying the interaction between EDs and the main hospital as well as reviewing current decision-making practices. Lin et al [51] models the ED to hospital patient flow in two streams: arrival to disposition and disposition to hospital admission. The aim is to estimate the ED waiting times and subsequently steady state number of ED and inpatient unit hospital (IU) resources needed to achieve the target waiting time recommended by the Canadian Triage and Acuity scale. The second stream which focuses on boarding is modeled as one with servers and system capacity constrained to the number of IU beds, no buffers and a first-come-first-serve (FCFS) queue discipline. The researchers posit that the waiting times in the ED are dependent on boarding time which itself is a function of the hospital inpatient LOS. This hypothesis is validated in an earlier study on the relationship between IU LOS and ED wait times by Broyles and Cochran [52]. Using data from a local hospital and adjusting ED and IU resources in analytical and Monte-Carlo experiments based on ED arrival rates and IU LOS, they make an insightful conclusion that carrying buffer IU capacity is a better strategy than increasing ED size. This calls into question the practicality of the current state practice of boarding at the ED.

In addition to queueing models, Markov processes/chains have also been used to model emergency care processes, by themselves [53] or as tools for analyzing queuing models [54]. A Markov chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event. The nature of this probability, called the "Markovian property" is thus memoryless. Since patient flows through the healthcare system involve numerous events that evolve during the process of care, with the evolved state usually determined by the preceding state, modeling patient flows as Markov models is reasonable. To illustrate, Zhu et al [55] focuses on the handoff process from ED to IU, the process that influences boarding. The researchers model the handoff process as a Markov chain-based transient model with a FCFS queue (boarding patients) with a finite capacity and a single server. Conducting numerical experiments, the researchers show that waiting time (boarding) is more sensitive to service rate when servers are available than it is to the rate of unavailability of servers. The authors postulate that communications between departments is a main determinant for this service rate and as such, improving communication between departments could reduce boarding time.

Analytical modeling for EDs has thrived because of its ability to provide simple equations that show the relationship between variables like treatment times, bed capacity and physician utilization, and thus making learnings easy to apply practically [56]. However, these equations are often based on simplifying assumptions per the model being adopted, constraining true representation of the complexity of ED operations. For instance, most studies (but not all, e.g. [47]) assume that patients wait until service is complete, ignoring the leave-without-being-seen (LWBS) population, which is a criticalED operations outcome. Queueing models usually also assume that patients move from service-to-service based on one key server being available (bed or physician), simplifying the reality that service at certain points in the ED process require waiting for availability of multiple resources.

2.1.3 Simulation Models

Developing accurate models for most systems, especially for complex systems like EDs, is challenging as it is difficult to fully capture the stochasticity in the process. Simulation models are unique in their ability to imitate system behavior very closely including time-dependence and stochastic characteristics, thus relaxing the strictness of assumptions typically made with other types of models. As a result of this, simulations are useful in investigating ED operations and performance as well as testing improvement options. Due to their usefulness in analyzing ED operations, simulation modeling is a well-used technique in literature. Paul et al [57] and Salmon et al [58] provide detailed literature reviews of simulation model use for emergency departments. There are three main simulation techniques, all of which have been used in modeling ED operations: system dynamics, discrete-event and agent-based. System Dynamics (SD) is a modeling approach that is focused on the principle that disparate components of a system are related and that they affect each other, effectively determining the emergent behavior of the system [59]. Due to their nature as well as their ability to model systems with a holistic view, SD models have been applied in simulating ED operations particularly with understanding the general impacts of patient demand, resource availability on ED performance [60] [61] [62]. Some research studies have used SD models in understanding boarding and its impacts. For instance, Rashwan et al [63] investigates the impact of boarding and delayed discharges on Irish hospitals, especially the influence of elderly patients on this issue to highlight the current aging population trend. The researchers develop an SD model to represent the flow of elderly from origin (home, nursing home) to their final destination (home, rehab, acute hospital) where the modeled stock are the upstream beds needed after ED service. The model is then used to evaluate the effectiveness of policy interventions on four key metrics, two of which are related to boarding counts. The research examines three main interventions: increase of downstream beds, increased access to community service and increased discharge rate from long-term care. Simulation results showed that a combination of all three interventions offer the lowest boarding rates. Results also showed that simply increasing upstream bed capacity does not improve delayed discharges, a conclusion validated by other researchers. This research demonstrates the strength of SD simulation: its ability to model highly complex systems at aggregated and strategic levels, allowing for insights into massive systems with interconnected systems such as EDs, hospitals and their downstream components. SD models are largely deterministic however and cannot fully capture all the complexity or stochasticity of the systems modeled [59].

Discrete-event simulation (DES) models system operations as a sequence of events where each event occurs at a specific instance of time and represents a change in the system's state [64]. In DES, the objects of interest are individually represented with relevant attributes assigned to each individual. These attributes determine what happens to the individuals throughout the simulation and the individuals can be tracked throughout the simulation. This characteristic allows for capturing more complexity and randomness in processes/systems than the SD. As a result, DES has found applications in ED operations modeling from resource capacity and configuration [65] [66] to patient flow pattern assessments [67] [68] and crowding assessment [69] [70]. DES models have also been useful in analyzing patients' waiting times to understand influencing factors [71] [72] including boarding times [73]. De Boeck et al [74], breaking away from the typical practice of modeling boarding from the perspective of the hospital, developed a DES model to analyze the impact of boarding patients from the perspective of the ED. The research focuses on the resource burden that boarding patients places on the ED, specifically examining the decisions that physicians have to make regarding which patients to treat first. Given the focus on physician decision-making, the researchers use the DES model to evaluate the best patient prioritization policy. Using a specific Israeli hospital as a case study, ED process flow for four types of patients (orthopedic, surgery, trauma, internal) is modeled from their entrance to the ED to their departure to the hospital. Additionally, different styles of boarding is modeled: boarding with only bed dependency, boarding with physician and bed dependency and boarding without resource dependency. Four patient prioritization policies are evaluated; three static (FCFS, boarding first, non-boarding first) and one dynamic (where patients are prioritized based on how long they have been waiting for the doctor). The researchers run several simulations under varying conditions to understand the impact of boarding on LOS and waiting time in physician queue. The results showed that the boarding patients are not impacted by static policies; however, non-boarding patients are impacted by policies that prioritize boarding patients. This emphasizes the effect boarders have on the treatment of other patients. Further, this study highlights the many advantages of DES over SD especially its flexibility and ability to include detailed complexity. The researchers can include special patient attributes like treatment needs and boarding styles to drive different flows within the same model, thus allowing more process complexity to be simulated. However, the study also shows the limitation of DES. The physician's decision-making is simplified using simple routing logic and this simplification cannot take into account any additional variables that real-life physicians may consider like additional high priority tasks, patient deterioration or those related to patient behaviors like leaving early. The model also does not consider any interactions that patients or physicians may have with their environment which may change the patient's flow or the physician's decision like crowding levels.

ABS is a computational framework for simulating dynamic processes that involve agents which act on their own without external direction in response to environmental situations encountered during the simulation [75]. The key difference between ABS and DES is that ABS focuses on the perspective of the agent as the central part of the model. This is unlike DES, where the model is built around the process [76]. Agent-based simulation (ABS) is not yet as common for modeling ED operations as DES; only ~10% of existing ED operations' literature over the last two decades used ABS [58]. Similar to DES, ABS has been used in the investigating ED staff configuration [77] [78] [79] as well as identifying influencing factors for ED performance [80] [81].

There are many illustrations of ABS' advantage in modeling complexity over other simulation models. One illustration is Yousefi and Ferreira [82]'s investigation of decision-making for ED staffing allocation. The research examines the usefulness of a self-organizing, real-time approach to staff allocation compared to the traditional approach of supervisors making staffing decisions. The self-organizing approach is a group decision-making approach where the final decision is collated from individuals based on their level of experience and work in the ED. The researchers develop an agent-based model with several active agents that interact with each other and their environment to make decisions. The agents include doctors, lab technicians and nurses that can move through their stated tasks and participate in group-decision-making sessions. The model's agents also include patients that can decide to leave the ED based on the ED's condition. Uniquely, these patients also deteriorate in medical condition based on the conditions of their environment. To examine the impact of their proposed self-organizing approach, the researchers run several simulations with varying staffing availability. Key performance measures (LWBS, LOS, wait time, number of discharged patients, wrongly discharged and deaths) were pulled and compared to a base model with the traditional decision-making. Overall, the self-organizing approach led to better outcomes in all performance measures except for number of patients that are wrongly discharged, a factor that relies on clinical decision-making that was not modeled. Simulation methods like DES and SD as well as analytical methods do not provide easy ways to model the behaviors like the group decision-making behavior or the effect that patients abandoning service early have on decision-making.

There are additional ABS-based studies that have focused on the impact of patient decision-making on ED performance. Yousefi et al [83] created an in-depth agent-based model to simulate the behavior of patients in the ED. The study focused on the decision-making of patients that leave the ED without receiving the treatment they originally sought. Considering patients' behavior, the study then uniquely leverages ABS and cellular automata techniques (CA) to evaluate the best operational policy to reduce the number of LWBS patients as well as patients' LOS using a

Brazilian tertiary hospital as a case study. The patient agents can decide whether to stay in the ED using a 1-D CA with two behavioral parameters: the agent's memory on their waiting time as well as their neighbors' waiting time experience. During model verification, it was seen that the use of the CA alone improved the ability to mimic the real system's LOS by 11%. This points out a key property and advantage of ABS; agent behaviors can be represented in many ways using simple if-then rules or probabilities or combining with more complex and flexible methods such as CA or reinforcement learning or neural networks.

ABS has also been used to assess brand-new strategies for improving ED boarding. Diving into patient workflow re-organization, Ajmi et al [84] propose the computer orchestration of a patient's workflow based on the ED's current state. The research study focuses on the automatic direction and re-direction of patients through ED process steps based on specific ED performance indicators (PI), including cumulative wait time (CWT), LOS and measures for boarding – IU bed availability and availability of right patient file at the right time (PFT). The study also introduces a new PI called remaining patient care load (RPCL) which measures the percentage of care remaining for a patient i.e. if a patient is at triage, their RPCL is higher than a patient that is awaiting lab results. The researchers design a three-level architecture; the first level is the information layer while the last two layers contain an ABS model with several agents capable of communication. This ABS model is unique in its level of detail as workflow progression is driven on a task per patient level as opposed to just a patient level. The model includes several decision-making agents: reception and identification agent (RIA), patient workflow instance agent (PWIA), scheduling and orchestration agent (SOA), monitoring agent (MA) and medical staff agent (MSA). Simulation experiments are designed and run to evaluate the efficacy of the automatic re-direction of patients using the case study of a French ED: static (where patient tasks are programmed at execution) and dynamic (where patient tasks can be changed during execution). In the dynamic environment, the SOA reorganizes the schedule of patients' tasks in response to information on the patients or ED (e.g., presence of more urgent patient, lack of resources, etc.) as well as specific PIs – LOS, RPCL and CWT. In the scenarios with LOS and CWT driving orchestration, sub-optimal results are received. Here, if the ED experiences any surge of patients, the medical staff become overloaded, and the ED becomes overcrowded far above levels in the static orchestration. But with CWT and RPCL, the dynamic orchestration is shown to provide improvements over static orchestration even in scenarios with surges in new patient arrivals. This study shows the power of ABS, highlighting the technique's prowess in modeling highly complex details as well as interactions between systems and their entities (homogeneous and heterogenous alike). Compared to SD and DES styles, ABS is great for modeling when there are many decision-making points that can drive system behavior and performance.

2.2. Prescriptive Models for ED Crowding

Prescriptive models attempt to quantify the effect of future decisions with the aim of prescribing the best decision under certain criteria. The main technique for prescriptive modeling is mathematical optimization/programming. Mathematical optimization involves minimizing or maximizing a real function by systematically choosing input values from a specified domain and finding the best available value of the function. Optimization is a large field with many techniques: convex, integer, quadratic, nonlinear, combinatorial, dynamic as well as goal programming, heuristics and optimal control theory. Several of these techniques have been applied to understand and optimize ED performance. Linear programming techniques have been used to identify the optimal ED staffing capacities [85] [86]. Mixed integer programming has been used to model EDs with the aim of optimizing ED staffing schedules [87] [88], patient waiting counts [89] and times [90] [91] [92]. Goal programming techniques have also been used to optimize ED staffing schedules [93] [94]. Stochastic control theory, a subfield of optimization, has also been applied to ED performance problems. For instance, Lee and Lee [95] study the problem of which patients to admit to the ED during a surge scenario (e.g. after a natural disaster). The researchers formulate the problem as an admission control problem and successfully use a Markov Decision Process (MDP) model to make the patient admission decision. Another subfield of optimization, heuristic/meta-heuristic optimization has also been used to analyze ED performance. These techniques are different from classic optimization techniques as they focus on finding a sufficiently good solution to a problem, not necessarily an optimal solution. They are useful for problems where the problem space is large, information is incomplete or imperfect or there is limited computational capacity. Heuristic optimization has been used to identify ED staffing schedules that yield good ED performance [96] [97]; similarly meta-heuristic techniques have been used for the same purpose [98].

Literature review of optimization in ED research shows that most studies are focused on the optimization of resources, mostly staff, to improve ED performance. Other strategies such as treatment priority or bed assignment are not common. Uniquely, Luscombe and Kozan [99] leverage heuristic, meta-heuristics and other OR techniques to provide real-time patient-bed assignment and task-resource allocations. The goal of the model is to assign each patient to an appropriate bed and schedule the treatment tasks for processing on the correct resources. The model considers two objectives; minimizing the weighted response time between arrival and bed assignment (the weight is the triage class) for patient-bed assignment and minimizing the total care time of all patients for task-resource allocation. The researchers create a dynamic algorithm to achieve this goal; the algorithm uses disjunctive graphs and tabu-search techniques to consider both objectives. The study shows that their proposed technique is valuable and practical by testing against real-life scenarios as it was able to provide reasonable recommendations in <2seconds. An advantage cited for using analytical techniques over prescriptive ones is that they are easy to implement, particularly in real-time. This research shows that optimization techniques can provide real-time value to ED operations management. The study still underscores however, some of the other drawbacks of optimization. Not only are these techniques complex and time-consuming but they are mostly deterministic in nature and do not accommodate stochasticity easily. This is exemplified by the researcher's acknowledgement in their conclusion that their findings are limited to deterministic treatment pathways which is not always the case in real-life EDs.

2.3 Predictive Models for ED Crowding

Predictive models are mathematical models that seek to predict future events or outcomes by analyzing patterns from historical data that are likely to forecast future results. The last two decades have seen the rapid advancement of predictive modeling through the rise of artificial intelligence (AI) techniques: data mining, knowledge discovery and machine learning. This advancement has allowed academics, public and private enterprise to embrace these techniques and proliferate them across all industries, including healthcare. Healthcare and AI communities have been collaborating for several years now across many facets of healthcare including ED study. Shafaf and Malek [100] provide a review of machine learning in ED-focused research. Key applications include prediction of general population demand for ED services [101] [102] [103], improvement of triage systems [104] [105] and proactive identification of patients in the ED with high risk for poor clinical outcomes such as patient deterioration/disease progression [106] [107] and mortality [108] [109]. Predictive models using AI techniques have also been used in predicting ED crowding measures like patient wait times [110] [111] [112] and LOS [113] [114]. Underpinning the use of predictive modeling for ED research is the idea that knowledge of future events or states can be harnessed by ED operators to make better/quicker clinical and operational decisions. For instance, there are a lot of research studies focused on the prediction of ED patient disposition at the start of the ED process. Researchers have been able to make reasonably accurate predictions using varying levels of information available: simple demographic and administrative information available after triage [115] [116] to more complex information including patient history and clinical information [117] [118]. Researchers often cite the ability for this knowledge to be useful in making inpatient bed requests early. Golmohammadi [119] built a fairly accurate Artificial Neural Net (ANN) predictive model capable of identifying ED patients that would be admitted to the hospital. The researcher posited that knowing this prediction will quicken the process of inpatient bedding and consequently reduce ED boarding. Uniquely, this study also provides association rules (using data mining techniques) that show the relationship between high-impacting factors and likelihood of admission. The author provides these as rules-of-thumb that can serve as a substitute to the more complex ANN model. However, the research study, like similar studies using AI techniques, neither provides details on how the association rules or ANN model can be implemented in a real-ED setting nor quantifies the impact of using such a prediction model on ED crowding. To further illustrate, Lee et al [120] consider real-life ED applicability by dealing with the progressive accrual of clinical information throughout the ED caregiving process for their unique predictive model that identifies patients admitted to four types of hospital wards. While the researchers are probably correct in their assertion that that this granular prediction is more useful to hospital staff for planning, they also do not provide any quantifications confirming this hypothesis. This is likely because without combining predictive models with other models, it is hard to understand their applicability and impact in their intended systems/problem space. Lee et al [121] emphasizes this point by successfully applying fork-join queuing models to predictive patient disposition models to highlight and quantify the benefit of using predictive admission data to make inpatient bed requests, thereby reducing boarding.

2.4 Hybrid Systems Models for ED Crowding

According to Mustafee and Powell [122], Hybrid Systems Modelling (HSM) can be defined as the combined application of simulation with methods and techniques from disciplines like Applied Computing, Business Analytics, Computer Science, Data Science, Systems Engineering and OR. These methods and techniques do not necessarily have to be combined with simulation in the implementation / model development stage; they can be applied at any stage including planning, model verification, validation and experimentation. HSM is emerging in ED crowding research and has been used in most of the same applications as single-modeling techniques. Generally, the most common use of OR techniques in ED is in resource allocation/planning and as such, HSMs are gaining ground in this application. Examples include simulation-optimization techniques [123] [124] [125] [126] and simulation-queuing techniques [127] [128]. Simulation hybrid models have also been used in estimating ED crowding measures. Simulation-queueing models [129] and simulation-predictive models [130] have been used to estimate patient wait times. Harper and Mustafee [131] introduce a HSM that leverages the time series machine learning algorithm seasonal ARIMA (SARIMA) to predict the number of ED patients up to 4-hours ahead and discrete-event simulation to test the impact of corrective policies on these future crowding levels in real-time. While the research is still ongoing, the HSM introduced is expected to be valuable as it avoids the pitfalls of typical prediction model research by creating a holistic decision-making tool for controlling ED overcrowding.

Hybrid models have also been applied to research focused on patient flow improvement. Hybrid models with simulation and analytical techniques (e.g., queueing theory [132]) have been used to propose patient treatment priorities/times. Bruballa et al [133] combine a unique analytical (formula-based) model focused on patient wait times with a detailed ABS model to form an intelligent scheduler for non-urgent ED patients. The formula-based model presents the patient's flow through the ED in stages, focusing on subsets of ED-LOS: wait time and actual service time. This unique model considers the impact of staff experience configuration on both the measures and ED throughput. Experience levels of staff is incorporated into the main outcome, theoretical throughput (ThP) which measures the ED's patient attention/ response capacity. The researchers then develop an ABS model capable of dynamically adjusting the incoming patient pattern to match the ED's ThP. The model's scheduling algorithm works by dynamically adjusting an appointment scheduling table that considers a patient's arrival hour and expecting waiting time using this information to "schedule" a treatment time. The researchers propose that the patients are informed of their treatment hours and asked to remain at home until the treatment time, improving patient satisfaction through a reduction in waiting time. Simulation experiments using the historical data from a Spanish hospital show that using the policy from the scheduler reduces wait times by >20% across all arrival times compared to the hospital's traditional policy. Additional sensitivity experiments show that the scheduler still reduces wait times even when a high concentration of patients arrive in the central hours of the day or when there is an unexpected surge like a serious accident. The research work relies on ABS as a method of properly representing the complexity of the ED and uses analytical models to guide the pseudo-optimization of wait times.

The most common HSMs are simulation-optimization models and they have also been applied to patient flow improvement problems [134] [135]. Allihaibi et al [136] combine a heuristic algorithm with a DES model to arrange the priority of bed assignment for patients arriving at the ED. The researchers create a patient-centric detailed DES model where patient flow through the ED process is dependent upon triage category and the category of clinical complaint. Three main pathways are modeled in the DES model: resuscitation for high acuity patients, observation for low acuity patients and an acute pathway for all other patients. Each pathway represents a treatment area with its own resources (beds). The bed assignment heuristic algorithm focuses on minimizing patient wait times by reordering patients waiting for bed assignment within each pathway. The algorithm does this by minimizing waiting time between all pairwise patient arrivals and waiting time based on treatment time which is dictated by the complaint presented. Patients with higher waiting times are moved to the front of the bed assignment queue within their pathway. This research is one of the few that explicitly outlines bed assignment policy as most other researchers focus on physician treatment priority. Using data from an Australian hospital, the researchers assessed the effectiveness of the algorithm by comparing to the current hospital situation, FCFS policy and the policy of prioritizing patients based on the shortest anticipated treatment time. In all cases, the proposed bed assignment policy is superior, providing >9% improvement in patient wait time without degrading resource utilization (i.e., bed and clinicians).

Less common but emerging HSMs that involve the combination of simulation and predictive models have also found applications in patient flow research [137] [138]. In an award-winning research, Lee et al [139] combine predictive modeling with a simulation-optimization model to optimize ED workflow through the implementation of operations improvement activities along with patient flow updates. Leveraging existing simulation-optimization framework (RealOpt ©), the researchers develop an ED ABS model. The researchers used machine learning algorithms to identify patients that will return to the ED as readmissions within 72hours and 30days respectively, based on key data patterns from demographic, socio-economic and clinical information. The ML algorithm is embedded within the simulation model and is used to create a flag for these patients so that they can be identified and observed in a CDU before exiting the ED. The ML model is trained externally using historical data and then predictions are made within the simulation based on the predicted model. The researchers then used nonlinear mixed integer programming to identify global solutions for achieving best ED performance in terms of utilization, throughput and wait times. The identified solutions provided >9% improvement to patient wait times. This study provides a good template for incorporating machine learning algorithms into simulation-based models. Additionally, it highlights the strengths of using HSMs compared to single-model approaches, particularly in patient flow studies. Without the use of simulation, the practicality/applicability of the readmission machine learning algorithm is hard-to-evaluate. In general, hybrid models using simulation, optimization, analytical and machine learning techniques allow for more realistic modeling of the ED behavior with fewer simplifying assumptions and lower computational costs [140].

2.5 Gaps in Literature

This literature review comes to the same realization as He et al [141]: strategic optimal decisions based on a macroscopic view coupled with operational decisions based on a microscopic view can yield more efficient techniques and their application to the dynamic and complex nature of healthcare can potentially improve care delivery, reduce cost, and save lives. This revelation is likely why HSMs continue to be a growing trend in ED research.

In addition to highlighting the strengths of existing research, the literature review also revealed some gaps that will be addressed in this dissertation. First, despite the consensus that boarding has significant negative impact to ED crowding and performance, <20% of the OR-focused literature reviewed explicitly model and consider boarding. Most of those that include boarding simply conclude that reducing boarding impact requires improvements to the hospital's resource allocation/capacity or to the interaction between hospitals and the ED. Also, solutions proposed are typically not in control of ED administration, thus making actual implementation difficult. This research focuses on developing solutions to boarding that are within the purview of the ED administration and can be deployed within the ED with minimal changes to the main hospital.

Second, majority of ED research do not model the ED completely, typically opting to model the ED as a standalone unit and ED crowding as an ED problem rather than a hospital system problem. Due to this systems engineering gap in literature, currently proposed ED crowding solutions focus on ED resource allocation and capacity, physician prioritization of patients as well as strategies to reduce service times (e.g. lab turnaround). While these solutions offer relief to ED crowding, they often do not consider the impact of downstream inpatient care processes and as such, are limited in the LOS relief they provide ill patients waiting to be admitted (~13% of all patients). To counter this, some research have examined non-capacity planning-related bed strategies to reduce boarding effects. Bed management, the hospital function responsible for reviewing the status of the ED and the hospital (i.e. patient census and bed occupancy rates) to ensure a smooth flow from ED to hospital, is and indicator has been shown in non-OR based studies to reduce boarding [142] [143]. There are other researches that focus on pulling forward the inpatient bed allotment decision (usually made by hospital bed managers) to the ED using OR models [73] [121] [144]. There are also novel approaches that focus on the 'optimal' timing for assigning a patient to an ED bed. Today, ED bed assignment is usually based on patient criticality as well as simple strategies like the longest wait time or estimated shortest processing time. Only a few research seek to optimize boarding or ED crowding measures like wait times based on bed assignment [99] [136] [145]. To address this gap, similar to [136], this dissertation will develop a heuristic algorithm for assigning beds to patients after triage.

Third, this dissertation leverages ABS as a key technique in its assessment of the ED boarding problem. The literature review of ABS in the context of ED crowding reveals that developed models are either very high-level, focusing on movement of the patient through ED process steps, or very specific, focusing on agent (patient/clinician) behavior while simplifying the process flow steps. The ABS model developed for this dissertation does both, providing a detailed view of the ED processes (and inpatient admission) inclusive of agent behaviors and interactions that likely drive system performance, which is a departure from existing literature. This approach will ensure that the simulation model is as close to reality in terms of stochasticity and complexity.

Finally, forecasting ED crowding literature review reveals that using predictive models alone (as well as analytical/simulation models alone) is common in literature but there is a dearth of research on HSMs that include ED crowding forecasting models. Literature review of HSMs with predictive models show the ability to use predictive model results to drive process behavior and impact ED performance. This dissertation intends to develop a HSM that combines simulation with models that predict future boarding levels based on current ED and hospital crowding levels.

To conclude, this research aims to address gaps in existing literature by modeling the crowding problem holistically, with the aim of identifying reasonable solutions that minimize ED crowding.

2.6 Research Questions

In addressing the gaps, this dissertation aims to answer the following questions:

1. What is the value of creating a simulation model that includes detailed process steps and human decision-making behaviors? Does such a detailed model yield better decision-making/model outcomes than the typical simulation model found in literature?
2. What are the main human and operational factors that can be used to accurately predict future boarding levels in an ED?
3. How effective are bed assignment strategies compared to existing strategies at managing ED boarding and ensuring reasonable ED crowding levels?

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CHAPTER 3: INVESTIGATING EMERGENCY DEPARTMENT SIMULATION MODEL COMPLEXITY

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3.1 Introduction

Emergency Department (ED) crowding continues to be a worsening problem across the globe. In the United States, ED crowding has been a growing phenomenon in the last three decades. The study of ED crowding is important because overcrowding has been linked to detrimental effects like larger exposure to clinical errors [1] and a higher mortality rate [2]. Boarding has been widely acknowledged as the main cause for ED overcrowding [3] and as such there is a growing body of research on the topic. Studies range from exploratory to understand the causes of overcrowding [4] [5] to prescriptive where solutions for overcoming overcrowding are provided [6] [7]. Simulation has become a go-to tool for understanding ED crowding in general [8] [9] [10]. This is due to the availability of simulation tools and the relatively low barrier of entry, allowing different professionals from Operations Researchers to Medical Professionals to easily learn and build models [7] [11]. Only a few however, are focused on boarding specifically. ED systems are very complex, with highly unpredictable inputs and process flows and numerous feedback loops, making it hard to model accurately. Simulation models are useful because they can handle the complexity of such systems.

In general, simulation models are abstractions of real-world systems used to reduce, yet mimic, the complexity of the real world. Simulation modelers are often told to keep the model small and simple, focusing on creating models that match up to pre-outlined simulation/research objectives. This advice is sage as simulation requires data, time, and computational power to build and more complex models tend to require these resources that may be scarce. Simulation model complexity is not a well understood area and can mean different things to different people [12]. But the consensus is that parsimonious models (i.e., "bare minimum") are better than complex models as they tend to provide better predictions [13] [14]. However, it can be difficult to identify just how parsimonious a model should be to get the appropriate predictive power. It is just as easy to be tempted to include all details as it is to be sparing.

In this study, we create two different models of the same emergency department using discrete event simulation (DES) and agent-based simulation (ABS) techniques. Both models are designed for the simulation objective of assessing ED boarding. Both models can be regarded as parsimonious for the objective, but DES+ABS model is denoted as more complex due to additional details not commonly found in existing literature. We compare the differences between the outputs of the model to determine if their distributions are the same. The analysis aims to address two questions: (1) what are the impacts on ED output predictions when more complex ED details are added and (2) is there an appropriate level of complexity for ED models that study boarding?

The rest of this paper is organized as follows. "Related literature" reviews the relevant literature while "Methodology" presents the simulation model design, validation and statistical analysis form comparing the different simulation models. "Results" presents the results of our comparative analysis. "Discussion" discusses the main findings and potential implications for future simulations as well as clarifies the limitations of our study. Finally, "Conclusions" provides some conclusive considerations and future work.

3.2 Related Literature

Research has highlighted that growing model complexity has impact on all aspects of the simulation process from validation and verification to correctness, ease of use, performance, and cost [12]. Astrup et al. [14] asserts that model size and complexity have an impact on its ability to predict accurately. Ahmed et al. [12] show that the concept complexity itself is hard to define as their interview-based research with 20 experts did not yield any consensus on definition. Ladyman and Wiesner [15] also show that it is difficult to define complexity as a single entity, highlighting features such as number of interactions between components, feedback between interactions, self-modification, robustness and so on as measures for complexity.

Regardless of the definition of complexity, several researchers have attempted to measure the impact of complexity on the effectiveness of models aimed at specific research objectives. Gasser et al. [16] added additional data elements to existing finite element simulation models to assess the risk of abdominal aortic aneurysm rupturing and they found that additional data elements improved predictability. De Rosa et al. [17] developed a methodology to reduce simulation model complexity iteratively and identified a tradeoff between output accuracy and computational simulation costs for residential building simulations. Their main conclusion was that the right tradeoff between accuracy and complexity is based on the specific application intended for the model. Mills et al. [18] evaluated two types of subject-specific biomechanical simulation models that accurately represent the ground reaction forces and kinematics that gymnasts experience during landings. Their study revealed that compared to muscle-driven models, torque-driven models, while more common and computationally cheaper, better predict results that match actual performances, but failed to capture the internal loading of the joints which is important to assess injury risk.

While not aimed at complexity, other studies have worked on identifying the impact of different modeling strategies on model performance. Majid et al. [19] evaluated which simulation modeling strategy (ABS vs DES) created the best representation of the women's wear fitting room in a UK retailer when focused on impact of the behavior of the single server on customer waiting times. They found that both modeling techniques yielded good representations of reality but that there were differences in variability with ABS delivering variability that matched better with real/observed data. Halasa et al. [20] compared two different, but widely used, simulation models for predicting the spread and impact of cattle foot-and-mouth disease, with the aim of assessing if the model design had an impact on predicted financial impact of a disease epidemic. They identified that the different models produced statistically different results and, like Majid et al., observed differences in variability captured by both model designs.

Literature review did not yield any similar studies on comparing the impact of simulation model complexity or simulation model strategies with regards to emergency department simulation. This study will provide the first of its kind comparison of the predictive nature of two different ED simulation models with varying details/complexities. These models aim to explore ED boarding and are designed with that objective in mind. To compare the predictive nature, we will examine typical ED metrics like length-of-stay (LOS), left-without-being-seen (LWBS) rates, boarding time and so on. We will assess the differences between these models looking at simulation results when strategies that impact ED boarding are applied.

3.3 Methodology

3.3.1 Study Site

To achieve our aim, we focus on the operations of a typical mid-size level 2 trauma emergency department in the California. The ongoing COVID pandemic made access to hospitals for research difficult so for the details of our ED, we relied on information provided by administrative and clinical staff from three hospitals within the same hospital group located in California metropolitan areas. The information provided was used to develop a simulated ED with characteristics akin in profile to the EDs that our panelists work in currently. Our case study ED is an urban, medium volume, non-teaching community hospital, with ~78,000 ED visits annually. It is attached to a 385-bed hospital and the hospital plans for ~300 beds for non-ED related visits like elective surgeries. The ED has 49 treatment spaces in total, 29 fully monitored beds (4 of which are designated specifically for trauma care/resuscitation) and 20 additional treatment spaces, which are typically hallway beds or chairs/recliners.

3.3.2 The Simulation Study

3.3.2.1 Simulated Workflow

Patients originate from outside the hospital either via an ambulance or by personal transportation (walk, bus, car, etc.). Once in the hospital, these patients are referred to the ED. At the ED, nurses assess the patient's medical needs using a process called triage. The triage process aims to prioritize patient care based on illness/injury, severity, prognosis, and resource availability so that diagnostic/therapeutic measures can be initiated as appropriate [21]. In the US, the emergency severity index (ESI) is the algorithm used. ESI is a clinically relevant five-level stratification system that classifies patients into five groups from 1 (most urgent) to 5 (least urgent) based on acuity and resource needs [22]. Patients wait their turn for medical care according to their ESI. After receiving medical care from physicians, the patient is dispositioned either to be discharged with care instructions, admitted to the ED's attached hospital for further treatment or transferred to a different hospital. For non-transfer cases, patients will wait until the hospital has a bed available at which point the patient officially exits the ED to the main hospital. This waiting period is known as boarding and depending on the hospital's process, patients may be boarded in the ED or the main hospital. If they are boarded in the ED, the ED bears responsibility for these patients, providing continuous care until they are admitted to the hospital. Figure 3-1 below provides a visualization of the ED patient pathway.

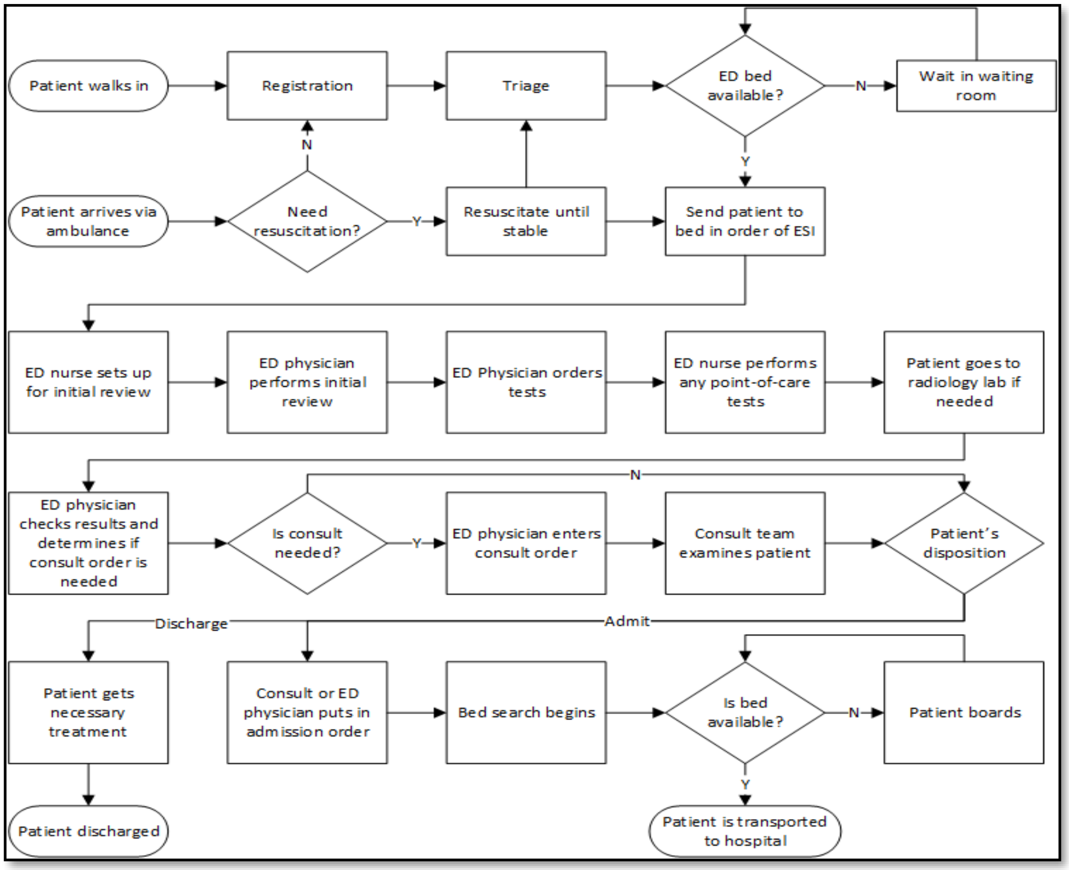

Figure 3-1: Typical ED Patient Workflow

<u>3.3.2.2 Simulation Inputs</u>

The simulation inputs were derived from a combination of data available in literature as well as from interviews with the ED Subject Matter Expert (SME) panel. The interviews with five panelists focused on pre-COVID experiences to minimize the influence of COVID surges on our model. Our simulation relies on four categories of data inputs: patient-demographic information, patient-clinical information, resource availability schedules and process step times.

For patient demographics, we chose not to include age, gender, or race in the design. Since we did not model any clinical or personal decisions that would rely on them, none of these attributes would influence the model behavior and study outcomes. We focused data collection with our panelists on patient arrival patterns which influence model behavior. The ambulance and walk-in patient arrival patterns details were sourced by scaling down the arrival patterns from one of our previous simulation studies [23]. The ED SME panel reviewed the arrival patterns (hourly, daily, seasonally) and deemed it to be close to the patterns observed in their respective centers.

Relevant patient clinical information that influences model design and behavior include proportions of patients by ESI, chief complaint, physician disposition and patient's use of testing, imaging and IV resources. To get the right input for ESI proportions, ED SME panelists were provided with ESI ratios seen in literature [6] [24] [25], using this information as well as their own experiences, they provided data that reflected normal operations for their centers pre-COVID to the extent possible. The panelists provided their data independently. Then the recommendations were reviewed, discussed and the final data to be used for the model was selected based on the discussions. This same process was followed for determining the right disposition (based on information from [6] [23]) and patient's chief compliant as well as use of testing, imaging and IV resources (based on information from [23]).

For resource availability and process step times the panelists provided resource availability numbers based on their experiences also. For bedside nurses, California has a law governing nurse-to-patient ratio, therefore nurse schedule is created based on patient arrival patterns. For process step times, given the nature of our data collection process, we assumed all process steps followed a triangular distribution. This is not unreasonable as we find that based on observed data, existing literature tend to use triangular and uniform distributions [25] [26]. The panelists provided their minimum, maximum and mode estimates for each step independently and the final numbers were determined using a consensus process. There is a paucity of available numbers in literature and where it exists, the studies did not always include all details needed for all the process steps being modeled.

3.3.2.3 Differences between the models

We created two simulation models using AnyLogic™ 8.7.8 based on the ED workflow (Figure 1) and using the same simulation inputs. Our two models vary in the level of details simulated. A summary of these differences is provided in Table 3-1. In both models, the ED workflow is implemented broadly as a M/G/s/K queue with 12 sub-queues using discrete-event simulation.

One model (DES+ABS) included the same aforementioned ED workflow, but additional details were added. First, for the clinical resources like nurses and doctors, process steps/tasks were given priority like real-life. Our study center prioritized completing treatment of existing patients as a way to improve throughput and as such, all tasks involving existing patients (e.g., physician reviews, discharge papers) are prioritized over moving new non-critical patients into beds. Note that for both models, moving critical/trauma patients to beds continued to be prioritized as this is standard clinical procedure globally. Second, the patient decision to LWBS was implemented using agent-based simulation. Patients decide whether to keep waiting for an ED bed based on the crowding status of their environment. We leverage the cellular automata LWBS decision process described in [27]. A patient in queue for an ED bed will wait until a tolerance point and then decide whether to leave or wait for more time based on how many of their neighbors (i.e., patients that were already in the waiting room) have been assigned a bed. Figure 3-2 shows the patient's decision process. We model this process using ABS techniques. Third, we break down the physician orders post initial review into imaging process, point-of-care (POC) tests, non-POC tests and the use of IV. This is different from literature (e.g., [25]) where the use of radiological tests are the only resources modeled given the higher correlation to overcrowding [28] or all resources are combined as a single resource (e.g., [29]). Specifically, we create probabilities of patients based on their chief complaints across different permutations of these resources. We make this decision because we observe that chief complaint is a better predictor for types of resource used compared to ESI as its pseudo R-squared is 10 times higher than the pseudo R-squared for ESI. The R-squareds were obtained by running two Multinominal Logit Models with target as type of resource used (e.g., IV only, Imaging + IV, etc.) and independent variables as ESI and Chief complaint system.

Table 3-1: DES and DES+ABM Model Design Comparison

Main Design Choice	DES	DES + ABM
Task assignment for resources	Tasks are not prioritized for resources; they are seized by the longest waiting patient in queue.	Resuscitation has highest priority but all other tasks across all queues are also prioritized, and resources attend to patients in order of priority and wait time
Clinical resources used	Modeled as four types: consultation, radiological tests, point-of-care tests and all other resources	Modeled as seven types: consultation, radiological tests, point-of-care tests, intravenous treatment (IV) and combinations of tests and IV
Task assignment for resources	Tasks are not prioritized for resources; they are seized by the longest waiting patient in queue.	Resuscitation has highest priority but all other tasks across all queues are also prioritized, and resources attend to patients in order of priority and wait time
Patients leaving before treatment	Modeled as time-out in queue based on ESI since critical patients tend to wait longer	Modeled using state chart of decisions based on waiting time and perceived waiting time of other patients in the waiting room
Bed cleaning	Not modeled	Included as delay after patient leaves

Lastly, to ensure that we capture all the variables that impact access to a bed, we added the time it takes to clean a bed between patients. This sub-process is not typically modeled in literature but studies such as [30] include it as part of their simulations since beds are not immediately available once a patient leaves.

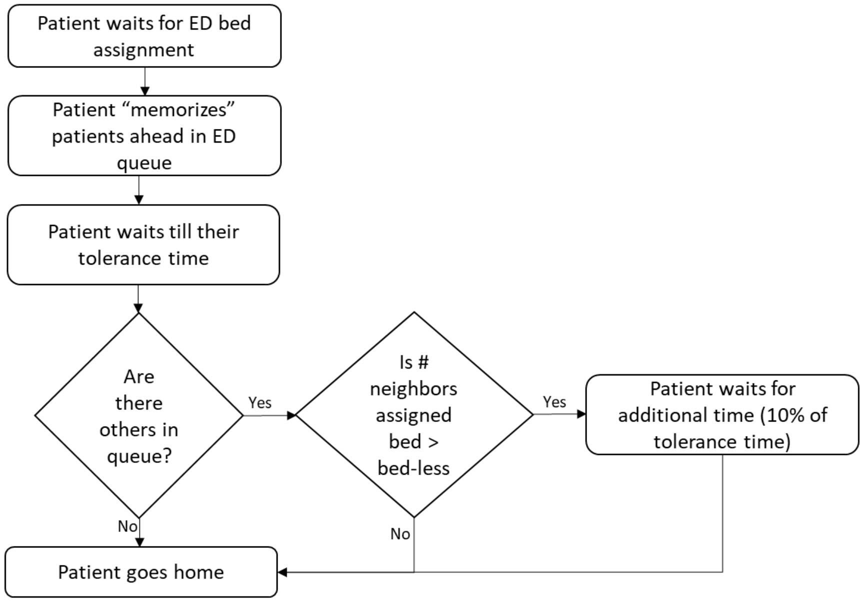

Figure 3-2: Patient LWBS Decision Process modeled using ABS

Note that while the second model (DES) does not consider clinical task priority or bed-cleaning, it does consider LWBS but it is modeled in the typical discrete-event model fashion of queue abandonment using the same waiting tolerance numbers as DES+ABS. The tolerance numbers were sourced directly from Shaikh et al.'s survey of LWBS patients [31]. The study highlighted that most patients (51% and 32% respectively) are either willing to wait up to 2-hours for service or wait infinitely, 17% of patients will wait for times between 2-hours and 8-hours. We convert this behavior into a custom distribution in our model. In DES model, we also break down resources a little more than In literature but less than in DES+ABS model. In DES model, we simply model the use of imaging tests or laboratory tests and aggregate all other resource use into one bucket, rather than breaking into specific permutations like imaging and testing vs testing only. Note that in both models, we model explicitly the use of consultants given their noted impacted on patient length of stay [28].

3.3.2.4 Verification & Validation (V/V)

We perform V/V before we begin using the model to assess results. Verification and validation help us determine if a model and its results are appropriate for a specified application. Verification focuses on ensuring that the implementation of the model using AnyLogic is correct (e.g., no logical errors), while validation focuses on ensuring that the model's results are within a reasonable range of accuracy consistent with the intended application of the model [32].

Model verification was done by manually reviewing outputs at each process step where Java programming was used or AnyLogic default settings were updated, to ensure that the model behaved as expected. Additionally, the models were run for varying lengths of time (1 – 45 simulated days) to ensure that no errors were generated as the model became larger.

Given our unique data collection method, it was not possible to perform model validation in the typical method of comparing simulated output to real/observed output. Thus, for our study, we leverage metamorphic validation, an enhancement to the software testing technique metamorphic testing. Introduced by Olsen and Raunak [33], metamorphic validation calls for the design of metamorphic properties for the simulation model type (DES/ABS), followed by the description of metamorphic relations (MR), which are definitions of changing behaviors given changes in the model design or its parameter and finally conducting experiments to test the MRs.

The validation experiments focus on the impact to the following metrics suggested by the ED SME panel: patient length of stay in the ED from arrival to departure (LOS), number of patients that left prior to being assigned a bed (LWBS) and bedside nurse utilization.

We use the metamorphic validation methodology for hybrid models described in the research dissertation put forward by Farhan [34]. This method allows us to validate the individual DES and ABS sub-models as well as the overall model. As such, we conduct experiments on the DES model independent of ABS workflows by turning off the ability of the ABS model to enact changes to the DES model flow. In this case, we are still able to count how many people make the decision to leave; however, the patients still remain in the system and use ED resources which does influence the model as ED is filled with more people than usual.

Table 3-2: Metamorphic Relations.

Category	Code*	Parameter or Property	Type of change	Expected Answer	Experiment Answer
D1 - Resource	DES1	Number of bedside nurses	Increase: Add 1 nurse (under 3 different patient arrival patterns in DES2)	LOS decreases, LWBS decreases, UTIL decreases	Both Models: LOS decreases, LWBS decreases, UTIL decreases.
D2 – Process Parameters	DES2	Inter-arrival time for patients	Increase: Add 1 to each hour between 9am – 9pm; add 1 to each hour, add 2 to each hour	LOS increases, LWBS increases, UTIL increases	UTIL stays flat (DES+ABS). UTIL increases (DES). Both Models: LOS increases, LWBS increases,
	DES3	Delay time for single service block (lab results waiting time)	Increase: Add 1, 2 & 3 mins to each parameter in triangular process time	LOS increases, LWBS increases, UTIL stays flat	Both Models: LOS increases but stays relatively flat between 2 and 3mins. LWBS increases. UTIL stays flat.
	DES4	Number of admitted patients pulled hourly	Increase: Add 1 patient to each hour (under 3 patient arrival patterns in DES2)	LOS decreases, LWBS decreases, UTIL increases	Both Models: LOS decreases. LWBS decreases. UTIL increases.
D3-Workflow Steps	DES5	Combine service blocks	Simulate physician-in-triage by combining triage nurse and initial physician assessments under DES2 conditions	LOS decreases, LWBS decreases, UTIL decreases	Both Models: LOS decreases, LWBS decreases, UTIL decreases.

A4- Interactions between agents	ABS1	Ratio of bedded to bed-less neighbors	Increase: Increase ratio from >1 to ≥1.5 and ≥1.9 (under 3 patient arrival patterns in DES2)	LOS increases, LWBS decreases, UTIL stays flat	<u>DES+ABS only</u>: LOS increases. LWBS decreases. UTIL stays flat.
A5 – Interactions between agents and environment	ABS2	Waiting Tolerance Time	Decrease: Reduce the minimum waiting tolerance time to 60mins and 90mins (under 3 patient arrival patterns in DES2)	LOS decreases, LWBS increases, UTIL stays flat	<u>DES+ABS only:</u> LOS decreases. LWBS increases. UTIL stays flat.

* Note: DES coded MRs are for the discrete-event model, and ABS coded MRs are for the ABS model.

Table 3-2 shows the results of the validation process. The categories D1 – D3 and A4 – A5 are property categories suggested in [33]. We assess the results by checking for the trends expected [34]. Both our models behave as expected and similarly in general. We notice that when more patients are added to DES+ABS, nurse utilization stays relatively the same. This may be attributed to the fact that our LWBS patients do not leave the ED and as such, they have already saturated bed occupancy, thus leaving no real room for patient growth for the nurses. Also, for DES+ABS, similarly for DES3, the model behaves as expected and an increasing trend is observed but only up to the addition of 3-mins. When 3-mins are added to the lab processing time, there is no increase observed in LOS compared to LOS when 2-mins were added. DES model shows increases across all time additions, but the increases seen from 2-mins to 3-mins is 80% lower than the increase seen from 1-min to 2-mins. This could suggest that when it comes to lab processing times, there might be a saturation point with reduced impact on LOS. Patients that are admitted are more likely to use lab resources and their LOS is largely dependent on inpatient bed availability not lab processing times. Reviewing the results with the ED SME panel, the behaviors from both models are similar to what is expected from a real system, so we conclude that our models are reasonable representations of a real ED system.

3.3.2.5 Simulated Scenarios

Three experimental scenarios were run for each model: one scenario is the base scenario where the models are run with no changes to simulate the normal behavior of our case ED. For the other two scenarios, we look at different ED crowding management scenarios as prescribed by Emergency Medicine Practice Committee [35]. These kinds of scenarios can be used to study how to relieve boarding as part of reducing ED crowding. The two scenarios are: (1) increasing the number of ED beds by 5 and (2) moving the inpatient discharge time to 8am – 4pm.

Prior to running the experimental scenarios, we used Welch graphical method [36] to determine the appropriate warm-up which will ensure that we remove any bias introduced by the initial model states. The method showed that at 14 days, the ED bed utilization reached a steady state. In our subsequent model runs, we discarded all metrics collected prior to the 15th day and ran the models for an additional 7 days (i.e., total model run length is 21 days).

3.3.3 Comparison Between the Models

To gain an understanding of the ED performance, the metrics in Table 3-3 were recorded at the end of each simulation run. The values of each output metric were averaged over 30 replications for each experimental scenario [37]. The values from both models were compared to each other using the non-parametric Wilcoxon Signed-Rank Test [38]. We aim to assess if there is any difference in our population medians. Our data samples are independent but the differences between the medians do not appear to be consistently normally distributed across all outputs, so we use the non-parametric test instead of the paired Student's t-test.

Table 3-3: ED Performance Metrics

Metric	Definition
LOS	Average time in minutes a patient spends in the ED from arrival to departure either to their home or the hospital
ALOS	Average time in minutes an admitted patient spends in the ED from arrival to departure to the main hospital
Board Time	Average time in minutes an admitted patient waits for an inpatient bed after their inpatient bed request has been placed
DLOS	Average time in minutes a discharged patient spends in the ED from arrival to departure home
Bedside UTIL	Average utilization of the bedside nurse
LWBS	Average number of the patients who leave the ED before being assigned a bed as a proportion of total number of patients who entered the ED
Bed Wait Time	Average time in minutes that a patient spends waiting to be assigned a bed from arrival

We design our comparison experiment by treating DES model as a control group and DES+ABS as the treatment group where the additional details (ABS, resource utilization, bed cleaning and task prioritization) represent the variable being tested. For testing the differences between our test and control model outputs, we define the following hypothesis [39] and test for $\alpha = 0.05$ using the Wilcoxon method from the SciPy library for Python 3.0:

$$H_0 \rightarrow\ (A_i, B_i)\ are\ exchangeable\ i.e.\ (A_i, B_i)\ and\ (B_i, A_i)\ have\ the\ same\ distribution$$

$$H_1 \rightarrow for\ some\ \mu \neq 0, the\ pairs\ (A_i, B_i)\ and\ (B_i + \mu, A_i - \mu)\ have\ the\ same\ distribution$$

3.4 Results

Base Scenario: When the ED process is run with no change to the basic simulation inputs, 5^{th}, 50^{th} and 95^{th} percentiles values of the ED admit throughput observed through DES+ABS were respectively 497, 517 and 546 while the values from DES were respectively 497, 523 and 551 patients. The 5^{th}, 50^{th} and 95^{th} percentiles of the ED discharge throughput observed through DES+ABS were respectively 869, 917 and 959 while the values from DES were respectively 878, 925 and 984 patients. We see that our DES+ABS model has slightly higher throughputs.

The results of our Wilcoxon tests show that except for LWBS, we reject the null hypothesis that DES and DES+ABS outputs are interchangeable (Table 3-4). DES predicted considerably longer patient length-of-stay times for both admitted and discharged patients compared to DES+ABS (Table 3-4). Patient boarding times were different for both model types, with DES predicting longer times waiting for an empty inpatient bed (Table 3-4). There was also a significant difference in the utilization of bedside nurses, with DES+ABS predicting that nurses are much busier than in DES. The only insignificant difference between both models is observed with LWBS even though DES predicts slightly less LWBS rates than DES+ABS (Table 3-4).

Add Bed Scenario: When the ED's capacity was increased by 10% (i.e., 5 additional beds), we observe similar results as the base scenario in terms of the significance of the differences between the models (Table 3-4). We see that LWBS is reduced to at least a third of the base model's values in both models and that the difference between both models is still insignificant (Table 3-4). The one oddity observed is that while both models show an increase in LOS in general compared to base model, the discharge LOS in DES is lower than observed in the base model (Table 3-4). Similarly for bed wait model, we observe that bed wait time in DES is lower than that observed in the base model.

Discharge Timing Scenario: In this scenario, when we move the start of the hospital discharge early and uniformly distribute the number of beds available per hour, we observe that the differences between both models for the outputs LWBS and Board Time are insignificant (Table 4). The remaining outputs are deemed significant from the hypothesis testing. Across the board, all the observed values are higher than observed in the base model.

Table 3-4: Results from Experimental Simulation Runs

Scenario	Metric	DES+ABS	DES
Base	LOS	205*** (192 – 221)	250 (222 – 282)
	ALOS	392*** (360 – 423)	443 (403 – 479)
	Board Time	283* (253 – 314)	297 (269 – 315)
	DLOS	104*** (97 – 113)	149 (120 – 174)
	Bedside UTIL	80%*** (77% – 82%)	60% (59% – 61%)
	LWBS	1.9% (0.4% – 4.7%)	1.4% (0.1% - 4.2%)
	Bed Wait Time	14*** (13 – 15)	23 (16 – 32)
Add 5 more beds	LOS	209*** (195 – 229)	251 (233 – 281)
	ALOS	399*** (370 – 432)	445 (411 – 486)
	Board Time	289** (264 – 318)	306 (274 – 325)
	DLOS	106*** (102 – 117)	145 (129 – 169)
	Bedside UTIL	81%*** (79% – 82%)	61% (59% – 62%)
	LWBS	0.5% (0.02% - 4.2%)	0.4% (0.02% - 3.8%)
	Bed Wait Time	14*** (13 – 15)	19 (15 – 30)
Change discharge timing to 8am – 4pm	LOS	252*** (238 – 267)	344 (266 – 460)
	ALOS	531*** (500 – 565)	628 (535 – 750)
	Board Time	439 (403 – 469)	447 (409 – 487)
	DLOS	92*** (85 – 95)	184 (124 – 286)
	Bedside UTIL	81%*** (78% – 82%)	65% (63% – 67%)
	LWBS	9.6% (6.4% - 14.5%)	8.4% (2.8% - 16.5%)
	Bed Wait Time	18*** (14 – 19)	61 (29 – 126)

Model results are shown as median of output values followed by 5th and 95th percentiles.
*** refers to a p-value <0.001,** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

3.5 Discussion

Generally, we observe that DES, our control model, showed longer patient length-of-stay. The tendency for DES to predict longer LOS across all patient types is interesting and unexpected given that there is no extra time for bed cleaning which added at least 4-mins to the time to get a bed assigned. We posit that this tendency is due to the difference in modeling choice for our clinical resources (doctors and nurses). In DES+ABS, our clinical resources prioritize tasks to turn patients out of beds quicker and use this to decide which patient to attend to (aside from patient criticality which is accounted for in both models). For example, a non-critical patient with a lower priority begins waiting for a bedside nurse at 10:00am and another non-critical patient with a higher priority starts waiting at 10:05am; in DES+ABS, once a bedside nurse becomes available, the 10:05am patient will be attended to first. In DES however, the patient who was waiting at 10:00am will be attended to first. Focusing on the discharge LOS where process times are the biggest influence, we see that LOS variability is larger in DES compared to DES+ABS likely due to this first-come-first-served priority as any non-critical patient at any stage in the process path can pull a clinical resource if they arrived in the resource waiting queue ahead of another patient.

The effect of this prioritization policy is particularly evident in the differences between bed wait times. DES+ABS' bed wait times are lower and more consistent than DES' bed wait time across all scenarios since DES+ABS prioritizes getting patients out of beds quicker. Also, it is likely that the observed difference in boarding time, even though the inpatient hospital pulls in the same number of patients at the same time in both models, is related to this modeling choice as patients in DES likely enter the inpatient admission queue at later times than in DES+ABS, meaning that they are more likely to wait until the next inpatient pull period.

We observe that both models do not have significant differences in LWBS rates. This is particularly interesting given the stark differences in modeling styles. DES+ABS attempts to mimic the human interaction with their environment and the impact on the decision-making process while DES uses the common method of modeling queue abandonment after a specified time. The result shows that the additional complexity of leveraging ABS techniques for LWBS decision does not necessarily offer any additional value as it relates to the LWBS metric. However, this does not mean that ABS module does not have any influence on the overall model behavior. Studies specific to the influence of the ABS module will be useful to definitively conclude.

Another interesting observation is that nurse utilization is considerably lower in DES vs DES+ABS, despite similar throughputs from both models. This discrepancy however could be explained by our modeling choice for the resource use. In DES, patients' resource use is captured as mutually exclusive in this manner: 1) no resource use at all, 2) use of imaging resources, 3) use of testing resources or 4) use of other resources. However, in DES+ABS, there are more permutations for resource use as we consider resource use independent (e.g., use of imaging and IV vs use of only imaging or use of all three resources.) Each resource use involving the nurse has a specific time for applying each resource i.e., the time to deliver POC tests and IV is the sum of the times to do each task. This modeling choice allows us to capture more precise service times rather than generalizing service times and thus impacts how much time a nurse spends with an individual patient. In DES, since we assume that any patient that requires imaging only uses an imaging resource (which still allows us to capture similar wait times as DES+ABS for results processing), as such the nurses in DES perform less tasks, leading to lower utilization.

When we tested the different boarding management policies, our models generally agreed on the implications to ED performance metrics. When the ED was physically expanded by 10% with no other changes, we observe that its performance deteriorated compared to the base scenario. Overall, LOS did not improve but increased slightly in both models. A slight disagreement between models was observed here. While LOS increased for both models, for DES, there was a decrease in median discharge LOS that was not observed in DES+ABS. A similar disagreement is observed with the bed wait time metrics. In DES+ABS, the bed wait time remains flat but in DES, the bed wait time is reduced compared to the base scenario. This reduction in wait time is likely why the discharge LOS is reduced as discharged patients, who are unencumbered by waiting for inpatient beds, spend a little less time waiting. The lack of change in DES+ABS' bed wait time highlights that the wait time is a consequence of other process considerations like flow management and clinical resource availability, not just physical availability of beds. Regardless of this difference in wait times, both models agreed that the bed capacity increase reduces the LWBS by ~70%, an expected result since there are more beds for patients to be assigned. Our results aligned with the Han et al. study on the effect of ED capacity expansion on crowding [40], where it was observed that increasing the bed capacity increased both LOS and boarding times but reduced LWBS.

One strategy suggested to reduce boarding is to change discharge times. Khare et al. [41] recommends changing hospital inpatient discharge times from 8am – 4pm with uniform discharge volumes. In their study, this delivered a 96% reduction in boarding hours. When we made this change to our model however, we observed the opposite effect in both models. The change deteriorated the performance of our ED in both DES and DES+ABS. Boarding times, LOS, LWBS, bed wait times and nurse utilization increased in both models. One noteworthy observation is that in DES+ABS, there is a reduction in the discharged LOS compared to the base scenario. The most likely reason for this observation is that there are high levels of patients leaving the model, at least 6%, forcing a reduction in the LOS for discharge patients. A comparable change in ALOS is not noticed because the LOS for any admitted patients who chooses not to leave will always be more influenced by boarding times. We also observed that the increased boarding times in both models are high but not significantly different. Another noteworthy observation is that in DES specifically, we observe that the variability has increased greatly compared to the variability of the metrics in the base model. While it is unclear why this variability has increased, it is obvious that the change in the discharge times causes DES performance to be less predictable. The observed reduced performance due to this discharge timing change does not mean that such a change is unimpactful to boarding. It is possible that our ED already has the optimal discharge timing or that there are other discharge timing configurations that work better for our ED.

Overall, our models agreed on the outcomes of the management policies enacted; neither is good for improving the performance of our specific ED regardless of the model design used. With that said, we observed that there were significant differences in the output metrics from each model design even though the general result is the same for both models. This indicates that the choice in model design has an influence on the results we get, but that ultimately both designs are sufficient for studying ED performance.

Unfortunately, we cannot make any conclusion on which model design is better using these results. Given the closeness of the results, we would need to compare the outputs of both models to actual observed data and determine which is closest. In consulting with SMEs on the results of the simulations however, they state that DES+ABS' outputs are closer to the observed reality of their existing EDs across all metrics. They also stated that DES' outputs are also reasonable but that the nurse utilization was not reflective of reality. Neither model design consider breaks or additional tasks that nurses perform which is adds 10% utilization. For DES, when this is considered, utilization is still ~70%, far below the ~90% utilization that SMEs experience today. This means that while our DES model may be useful for understanding ED performance for measures like LWBS, it is not a good design for research focused on bedside nurse utilization.

When conducting any modeling exercise, it is also worth considering the effort to develop the models and to decide on a trade-off for accuracy. For this research, including the additional details in DES+ABS added 6-hours to our data collection, model development and validation time compared to DES-only model. Given that our research focuses on boarding management and its impacts on LWBS, LOS and nurse utilization though, this additional effort was deemed worthy.

3.6 Conclusion

In this study, we investigated whether a more complex/detailed model design creates a different representation of an emergency department that aims to study boarding and ED crowding in general compared to a less complex model. To do this, we modeled a fictional California ED using two different model designs. We used a fictional ED as we could not collect real data due to the COVID pandemic. We alternatively collected data from literature and interviews with ED personnel on their pre-COVID experience. We then leveraged metamorphic validation to ensure that our designs were representative of a real system. The validation showed that both designs are good representations.

We compared the behaviors and outputs from both model designs using statistical experiments. These experiments compared both designs in three scenarios, one base scenario and two scenarios focused on changes that are expected to reduce the impact of boarding. The experiments highlighted that the more complex model yields statistically different outputs versus the simpler model except for LWBS, highlighting that either model will produce the same result in a study specific to LWBS but not the remaining outputs. Review with SMEs revealed that our more complex model is closer to observed reality since its bedside nurse utilization is more similar to reality than the simpler models. However, we could not conclude in this study, which design is closer to reality since we did not compare model output to real data.

Our analysis related to reducing boarding revealed that our more complex model was more predictable when hospital discharge timing changed, a key boarding reduction strategy was applied, suggesting it to be a more reliable model for testing different scenarios related to boarding. Unless data shows that our simpler data does not mimic real/observed data well, it may be a reasonable design for other ED studies. From a practical point of view, our complex model requires more data collection efforts than our simpler model. While both models are flexible, the simpler model is arguably easier to apply structural changes to than the complex model.

In general, our study agrees with existing literature that the right model design for a problem should be one that is parsimonious for that problem. For instance, our work showed that to study LWBS, it may not be necessary to model the complexity of human decision-making via ABS, using simple queue timeout as part of a DES model likely suffices. To study nurse utilization though, it may be necessary to include task prioritization that nurses do as part of their work to get an accurate view.

For future work, we would like to make our study more robust by including statistical analysis comparing to observed data. We would also like to study the individual impacts of each "detail/complexity" added to our complex model by comparing to the "simpler" model. This will allow us to conclusively decide what level of complexity/what specific detail is needed for a better representation of the real system.

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CHAPTER 4: PREDICTING EMERGENCY DEPARTMENT BOARDING LEVELS AS A MEASURE OF CROWDING

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4.1 Introduction

Emergency Department (ED) crowding occurs when there are insufficient resources to meet the demands for emergency services. Given the unpredictable nature of emergency services, ED crowding is an expected outcome. The COVID-19 pandemic highlighted the fragility of this system as governments around the world worked to limit ED crowding and corresponding strain of these emergency services. But even before the pandemic, it was reported that more than 90% of EDs in the United States are often overwhelmed [1]. Expected or not, ED crowding has detrimental effects inclusive of poorer patient outcomes, higher costs and the inability of staff to adhere to guideline-recommended treatment [2]. Hospital administrators, physicians, nurses, and academic researchers have been studying this problem for decades. Prior to solving any problem, it is important to measure the problem accurately. A systematic review revealed more than 2000 studies related to ED crowding measurement; the authors thoroughly reviewed over 100 studies and identified eight ubiquitous measures [3]. These measures include ED occupancy, ED length of stay (LOS), ED volume, ED boarding time & count, waiting room count, National ED Overcrowding Scale (NEDOCS) and Emergency Department Work Index (EDWIN). These measures are used by ED administrators and staff to assess the status of their ED and decide on reactive strategies (e.g., ambulance diversion). However, these measures are not predictions of future state but rather expressions of current state and as such, can easily be used to take proactive action. Additionally, five of the eight measures are focused on number of people attending the ED. Only the ED LOS and boarding counts & times explicitly consider the impact of waiting for a hospital bed to be available for admitted patients (i.e., boarding). This is relevant as other studies have established that boarding is the most influential cause of ED crowding [4]. Note that there are many definitions of boarding across literature, typically defined across different time points (e.g., 2 hours after admit decision) [3]. For our study, we use the American College of Emergency Physicians' definition which states that boarding begins once an admit decision has been made for a patient [5].

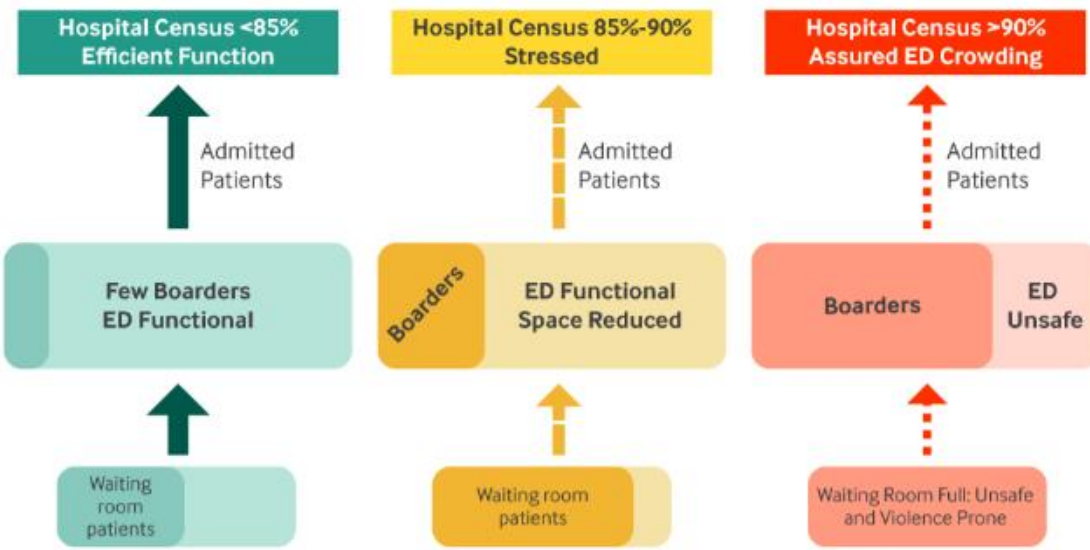


Figure 4-1: Impact of Boarding Admitted Patients on ED Function [6]

Figure 4-1 illustrates why understanding and planning for boarding levels is impactful to ED function and ultimately patient satisfaction. When the hospital cannot pull in patients from the ED and they "board" in the ED, it reduces the ED capacity, thus increasing the wait time for new patients to get serviced leading to stressors for staff.

In this study, we introduce a new predictive ED crowding measure focused on future boarding counts that aims to serve as an early warning indicator for ED crowding. The goals of this study are twofold. Firstly, we want to understand what easily accessible factors can be used to predict future boarding levels. And secondly, we evaluate the feasibility of predicting how crowded an ED will be in several future time steps by predicting boarding levels specifically, which is one of the most influential factors for crowding.

The rest of this paper is organized as follows. “Related literature” reviews the relevant literature while “Predictive Analysis” presents the data used in the analysis and discusses the prediction strategy. “Results” presents the results of our predictive analysis. “Discussion” discusses the main findings and potential implications for ED management as well as clarifies the limitations of our study. Finally, “Conclusions” provides some conclusive considerations and future work.

4.2 Related Literature

Creating early warning signals for ED crowding has an important healthcare research area in the last two decades. Over a decade ago, Weiss et al. introduced the NEDOCS score for assessing the ED crowding level using statistically relevant predictors highlighted by a mixed effects linear regression model [7]. Emergency Department Work Index (EDWIN), a slightly older index, measures ED crowding by focusing on the number of patients in the ED as a ratio of resources available to serve the patients (physicians and licensed beds) [8]. More recently, Severely overcrowded-Overcrowded-Not overcrowded Estimation Tool (SONET) was developed to more accurately estimate crowding in high volume EDs avoiding NEDOCS’ tendency to overestimate severely crowded status [9]. These signals provide invaluable insight to the ED status and may allow administrators to avoid full crisis modes, but they are not predictive in-nature.

More recently, predicting/forecasting ED crowding levels has been more thoroughly studied by clinicians and researchers. There have been studies predicting ED crowding as a measure of ED volume [10] [11] [12] [13], daily occupancy rate [14] [15] [16], ED LOS [17], patient wait times

[18] [19] and so on. A variety of techniques are leveraged in creating these forecasts including simulation [20] [21]. However, the most common technique for making these predictions are traditional univariate time series (e.g., [11], [12]) and multivariate time series (e.g., [15], [16]). The application of non-time series focused predictive models such as regression, decision-tree modeling, deep neural net learners and others is also becoming prevalent in literature (e.g., [10], [13], [18]). Regardless of the methods used, these studies have highlighted the ability to predict ED crowding ahead of time providing stronger warning signals that administrators can leverage well before getting into overcrowding scenarios. For instance, Hoot and Aronsky [22] investigated the use of logistic regression and recurrent neural net models to predict ED ambulance diversion status an hour into the future. The study compared the predictive power of these forward-looking models to the NEDOCS and EDWIN scores in the validation time period, concluding that the use of these models will provide early warning signals given their higher predictive power over NEDOCS and EDWIN.

In our review of literature, we came across many indicators for ED crowding like ED LOS, ED volume, etc., but there are only a few papers explicitly predict boarding despite the influential nature of boarding on crowding. Hodgins et al. [23] uses logistic regression to investigate the operational, clinical and personal factors that whether a patient will board for more than 2hrs, without focusing on the use of the prediction to measure ED crowding. They identified 6 key factors significantly associated with boarding for more than 2 hours, including day of presentation, patient age and so on. Ding et al [24] use quantile regression to perform similar analysis to understand factors that influence boarding times. Hoot et al. [21] predict future the number of boarding patients (up to 8 hours ahead) using discrete-event simulation, specifically predicting boarding, and waiting counts as well as occupancy rates. Similarly, Asaro et al [25] predict a variety of process throughput times in the ED including boarding times, focusing on understanding how different types of factors (patient-specific and system-specific) contribute to predictive performance. Our study contributes to the understudied field of predicting boarding. We assess the viability of predicting the number of boarding patients several hours ahead using different types and combinations of variables.

4.3 Prediction – Materials and Methods

4.3.1 Study Design and Setting

The COVID-19 Pandemic put a strain on medical systems globally and made it difficult to conduct non-urgent studies. To source data for our analysis, we developed a detailed agent-based simulation of an ED and collected data from the model. The study ED is an urban, medium volume, non-teaching community hospital, with ~78,000 ED visits annually. It is attached to a 385-bed hospital and the hospital plans for ~300 beds for non-ED related visits like elective surgeries. The ED has 49 treatment spaces in total, 29 fully monitored beds (4 are designated specifically for trauma care/resuscitation) and 20 additional treatment spaces, typically hallway beds or chairs/recliners.

The primary outcome for the study was the hourly number of patients waiting in the ED after being admitted to the hospital (i.e., boarding patient counts). A patient is identified as a boarding patient once the admission order has been put in with the hospital. We collected the boarding counts at the end of the 24h of each day. We did not include a time restriction because there is no consensus on the right amount of waiting after admission decision. Ultimately, capacity, and other unique characteristics of an ED dictate how much waiting time is detrimental to its function. Our outcome is easily customizable to any specific ED's definition.

Aside from boarding patient counts, we collected the count of patients being processed at all stages of the ED process e.g., registration, triage, laboratory testing, etc. We collected patient specific information such as their chief complaints to check for interactions with queue counts. All these variables are used to create the department-wide predictor variables.

4.3.2 Data Analysis

45days of data corresponding to 1,080hours were extracted from the simulation model for prediction after the appropriate simulation warm-up period. Data analysis was carried using various Python 3 packages. Initial graphical analysis revealed that hourly boarding counts have hourly and day-of-week effects as seen in Figure 4-2. We observed that the period from 11pm to 8am (next day) has the lowest number of boarders. We also see that the weekend (Friday – Sunday) has a smaller number of boarders with Mondays being the busiest of days. Our observations are like those observed by Hodgins et al. [23], bolstering the efficacy of our simulation data.

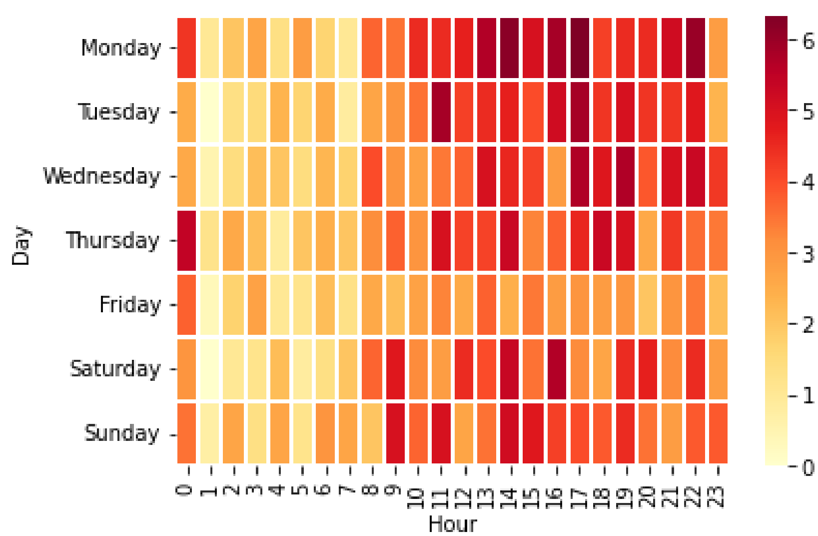


Figure 4-2: Hourly/Daily Heatmap representation of boarding counts for study data

We further process the simulation data and create predictor variables using queue counts and patient characteristics as well as the utilization of key nurses and physicians. We examined the correlations between current boarding counts and these predictor variables in Figure 4-3. Specifically, the predictor variables are of two types. For the first type, we count the patients in each major process step as variables e.g., #PtsAwaitingScan. For the second type, we count patients based on two characteristics (chief complaint and criticality of care) in two main parts of the process where these characteristics may be influential: waiting for next resources after initial doctor review (e.g. #PtsInjurySeenByDoc) and waiting for initial bed assignment, respectively (e.g. #PtsESI3AwaitingEDBed).

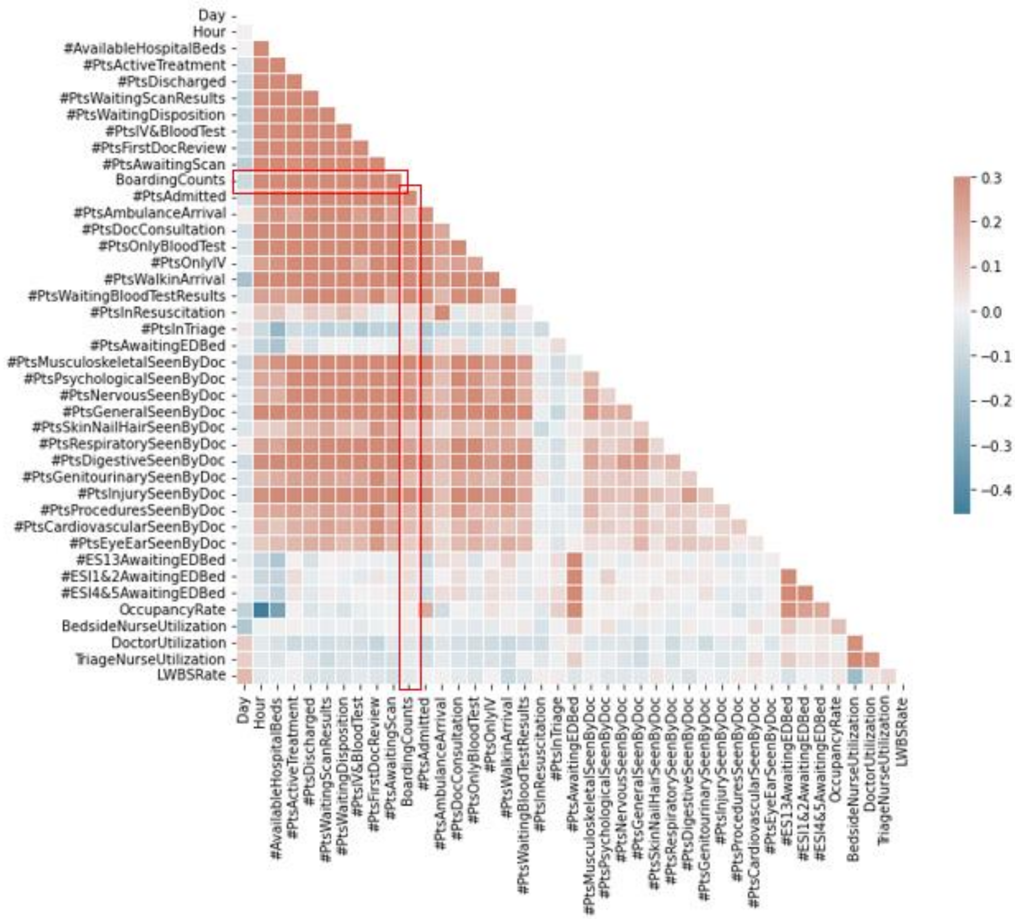


Figure 4-3: Boarding Patient Counts Correlation Analysis

We see that boarding counts have positive correlations with some of these variables such as patients arrived by personal transportation (walk, bus, car, etc.). or ambulance, patients waiting for queues related to imaging tests as well as patients with certain complaints like digestive or musculoskeletal issues that have already been seen by the doctor. However, current boarding counts are not correlated to the current utilization of any clinical staff or rate of patients leaving the ED without being seen. The correlation analysis sheds light on the temporal effects; we see positive correlation with time of day but very weak negative correlation with the day-of-week.

4.3.3 Predictive Analysis

We aim to predict the count of boarding patients in future time steps so naturally our problem presents itself as a time series forecasting problem. However, our literature review showed that other approaches work for time series predictions like regression. Thus, we will examine some of these approaches to test their predictive ability for our problem.

4.3.3.1 Performance Measurement

Across all models that were trained for our forecasting problem, we compared prediction performance by analyzing testing errors and investigating how well the model explained the variance observed in our target variables (i.e., goodness-of-fit). We focused on four metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE) and coefficient of determination (R-sq). The formulas for calculation are shown below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \ ;$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \ ;$$

$$\text{MASE} = \frac{MAE\ calculated\ for\ current\ prediction}{MAE\ calculated\ for\ predictions\ using\ a\ naive\ method} \ ;$$

$$\text{R-sq} = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2}$$

Where y_t is the observed boarding counts in the specific hour t; $\hat{y}_t$ is its corresponding forecasted value, n is the number of hours being forecasted and $\bar{y}$ is the mean of the observed actuals across n. For MASE, naïve forecast method typically refers to a one-step ahead forecast where forecast is simply the last observed value i.e., $\hat{y}_t = y_{t-1}$.

These metrics were found to be used across literature for assessing predictive capability. We did not use Mean Absolute Percentage Error (MAPE) because it gives infinite or undefined results when one or more time series data point equals 0, which is naturally occurring in our dataset (i.e., when there are no boarding patients in the system).

Performance reported in this study was based on predictions on a test data set. The data collected was split into a training set and a test set. The test set represents the last week of data in the dataset that remains unseen by the forecasting models. As part of training, model parameters are tuned to identify the optimal parameters that minimize the different loss functions for each model.

4.3.3.2 Regression Approach

We assessed the ability of three regression-based models to predict future boarding counts. These models include Elastic Net Regression, Random Forest Regression and XGBoost. Specifically, the XGBoost models were tried after our first set of experiments revealed that Random Forest provided good predictions. Since we aim to understand the factors impacting our target variable, we opted for these models for their ability to provide feature relevance. Additionally, these models can deal with any issues related to correlation among our input variables which is highly likely given the ED process.

Elastic Net Regression is a regularized linear regression technique that improves model predictiveness by constraining or shrinking the regressor coefficient estimates towards zero, discouraging learning a more complex or flexible model and thus avoiding overfitting. Prior to elastic net, regularization occurred by adding a penalty term either equal to square of the magnitude of the coefficients (ridge regression) or equal to absolute sum of the coefficients (lasso regression). Both methods have their limitations; to overcome these, Zou and Hastie [24] introduced elastic net, a method that adds both ridge and lasso penalty terms, which overcomes the individual limitations of lasso or ridge.

For this problem, we have a multivariate linear regression model in which we observe $Y = X\beta + e$ where Y is the matrix of the boarding counts in the specified future time step; X is a matrix containing the various covariates; β is the unknown sparse coefficients matrix and e is the matrix of errors. Rather than using regular least squared estimators to estimate β, we use a regularized estimator that includes both lasso λ_1 and ridge λ_2 penalty terms:

$$\hat{\beta} = \ arg\min_{\beta}(\|y - X\beta\|^2 + \lambda_2\|\beta\|^2 + \lambda_1\|\beta\|_1)$$

Random Forest Regression is a technique where multiple decision trees are "bagged" as part of the prediction process [25]. During the model learning process, a random sample of the training set made up of Y and X as previously described is selected and a regression tree (f_b) is trained on that sample. This process is carried out B times such that each time another random sample is selected with replacement from the training set. After training, final predictions are made by averaging the predictions of all the individual regression trees:

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x)$$

Extreme Gradient Boosting (XGBoost) is an implementation of gradient boosted decision trees introduced by Tianqi Chen to execute the boosting process in a fast and resource-efficient way. Unlike bagging in Random Forest, the boosting process leverages results from the previous decision trees (weak learners) by minimizing a loss function iteratively until the most optimal learner has been identified.

An initial weak learner is created using the training set where are gradients $g_m(x_i)$and hessians $h_m(x_i)$calculated for the data set X, Y. The optimization problem in (1) is solved and the overall model across m weak learners is updated with (2). The final model (3) is the strongest learner.

$$\hat{\phi}_m \ = \ arg\min_{\phi\epsilon\Phi} \textstyle\sum_{i=1}^{N} \frac{1}{2} h_m(x_i) \left[-\frac{g_m(x_i)}{h_m(x_i)} - \phi(x_i)\right]^2 \quad (1)$$

$$\hat{f}_m(x) = \alpha\hat{\phi}_m(x) \quad (2)$$

$$\hat{f}(x) = \hat{f}_M(x) = \sum_{m=0}^{M} \hat{f}_M(x) \tag{3}$$

Unfortunately, none of these models can predict a sequence of future values and as such, the data had to be preprocessed with dependent variables created. We wanted to investigate how far into the future we can predict so we created four dependent variables of boarding counts looking 1-hour, 2-hours, 4-hours, and 6-hours ahead. These dependent variables were then regressed against different independent variables which were scaled using their means and standard deviations. Each model was tuned to find optimal parameters as described in 4.3.3.1.

In the first set of experiments, we regress against the operational and personal characteristics mentioned in section 4.2. In the second set of experiments, we included time-based variables which were different lagged variables for two operational variables: boarding counts in the three previous time steps and number of patients pulled in by the hospital in the three previous time steps. Across both experiments, we leveraged cross-validation techniques to estimate the performance of each model during the parameter-tuning process on unseen data sets; this is impactful so that the model parameters that are selected are the ones most likely to predict well on unseen data sets. Specifically, we use a variant of 5-fold cross validation. This variant uses train/test indices to split time series data samples that are observed at fixed time intervals, in five train/test sets. In the *kth* split, it returns first *k* folds as train set and the $(k+1)^{th}$ fold as test set. Note that unlike standard cross-validation methods, successive training sets are supersets of those that come before them.

4.3.3.3 Univariate Time Series Approach

Univariate time series forecasting relies on the use of previously observed values of the target variable as the only predictor of future values. In this study, we use three algorithms to predict the boarding counts in future time steps as our target variable: Auto Regressive Moving Average (ARMA) and ExponenTial Smoothing or Error, Trend and Seasonal Model (ETS).

ARMA is one of the most common univariate forecasting techniques. The models typically consist of two polynomials for describing a time series. The first part, autoregression (AR), is a regression of the response variable on its own past/lagged values. The second part, moving average (MA), is a regression of the response variable on the lagged values of the errors from the AR model [26]. We can illustrate predicting future boarding counts using ARMA models as follows:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Where Y_t is the boarding count at time t, Y_{t-1} , which represents the lagged boarding counts, ε_t and ε_{t-1} are the error terms, p and q are the orders of the AR and MA part respectively and φ_i and θ_i are parameters for the AR and MA models, respectively. For simplicity, ARMA models are notated as ARMA (p, q).

If the data to be predicted is seasonal and the period is longer than monthly, then the ARMA models may not perform very well as they were designed for shorter periods. To assure effectiveness, we include the use of models that are better suited for more complex seasonality. One of such techniques is dynamic harmonic regression where Fourier terms are calculated for the seasonal data and added to the training data with a classic ARMA model. In such a model, the seasonal pattern is handled by the Fourier terms and the short-term time series dynamics are handled by ARMA errors [27].

ETS is the other most used forecasting technique. Also proposed in the 1950s, these models produce future forecasts as weighted averages of past observations, placing higher weights on more recent observations [28]. There are several permutations of these models depending on what components they focus on (e.g., trend, seasonal) and the method that they use to cancel the effect of random variation (e.g., additive, damped). The resulting models are state space models that describe the observed data and how the unobserved components or states, like trend, change over time [29]. ETS models are notated as ETS (T, S) where T and S define the trend and seasonal types respectively. Mathematically, ETS models consists of two main equations, the first is the forecast equations showing how the point forecast is calculated as a combination of the error corrections, while the second is the smoothing equation capturing how the errors are adjusted over the process. So, if we assume that boarding counts have additive seasonal components, we can use the equations below to illustrate the ETS (N, A) model.

$$Y_t = \ell_{t-1} + s_{t-m} + \varepsilon_t \tag{1}$$

$$\ell_{\mathrm{t}} = \ell_{\mathrm{t}-1} + \alpha\varepsilon_{\mathrm{t}} \tag{2}$$

$$s_t = s_{t-m} + \gamma\varepsilon_t \tag{3}$$

In (1), the forecast equation, Y_t is the boarding count at time *t*, ℓ_{t-1} represents the previous level of error correction and ε_t is the error term/residual. (2) and (3) are the smoothing equations where ℓ_t is the current level of error correction, s_t and s_{t-m} represent the seasonal components at time *t* and *t-m* respectively such that m is the length of seasonality; α and γ are smoothing parameters.

4.3.3.4 Multivariate Approach

Multivariate techniques involve the use of previously observed target values along with additional predictors that influence the target variable. These predictors, known as exogenous variables, are measured at time *t*. For multivariate forecasting in this paper, we use ARMAX models i.e., ARMA models that include exogenous variables (X). In this model, we regress but don't auto-regress on the variables; the ensuing model can be illustrated as

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{n} \beta_i x_t^i$$

This representation is the same as the ARMA one with terms related to the exogenous variables such that there are *n* exogenous variables x_t^i defined at each time step *t* with coefficients β_i.

4.3.3.5 Preliminary Analysis

Prior to applying the forecasting approaches, we need to understand the time series better so we can make the right model parameter decisions. First, we decompose the time series to check visually if our data has any trend or seasonal components. The second graph in Figure 4 shows that the trend component of our time series is almost straight with some spikes in the data, but nothing is indicative of a consistent trend. In the third graph, we see clearly that there is a seasonal component observed roughly every 24hrs. We further investigate this seasonality by creating a periodogram of our time series to identify the dominant periods. The periodogram confirms that 24hrs are the most dominant period as they have the highest spectrum (1140), and the next highest spectrum of 102 is 2.667hrs.

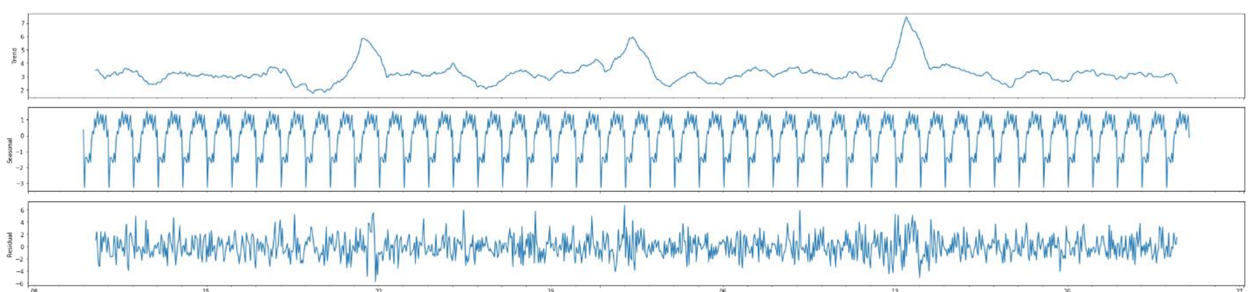


Figure 4-4: Boarding Patient Counts Time Decomposition

The seasonality observed needs to be considered; as such, we consider this in our implementation of the models. For instance, we implement SARMA, a variant of ARMA models that explicitly considers the seasonal component of our data. SARMA models are notated as $ARMA(p,q),(P,Q)_m$,where m is the number of observations per year; P and Q are the orders of the AR and MA parts for the seasonal component of the model respectively.

After understanding seasonality, we assess the stationarity of our data. ARMA techniques are built on the assumption that the underlying data is stationary, so we need to test for stationarity and make any treatments prior to forecasting. Note that ETS models do not make the same assumption.

Stationary data must satisfy three conditions: constant mean, constant variance, and constant covariance between periods of identical distance. To test, we leverage the Augmented Dicky Fuller (ADF) test where the null hypothesis is that the time series is not stationary. Conducting the test using the *statsmodels* python package, we get a p-value (2.9×10^{-5}) much less than our 5% significance level, allowing us to reject the hypothesis that our time series is not stationary. The implication of this result is that we do not need to make any treatments for stationarity during the modeling process like “differencing” for our ARMA models.

4.4 Prediction Model Results

4.4.1 Regression Results

We predicted the boarding counts 1, 2, 4 and 6-hours ahead using two different set of regressors; one set included 23-hour lagged features of the boarding counts (one for each previous hour). We tested the model performance by predicting on a test data set of one week and collected performance metrics. In Table 4-1, we observe that all models offer better predictive performance compared to simply using historically observed variables as observed in the MASE values <1. We also see that RFR model generally offers the best performance, typically providing better performance on at least two of four metrics. We see that using lagged features did not typically offer better performance for RFR and XGB models except for the ENR models, providing better performance for 1-, 4- and 6-hours prediction. We also notice from Table 1 that we have the best performances when predicting 1-hour or 6-hours ahead. Surprisingly, our worst predictive performance is observed in predicting 2-hours ahead. Overall, we had our best performance when predicting 1-hour ahead with the RFR model where we achieved the lowest RMSE (1.60) and lowest MAE (1.26) using no lagged features compared to XGB (1.72 and 1.35, RMSE and MAE respectively) and ENR (1.69 and 1.39, RMSE and MAE respectively). When we predicted more than 2-hours ahead, we observe that the ENR model performance dropped by almost half. RFR and XGB models performed similarly when predicting 2-hours and 4-hours, providing their worst performance compared to 1- and 6-hours predictions.

Table 4-1: Performance comparison of different regression models

Target	Feature Set	Model	MAE	RMSE	MASE*	R-sq
Boarding counts 1-hour ahead	All features but no Target Lags	**Random Forest Regression**	**1.259**	**1.604**	**0.655**	**0.374**
		XGBoost Regression	1.354	1.720	0.704	0.279
		Elastic Net Regression	1.386	1.696	0.721	0.300
	All features + Lagged Target	Random Forest Regression	1.262	1.607	0.656	0.372
		XGBoost Regression	1.530	1.720	0.704	0.280
		Elastic Net Regression	1.380	1.698	0.718	0.299
Boarding counts 2-hours ahead	All features but no Target Lags	Random Forest Regression	1.387	1.710	0.744	0.298
		XGBoost Regression	**1.361**	**1.723**	**0.731**	**0.288**
		Elastic Net Regression	1.432	1.729	0.769	0.282
	All features + Lagged Target	Random Forest Regression	1.386	1.716	0.744	0.294
		XGBoost Regression	1.379	1.696	0.740	0.309
		Elastic Net Regression	1.436	1.744	0.771	0.269
Boarding counts 4-hours ahead	All features but no Target Lags	**Random Forest Regression**	**1.340**	**1.660**	**0.592**	**0.339**
		XGBoost Regression	1.497	1.824	0.662	0.202
		Elastic Net Regression	1.605	1.919	0.710	0.116
	All features + Lagged Target	Random Forest Regression	1.387	1.722	0.613	0.289
		XGBoost Regression	1.510	1.830	0.668	0.196
		Elastic Net Regression	1.557	1.884	0.688	0.148
Boarding counts 6-hours ahead	All features but no Target Lags	**Random Forest Regression**	**1.328**	**1.668**	**0.558**	**0.332**
		XGBoost Regression	1.450	1.800	0.609	0.222
		Elastic Net Regression	1.592	1.913	0.669	0.121
	All features + Lagged Target	Random Forest Regression	1.365	1.706	0.573	0.301
		XGBoost Regression	1.510	1.887	0.634	0.145
		Elastic Net Regression	1.528	1.863	0.642	0.167

*- MAE for naïve forecast at 1hour = 1.923, 2hours =1.863, 4hours =2.262 and 6hours =2.381.

In addition to providing reasonable predictive performance, some of the models explained at least 30% of the variability in the target variable as evidenced by the R-sq scores ranging from 0.29 – 0.37. We investigated the model results to understand what features were driving the explanation of this variance by collecting feature importance from the models. We focused on the top 10 ranked important features from each model. In Table 4-2, we see that there are 16 of these features. Based on their ranked importance, we can see that some of these 16 are ranked as a top 10 feature in

>50% of the models. These features relate to the current hour of the day, number of walk-in arrivals at the top of the current hour, number of resuscitation patients, number of patients that have been seen by a physician, number of patients waiting to undergo imaging or receive imaging results, number of patients waiting for the final physician disposition, number of patient being attended to by a nurse for intravenous treatment or collecting blood and the lagged feature that tracks the boarding counts in the previous three hours.

Table 4-2: Feature Importance Rank Comparison*

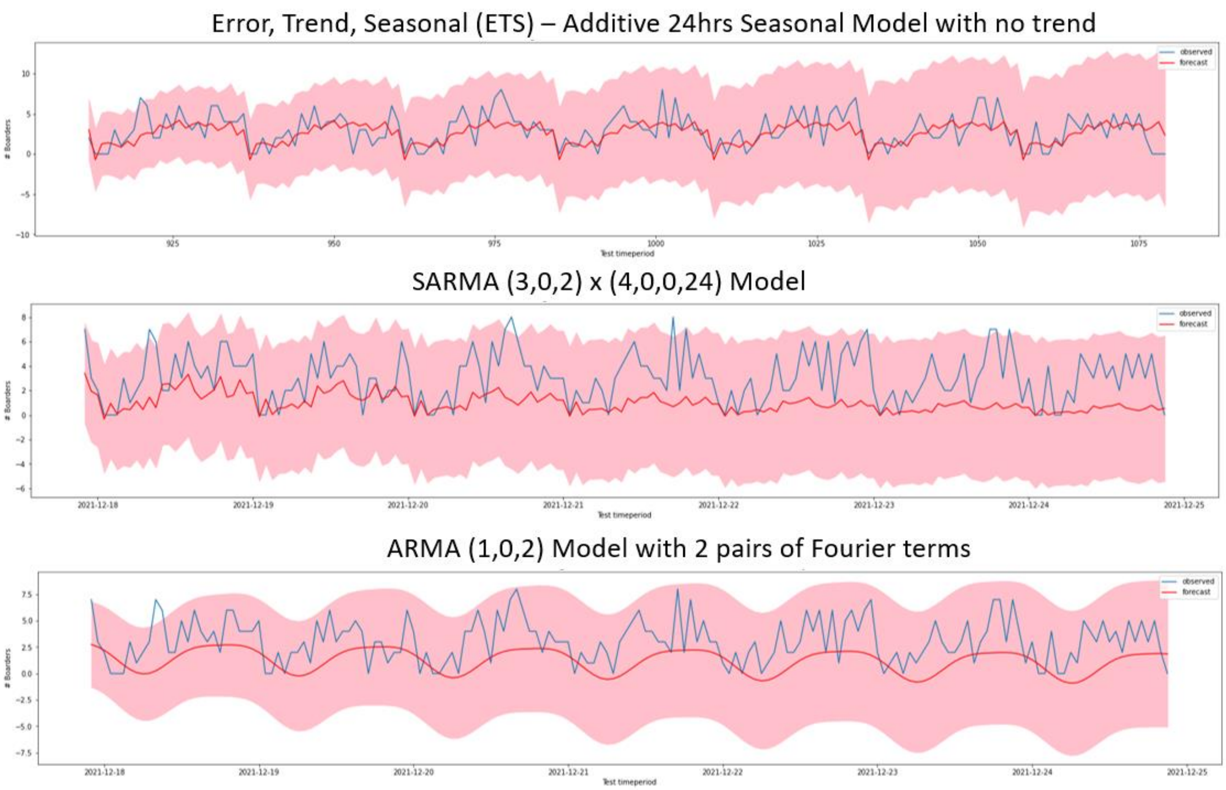
Feature	**Random Forest**				**XGBoost**				**Elastic Net**			
	1hr	2hrs	4hrs	6hrs	1hr	2hrs	4hrs	6hrs	1hr	2hrs	4hrs	6hrs
# Patients that have had their first doctor review queue	1	2	3	7	1	2	5	3	4	2	21	24
Hour of the Day (0 – 23)	2	5	1	4	6	6	3	1	3	4	19	4
# Walk-in patients that have entered the ED	4	3	4	9	7	3	9	2	2	3	7	31
Occupancy Rate	18	7	5	8	21	20	14	6	12	10	1	3
# Patients waiting for scan results	3	4	9	11	3	5	19	5	1	28	26	2
# Patients undergoing IV treatment and have had blood work	6	19	13	29	4	7	24	27	6	18	9	9
Day of Week = Friday	38	24	8	6	36	16	12	11	14	12	12	8
# Admitted patients pulled to inpatient beds two hours prior	48	9	14	23	45	4	21	8	11	9	35	NU
# Admitted patients pulled to inpatient beds three hours prior	8	14	23	1	48	NU	7	12	5	15	5	1
# Patients that have passed	7	8	6	46	17	31	13	14	NU	NU	16	NU

through the doctor disposition queue												
# Patients who have been dispositioned as discharged	11	21	17	17	41	23	18	7	NU	NU	17	7
# Patients who have been dispositioned as admitted	20	6	2	33	34	8	1	4	NU	11	10	NU
# Ambulance patients that have entered by the ED	10	10	21	40	11	14	27	41	10	7	14	NU
# Patients actively being treated by a physician or consultant	13	17	27	52	44	41	39	24	9	NU	22	NU
Day of Week = Monday	51	51	32	49	8	NU	47	24	25	19	39	32
# Patients waiting to be scanned	5	28	NU	38	9	29	45	25	8	NU	NU	NU
# Resuscitation patients	9	25	NU	20	10	15	22	22	7	5	18	12

* - NU in the table means that the feature was not used by the specific model.

4.4.2 Univariate Time Series Results

We used hyperparameter tuning techniques to identify the best parameters for the models prior to training. Again, we examined the model performance by predicting on a test data set of one week and collected performance metrics. In Table 4-3, we see that the SARMA model produces the worst results across all performance measures, a likely indicator that there are underlying unknown patterns in the data. The dynamic harmonic regression method (ARMA with Fourier terms) provided slightly better performance (2.21 and 2.80, MAE and RMSE respectively) compared to the SARMA model (2.16 and 2.65, MAE and RMSE respectively). We observe that the ETS model provides good predictive performance across the board, like the non-traditional forecasting techniques (1.35, 1.72, 0.69, 0.29; MAE, RMSE, MASE and R-sq, respectively).



*Note that red lines represent the predicted values

Figure 4-5: Univariate Time Series Forecasting Results on test data

As expected for these models, the further into the future predictions are made, the lower the predictive power as evidenced by the widening of the prediction intervals in Figure 4-5. We observed that prediction intervals get much wider after the first ~24hours. But in the ETS model, we observe that prediction intervals are relatively steady until after the first ~48hours.

For both ARMA models, two lagged forecast errors are used in prediction. However, there are a difference in the number of lags of the boarding counts that are used. The ARMA with Fourier use only the previous hour of the boarding counts, while the SARMA model uses the boarding counts in the previous two hours as well as the counts in the previous four hours as its seasonal component.

Table 4-3: Performance comparison of different time series forecasting models

Type	Model	Model AIC	MAE	RMSE	MASE*	R-sq
Univariate Time Series Forecasting	SARMA (2, 2) x (4, 0, 24)	3833.486	2.205	2.803	1.126	-0.894
	ARMA (1, 2) with Fourier terms	3798.585	2.163	2.654	1.105	-0.698
	ETS (N, A)	**-**	**1.347**	**1.717**	**0.688**	**0.292**
Multivariate Time Series Forecasting	SARMAX (2, 0) x (4, 0, 24) with subset of features	3445.895	1.203	1.551	0.614	0.420
	SARMAX (0, 1) x (4, 0, 24) with all features	**3213.995**	**1.139**	**1.462**	**0.582**	**0.485**
	ARMAX (0, 1) with Fourier terms and subset of features	3229.631	1.193	1.522	0.609	0.442
	ARMAX (1, 2) with Fourier terms and all features	3293.694	1.167	1.495	0.596	0.460

*- MAE for seasonal naïve forecast = 1.958

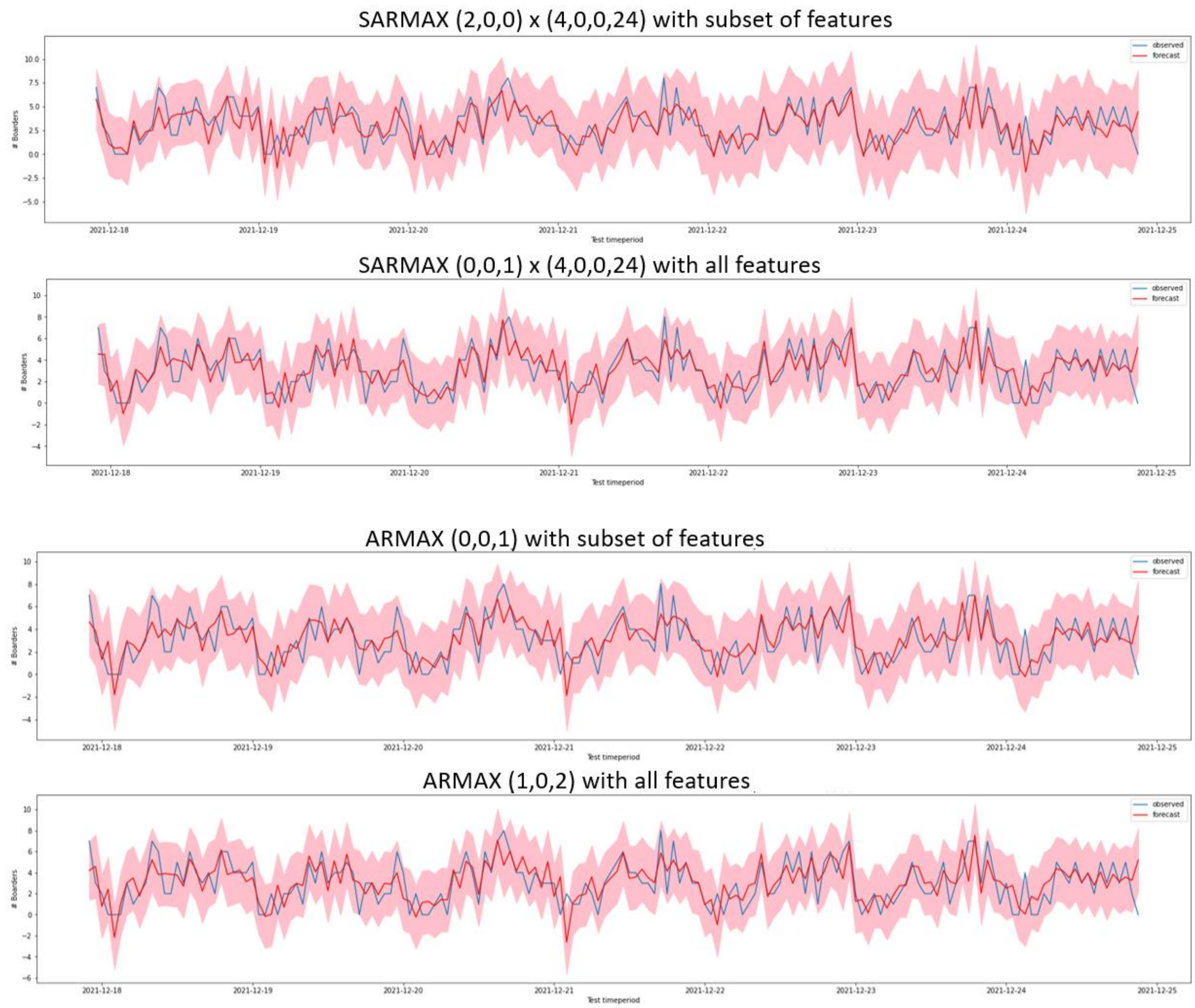
4.4.3 Multivariate Time Series Results

For multivariate methods, we ran two ARMA experiments by predicting using all features available as well as a subset of the features. The subset of the features used are the top features deemed to be important for future time steps prediction by >50% of the regression models as described in section 4.3.4.1. In Table 4-3, we can see that when subset of features is used, our best models required 0,1 or 2 lagged forecast errors in the moving average part and 0,1 or 2 lagged values of the boarding counts in the autoregressive part. Additionally, for the SARMA models, four lags of the boarding counts were used like the univariate model.

Our best performing multivariate model is the SARMAX model that leverages all the available features to predict the boarding count when provided hourly inputs. The model offers the lowest MAE and RMSE, 1.1 and 1.5 patients, respectively (see Table 4-3). It also offers the best MASE of 0.6, meaning that we almost doubled predictive accuracy compared to just using historical values. Additionally, the variables used in this model can predict 49% of the variation in the future boarding counts. The ARMA-Fourier model with all variables is the second-best model with performance metrics: 1.35, 1.72, 0.69, 0.29; MAE, RMSE, MASE and R-sq, respectively.

From Table 4-3, we observe the value that the additional exogenous variables bring to the ARMA by examining the differences between AIC values for the SARMA and ARMA-Fourier when new variables are added. We can see that for both models, by adding the subset of features, we reduce AIC by 500+ points, showing that these additions offer significant improvement. Similarly, when all features are added, we observed AIC reduction in both models. However, for the ARMA-Fourier model, this reduction is <100points while it is 200+ points for the SARMA model.

Aside from performance metrics, we assessed the residuals from all fitted ARMA models for goodness-of-fit using the Ljung-Box Q test as well as residual and autocorrelation plots. All models yield Ljung-Box test statistics greater than the 95% quantile of the chi-squared distribution with the number of lags being tested, allowing us to accept the hypothesis that our model's residuals have no autocorrelation. This was confirmed by the autocorrection plots. The residual plots reveal that our residuals are normally distributed, allowing us to conclude that our model errors are random and that our model is valid.



*Note that red lines represent the predicted values

Figure 4-6: Multivariate Time Series Forecasting on Test Data

4.5 Discussion

In this study, we assessed the viability of predicting the number of boarding patients that will be present in an ED in future timesteps. Prior studies have shown the benefit of predicting future ED overcrowding indicators like arrivals and LOS over simply scoring current crowding. However, there are only a handful of studies that predict future boarding outlook, despite boarding being the most influential factor for ED crowding. Our study showed that future boarding levels can be predicted with reasonable accuracy in different timesteps from 1-hour to 1-week ahead. These predictions can provide information for ED/hospital administrators to make decisions and preemptively alleviate over-crowding situations. For example, if there are one-week ahead forecasts available, they can share with the hospital administrators to create different inpatient discharge strategies and improve bed availability for ED patients. There are studies that have already validated the efficacy of this in reducing ED over-crowding [171]. Even when there are shorter-term forecasts such as 1-hour or 6-hours ahead, ED administrators could make different decisions on how patient beds are assigned "real-time" e.g., dynamic triggers of when to use clinical decision units to "house" and monitor patients that will need inpatient beds.

A key objective in this study was to predict boarding levels in future time steps. We forecasted boarding levels up to 7 days using an exponentially additive smoothing seasonal model, with the variation in our model's errors between 1.3 and 1.7 patients. We forecasted boarding levels 1-hour ahead using a variety of regression models and a seasonal ARMA model with exogenous variables, achieving variation in models' errors as low as 1.1 patients. Using the different regression models, we also forecasted boarding levels 2-, 4- and 6-hours ahead, all with variation in model errors lower than 1.8 patients. The variation in errors we achieved are reasonable for our data set, where values range from 0 – 7 patients with median and average around 3 patients. All our models also achieved MASE lower than 1 (0.58 – 0.61), showing actual forecasts did much better out of sample than a naive forecast did in sample.

We also achieved our goal on understanding the factors that are impactful to future boarding counts in this study. Comparing all models where 1-hour forecasts were obtained, we see that time-series specific factors such as historical boarding counts including any seasonality components (ETS R-sq: 0.29) and only ED operational factors (Random Forest without lags R-sq: 0.37) could explain some of the variation in future boarding counts. This additional explanation of variance makes sense intuitively; ED processes are highly stochastic especially when related to demand. Thus, it is reasonable that data showing context (e.g., patients demanding future inpatient bed use) improve predictability over only historical trends/seasonality. To bolster this, previous studies have shown that actual demand for ED services (i.e., arrivals) have been shown to be better predicted by including additional variables including ED operational variables [11]. A key outcome from our study was that it highlighted the importance of including past forecast errors as an input along with the other variables (SARMAX R-sq: 0.49). The relevance of these forecast errors is more obvious when we compare regression techniques where the lagged values of boarding counts were explicitly regressed on like the SARMAX model; we were only able to achieve 0.37 explanation of variation (Random Forest Regression with lags).

Our regression-specific models also revealed which features were highly relevant to future boarding levels up to 6-hours. We observed that, for our study site, the most important factors are related to the current hour of the day, number of patients who have been initially reviewed by a physician, number of people who have walked into the ED as well as the number of patients waiting on results from imaging tests. Because our data was sourced from a simulation, our study did not use patient specific information such as age or gender which have previously been shown to impact boarding [23]. We did include other validated factors from literature such as triage level and complaint type (which drives inpatient bed need). While these factors were not deemed as highly relevant in our individual regression techniques, they added some predictive value (when included to time-series data) as evidenced by the reduction in AIC and improvement in prediction errors observed post-addition. It is likely that overlooked factors like patient demographics could continue to improve predictive performance. The same is true for unexplored factors, like inpatient details, including LOS, bed availability, and nurse availability, that have been shown to also impact boarding.

There are very few studies in literature like our study where there is a focus on predicting boarding counts and assessing the impact of certain various factors directly on boarding. Asaro et al [25] explained 9% of the variation in boarding time utilizing both patient (e.g., resource use) and system variables (e.g., arrivals, occupancy, calendar). Their paper utilizes similar but fewer variables than our study and compares the impact of using just patient or system variables. They show that using one set of variables instead of both sets offers lower explainability. This observation bolsters our decision to include additional queue-census, utilization measures as well as historical boarding information along with patient variables like chief complaint as reasonable since we achieved higher explainability of 29% - 49%. While our methodology differs from Hoot et al [21] where simulation is the prediction mechanism, we see that we generate results similar over-estimating errors. Comparing absolute errors for boarding counts across all sites predicted in [21] to the median boarding counts, we observe that over-estimation errors can range from 22% - 90% of the median boarding counts. Our prediction models have over-estimation ranges from 36% - 56% when our resulting mean absolute errors are compared to mean boarding counts.

There are caveats worth noting prior to interpreting the results of this study. The training and validation data were sourced from the simulation output of a generalized ED. The ED study site was modeled after the processes and inputs of three different EDs operating in Southern California, USA. They do not represent a generalizable version of all EDs across USA. It is possible that the relationships drawn between operational factors and boarding counts in this study are non-existent in EDs that operate differently. However, the methods described in this paper for identifying relationships or predicting future values are easily replicable for any type of ED if the type of data described in this paper can be collected.

4.6 Conclusion and Future Work

To mitigate the harmful effects of ED overcrowding, clinicians and administrators need to understand the future status and make plans. ED overcrowding is complex and multi-faceted but existing research has shown that its most influential factor is boarding of patients who need a hospital bed after the ED process has been completed. Other research related to short-term forecasts that can serve as a warning signal for ED overcrowding has focused on other factors such as ED arrivals. Research on predicting boarding specifically has either focused on understanding factors or simply forecasting future values. To the best of the authors' knowledge, this is the first paper that defines an approach that evaluates the impact of ED operational factors on future boarding counts and provides relatively accurate predictions of future boarding counts from 1-hour to 1-week ahead. These forecasts can be used by clinicians and administrators to make decisions around resource allocations within the ED or across both the ED and the hospital.

While we have achieved the good predictions for future boarding levels in this study, we want to explore future work. We know that there are likely more factors that impact future boarding levels such as inpatient ward information or patient demographics that might improve our causal predictions. Once healthcare systems are more stable in operations following the pandemic, we would like to use data sourced directly from hospital records to understand the scalability of our proposed approach.

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CHAPTER 5: HYRBID SYSTEM MODELING FOR BED ASSIGNMENT TO MANAGE EMERGENCY DEPARTMENT CROWDING

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5.1 Introduction

Emergency Department (ED) crowding is a global healthcare problem, and the United States healthcare system is not an exception. According to the CDC, ~50% of EDs experience overcrowding (where demand for service exceeds ability to provide service). ED crowding is a major health care problem which leads to many undesirable outcomes such as higher number of medication errors (e.g., wrong dose) [1], higher mortality risk [2], likelihood of readmission including poor administrative outcomes like lost revenue due to patients leaving without being seen (LWBS) [3] and increase ED staff stress [4]. Many researchers have investigated the causal factors for ED crowding and agree that ED boarding, where patients who have already been provided emergency service but are waiting on a hospital bed, is the most influential factor [5] [6]. Boarding itself has been found to be directly impactful to adverse outcomes such as increased mortality rate in the ED [7]. Despite the plethora of research on prediction of ED crowding as a means to create early warning signals by predicting ED crowding measures like ED length-of-stay (LOS) [8], ED volume [9], daily occupancy [10], ambulance diversion [11], and so on, there are only a handful of research that focus on predicting boarding [12] [13], the most influential factor. Additionally, there are several interventions that have been proposed, studied, and validated to improve ED crowding in general such as physician-in-triage [14], fast-track [15], immediate bedding of critical patients [16], bedside registration [17], updated resource allocation [18] as well as some for ED boarding management like better inpatient bed discharge [19] and inpatient bed reservation strategies [20]. Despite this, there are not a lot of studies dedicated to boarding management for EDs, largely since boarding management needs to be a systems-wide initiative which tend to be difficult to get support for implementation because of revenue implications. A particularly overlooked area of study for boarding/crowding mitigation strategies for ED is bed assignment. While solutions like fast-track and immediate bedding can be considered as bed assignment, there are only a few studies [21] [22] [23] focused on making decisions of what the right bed to assign a patient is especially during ED crowding.

In this study, we want to investigate the influence of boarding on ED crowding, specifically ED LOS to define ED-actionable strategies that minimize the influence of boarding. Specifically, we want to identify an early warning signal for boarding capable of detecting boarding levels that result in ED crowding and its consequent adverse outcomes. We also want to evaluate a prescriptive strategy for bed assignment in the ED that is focused on responding to early warnings of future ED boarding, specifically EDs that have already invested in fast-track.

The rest of this paper is organized as follows. "Related literature" reviews the relevant literature while "Simulation and Prediction Models" describes the materials, methods and results related to building our main simulation and prediction models. "Bed Assignment Intervention" presents our proposed bed assignment strategy and the results of our experiments related to this intervention. "Discussion" discusses the main findings from the study and potential implications for ED management as well as clarifies the limitations of our study. Finally, "Conclusion and Future Work" provides some conclusive considerations and future work.

5.2 Related Literature

As predictive modelling has improved over the last couple of years, there has been a growing trend in ED crowding research focused on predictive modeling [24], using a variety of techniques from simple regression to simulations and complicated neural networks. For instance, there are several studies focused on predicting early warning signals of ED crowding as a measure of ED volume [25] [26], daily occupancy rate [27] [28], patient wait times [29] [30] [31] and others. Additionally, there has been research focused on predicting ED relevant factors/decisions/metrics with the intent of improving decision-making and ultimately reducing crowding. There are several studies on predicting the disposition of patients to make ED workflow decisions [32] [33] [34] and readmission risks to ultimately reduce future visits and managed volume [35] [36] [37]. There are not yet many studies around predicting boarding. Hodgins et al [12] uses logistic regression to investigate the operational, clinical, and personal factors that impact if a patient will board for >2hrs, without focusing on the use of the prediction to measure ED crowding. Hoot et al [13] predict the number of boarding patients (up to 8 hours ahead) using discrete-event simulation, specifically predicting boarding and waiting counts as well as occupancy rates. While Hoot et al were able to predict boarding, they did not develop an early warning signal or indicator that could be used to make future decisions. Our literature review did not yield any research related to creating boarding-specific early warning signals to manage ED crowding. Our study will contribute to the nascent field of boarding prediction while creating the first early warning ED crowding signal linked directly to boarding.

The creation of the early warning signal, while helpful itself, is not an intervention technique that can influence ED crowding. Predictive models are useful but need to be implemented to make an impact. Researchers have found techniques that incorporate predictive modeling with other model types (hybrid modeling) in a technique to create more prescriptive models that can drive impact.

A particular growing trend in emergency department research is hybrid systems modelling (HSM). Hybrid Systems Modelling (HSM) can be defined as the combined application of simulation with methods and techniques from disciplines such as Applied Computing, Business Analytics, Computer Science, Data Science, Systems Engineering and OR [38]. Simulation – Optimization models are the most used approaches in the context of ED. In one of the few studies related to ED bed assignment, Allihaibi et al [23] combine a heuristic algorithm with a discrete-event simulation to reprioritize bed assignment for patients arriving at the ED. Bruballa et al [39] combine a unique analytical (formula-based) model focused on patient wait times with a detailed ABS model to form an intelligent scheduler for non-urgent ED patients. Chen et al [40] leverage discrete-event simulation model to identify the best resource allocation strategy optimizing stochastically constrained budgets. There are also hybrids of simulation and predictive models. Harper and Mustafee [41] introduce a HSM that leverages the time series machine learning algorithm seasonal ARIMA (SARIMA) to predict the number of ED patients up to 4-hours ahead and discrete-event simulation to test the impact of corrective policies on these future crowding levels in real-time. Hunter-Zinck et al [42] leverage a simulation model to show the impact on real ED processes for embedding their multilabel predictions of medical resource orders that a patient will use (e.g., labs, tests, etc.).

Less common HSMs are simulation-optimization-predictive combinations. These types of models use machine learning/predictive modeling to enrich simulation-optimization, merging the efficiency of predictive modeling with the solution-finding properties of simulation-optimization. Lee et al [43] combine predictive modeling with a simulation-optimization model to optimize ED workflow. They leveraged simulation-optimization to find the optimal resource allocation configuration in scenarios where patients who have been flagged (by a predictive model) as readmission risks are treated separately in a clinical decision unit. Yousefi and Yousefi [44] train predictive models on the output of an agent-based simulation model to reduce the search space needed during a simulation-optimization for identifying the best resource allocation that minimized patient's door-to-doctor time. So far in our review of literature, HSMs that combine predictive, simulation and optimization have only been leveraged in resource allocation problems. Our study will contribute to research by introducing the first-of-its-kind predictive-simulation-optimization HSM related to optimal bed assignment strategies.

5.3 Simulation and Prediction Models

5.3.1 Simulation Study Design and Setting

For this study, we developed a simulation of a typical ED in California, USA. The study ED is an urban, medium volume, non-teaching community hospital, with ~78,000 ED visits annually. It is attached to a 385-bed hospital and the hospital plans for ~300 beds for non-ED related visits like elective surgeries. The ED has 49 treatment spaces in total, 29 fully monitored beds (4 are designated specifically for trauma care/resuscitation) and 20 additional treatment spaces, typically hallway beds or chairs/recliners. The ED's workflow (shown in Figure 5-1) is typical; patients enter the ED either via ambulance or personal transportation (walk, bus, car, etc.), they go through a registration (if their condition allows for it) and then they are seen by a triage nurse who takes preliminary assessment to determine criticality. The patients wait for a staffed bed to be available; once they are in a bed, they are attended to by a physician who determines the appropriate treatment and sends the patient home or to the hospital.

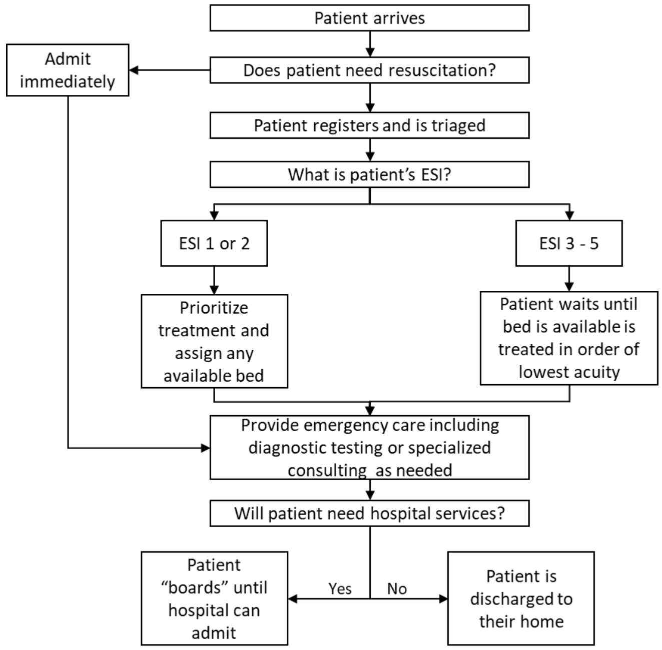

Figure 5-1: Typical Patient ED Workflow

The ED was verified by reviewing that all code worked appropriately. COVID-19 impeded our ability to collect data empirically for our study and as such we could not validate our simulation by comparing with real-life data. We successfully validated our model's ability to represent our study ED using metamorphic validation [45] instead. Metamorphic validation calls for the design of metamorphic properties for the simulation model type (DES/ABS), followed by the description of metamorphic relations (MR) which are definitions of changing behaviors given changes in the model design or its parameter and finally conducting experiments to test the MRs.

5.3.2 Simulation Data Analysis

Our early warning indicator for ED crowding aims to predict "crisis" before it happens so that hospital staff can take proactive actions to avoid the crisis. Hospital systems typically set targets for ED LOS for both admitted patients (ALOS) and discharged patients (DLOS). Staying within these targets help ensure patient satisfaction while avoiding undesired consequences such as ambulance diversion. Given its correlation to bad ED outcomes, EDLOS has been used as an indicator for crowding in other studies [46] [47]. It has also been shown to be a reasonable indicator for changing crowding conditions; in a comparative study for ED crowding measures, the researchers identified that LOS was just as helpful in highlighting worsening crowding conditions as NEDOCS and EDWIN [48].

We use a simulated ED for our analysis. The simulated ED was built in conjunction with healthcare providers from a hospital system in Southern California, USA. One month of data was extracted from the simulation after the appropriate simulation warm-up period. Before collecting results from any simulation model, it is critical that the model is run for enough time that allows all aspects to get into conditions that are typical of normal running conditions. We performed Welch Graphical method to understand this and observe that at day 10, our bed occupancy achieves steady state, thus we set our warm-up period for 10days and discard any results obtained prior to day 10. We performed data analysis to understand the relationship between boarding of patients and crowding levels based on LOS. Our analysis showed that when high boarding levels are high in a specific hour, patients experience higher LOS in subsequent hours. We defined boarding levels in relation to the capacity of the main ED.

$$Boarding\ level\ (\%) = \frac{number\ of\ boarding\ patients}{total\ number\ of\ treatment\ spaces\ in\ the\ ED}$$

When we measured LOS 6-hours after an occurrence of high boarding count, we observed that average LOS across all patients increased by at least 1 basis points, with the highest increase expectedly seen in admitted patients.

Table 5-1: Patient average EDLOS 6-hours ahead followed by current boarding levels

Boarding Levels	Average ALOS	Average DLOS	Average LOS
0% - 30%	355 mins	107 mins	195 mins
>30% - 60%	362 mins	108 mins	197 mins
>60%	426 mins	113 mins	224 mins

Referring to Table 5-1, we can see that when >60% of the ED is occupied by boarding patients, average LOS is increased by 14%, even discharged patients experience 6% LOS increase. This shows that for our study site, boarding counts should be kept minimal (at least <30% of the ED's capacity) to avoid the impact they have on ED LOS and crowding.

5.3.3 Predictive Model

We aim to predict boarding levels in the future, specifically 6 hours from the current time given its impact on patient EDLOS using classification techniques for our predictions. We created a target variable, the boarding level, as a function of hourly boarding counts 6-hours ahead based on current ED status. Our target variable is multi-class with three classes: **0** when boarding levels are <= 30% (i.e., **normal** boarding), **1** when boarding levels are between 31% and 60% (i.e., **high** boarding) and **2** when boarding levels are >60% (i.e., **severe** boarding). We extracted status of different parts of the ED workflow shown to influence future boarding counts from the authors' previous study (Chapter 4 of this document), including counts of patients triaged, seen by the doctor for first review, waiting for a bed, waiting to use imaging resources and others. These predictors, shown in Appendix A, are accessible via most hospital electronic hospital record (EHR) systems. These statuses are collected on an hourly basis and serve as regressors for our supervised classification models. For our prediction exercise, we experiment with three algorithms: Logistic Regression **(LR),** Random Forest **(RF)** and Support Vector Machines **(SVM)**. Thus, we will examine some of these approaches to test their predictive ability for our problem.

5.3.3.1 Predictive Modeling Experiments

We obtained eight weeks of data from our simulation model and pre-processed the data to obtain the predictor and target variables. We split our data into two: a training data set consisting of seven weeks of data and a test data set consisting of one week of data. Each model was trained with the training data set then performance was validated on the test data set. During training, each model's parameters was hyper-tuned to identify the best parameters for predicting on our data. We also use 10-fold cross-validation techniques to ensure that prediction results can be generalized to unseen data sets. We measure model effectiveness using three metrics commonly used for classification models: precision, recall and F1-score. We calculate each of these metrics for each class in our target variable to examine how well our model does at identifying all boarding levels. We chose not to use accuracy or AUC-ROC because the classes in our target variables are not balanced across our data sets. Figure 5-2 shows a distribution of target variables in our data set. These metrics can be misleading when there is imbalance across classes.

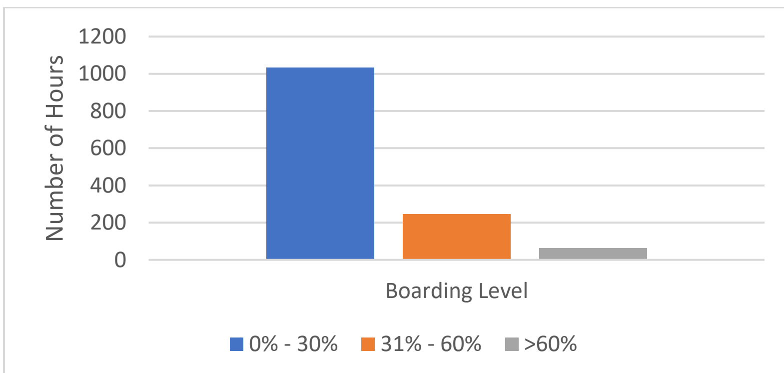

Figure 5-2: Distribution of Hourly Boarding Levels

After hyper-parameter tuning, we get the best results from: (1) Logistic Regressor regularized with the L2 penalty using a regularization strength of 0.01where the cost function is solved using Newton-Raphson method; (2) Random Forest Classifier with 100 trees only 10 nodes deep that are split only when there is >4 samples available and (3) SVM Classifier using a radial basis function hyperplane to separate the data into groups with a hyperplane control gamma of 0.001. These models are run against the test dataset to evaluate their performance on unseen data. Table 5-2 shows the results of this validation. We can see that the Random Forest Classifier performs best across all metrics for all classes, showing a good ability to identify the different boarding levels.

Table 5-2: Predictive Model Results Comparison

Target	Metric	LR	RF	SVM
0 (0% - 30%)	Precision	0.92	0.94	0.96
	Recall	0.97	0.99	0.99
	F1-score	0.94	0.96	0.97
1 (31% - 60%)	Precision	0.77	0.88	0.88
	Recall	0.57	0.70	0.77
	F1-score	0.65	0.78	0.82
2 (>60%)	Precision	0.67	1.00	0.67
	Recall	0.67	0.67	0.67
	F1-score	0.67	0.80	0.67

5.3.3.2 Final Predictive Model Evaluation

To test robustness of our predictive model, we update the arrival data for the simulation to increase the daily patient arrivals by 10% i.e., our ED now processes 85800 visits annually. We extracted one week of data after the simulation warm-up period. We then predict future boarding levels using the trained Random Forest Classifier. The prediction results reinforced that our classifier preforms well: 87% overall precision, 93% overall recall and 90% overall F1-score. The performance details for each class of boarding level are shown in Table 5-3.

Table 5-3: Random Forest Results for Surge Scenario

Target	Metric	RF Results
0 (0% - 30%)	Precision	0.86
	Recall	0.99
	F1-score	0.92
1 (31% - 60%)	Precision	0.85
	Recall	0.73
	F1-score	0.79
2 (>60%)	Precision	1.00
	Recall	0.75
	F1-score	0.86

5.4 Bed Assignment Intervention

5.4.1 Fast-Track Intervention

5.4.1.1 Simulation of Fast-Track ED

There are many interventions that have been proposed, implemented, and shown to mitigate ED crowding, including bed assignment/control strategies like the implementation of immediate bedding, physician-in-triage, and fast-track workflows. Of these, fast-track workflow is most common strategy in practice, according to a 2017 nation-wide survey of US hospitals [49]. In a fast-track workflow, patients deemed to be non-critical after triage (ESI 4 & 5) are assigned to a different treatment area in the ED. Non-critical patients typically present with conditions that require treatments like wound dressings and medication prescriptions. The different treatment area is typically called the fast-track area and has its own treatment spaces and clinical resources. In the fast-track area, these patients can be quickly attended to, reducing their EDLOS and their likelihood to leave the ED without being seen. This has healthy outcomes for the ED. Overall EDLOS is lowered, reducing ED crowding; LWBS rates for the ED is also lowered, reducing revenue loss, and improving likelihood of better patient satisfaction.

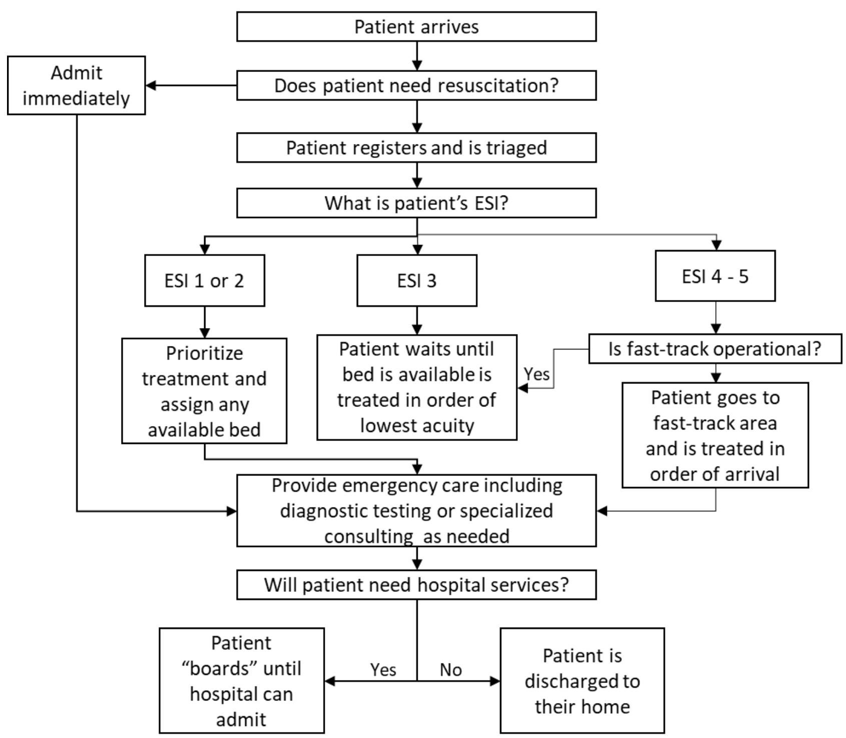

Figure 5-3: Patient flow in ED with Fast Track

In our study, we evaluate the impact of implementing a fast-track strategy for our ED. We added a fast-track area that contains five beds. The area is staffed by one physician and two licensed vocational nurses that are certified to perform IV services. The area uses the same laboratories and scanning capabilities as the ED. The fast-track workflow (detailed in Figure 5-3) and staff operate between 10am – 10pm, the period of the day with higher arrival rates to the ED. After 10pm however, the fast-track beds are made available to the ED, with an additional nurse added to the night schedule to both comply with regulations and accommodate the increased capacity.

5.4.1.2 Fast-Track Simulation Evaluation

Our new simulation model is validated metamorphically to ensure that it is representative of a real ED with a fast-track system. We collect 30 days of data after running the model for the appropriate warm-up period for 30 replications and collect important ED key performance indicators (KPIs), such as EDLOS, LWBS rate, bedside nurse utilization and hourly throughput of discharged & admitted patients. In Table 5-4, we compare the results from our fast-track ED to our regular ED to understand how implementation of the fast-track ED impacts crowding and other KPIs.

Table 5-4: Fast-track vs Regular ED – KPI Statistical Comparison

KPIs	**Regular ED**	**Fast-track ED**
ALOS (mins)	362 (333 – 401)	373 (342 - 392)
DLOS (mins)	108 (97 – 120)	103 (94 - 120) *
LOS (mins)	199 (183 – 216)	200 (179 - 209)
LWBS (%)	2.7 (0.4 – 5.4)	1.0 (0.0 – 4.0) ***
Bedside Nurse Utilization (%)	79.9 (76.5 – 82.8)	74.8 (73.1 – 82.8) ***

Model results are shown as median of output values followed by their ranges.
*** refers to a p-value <0.001,** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

Given that we expect our main ED Crowding indicator (LOS) and other KPIs such as LWBS to be lower in the fast-track implementation as observed in literature, we performed statistical tests to identify if the results obtained from the fast-track ED are lower than those obtained from the regular ED. We leveraged the Wilcoxon-Mann-Whitney's non-parametric test available from the SciPy library for Python 3.0, testing the following hypothesis at 95% significance level:

$$H_0 \rightarrow median\ value\ of\ KPI\ from\ Fast-track\ ED$$
$$=\ median\ value\ of\ KPI\ from\ Regular\ ED$$

$$H_1 \rightarrow median\ value\ of\ KPI\ from\ Fast - track\ ED$$
$$< \ median\ value\ of\ KPI\ from\ Regular\ ED$$

The results highlighted in Table 4 show that the Fast-track ED offers good improvement of LWBS rates, reducing by more than 50% of the values observed in Regular ED. Similar statistically significant reductions are observed in the bedside nurse utilization as well as DLOS. Both of which are logical, given that patients likely to be discharged have a different process flow and do not burden the "regular" ED. We observe that there are increases to ALOS and LOS in the fast-track ED, but these increases are insignificant and thus we can assume that fast track doesn't influence the ALOS or LOS in the study ED.

We notice that there are DLOS and LWBS reductions observed from our fast-track implementation; however, we observe no influence on overall LOS and ALOS. We posit this is because of the ESI distribution in our study. Table 5-5 shows the differences between our study ED's ESI distribution, what is expected according to the ESI Implementation Handbook [50] and the 2017 National Hospital Ambulatory Medical Care Survey (NHAMCS) [51] observed distribution.

Table 5-5: Expected and observed ESI distributions

ESI level	Study Site	ESI Implementation handbook	NHAMCS 2017
1	2.1%	1% - 3%	0.9%
2	23.3%	20% – 30%	9.9%
3	60.3%	30% - 40%	33.9%
4 & 5	14.3%	20% – 35%	27.9%
Unknown	N/A	N/A	22.3%

Our study ED appears to handle a larger volume of critical patients than what is expected and as a result, this influences the viability of fast-track given the low proportion of ESI 4 and 5 patients. To evaluate this, we run a sensitivity analysis of the fast-track implementation at varying proportions of ESI 4 -5 patients. We perform a similar statistical testing to validate if fast-track implementation offers better ED outcomes. Table 5-6 highlights the results of this testing. We observe that the higher the proportion of ESI 4-5 patients, the better the overall ED outcomes observed. Starting at 25%, all improvements are statistically significant, and the outcome improvements are similar to observations from literature [52].

Table 5-6: KPI Improvement Sensitivity Analysis at Varying Levels of ESI 4 & 5 Proportion

KPIs	**5%**	**10%**	**Baseline**	**20%**	**25%**	**30%**	**35%**
ALOS (mins)	0	0	-11	0	-16 ***	-10 ***	-12 ***
DLOS (mins)	-3	-3	-5 *	-9 ***	-6 ***	-8 ***	-11 ***
LOS (mins)	-3	-2	-1	-8 *	-6 ***	-12 ***	-15 ***
LWBS (%)	-1.2***	-1.8***	-1.7 ***	-0.7 ***	-1.9 ***	-1.4 ***	-1.2 ***
Bedside Nurse Utilization (%)	-0.6	-3***	-5.1 ***	-7.8 ***	-8.3 ***	-11.0 ***	-12.5 ***

Model results are shown as differences between medians of both models' output values
*** refers to a p-value <0.001,** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

5.4.2 Fast-Track Pod Bed Assignment Intervention

5.4.2.1 Description of Fast-Track Pod Bed Assignment

We are proposing a bed assignment strategy to further alleviate the incidence of ED crowding. We want to use the knowledge of future boarding levels to drive how beds are assigned in an ED that has implemented fast-track. We propose that when an ED is predicted to experience any situation where boarding levels are predicted to be higher than 30%, some beds in the fast-track area become allocated to ESI 3 patients. We will refer to these beds as "pod" beds going forward. ESI 3 patients waiting on a bed assignment after being triaged are assigned to the first available regular or pod bed, based on the time they were triaged. These pod beds are available for assignment until the number of future boarding levels >30% over subsequent hours are at an acceptable level. After this, the pod beds revert to being fast-track beds. Details on the workflow are shown in Figure 5-4.

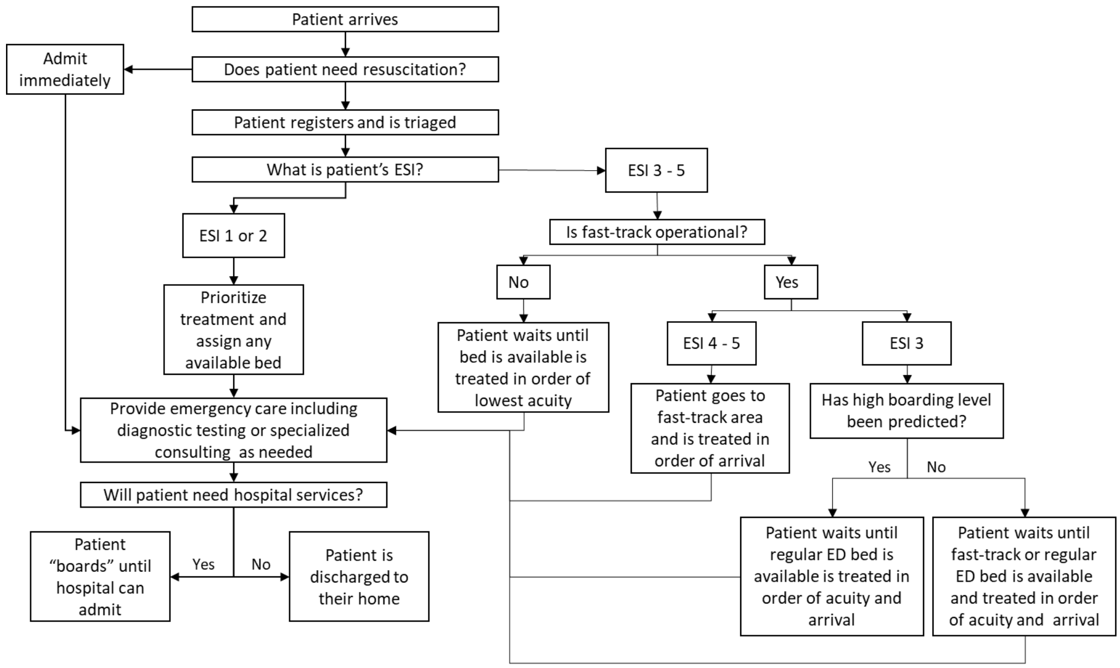

Figure 5-4: Proposed Patient Workflow in ED with Fast-Track Pod Bed Assignment

5.4.2.2 Simulating the Pod Bed Assignment Intervention

We updated the fast-track simulated ED to include the bed assignment strategy in section 5.4.2.1. We embedded the trained Random Forest Classifier from section 5.1 into the updated simulation model using the ONNX wrapper developed by Tyler Wolfe-Adam [53]. We created a collection of predictor variables that are updated in real-time every hour in our simulation model. These predictors are fed into our classifier which then predicts the boarding levels 6-hours ahead. To enact the pod bed intervention, we created several variables that trigger the bed assignment process in the main simulation. The first variable ("var_pred") captures the predictions from our classifier whether 0, 1 or 2 boarding levels. The second variable ("var_previous") is the number of future boarding levels to monitor to determine when the fast-track pod bed assignment should revert to regular fast-track. The third variable ("var_stop") is used to define the severity of future boarding levels that will trigger reverting to fast-track; it is a sum of the monitored future boarding levels captured by "var_previous". A function with a binary output was created to monitor the values of these variables to determine when the fast-track pod bed assignment strategy is active. The function is defined as:

$$f(x_t) = \begin{cases} 0, & \sum_{t+var\_previous}^{t} x_t \leq var\_stop \\ 1, & x_t \geq var\_pred \end{cases}$$

Where x_t represents the predicted boarding level at hour *t*.

5.4.2.3 Simulation-Based Optimization for Pod Bed Assignment

There are multiple values for each of the variables related to triggering our bed assignment strategy. For instance, "var_stop" can theoretically take on values > 1. To determine the best values that will yield the lowest crowding scenarios, we leverage simulation-based optimization techniques using the inbuilt optimization engine in AnyLogic, our simulation software [54]. In addition to the trigger-related variables, we also need to understand the optimal number of pod beds that can be assigned from the fast-track pool to ensure minimal crowding.

First, we define the optimization problem. Optimization problem typically contains a set of decision variables, objective functions, and a set of constraints. As mentioned earlier, to minimize ED crowding, the aim is to identify the best values for turning on & off our bed assignment strategy as well as the right number of fast-track beds to allocate to this strategy. In this study, we focus on EDLOS as the proxy for measuring ED crowding; thus, we want to minimize EDLOS in our study. Our optimization problem can thus be written as follows:

$$Min\ Z\ =\ f(X_1, \ldots, X_n)$$

Subject to:

$$Min\ Y\ =\ g(X_1, \ldots, X_n)\ \leq\ predefined\ LWBS\ target$$

$$1\ \leq\ X_1\ \leq\ 5,$$

$$X_2 = \binom{1}{2},$$

$$1 \leq X_3 \leq 12,$$

$$0 \leq X_4 \leq 12,$$

$$X_i \; integer \; for \; i = 1, 2, \ldots, n$$

In our objective function, Z represents the average hourly EDLOS and X_n are the decision variables. Z is simply the output of the simulation model after decision variables have been changed, there is no analytical form. X_1 represents the number of beds that will be kept as fast-track beds. X_1 is bound from 1-5, meaning that at least 1 bed must always be available for fast-track during fast-track operating hours. X_2 represents our predicted boarding level "var_pred"; it is set as a binary choice of 1 and 2 which represent boarding levels where 31% - 60% and >60% of ED beds are occupied by boarding patients. We did not add class 0 as an option because we do not intend to trigger the bed assignment process permanently. X_3 represents our monitoring variable, "var_previous". We set a lower bound of 1 hour because we want to measure at least 1 future prediction as a stop and a higher bound of 24 hours because we do not want to run the pod assignment throughout the day. X_4 represents our stopping criteria, "var_stop" and it is bound between 0 (no future boarding) and 12 (future boarding every hour for 12 hours at least). Y presents an additional constraint related to LWBS rates. We want to make sure that we do not create a situation where LWBS is worse than in our current ED at least as LWBS rates have direct impact on our ED's revenue.

The full optimization problem is entered into AnyLogic's optimization engine powered by OptQuest. OptQuest allows researchers to perform optimization experiments with models by doing parameter sweeping across the simulation space and using metaheuristic optimization and randomized search algorithms to explore the simulation space in search of an optimal solution [55]. To constrain the computational needs for our experiment, we run 300 simulations of our model. We chose 300 after running the model for 1000 runs, obtaining the EDLOS standard deviation from these runs and calculating the required sample size to achieve 95% confidence interval, with an EDLOS error of 1-min using this formula $n = \left(\frac{Z\sigma}{E}\right)^2$; such that n = number of samples required to ensure 95% confidence interval; Z is the value from the standard normal distribution at 95% confidence interval, σ is the standard deviation of LOS obtained from 1000 runs and E is the desired margin of error for LOS. The required sample size obtained was 283 so we rounded up to 300 samples for simplicity (i.e., simulations needed).

Since there are stochastic inputs in our simulation, we also run each simulation with 2 – 30 replications using random seeds, with the exact number of replications for each simulation determined by OptQuest based on achieving 95% confidence interval and 5% error rate. We set each simulation to run for three weeks with our warm-up period of 10 days. Model settings are highlighted in Figure 5-5.

Our simulation-optimization problem of finding the optimal decision for achieving minimum EDLOS by searching through combinations of our parameters is a single-stage stochastic optimization problem. OptQuest attempts to find a specific decision *x* among a domain of all feasible decisions (*X*) that minimizes EDLOS while maintaining low LWBS rates. Because we can only ever know LWBS rate after we've made the decision, we can note that we receive random information on LWBS and denote that as ζ. We can thus say that we are aiming to minimize a random function $F(x, \zeta)$. Given the random nature of ζ, we can't directly optimize this function and so we will minimize its expected value, $\mathbb{E}[F(x, \zeta)]$. Thus, the objective for OptQuest becomes:

$$\varsigma^* = \min_{x \in X} \{ f(x) = \mathbb{E}[F(x, \zeta)] \}$$

Where there is a set of optima $S^* = \{x \in X : f(x) = \varsigma^*\}$ in an assumed convex *X* decision space.

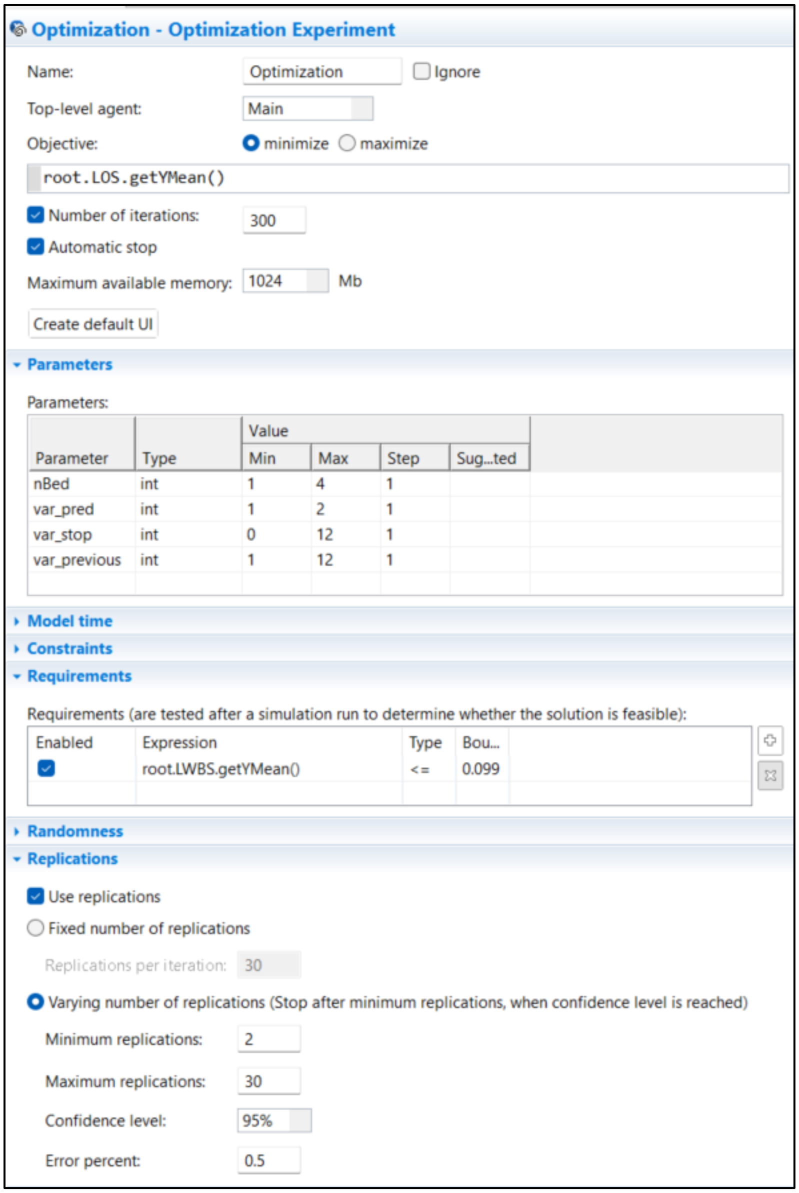

Figure 5-5: Simulation-based Optimization Model Settings

After the simulation-optimization process was completed, the model identified an optimal solution (minimum average LOS of 181mins) showed in Figure 5-6. We can see that the best solution that fulfills all our optimization constraints is one where we turn on the pod best assignment strategy when the predictive model first identifies a severe boarding level (i.e., predicted value = 2). To achieve low crowding, 3 beds must still be available for fast-track meaning we can only set aside 2 pod beds. The optimal solution also shows that we should monitor future predictions of boarding levels up to 5 hours ahead and turn off the pod assignment intervention only when there are no predicted high boarding levels in the future.

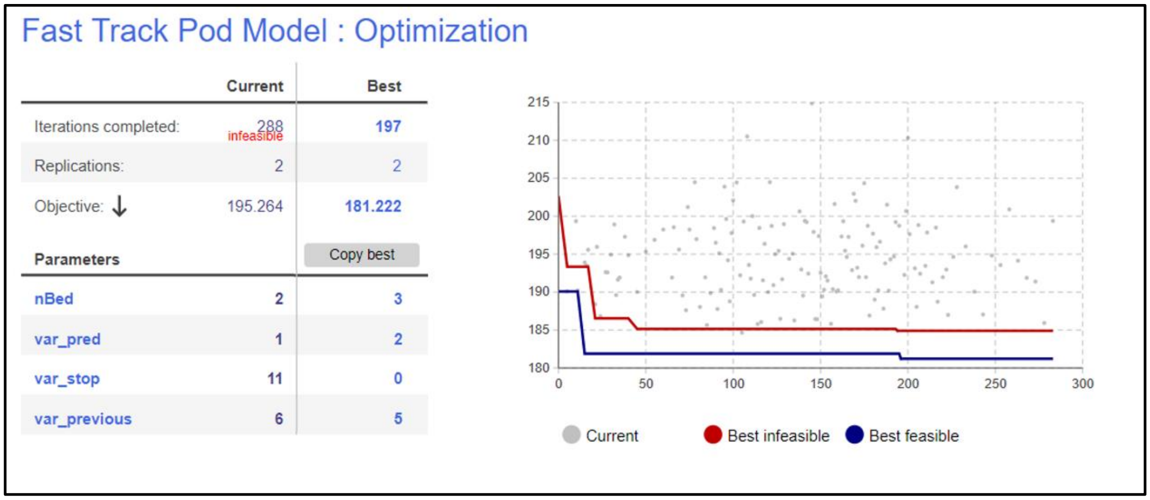

Figure 5-6: Pod Bed Assignment Optimization Results

5.4.2.4 Pod Bed Assignment Influence on ED Outcomes

We configured our fast-track pod assignment simulation model to the optimal parameters identified in section 5.4.2.3. We ran 30 replications and collected values of KPIs after two weeks of running past the appropriate warm-up. We used the Wilcoxon-Mann-Whitney test to compare these KPIs to previously collected KPIs from running the fast-track and regular ED workflows. We aimed to understand if the KPIs from the pod workflow were lower (i.e., better) than those from the other two workflows.

Table 5-7: Pod Bed Assignment Intervention Results

KPIs	**Pod Fast-track ED** +	**Compared to Regular ED** ++	**Compared to Fast-track ED** ++
ALOS (mins)	362 (346 - 411)	0	-11 *
DLOS (mins)	101 (93 - 110)	-7 ***	-2 **
LOS (mins)	195 (180 - 216)	-4 *	-4 *
LWBS (%)	1.3 (0.3 – 3.3)	-1.4 ***	-0.3
Bedside Nurse Utilization (%)	75.2 (73.6 – 76.7)	-4.7 ***	-0.4

+ - Model results are shown as median of output values followed by their ranges.
++ - Results are shown as differences between medians of both models' output values
*** refers to a p-value <0.001,** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

The results in Table 5-7 highlight that our pod bed assignment intervention yields statistically significant better ED crowding outcome compared to fast-track implementation at our study site, providing 4 mins reduction in overall average LOS (11 mins reduction in ALOS and 2 mins reduction in DLOS). We also observe that LWBS rates are similar across fast-track and pod interventions, meaning that the implementation of pod does not interfere significantly (0.3% decrease) with the benefits of traditional implementation of fast-track in our ED. The same observation is made with the bedside nurse utilization. Compared to the study site directly, we observe statistically significant improvements across all KPIs, except for ALOS.

We also performed sensitivity analysis like section 5.4.1.2 to understand how the implementation of the currently optimized pod bed assignment would impact ED outcomes if different ESI 4 & 5 patient proportions were observed. Our results in Table 5-8 show that pod bed assignment offers statistical improvement over the regular ED configuration regardless of the proportion of ESI 4&5 patients in the system. However, this improvement cannot be isolated from the fast-track implementation for all metrics except bedside nurse utilization. This is confirmed when our pod assignment implementation is compared to the results from the fast-track implementation. Our statistical tests show that we must accept the null hypothesis that the medians from both models are not different for LWBS and ALOS in some cases, and as such, there is likely no additional improvement that the pod bed assignment will offer in these scenarios. We do observe that when the proportion of ESI 4&5 are lower, LOS is statistically lower compared to fast-track implementation. The overall result when compared to fast-track is not surprising as our pod bed assignment strategy was optimized specific to our study site's original ESI distribution and would likely need to be readjusted to offer any additional benefit.

Table 5-8: Pod Bed Assignment Sensitivity to Varying ESI 4 & 5 Proportion

ED Type	KPIs	5%	10%	Baseline	20%	25%	30%	35%
Fast-Track	ALOS (mins)	-3	-5.5	-6	-6	+1	-2	0
	DLOS (mins)	-3.9*	-3.6*	0	0	-1	+5	+6
	LOS (mins)	-1.3*	-3.3*	-2	-2	+1	+1	+4
	LWBS (%)	+0.7	+0.1	+0.2	+0.2	+0.8	+0.5	+0.7
	Bedside Nurse Utilization (%)	-1.1 ***	-1.3 ***	-0.5*	-0.5*	-0.9*	-0.4*	-1.3*
Regular	ALOS (mins)	-3	-4.1*	-6 *	-6 *	-15 ***	-12 ***	-22 ***
	DLOS (mins)	-6.9 ***	-5.6 ***	-9 ***	-9 ***	-7 ***	-8 ***	-5 *
	LOS (mins)	-8.3 ***	-5 ***	-10 ***	-10 ***	-13 ***	-11 ***	-11 ***
	LWBS (%)	-1.4 ***	-1.7 ***	-0.5 ***	-0.5 ***	-1.1 ***	-0.9 ***	-0.5 **
	Bedside Nurse Utilization (%)	-1.7 ***	-4.3 ***	-8.3 ***	-8.3 ***	-9.2 ***	-11.4 ***	-13.7 ***

Model results are shown as differences between medians of both models' output values
*** refers to a p-value <0.001, ** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

To validate this, we run another experiment focused on understanding if improvement over fast-track implementation can be observed at high ESI 4&5 proportions. First, we set the ESI proportions to match NHAMCS's distribution in Table 5-5 where ESI 4 & 5 represent >27% of the population (vs 14% in study site) and ESI 3 represents ~44% (vs 60% in study site). Next, we optimize the pod bed assignment strategy specific to this new proportion. Then, we run the pod best assignment strategy at the optimized parameters for 30 replications to collect one month of KPIs. We do a similar set of runs with the fast-track implementation. Finally, we perform similar Wilcoxon-Mann-Whitney test to understand if pod bed assignment offers better outcomes.

The results from the optimization (Figure 5-7) show that number of pod beds to allocate is only 1 and that this bed is made available when the first severe boarding level (i.e., boarding level is 2) is detected and only turned off if the predicted severity of boarding for the next 4 hours is less than

11. Since the highest boarding level is 2, in practice, this means that there must not be four consecutive severe boarding levels before the pod bed is reallocated to fast-track.

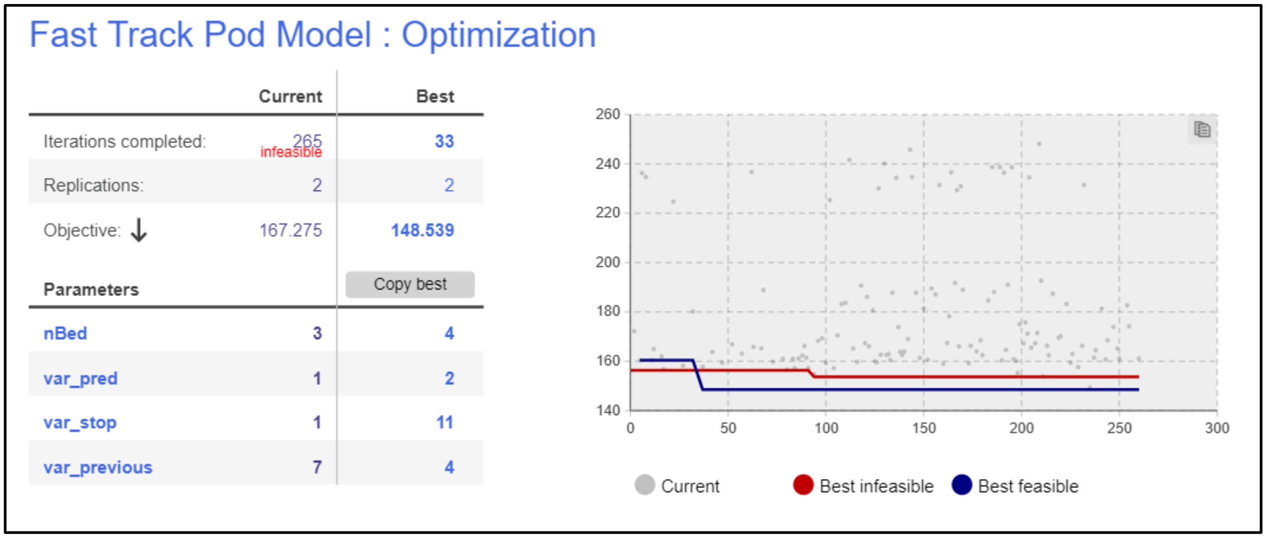

Figure 5-7: Pod Bed Assignment Optimization for NHAMCS ESI Distribution

The results of the statistical tests are highlighted in Table 5-9. We observe that for overall EDLOS, while pod bed assignment offers a smaller range, there is no statistical significance but the medians from both models are the same. DLOS from both models are similar also; however, ALOS is statistically lower from the pod assignment strategy than the fast-track implementation.

Table 5-9: KPI Comparison between Pod Bed and Fast Track for NHAMCS ESI Distribution

KPIs	**Pod ED**	**Fast Track ED**
ALOS (mins)	335 (310 - 370) *	344 (307 - 391)
DLOS (mins)	95 (84 - 106)	92 (82 - 106)
LOS (mins)	161 (142 - 178)	161 (145 - 182)
LWBS (%)	0.4 (0.1 – 1.6)	0.2 (0.0 – 0.7)
Bedside Nurse Utilization (%)	65.2 (62.5 – 66.3)	64.8 (62.0 – 65.6)

Model results are shown as median of output values followed by their ranges.

*** refers to a p-value <0.001, ** refers to a p-value <0.01, * refers to a p-value <0.05 and no sign refers to p-value ≥0.05.

5.5 Discussion

In this study, we focused on the impact of boarding on ED crowding levels (defined as high EDLOS) and aimed to understand how the knowledge of future boarding levels could be used to make operational decisions. There are a lot of studies focused on ED crowding and ED LOS, with a few dedicated to understanding boarding specifically and much fewer attempting to predict boarding levels. Our study verified what other literature has already verified, that boarding influences ED LOS. Specifically, we showed that boarding in a particular hour has implications for ED crowding in future hours. We observed that for our study site, a simulated ED, every 30% increase in the proportion of boarding patients occupying the ED leads to a 1% - 14% increase in overall EDLOS. This increase in EDLOS was shown not to only impact patients waiting for hospital admission (2% - 20% increase) but also patients that are discharged home (1% - 6% increase). We posited that this relationship signifies that future boarding levels can be used as an early warning indicator for ED crowding, driving ED/hospital administrators to make decisions and avoid over-crowding situations. We stratified our boarding levels as normal (when ≤30% of ED is occupied by boarding patients), high (when 31% - 60% of ED is occupied) and severe (when >60% of ED is occupied).

A key objective for this study was to show how an early warning signal can be derived using operational data that is typically available from EHR systems. We were able to use details on queue volumes along major steps of a patient's journey in an ED (e.g., number of patients triaged, number of patients waiting on a bed, etc.) as well as other information such as utilization of resources (nurses, doctor, beds) and calendar information to predict boarding levels (i.e., normal, high and severe) 6-hours ahead. We chose to predict 6-hours ahead because we wanted to ensure that there was ample time for corrective action to take place. While we can predict next hour with higher accuracy as highlighted in our previous work, there is likely not enough time for ED staff to take actions. For our boarding level prediction, we evaluated three different well-validated algorithms (logistic regression, random forest, and support vector machines) to perform multi-class predictions. All three models offered good results, with F1 scores ranging from 0.67 to 0.97 for each boarding level. F1 scores represent a good balance between precision (reducing false positives) and recall (reducing false negatives). Typically scores above 0.8 are considered good predictive performance [56] and our tuned Random Forest Classifier was able to achieve 0.8 scores across all three boarding levels. To validate that our classifier would behave reasonably for our study site, we implemented a surge scenario (i.e., increased patient volumes) and we were still able to achieve 0.8 scores across all three levels, indicating that our classifier was well trained and not under- or over-fitting. This early warning indicator can be used by ED staff to drive different actions to manage crowding. For example, if possible, the early warning signal can be used to determine when to use inpatient hallways to house boarding patients and free up ED capacity.

To achieve the main research goal of understanding how the boarding early warning indicator can be used to alleviate ED crowding, we develop a novel bed assignment protocol based on the existing and commonly used fast-track protocol. This protocol, called pod bed assignment, is available to EDs where fast-track has been implemented and has shown value and for EDs where fast-track is being considered for implementation because there is perceived value. Our pod bed assignment protocol calls for carving out some of the fast-track capacity when there are predicted future high or severe boarding levels for the treatment of ESI 3 patients to alleviate the pressures on the regular ED process. Fast-track implementation is used by ED/hospital administrators largely because it offers better LWBS rate (and consequently higher revenues directly and through reduced ambulance diversion), it is important that the implementation of pod bed assignment did not take away this value while providing better ED LOS outcomes. As such, we formulated an optimization problem to minimize ED LOS without impacting LWBS rates. We used simulation-based optimization to solve this problem and identify the best parameters for our study site to implement the pod bed assignment. We were able to find an optimal configuration that leverages the predicted boarding levels to allocate fast-track beds to ESI 3. We conducted statistical tests which showed that compared to implementing in our study site, we could alleviate LOS by 4 mins (2% reduction) across all patients while reducing LWBS rates by >50%. When we compared the pod implementation to fast-track, we observed that while it did not yield any additional benefit to LWBS rates or bedside nurse utilization, it offered 2% improvement for ALOS, DLOS and LOS, highlighting its efficacy. It is worth noting that while these improvements seem small, they likely offer high ROI as the cost of implementing this protocol is relatively low if the ED has already committed to fast-track layout construction. The entire protocol is driven by data that is likely already available and doesn't require additional investment. The advent of machine learning-as-a-service makes it easy to create these predictions. The biggest upfront cost is the resource (time/person) to develop the predictive algorithm and identify/implement the best protocol trigger parameters for the specific ED.

We also evaluated the robustness of our technique by simulating different scenarios where an ED treats more non-critical patients (i.e., ESI 4 & 5) than our study ED. We observed that our pod assignment protocol, even after re-optimization for the new ESI distribution, offers better ALOS compared to only implementing fast-track (3% improvement), but little to no benefit for other measures such as DLOS or LWBS. Prior to re-optimization, we observe that at levels higher than 20% of non-critical patients in the ED, there is almost no benefit to using the pod assignment protocol compared to simply using all fast-track beds for non-critical patients. ESI distributions vary from ED to ED as shown in [57] from as little as 6% for non-critical patients to as high as 37%. In our study where non-critical patient population is lower than 20%, the pod bed assignment was proven to reduce ED crowding. This could be applicable in scenarios such as flu seasons or the ongoing pandemic where ED visits tend to skew towards higher criticality.

Our study is limited by several factors. First, due to the ongoing pandemic, we did not have access to actual data directly, so we leverage simulation output for our analyses. While we validated that the ED is representative, we acknowledge that this poses some limitations in direct applicability to our results. Second, the study is still a single center study as we only built one representative simulation, as a result, we are not sure of its direct applicability to other types of EDs with different processes, workflows, patient, building and staff characteristics. Lastly, our implementation of fast-track is specific. We assumed that our fast-track implementation is such that it is open 24 hours but serves as a true fast-track only during specific hours. This type of implementation has implications on hospital billing practices in the US (i.e., Type A vs Type B Medicare billing practices). Our pod bed assignment protocol was designed and tested on this implementation and in this study, we did not provide any cost analysis focused on the financial implications of leveraging our proposed pod bed assignment protocol.

5.6 Conclusion and Future Work

ED crowding is an ongoing global crisis that has been shown to have several detrimental impacts on healthcare outcomes including higher risk for adverse events. Research has already highlighted that boarding is the most influential factor related to ED crowding. However, there is not a lot of research related to manage boarding as it relates to ED crowding. While it is acknowledged that boarding is really an upstream supply problem which can best be addressed by the inpatient portion of the hospital, necessary systems-wide interventions are not typically made, and the ED continues to bear the brunt of boarding's impact. In this study, we accomplished three objectives related to easing the impact of boarding on ED. First, we showed how current boarding levels influence future ED LOS, a measure of ED crowding. Second, we created early warning signals based on predicting boarding levels 6-hours ahead, allowing ED administrators ample time to plan mitigation strategies. Lastly, we developed a novel bed assignment strategy for EDs that have implemented fast-track. This strategy provides an effective way to assign beds during fast-track operational hours that yields lower EDLOS while still providing lower LWBS rates associated with fast-track implementation.

To the best of the authors' knowledge, this study is the first of its kind across all three objectives. We achieved good results across our descriptive, predictive, and prescriptive models and we want to explore future work. In this study, we want to explore deep-learning techniques for our predictions of future boarding levels. These techniques have been shown to outperform techniques such as Random Forest and SVM that we used in this study. Additionally, our single-center study was based on a simulated ED; we want to conduct a multi-center study to understand the scalability of our approach leveraging data and partnerships from EDs with varying processes, layouts, workflows, and other characteristics. Access to more data will help in our goal to improve the prediction model and refine our early warning signal. Lastly, we want to partner with an emergency department to validate, analyze and improve the impact of our proposed bed assignment approach on ED outcomes.

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CHAPTER 6: CONCLUSION

This dissertation contributes uniquely to the growing body of Operations Research (OR) in healthcare literature, particularly the application of simulation techniques for studying ED boarding. First, the research addresses the issue of the appropriate amount of complexity required for a simulation of an emergency department to study complex subprocesses such as boarding and early abandonment of treatment. The dissertation contributes to simulation modeling by evaluating the differences between a discrete-event simulation (DES) and combined agent-based (ABM) and DES for modeling the interactions between patients and emergency department resources. It also contributes by leveraging Metamorphic validation, a technique still new to simulation literature, in the validation of its simulation models. Second, it highlights the applicability of a growing body OR techniques called Hybrid Systems Models (HSM) to drive impactful improvement in highly stochastic and complex processes such as emergency department processes. Using hybrid simulation-predictive-optimization models, the research examines how early warning about future boarding levels in an ED can be operationally used to make bed assignment decisions for patients that are not severely ill/injured and ultimately achieve better ED crowding outcomes. The dissertation also contributes to literature on machine learning in emergency departments by demonstrating how various machine learning techniques can be used in the predictive modeling for future ED boarding.

The dissertation aimed to address three research questions (highlighted at the end of Chapter 2). The answers to these questions are summarized below:

❖ *What is the value of creating a simulation model that includes detailed process steps and human decision-making behaviors? Does such a detailed model yield better decision-making/model outcomes than the typical simulation model found in literature?*
  Using the same data, two simulation models were developed: a "simple" DES (similar to simulation models described in existing literature) and a "complex" DES+ABM model that

more closely mimicked human behavior and included additional process decisions. When results obtained from both models were compared, it was observed that not all model outcomes were similar. Outcomes such as patient length-of-stay (LOS) showed statistically significant differences greater than 40mins ($p < 0.001$) and bedside nurse utilization showed differences around 20% ($p < 0.001$). Similar statistically significant differences were observed for boarding and bed wait times. However, left-without-being-seen (LWBS) outcome showed differences between 0.1% - 0.5% that were deemed not statistically significant ($p > 0.05$). This showed that the additional human behavior details related to waiting and abandoning queues did not add any additional value in understanding LWBS rates. Thus, it is reasonable to conclude that the use of a simple or complex model should be driven by study intent. For studies where LWBS is the objective, the DES model would suffice but studies where LOS and its influencing factors are of interest, then the more complex DES+ABM simulation would be more appropriate.

- *What are the main human and operational factors that can be used to accurately predict future boarding levels in an ED?*

This question was answered by exploring several techniques for predicting hourly boarding levels in the ED using operational factors such as counts of patients in queues, utilization of resources and human factors like complaints presented. Regression-based techniques such as random forest, regularized linear regression (elastic net) and XGBoost as well as time-series forecasting techniques like Autoregressive Moving Average and Exponential Smoothing were explored. The models achieved good predictive performance with mean absolute scaled errors from accepted models ranging from 0.56 – 0.69, showing an ability to reduce prediction errors by almost half when compared to using naïve previous hour forecasts. The models offered insights into significance of various factors and were able to offer good explanation of future boarding (coefficient of determination: 0.29 – 0.49). The predictive analysis showed that calendar information (time/day), queue-based information, utilization of resources such as beds and lagged values of boarding are the most relevant for predicting boarding 1 – 6 hours ahead.

- *How effective are bed assignment strategies compared to existing strategies at managing ED boarding and ensuring reasonable ED crowding levels?*

  This dissertation proposed a novel dynamic bed assignment strategy that leveraged early warning signals of future ED crowding (indicated by high LOS). The efficacy of this strategy was examined by comparing to a well-known/validated strategy for managing ED crowding: Fast-Track. The strategy proposed by this research leverages a simulation-predictive-optimization HSM to predict when ED LOS will be impacted due to current boarding levels and trigger a change in bed assignment policy in real-time as a response to avert the impact of the future boarding levels. The bed assignment policy was shown to statistically drive improved LOS by 2% reduction across all patients compared to fast-track, while reducing LWBS rates by >50% overall for EDs. For EDs that already leverage fast-track, this new policy is an inexpensive way to optimize existing fast-track bed capacity as it doesn't require additional physical infrastructure or staffing investment, especially if the ED's visits are similar to the study site where volumes of critical patients are greater than 80%.