OPTIMIZING TASK SCHEDULING IN EMERGENCY DEPARTMENTS

by

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ABSTRACT OF THE DISSERTATION

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An Emergency Department (ED) is a health care service that delivers time-critical care to unscheduled patient arrivals. Due to an ever increasing number of arrivals, the number of patients often exceed the physical and staffing capacity resulting in long waiting times, patients leaving without being seen by medical staff and higher mortality levels. In this work we investigate the scheduling of staff and equipment resources in EDs. We propose a spatial agent-based simulation framework to quantify the impacts of staff decision processes, such as patient selection, on patient length of stay and waiting times. To explore the ED administration intuition that patient throughput could be increased by prioritizing short patient visits, and corroborate our findings from our simulations that the order in which providers see their next patient affects the length of time patients spend in the ED, we proposed a real-time scheduler that prioritizes short visits. We concluded that *Emergency Departments need an online system that is constantly adapting to find an optimal scheduling of patient tasks to available resources.* To that effect we propose a mixed-integer linear programming model (MILP) to find an optimal schedule of tasks to resources that minimizes the time spent in the ED for every patient. Our findings show a large fraction of unaccounted tasks on the JSUMC Electronic Health Records (EHR), and that time and motion studies would be needed to complement EHR's to accurately model ED scheduling.

Acknowledgements

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My loving husband Fábio, my partner in life. Thank you! I love you!

Dedication

To my grandfather, who by example taught me how gratifying life can be when we pursue what we love.

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Chapter 1

Introduction

Over the past 30 years, Emergency Departments (ED) have had an increase in demand. Today, EDs are a primary evaluation and treatment site for not only trauma and emergency medical care, but also acute psychiatric illness, domestic violence, sexual assault, drug and alcohol addictions, and other social and primary care issues. As evidence of this increased role, visits to the ED have increased by 20% while the number of EDs has declined by 10% [40, 44].

The result is that many EDs are chronically burned out. Symptoms of the mismatch between demands and resources include ambulance diversion and extended boarding times. An ED is overcrowded when there is no space left to meet the timely needs of the next patient requiring emergency care. The negative impacts of overcrowding have been quantified in numerous studies, as summarized in [12], and involve serious health effects including patients leaving without being seen, increases in medical errors, and statistically significant correlations between overcrowding and increased patient mortality. There is an estimated 20-30% increased mortality rate due to ED overcrowding [17]. The negative impacts on staff is low morale and staff becoming burned out, which increases turnover rate [26].

Strategies to reduce overcrowding in EDs include additional staff and protocol changes during surges, electronic white board systems, and systemic reforms to reduce or divert patient flow. The problem with such strategies is that as soon as demand increases the ED becomes overcrowded again. One facet of the problem is that ED staff and administrators have little in the way of quantitative tools and techniques to judge the effectiveness of changes in staffing, space, procedures or technologies without resorting to costly pilots and trials. Moreover, the available tools use probabilistic models that hide many aspects of the ED. One such aspect is the fact that providers (nurses, physicians and technicians) are constantly faced with decisions about what to do next, for example, among the waiting patients which one should be seen next? There were no studies to quantify the impact on the time a patient spends on the ED by scheduling decisions made by ED providers when deciding their next patient. Anecdotal evidence suggests that health-care providers typically follow a few rules-of-thumb based on their situational awareness, resulting in a set of self-created suboptimal guidelines, leading to inefficiency.

Our research started with a simple question: *Is there a correlation between how long a patient stays in the ED and the scheduling decisions providers make?* To answer that question we partnered up with Jersey Shore Medical University Center (JSUMC), where the ED administration and staff provided us with insights and a few hours of their data.

We started our investigations by proposing REDSim (see chapter 2) an agent-based ED simulation framework that models provider scheduling decisions along with the spatial layout of the ED. The framework allows for a greater range of studies on the impacts of how health-care providers make decisions, as well as the impacts of the ED's spatial reconfigurations in addition to staff levels and patient flow. Our experiments show that the order in which providers see their next patient has a direct impact on patients length of stay (LOS). Moreover, by choosing the patient that is physically closest instead of the longest waiting patient a provider can reduce the amount of distance covered during a shift, with the impact of a small increase in patient LOS, alleviating staff overburden.

To understand the situations and the decisions faced by staff when choosing which task to execute next, we requested 3 months of ED data from JSUMC. Unfortunately, we only acquired 12 hours of patient data. These 12 hours have two main problems: first, the task timestamp does not capture the real execution time, mostly because patient tasks and requests are entered in bulk into the system, not demonstrating the correct order of execution; second, there is no specific information on which staff member executed which task. These two undesirable characteristics of the data left us unable to understand the situations and the decisions faced by staff when choosing the next patient task.

Due to the aforementioned lack of detailed information, we decided to consider the JSUMC ED administration intuition that patient throughput could be increased by prioritizing short patient visits, those that require very few ED resources. To explore that intuition and corroborate our findings from the REDSim simulator that the order in which providers see their next patient affects the LOS, we propose a real-time scheduler that prioritizes short visits (see chapter 4). Short visits are visits in which a patient requires few ED resources, such as when the patient is at the ED to have medications refilled. These visits require fewer resources than longer visits and therefore should be over quickly.

Even though our experiments with our online scheduler show an 8% increase in patient throughput, it is known that it is not realistic to prioritize short visits at all times because long visit tasks will starve from the lack of resources. Even with mechanisms to prevent task starvation, the emergency department visits are so random in nature that there is no single scheduling policy that will work under all scenarios. We concluded that *Emergency Departments need an online system that is constantly adapting to find an optimal scheduling of patient tasks to available resources.*

To find an optimal scheduling of patient tasks to resources closely relates to the Flexible-Job Shop Problem (FJSP). The FJSP is a scheduling problem in which multiple jobs (patient visits) are processed on several resources (physicians, nurses, equipment, etc.). Each job consists of a sequence of tasks, which must be performed in a given order, and each task must be processed by any resource from a given set without preemption. The objective is to assign each task to a resource and to order the tasks on the resources, so that the completion time of the last task to be processed is minimized.

Casting the problem of scheduling patient tasks to ED resources as a FJSP entails (1) modeling a patient visit as a job, (2) treating the providers decisions on what patient to care for as the assignment of tasks to resources, and (3) treating the providers decisions on what task to execute next among all the tasks ready as the sequencing of operations on a resource.

The FJSP is a NP-hard problem. We experimentally confirmed Fattahi's observation [16] that FJSP is strongly NP-hard and combinatorial, and that to solve realistic cases for more than two jobs, in our case two patient visits, other approaches have to be used.

To that effect we propose a mixed-integer linear programming model (MILP) to find an optimal schedule of tasks to resources that minimizes the time spent in the ED for every patient (see chapter 5). Our model extends Previero's FJSP model [42] to intrinsically depict the ED by (1) allowing tasks to be processed by multiple resources (e.g. the Consultation task that requires a bed, a physician and a nurse), (2) assigning the same resource to all patient tasks (once a bed is assigned to a patient all subsequent tasks for that patient that require a bed must have the same bed), and (3) minimizing the LOS for all patient visits.

When we solve our MILP model for 15 patients with rather involved visits, a solution within 63% from the optimal is found in 57 minutes. Even though at first glance such a result might appear underwhelming, it is important to observe the following. As compared to the real-time scheduler using random selection of next patient task, which resembles the current staff practice in EDs, our model's solution improves the average LOS of patients by 11%. Furthermore, for 20 patients with simpler visits, the solver finds a solution within 73% from the optimal in 5 minutes and within only 27% from the optimal in 10 minutes. Finally, the time to find a valid solution could be significantly decreased by introducing additional constraints at runtime that would reduce the solution space.

The contributions of this thesis are: (1) a spatial simulation framework that allows the ED administration to test what-if scenarios without having to resort to costly pilots and trials or probabilistic models that hide ED processes such as providers choosing their next patient; (2) a real-time scheduler that showed that a simple computer science scheduling approach when applied to the ED context has a considerable impact on reducing the patient LOS; (3) a MILP model that intrinsically depicts the ED assignment of patient tasks to resources and the sequencing of the tasks on the ED resources; and (4) an initial investigation of additional constraints to reduce the solution space of the MILP model.

Chapter 2

A spatial agent-based simulation for studying Emergency Departments

Even though there are a myriad of strategies to reduce overcrowding in the ED, including staffing changes, protocol changes during surges, electronic white boards systems, and systemic reforms to reduce or divert patient flow, ED administrators lack the ability to quantitatively analyze the effectiveness of new strategies without resorting to costly pilots and trials.

Studies that have addressed this evaluation gap through simulation include [51], [8], and [14]. A key limitation of most of these works, however, is that they focus only on resources (number of staff, equipment, and rooms) as the dependent variables. The independent variables were often metrics such as length of stay (LOS), waiting times, and leave without being seen (LWBS) rates. Our simulation framework also focuses on a similar set of independent variables as metrics, but has two key distinctions for the dependent variables. First, it models provider decision making, and second, it models the spatial layout of an ED. Both allow a greater range of studies on the impacts of how health-care providers make decisions, as well as the impacts of the ED's spatial reconfigurations.

Our agent-based ED simulation, called REDSim, thus allows evaluations of the impacts of provider task selection. In a modern ED, providers continuously face local scheduling decisions about what task should they do next. Anecdotal evidence suggests that health-care providers typically follow a few rules-of-thumb based on their situational awareness, resulting in a set of self-created guidelines. REDSim allows users to evaluate the impacts of these local rules-of-thumb on the operation of the ED.

Capturing spatial effects can be important because the physical layout of the ED can influence the relative impact of new technologies. For example, tracking technologies or tablets may allow the staff to accomplish tasks with less physical motion. Re-arraigning the layout of the ED may have similar impacts. In future research, spatial ED simulation can be coupled with research on environment optimization [28] to re-arrange the layout while focusing on reducing the distance walked by staff during shifts to help mitigate staff burnout. Research on environment optimization studies layout rearrangement given an optimization function. It can ranges from pedestrian flow during normal times or studies on evacuation scenarios during an emergency. In the ED context, environment optimization could open a span of studies not only in aiding mitigate staff burnout but also understand the impact of the layout on metrics such as patient LOS.

Using real data including patient arrivals as well as staff and equipment levels we show how REDSim can be used to evaluate questions in the ED. We demonstrate its use for evaluating a patient selection algorithm, traditional staffing decisions, as well as showing its use in a sensitivity study.

2.1 REDSim framework

In this section we describe our REDSim framework. Our goal was to devise a *general and flexible* model to simulate a variety of patient flows, study resource allocation and spatial disposition as well as to capture human movements and behavior.

REDSim uses a *agent-based simulation (ABS) model with a discrete-event infrastructure*. State variables change at separate instants of time at which agents can initiate actions, communicate with other agents and make decisions of their own. The terms entities and agents are used interchangeably throughout the text.

The process is modeled using a workflow approach which can be seen as a series of connected tasks involving one or more entities. The workflow represents the patient moving through the facility from the initial *arrival* task, then probabilistically transitioning from one task to the next until its final *departure* task.

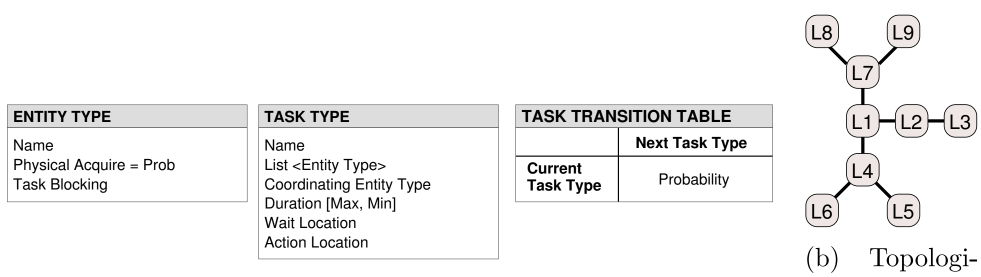
Each task is divided into four-phases to model the patient waiting for a provider (**wait**), the coordinating provider gathering resources for the task (**gather**), the task being executed (**action**), and the replacement of all gathered resources during the gather phase (**replace**). Once all four phases are completed the task is retired and the patient moves to its next task.

Using the four-phase task the framework ensures that every patient in the system is part of a task and is accounted for at all times. After the patient completes a task it is immediately transferred to the **wait** phase of the next task.

The next sections describe in detail the independent parts of the REDSim framework: the *input components* that model the system architecture (e.g. patient flow and the interaction between entities), the *hooks* that models provider behavior, and the simulation execution.

2.1.1 Input components

REDSim models the patient ED visit using the workflow approach where each task (nodes) represents an activity that takes place during the visit. The input components in Figure 2.1a specify the entities, their activities or tasks and their relationship with other entities for the ED workflow.



(a) Workflow components

(b) Topological map

Figure 2.1: Input components

Entities such as patients, staff, equipment, requests and tests are specified by the **entity type** component. Each entity on the system is an instance of an *entity type*. An *entity type* with the *task blocking* attribute models entities that need to go through an activity before the patient's current task moves from the *wait*-phase to the *gather*-phase. For example, if the patient needs an EKG test, it cannot be performed until the physician enters its request into the system, therefore request entity is blocking the EKG test task. Even though the patient is at the EKG test task the task stays at the *wait*-phase until the physician enters the request. The *task blocking* attribute forces the dependency between tasks, the pharmacist cannot fill a prescription until a physician enters its request into the system.

An *entity type* with the *physical acquire* attribute models stationary resources (e.g. stretchers) and their likelihood of being returned to their original location during the task *replace*-phase. For example, at the *gather*-phase the task coordinating entity must walk to the stretcher storage location to check if it is there or not. If available it is acquired for the task and will be returned to its storage location with some probability during the task *replace*-phase. If the stretcher is not into place at the *gather*-phase the coordinating entity must walk around the facility until it finds it. The *physical acquire* attribute models the frequent situations when equipment is not returned to its proper location.

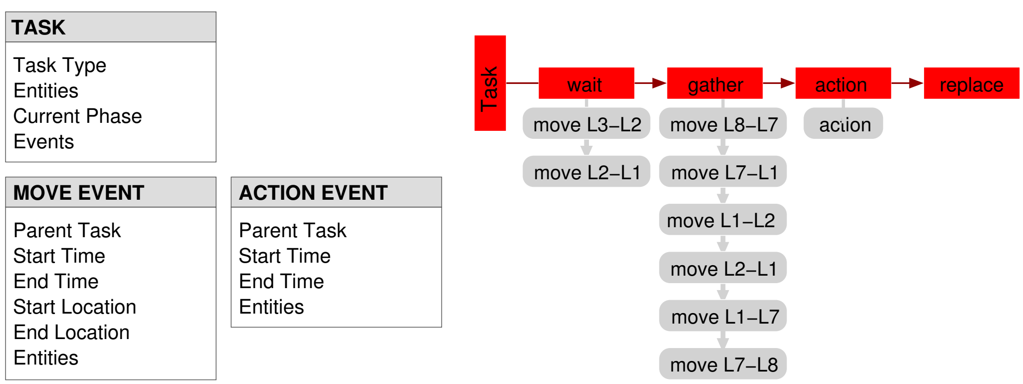
The **task type** specifies the workflow task nodes. Each task represents an activity that takes place or is related to an ED visit. It includes a set of entities (defined by the *entity type* list) that must be at the the *action location* for the activity to happen. The *task type* also specifies the task *coordinating entity type* which is responsible for gathering entities and the replacement of *physical acquire* entities to its storage position. It also specifies the range of time to be allotted for the task *action*-phase, the location where the patient is waiting at, and the location where the activity takes place. Using the triage task as an example, the nurse (coordinating entity) must conduct the patient from the waiting room (wait location) to the triage room (action location) in order for the triage activity to happen.

Once a task is complete the patient transitions to the next task according to the probabilistic **task transition table**. The table specifies the numerous patient flows available during a visit. The different flows are due to every patient having its own path of treatment, one can have only blood work done while another will have multiple exams.

To model entities' movement over the ED floor plan a **topological map** is used (Figure 2.1b). The map represents the connectivity of the environment in a graph structure, where vertices are distinctive locations on the floor plan and edges represent a direct path between them. To move an entity from one location to another the entity must follow the edges passing through each vertex between the two locations. To simulate an entity moving from a bed at location L4 to the pharmacy at location L9, the entity's location is updated at separate instants of time to follow the edges passing the locations L1 and L7 to arrive at the pharmacy.

2.1.2 Runtime components

The REDSim framework models the operation of the ED as a discrete sequence of events which are processed in a timely order. The two types of events either change an entity's location or its status. Figure 2.2a has the three main runtime components. A **task** is an instance of one of the input *task type* components, it maintains its entities and events, and keeps track of which phase it is at. The **movement** event moves the entity from one location to another by taking one adjacent edge on the topological map. The **action** event models change its entity's status to busy.



(a) Components (b) Example

Figure 2.2: Runtime

Figure 2.2b has the example of a triage task execution (at triage the patient waits in the main waiting area until a nurse calls him/her into the triage room). The execution proceeds as follows: once the triage task is created it immediately goes into the *wait*-phase. To move the patient from its current L3 location to the waiting L2 location one move event is created **(move L3-L2)**.

When a nurse (coordinating entity) becomes available it will choose one of the waiting tasks. At this point the chosen task transitions into the *gather*-phase and the nurse tries to acquire all remaining entities (patient at waiting area) and move into the action location (triage room). To acquire the patient the nurse moves from the triage room (L8) to the patient location (L2); for that 3 move events are created **(move L8-L7)**, **(move L7-L1)**, and **(move L1-L2)**. The nurse then acquires the patient and both entities move to the triage room (action location) which requires 3 more move events **(move L2-L1)**, **(move L1-L7)**, and **(move L7-L8)**. Once all entities are gathered at the action location the task transitions into its *action*-phase and the **action** event representing the triage being done is created. The triage task does not have the *replace*-phase which starts when the action event ends and the coordinator replaces all used resources to its original location. After that the task is retired.

2.1.3 Behavior components

Providers (nurses, physicians and technicians) are constantly faced with decisions about what to do next, for example, which patient should be seen next.

Provider behavior is modeled by functionalities/plugins added to pre-defined hooks. At the *end task* hook it must choose what to do next and at the *pick next task* hook which order the tasks are executed.

Once a provider becomes available it chooses what to do next by selecting one of the *end task* hook functionalities. It can choose to *take a break* or to *select a task to attend to*. If the latter is chosen, one of the functionalities of the *pick next task* hook is used to choose among the available waiting tasks.

2.2 Case study

In this section we describe how we applied the REDSim framework to model the ED at the Jersey Shore Medical University Center (JSUMC).

Figure 2.3 shows a map of the ED at the Jersey Shore University Medical Center (JSUMC). The area is over 350 ft. x 200 ft. It is divided by functionally: (1) Trauma, (2) Pediatrics, (3) Fast Track/Minor Care, (4) Waiting, (5) Triage, (6) Radiology, (7) Behavioral/Crisis, (8) General exam rooms/Urgent Care, and (9) Administration. In addition, within area 8 there are further zones; the central area is for clinical staff, and the outer areas are exam rooms.

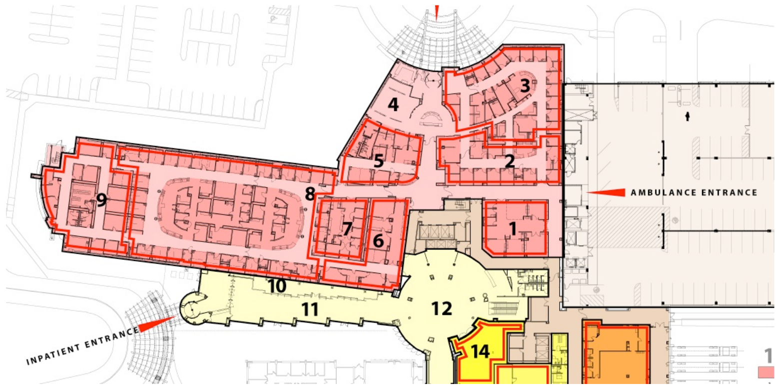


Figure 2.3: JSUMC Floor Plan.

We define an activity as a process in the patients' visit to the ED. Figure 2.4 is a simplified representation of the process and is the workflow used during evaluation. Each node in the graph is an activity, and each edge is a dependency.

When a patient arrives he is seen by a greeter, who takes the patients' name. The patient then waits to be interviewed by a triage nurse in a triage room. During triage the nurse uses the Emergency Severity Index (ESI) [19], which is a five-level triage algorithm that categorizes ED patients by evaluating both patient acuity and resource needs. First, the triage nurse assesses the acuity level. If the patient does not meet a high acuity level (ESI level 1 or 2), the nurse then evaluates expected resource needs to determine if the patient is ESI level 3, 4, or 5. The algorithm depicted in Figure 2.5 has four decision points that aid the nurse in assigning a ESI level. Patients assigned ESI level-1 have a high risk of death and require immediate physician involvement. ESI level-2 patients are high risk but stable and the primary nurse can initiate care through protocols without a physician immediately at the bedside. ESI levels 3, 4, and 5 have a lower death risk and can wait in the waiting room for the next available bed. These patients are assigned an ESI level with an estimate of how many resources the they are going to consume in order for the physician reach a disposition decision.

Once the patient is placed on a bed, vital signals are taken by a primary nurse

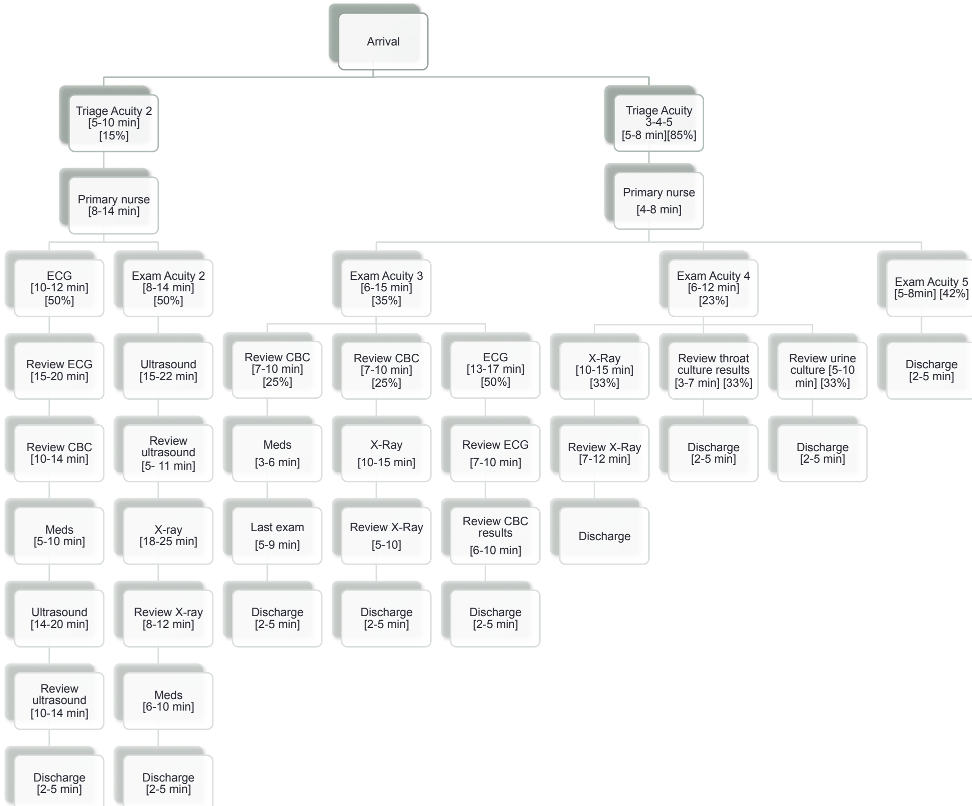


Figure 2.4: JSUMC Patient Flow.

followed by the consultation where the patient is seen by a doctor accompanied by the primary nurse. The next set of tasks depends on the patient condition as determined by the physicians' assessment. Tests are typically blood, urine and X-ray tests. When all the tests are completed, the ED physician makes a decision if the patient is well enough to be discharged, or must be admitted to the hospital.

When a patient is discharged, non-ambulatory patients require transport. Ambulatory patients can simply leave the ED with instructions for follow up care, if necessary. Admitted patients go through one of two possible paths: either their own physician is contacted for admission orders, i.e., the house doctor, or a resident is contacted. In either case, admission orders are required, which results in a hospital bed assignment. The patient hence remains boarded in the ED until the hospital makes the bed assignment.

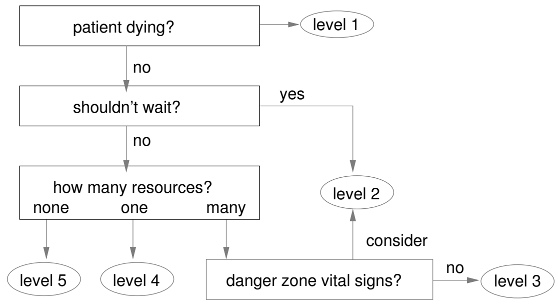


Figure 2.5: Emergency Severity Index Algorithm

2.2.1 Scheduling policies

To study providers' behavior we have four different selection algorithms. These algorithms are added to the *pick next task* hook described in section 2.1.3 at which the provider chooses its next task.

In the first algorithm, Highest Acuity (HA), the provider gives preference to the patient with the highest acuity (lowest ESI level index). If there are more than one patient with the same ESI level the provider chooses the one that has been waiting the longest. In the second algorithm, Longest Waiting (LW), the providers select the next patient based on waiting time. The idea here is to maximize fairness of patients' time. In the third algorithm, Shortest Distance (SD), providers select the patients who are the physically closest, thus reducing the amount of walking during its shift. In the fourth algorithm, Random (R), patients are selected at random.

2.3 Evaluation

In this section we present preliminary results of the JSUMC ED simulations. Figure 2.6 is a screenshot of REDSim during an execution. We measure the performance of the different decision making policies described in section 2.2.1 in terms of the length of stay (LOS) of patients. Lower LOS translates into higher patient throughput, thus alleviating overcrowding and enhancing the overall patient care experience. In addition, increased patient throughput using the same resources in the ED directly translates into reduced costs per patient.

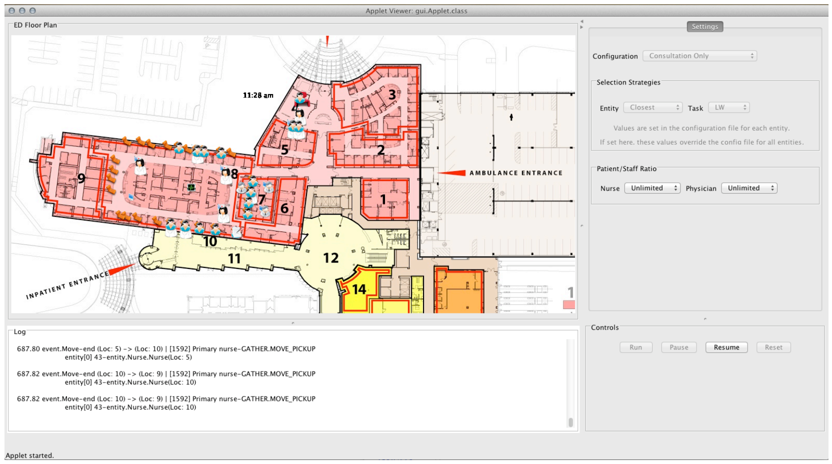


Figure 2.6: A REDSim screenshot during execution

The scheduling policy Highest Acuity (HA) gives preference to tasks related to patients with the highest acuity (lowest ESI level index), Longest Waiting (LW) gives preferences to tasks that have been waiting the longest while in Shortest Distance (SD) tasks that are closest to the provider are preferred, and in Random (R) tasks are selected randomly. We simulate patients with ESI level 2, 3, 4, and 5. ESI level 2 patients have preference over others because they are considered high risk patients.

The simulations mirror the *real values used in the JSUMC ED* for frequency of patient arrivals, staffing and equipment levels. Table 2.1 has the staff levels for each shift.The equipment levels are as following: 30 beds, 2 mobile EKG, 1 X-Ray, 1 ultrasound, and 4 workstations. Workstations are used to enter test requests, review test results and choose the next patient to be seen. Except for physicians, all personnel leave the ED at 7 AM, at 11 AM and at 11 PM. Physician shifts overlap in order to have higher number of attending physicians during peak hours (11 AM to 9 PM). At 7 AM there are two physicians, at 11 AM there are three and at 4 PM there are five attending physicians.

Figure 2.7 shows the frequency of patient arrivals. From midnight to 1 am, eleven patients arrive, from 1 AM to 2 AM one patient arrives, from 2 AM to 3 five patients and so forth. Patients arrive at random times within the hour period to simulate the unpredictable nature of the ED arrivals. The time of arrival for each patient is the

Table 2.1: Staff levels

Entity Type	Count							
	7AM-11AM	7AM-5PM	11AM-9PM	11AM-11PM	2PM-12AM	3PM-1AM	9PM-7AM	11PM-7AM
Triage Nurse	2	-	-	3	-	-	-	2
Nurse	6	-	-	9	-	-	-	6
Physician	-	2	1	-	1	1	1	1
PCA	4	-	-	6	-	-	-	4
Pharmacist	1	-	-	1	-	-	-	1

same throughout executions. ESI level 2, 3, 4 and 5 constitute 15%, 30%, 20%, and 35% of ED patients [19]. As of now we do not simulate ESI level 1 patients that are approximately 1% of ED patients. Instead we simulate these patients as ESI level 2.

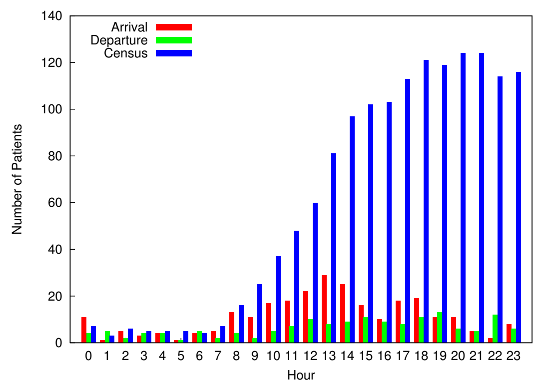
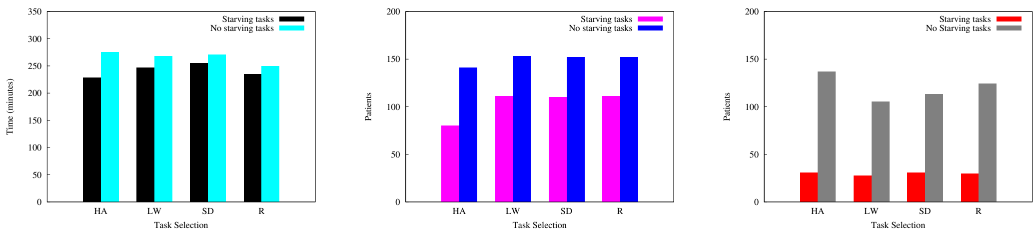


Figure 2.7: Number of arrivals, departures and the total number of patients currently in the ED.

Each execution simulates the ED over a 24 hour period. At the end of the 24th hour the execution is terminated even if not all patients have departed.

Figure 2.2 shows two simulations, in **Starving tasks** the next task is chosen according to the scheduling policies in place, there are no exceptions. On the other hand, **No starving tasks** aims to leave no task waiting longer than 2 hours even if it has a related high acuity patient. For example, if amongst the waiting tasks there are two X-Ray requests, one for a patient of ESI level 5 waiting for 2 hours and the other for a patient of ESI level 2 waiting for 1 hour the former is executed first.

Figure 2.2a shows that HA policy has the lowest LOS for the *Starving tasks* simulation. Patients stay on average 26 minutes (10%) less when compared to SD. But giving priority to high acuity patients leaves others starving, decreasing the number of



(a) Patient Length of Stay (b) Discharged Patients (c) Time to see a doctor

Table 2.2: Trade-off of favoring tasks that are waiting for more than 2 hours.

patients discharged. HA discharges 40 patients (25%) less than SD which can drastically increase the number of patients leaving the ED without being seen (LWBS rate). The number of patients leaving without being seen is one of the metrics used by ED to measure its performance. Therefore, lower LOS does not translate into higher patient throughput and in fact it if not careful it can increase mortality.

While SD is not the ideal policy to reduce LOS or increase patient throughput it may help reduce nurse burnout and increase patient satisfaction. Patient satisfaction levels are lower in hospitals with nurses that are dissatisfied or burned out; improving their working conditions may improve quality of care [36]. According to our simulations, nurses walk on average 300 more steps than physicians throughout their shift. Making small improvements such as reducing the amount of walking may contribute to an increase in job satisfaction.

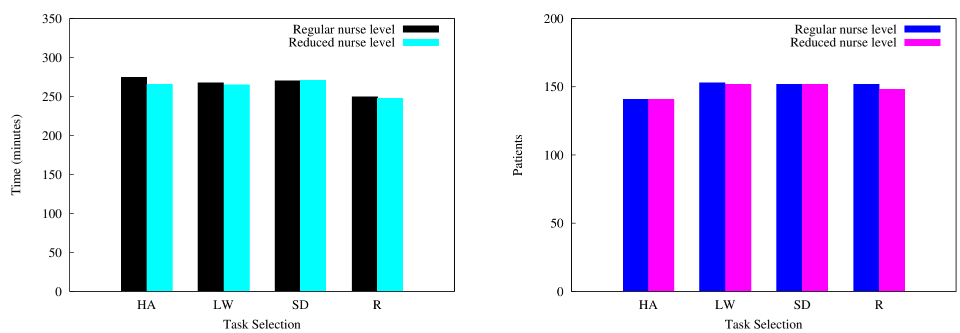
When preference is given to tasks that are waiting longer than 2 hours the LOS increases as seen Figure 2.2a. In the worst case (HA) LOS increases 20% while at the same time the number of discharged patients increases by 76%, which in some situations may be a good compromise. Figure 2.2c shows that the higher LOS is not the only downside of not letting tasks starve, the time to see a doctor for ESI level 2 patients increases by 105 minutes (70%). This increase may translate into higher mortality rates since high acuity patients have to wait much longer to see a doctor.

Although LOS is not significantly reduced (1.4%) the throughput increases 17% when comparing SD with HA. Therefore, on top of helping reduce nurse burnout it increases throughput.

In EDs things change very rapidly, while in one minute a scheduling policy may be the best choice in the next a high acuity patient arrives and the policy may become the worst option. Emergency departments need a system to analyze the trade-offs given a set of patients and conditions to determine which is the next task to be executed in order to improve the outcome.

2.3.1 Sensitivity of results

To better understand the relationship between input and output variables we conducted simple variations on the input. We use the **No starving tasks** execution as our base case for comparison. We varied staff levels and the time a task action takes. For the first variation we reduced 1 nurse from the 7AM - 11AM and 11PM - 7AM and 2 nurses from 11AM - 11PM. There is little output variation, as seen in Figure 2.3. What happens is that most of the time patients are waiting for tests (Lab work, X-Ray, Ultrasound) to be done and results analyzed.



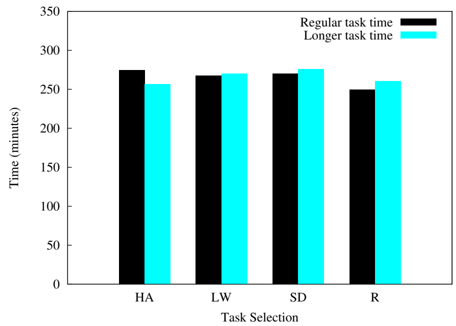
(a) Patient Length of Stay (LOS) (b) Discharged Patients

Table 2.3: Impact of reducing nurses level.

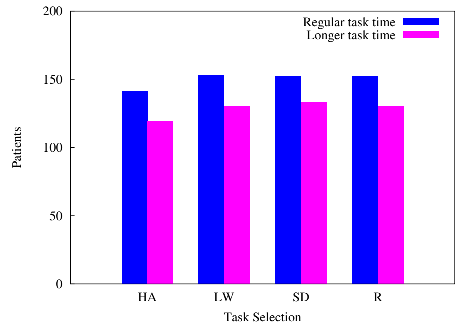
For the second variation we increased in 5 minutes the time it takes for test results to be analyzed. Three of the scheduling policies had an increase in LOS while all of them had the throughput reduced (Figure 2.4). The longer the tests take the longer the patient occupies a bed the lower is the patient throughput.

2.3.2 Validation

To validate REDSim we compare the mean service time for a 24 hour period of simulation against the real ED. Figure 2.7 shows the number of arrivals, departures and



(a) Patient Length of Stay (LOS)



(b) Discharged Patients

Table 2.4: Impact of increasing task time.

the number of patients in the system for a time interval T, and it can be interpreted as a queuing system. Let $a(t)$, $d(t)$ and $c(t)$ be the number of arrivals, departures and patients in the system at time t. The arrival rate $\lambda(T)$ is the total number of arrivals $A(T)$ divided by T, and the departure rate $\delta(T)$ is the total number of departures $D(T)$ divided by T.

In equation 2.1, we use Little's law [25] to compute the mean service time. Little's law only applies if the number of arrivals equals the number of departures. To compute the time at which all patients have left ($TTotal$) we must drain the remaining patients in the ED at the end of the experiment. Therefore, $TTotal = \frac{remaing\,patients}{\delta(T)} + T$. We can compute the mean number of patients dividing the total number of patients in the system ($C(T)$) by $TTotal$.

$$Mean\,service\,time = \frac{Mean\,number\,of\,patients}{\lambda(T)} \tag{2.1}$$

While the simulation LOS for the LW policy is around 57 minutes the real ED LOS is 138 minutes. We did not expect these values to match since we are only simulating the main ED while the hospital uses a fast track for ESI level 4 and 5 patients and an additional track for children that are not included in the simulation. Instead we use the entire patient frequency of arrivals for the main ED. We also do not have the information of how patients are distributed among the ESI levels, we used an estimate from [19].

JSUMC uses the time from arrival to triage, to bed assignment, to be seen by a doctor as well as LOS as performance metrics. We use these values to aid in the simulator validation as well.

Running experiments with the complexity of visits and accurate patient distribution among ESI levels to reflect the JSUMC ED operation is part of the future work.

2.4 Final remarks

REDSim is a simulation framework focused on investigations of the decisions made by ED staff members. We showed it can also analyze more traditional scenarios that examine resource optimization problems, such as staffing levels, as well.

Initial experiments show that the order in which physicians execute tasks has a direct impact on LOS and that a lower LOS does not necessarily increase patient throughput. We also note that there is no scheduling policy that works for all scenarios. We conclude that the ED would benefit from a system to provide heuristics that the staff can apply when the ED is in different situations.

REDSim also allow us to test the impact of various technologies before deployment. For example, we could examine if tablets improve LOS and reduce waiting times because staff move through the ED less. The fine-grained spatial component of REDSim could also allow us to quantify the amount of movement that was reduced. We are also planning an experiment to see if technology that flags tasks that are taking excessive time can improve waiting time and patient throughput. For example, tracking technology could identify if lab samples and results are held up, allowing staff to take action. If such delays could be reduced, it may greatly improve average waiting times.

On the next chapter we continue our investigation to understand the situations and the decisions faced by staff when choosing which task to execute next.

Chapter 3

Case Study Electronic Health Records

No studies have yet identified what kind of circumstances staff experience in the Emergency Department (ED) when choosing which task to execute next. Which are tasks that were waiting to be executed at the time? What would be the impact on patient length of stay (LOS) when one task is chosen over another? Are there choice patterns among the different classes of staff (nurses, physicians, technicians)? If so, does the pattern change towards the end of the shift, when people become tired? What factors influence nurses when choosing the next task? Is that different from physicians and technicians?

In this chapter we discuss our attempt to answer the questions above by analyzing ED patient records. Unfortunately, besides an insufficient amount of records released, the records do not identify the staff that performed each patient task. Being able to identify the staff that executed a task is crucial to understand the situations and the decisions faced by staff when choosing the next patient task. Without that information we do not have a complete and accurate view of the ED processes.

Our request included 3 months of electronic health record (EHR) from the Jersey Shore University Medical Center (JSUMC) Emergency Department along with the number of staff and equipment available during the 3 months. EHR is the digital version of the patient's chart.

Patient arrival is the first record of a patient into the system, and every activity that involves the patient is recorded thereafter. Activities include among others triage, bed assignment, medication and test requests, change in bed assignment, the patient being seen by a physician, nurse or technician, medication administration, and collection of samples. All activities are recorded as events in the EHR system on work stations grouped on each of the four corners of section 8 on the floor plan in figure 2.3 and are available to nurses, physicians and technicians. Triage nurses have their own work station on section 5 of the floor plan.

Under the United States Food and Drug Administration (FDA) agency regulations, an approval from the Institutional Review Board (IRB) is required to conduct research on human subjects records. All research conducted must either procure an authorization from research subjects or provide a way de-identify information, that is, prevent a subject identify from being connected with information.

In conjunction with the JSUMC ED administration we put together a IRB package that requested 3 months of EHRs. The package included a MD5 hash function to de-identify patients and staff. Once approved the JSUMC IT department would run a query to gather 3 months of EHR database. Alas, IT staff complained that the 3-month query was taking to long to run and only ran a 12-hour query. Moreover, IT staff wiped out the de-identified staff information from the query resulting dataset, information that would make it possible to discern between staff conducting each activity.

The acquired 12 hours of patient EHR ranges from 12:00 PM to 11:59 PM. In the next sections we discuss the acquired dataset, its undesirable characteristics and the information we foresee that can be inferred from the data.

3.1 Raw EHRs Dataset

As aforementioned, to protect patient identity the dataset has been anonymized by using the MD5 hash function on the patient name. The hash value was then substituted by a value representing the order of patient arrival in the ED. The acquired dataset is a log of every performed task or event in the ED, as it can be seen in the excerpt on table 3.1 for patient 23. The full set of patient's 23 tasks are listed in appendix A. The data has 12 fields, including patient name, their description follows:

Name. The name of the patient (anonymized). The value represents the order of patient arrival in the ED.

Acuity. A patient is assigned an acuity level during triage. The triage nurse uses the Emergency Severity Index (ESI) [19], which is a five-level triage algorithm that categorizes ED patients by evaluating both patient acuity and resource needs. First, the triage nurse assesses the acuity level. If the patient does not meet a high acuity level (ESI level 1 or 2), the nurse then evaluates expected resource needs to determine if the patient is ESI level 3, 4, or 5. The algorithm depicted in Figure 3.1 has four decision points that aid the nurse in assigning a ESI level.

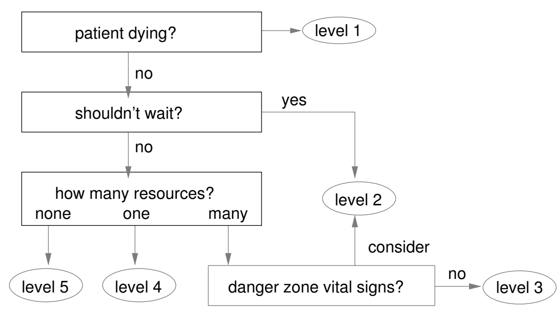


Figure 3.1: Emergency Severity Index Algorithm

Date. The date of the patient's visit to the ED. For the snippets of the dataset in this dissertation, this field has been altered to enhance patient anonymization.

Time. The timestamp for the event.

Event. The event name. This field seems to be actions in the system, available through a pull down menu. Examples are *Chart Entry Made*, *Order state change: automatic Order*, *Patient visited*, or *Patient Summary*.

Event Description. The event description, when present, qualifies the event. For event *Bed Assignment* at 14:26:09, the description lists the bed that was assigned to patient 23. On appendix A the event listed at 14:33:31 is *Order state change: automatic* while the description *Cbc W Diff (14:33) - Pending Ordered* specifies that there was an order for blood work. Oftentimes this field is empty, such as the event *Patient Arrival* at 14:21:00 or *Results viewed* at 16:31:29.

We define an ED visit as a sequence of medical tasks a patient goes through during the its stay in the ED.

Some tasks have many events: *Cbc W Diff* was pending order at 14:33:31, ordered at 14:33:35, printed at 14:41:16, sent to the lab at 14:47:34, in process at 14:48:16 and at 16:02:44 (possibly entries at the laboratory), returned at 15:02:33 and at 16:02:52 and reviewed by a physician at 15:48:18 and at 17:00:09.

Other tasks have only one event, such as at 14:39:20 the task *Patient Visited*, at 14:39:20 *Patient visited - Attending Physician*.

Mostly because staff is busy, events for several patients are entered in bulk in the system. This practice hides the real order of events in the ED. The dataset has all the events that happened but does not reflect their correct order of execution.

While processing the dataset we extracted all events that refer to a medical task, some events had no description (Patient Arrival) while others the description qualified it (Patient visited - Attending Physician).

Processing the dataset also involved discarding several of the event entries for each medical task. Since we did not know the time in which the task was executed, we extracted the event where the task is ready for execution, meaning, the event that requested the task. Therefore, for the *Cbc W Diff* task, we selected the event at 14:33:35. That is the time the physician requested blood work. After that a nurse must have retrieved a sample from the patient and sent the sample to the laboratory for analysis, the laboratory then analyzed it and sent a report back to the ED, which was then reviewed by the physician.

Events such as *Vital Signs Taken* at 14:36:59, or *Patient Visited* at 14:39:20 have no log of being ordered, the only log is when the event has already been done. Such events are kept as is. Because of that and the fact that we do not account for medications being filled at the pharmacy we decided to keep the administered time for medications. Therefore, we kept the event *Order State Change: Automatic - Acetaminophen* at 14:47:35 instead of 14:37:39.

Additional processing of the dataset involved finding events that are related to the same task, such as the four events at 14:33:31 (appendix A) that are further specifications of the blood work being requested at *Cbc W Diff*. Those four events belong to one task.

Given the detailed events on the dataset a tool such as REDSim can simulate every task event that occurred to quantify system bottlenecks as well as the impact of spatial re-arrangements and additional resources on patient throughput and length of stay.

Station. The work station is the identification of the computer where the event was recorded. In JSUMC the work stations are grouped on each of the four corners of section 8 on the floor plan in figure 2.3 and are available to nurses, physicians and technicians. The laboratory and radiology work stations are at their respective locations outside of the ED.

Given that nurses are assigned a set of beds to service during their shift, and given that the *Bed Assignment* event makes a record of the bed assigned to a patient, we might be able to map patients to a subset of the nurses, had we known the assignment of nurses to beds for each shift. The station identification could shed a light on the amount of physical motion nurses experience.

ENID. The encounter identification is the session identification when a staff logs in and then out off the station. All events with the same ENID were entered at the same login session, consequently at the same time.

Staff. The type of staff that logged in for the session and consequently inputed events. This field has Nurse, E.D. Physician, Scribe, Registrar, and PCA (technician).

ENID. Replicated encounter identification.

Patient ID. The patient identification in the system. For the snippets of the dataset in this dissertation, this field has been altered to enhance patient anonymization.

Outcome. The patient outcome is either *Admit* or *Discharge*. The *Admit* outcome is set for patients admitted into the hospital, while the *Discharge* outcome is set for patients that have been discharged from the hospital. Usually, patients admitted to the hospital stay a long time in the ED awaiting for a hospital bed. These patients incur additional strain to the already scarce ED resources.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:21:00	Patient Arrival		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:38	Encounter creation		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Event Timestamp Change		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Merge Complete		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Patient Move	Waiting	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Patient Visited		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:42	Registration	Patient Registration Page: Viewed Registration	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:49	Chief Complaint Modified		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:55	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:55	Patient Move	IT Waiting	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:26:09	Bed Assignment	ED18	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Chart Entry Made		DD21	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Chart Entry Made		DD21	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Patient Move	ED18	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Responsible Dept Assignment	Automatic : MAIN ER	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Staff Assignment		2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Staff Role Assumption		2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:19	Patient Summary	Patient Summary Page: Viewed Patient Summary	2030D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:26:23	Patient Summary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:24	Staff Assignment		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:28	View Chart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:34	Patient Summary	Patient Summary Page: Viewed Patient Summary	2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:26:40	Chart Template - Select Manual		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:43	Staff Assignment		2062D	745106	Nurse	745106	23023	Admit

Table 3.1: An exerpt of the raw dataset of patient 23 events

ID	Acuity	Date	Time	Task Name
23	2	4/13/17	14:21:00	Patient Arrival
23	2	4/13/17	14:26:09	Bed Assignment
23	2	4/13/17	14:27:14	Triage Complete
23	2	4/13/17	14:33:35	Lab Tests Cbc
23	2	1/30/13	14:33:36	Lab Tests PT W/ INR
23	2	1/30/13	14:35:22	Radiology CT Head/Brain
23	2	1/30/13	14:36:59	Vital Signs Taken
23	2	1/30/13	14:39:20	Patient Visited Attending Physician
23	2	1/30/13	14:47:35	Medication Acetaminophen
23	2	1/30/13	15:08:13	Medication NS 0.9%
23	2	1/30/13	15:39:10	Medication Zofran
23	2	1/30/13	15:50:28	Med Followup
23	2	1/30/13	16:40:00	Vital Signs Taken
23	2	1/30/13	17:03:01	Vital Signs Taken
23	2	1/30/13	17:18:04	Medication NS 0.9%
23	2	1/30/13	18:24:31	Vital Signs Taken
23	2	1/30/13	18:25:51	Medication Miscellaneous
23	2	1/30/13	19:20:23	Med Followup
23	2	1/30/13	19:43:42	Vital Signs Taken
23	2	1/30/13	20:49:18	Med Followup
23	2	1/30/13	21:11:06	Departure

Table 3.2: Processed tasks for patient 23

Table 3.2 lists the tasks extracted for patient 23 from all the tasks listed on appendix A. The *Name* field has been substituted by *ID*, the value represents the order of patient arrival in the ED. *Acuity* is the ESI level the patient has been assigned in Triage. The *Date* field refers to the patient's visit date to the ED. *Time* is the event's timestamp, and *Task Name* is a combination of event and event description.

3.2 Processed Dataset

In order to understand what kind of circumstances staff experience in the ED when choosing which task to execute next, the dataset would have to include each task execution time and the staff that was responsible for its execution. With that information we would have been able to emulate the 12 hours of patient tasks using REDSim, which would give us a detailed view of the ED process. The amount of time patients waited for each staff, how long did it take for tests to be completed, and what kind of patients each staff was assigned to.

But The acquired dataset has two main problems: the first is that event timestamp

ID	Acuity	Date	Time	Task Name	Staff
52	1	4/13/17	16:47:49	Rad Pelvic ultrasound ordered	
52	1	4/13/17	17:08:07	Rad Gallbladder ultrasound ordered	
52	1	4/13/17	19:47:04	Rad Abdomen ultrasound ltd/quad ordered	
52	1	4/13/17	21:02:18	Rad Pelvic ultrasound sent	Nurse
52	1	4/13/17	21:02:19	Rad Abdomen ultrasound ltd/quad sent	Nurse
52	1	4/13/17	21:02:19	Rad Gallbladder ultrasound sent	Nurse
52	1	4/13/17	21:27:05	Rad Abdomen ultrasound ltd/quad in process	
52	1	4/13/17	21:27:05	Rad Gallbladder ultrasound in process	
52	1	4/13/17	21:27:06	Rad Abdomen ultrasound ltd/quad returned	
52	1	4/13/17	21:27:06	Rad Gallbladder ultrasound returned	
52	1	4/13/17	21:27:09	Rad Pelvic ultrasound in process	
52	1	4/13/17	21:27:11	Rad Pelvic ultrasound returned	

Table 3.3: A brief extract of the pre-processed dataset to showcase the two main problems

does not capture the real execution time of each event; the second is that there is no specific information on which staff executed each event.

A snippet of the pre-processed dataset in table 3.3 showcases the aforementioned two main problems. To protect patient identity the dataset has been anonymized. In the following snippet the date and the patient ID of each of the tasks have been changed. The only fields that have not been changed are patient acuity, task timestamp, and the task name. Refer to previous section for a description of each field.

We analyzed the log of events in the raw dataset to extract the task execution time that the event refers to. A task can have many events as shown in table 3.3, where each of the 3 radiology tasks performed on patient 52 have 4 events.

Event timestamp should portrait the time an event is executed, but instead it portraits the time the event is entered into the system. Due to staff heavy workload, oftentimes there is no time to enter each event as it happens, so, events are entered in bulk in the system. Because of that the dataset *does not accurately depict the order of execution of events*. Suppose that Nurse A is busy while Nurse B is not. Both Nurses deliver patients medicines at the same time but Nurse B will enter all his or hers patient events on time while Nurse A will enter his or hers patient's events much later and the system logs will have an inaccurate order for these events. While analysis of such dataset is not completely accurate, the system does record the events related to a patient's visit. Therefore we can analyze patient's events related to a task, and given resource levels at the time of the visit we can have partial knowledge of resource utilization and allocation.

In the dataset shown in table 3.3, there are 3 radiology tasks performed on this patient, each has an entry for the time it was ordered, an entry for the time it was sent, an entry for the time it was in process, and an entry for the time it was returned. For radiology tests, an ED physician is responsible for requesting tests, and after the images have been taken a radiology physician must analyze the images, write a summary, and then mark the tests returned. The radiology results can only be read by the ED physician after they have been returned from the radiology department. First, note that the 3 orders are requested at different times, but they are all in process and returned with almost the same timestamp. We suppose the event to indicate that the task was performed is labeled *in process*, but since it has almost the same timestamp as the returned event we conclude that there are no entries to indicate the time each task was actually performed, only the time the radiology physician marked them returned. The lack of timestamp accuracy also hinders our ability to quantify the amount of time each task has taken to be completed. Secondly, note that *there is no information on which type staff executed the tasks*, only for the *sent* events were recorded by a nurse. We resorted to interviews to match staff types (nurse, physician, technician) to task type (consultation, triage, EKG). We chose to keep the *ordered* event for radiology and laboratory tasks, because that is the time the task is ready to be executed.

3.3 Final remarks

To understand the situations and the decisions faced by staff when choosing the next patient task, and to have a complete and accurate view of the ED we must be able to identify the staff that performed each event. Moreover, the dataset must have the exact time each task was processed so we could quantify the number of tasks waiting to be executed for a particular staff at any point in time.

If the EHRs had the exact time each event occurred and which staff member executed the event we would be able to identify which other tasks were waiting to be executed at the time. We also would be able to quantify the impact in patient LOS had the staff chosen another task in a real scenario. More interesting results would come from identifying choice patterns among staff, e.g. is there medical condition staff tend to avoid? If there were patterns among classes of staff (nurses, physicians, technicians) or at a finer per person level.

Without such information we geared our studies towards *quantifying the impact that the order in which tasks are executed have on patient LOS*. Even though the EHRs lack the detailed information we were looking for, we were still able to extract every medical task the patient was involved throughout the ED visit. And, given that JSUMC ED provided the number of staff and equipment available during the 12 hours of patient EHR we can explore the allocation of staff to patients tasks and the execution order of these tasks. Our main limitations include assigning staff to each of the dataset's tasks, and using a fixed task execution time for every task of the same type.

On the next chapter we explore the simple *short job first scheduling* technique following the JSUMC ED administration intuition that patient throughput could be increased by prioritizing short patient visits.

Chapter 4

A scheduling approach using decision trees

The acquired dataset includes every patient event that occurred during the Emergency Department (ED) visit, but it does not list information about the staff responsible for providing medical care. Furthermore, the event timestamp does not capture the event real execution time. Such information enables the identification of staff subset that provided medical care to a patient. It also provides the ability to identify which patient tasks were waiting for the staff when it was providing care to another. Had the dataset included such information we would have been able to quantify the impact on patient LOS had another staff been assigned to the patient. Moreover, we could quantify the impact on patient LOS incurred by the order in which that particular staff chose the next task to execute.

Since the dataset does not include information about the provider or the staff responsible for providing medical care, we lack a complete and accurate view of the ED to understand the situations and the decisions faced by staff when choosing the next patient task. Instead *we explore the allocation of staff to patients tasks and the execution order of these tasks* by dynamically allocating providers to tasks.

4.1 A dynamic scheduler

There are many ways to assign tasks to providers. We focused in exploring the JSUMC ED administration intuition that patient throughput could be increased by prioritizing short patient visits, and to corroborate our findings from the REDSim simulations that the order in which providers see their next patient affects the patients length of stay (LOS).

There are few studies that investigate dynamic ED scheduling of tasks to resources, two of which use genetic algorithms and tabu search to improve solutions, [50] [35]. These studies are looking for the best possible scheduling without considering human behavior and decisions. Often, staff follow a few rules-of-thumb based on their situational awareness, resulting in a set of self-created guidelines. *We aim to understand the impact of simple decision procedures on patient LOS.*

We use the dataset as an input into a dynamic environment where JSUMC resource availability is known and the patient next task to be executed is only available when the previous task has been concluded. There is one study in the literature that investigates physicians choice and processing order of tasks, ([55]). By intending to reduce the waiting time of high priority critical patients, it ranks patients according to their acuity, and then considers physician's load when scheduling patients to physicians. Except for physicians, the study disregard other ED resources, but it is an example of one rule-of-thumb providers follow when choosing their next task. Physicians choose a high acuity patient that will stay in the ED for a long time instead of choosing a lower acuity patient that might require only a couple of tasks before discharge. In chapter 2 we experimentally showed that giving priority to high acuity patients reduces the throughput of patients and leaves low acuity patients tasks starving. When starvation is mitigated by giving preference to tasks that have been waiting longer than 2 hours, patient throughput is increased.

High acuity patients stay longer in the ED, often these patients are stable and are only in the ED because they await being admitted to the main hospital. While they wait ED resources are consumed. The intuition of the ED administration is that by prioritizing shorter visits patient throughput would be increased.

Short visits are often lower acuity patients that require few ED tasks; sometimes the patient is there to have medications refilled. These visits require fewer resources than longer visits and therefore should be over quickly. By prioritizing such visits, ED resources would be freed sooner, allowing more patients to start their visit, which consequently increases patient throughput. To study that intuition using a real dataset we propose a real time scheduler that prioritizes shorter visits using decision trees as a classifier. In the experiments we used JSUMC number of resources listed in table 4.1, and the dataset has been processed to have only one entry for each task. We chose to keep the task entry that has the test task ordered by a provider because that is the time the task is ready for execution. The 12 radiology events on table 3.3 that refer to 3 radiology tasks in table 4.2.

Resource Type	Quantity
Greeter	1
Triage Nurse	3
Nurse	9
Physician	3
Technician	6
Lab Technician	1

Table 4.1: Resource Levels at JSUMC

ID	Acuity	Date	Time	Task Name
52	1	4/13/17	16:47:49	Radiology Pelvic ultrasound ordered
52	1	4/13/17	17:08:07	Radiology Gallbladder ultrasound ordered
52	1	4/13/17	19:47:04	Radiology Abdomen ultrasound ltd/quadrant ordered

Table 4.2: Processed dataset has only one entry per task

Next, we discuss how we use decision trees to identify patient visits as short or long.

4.2 Classifying ED visits

A decision tree is a predictive machine learning model that has a tree-like structure built from observations of an item. Once the tree is built, it is then used to predict an item's outcome. To classify the ED visits into short and long visits (outcome) we used decision trees where patient's tasks are used as observation items. Weka [1] generated the decision tree from our dataset. Weka is a collection of machine learning algorithms for data mining tasks. It contains tools for data preparation, classification, regression, clustering, association rules mining, and visualization.

Our complete dataset has 103 patients of which 66 patients (2/3 of the dataset) were used to generate the decision tree in figure 4.1. Weka uses 10-fold cross-validation to evaluate its predictive model that correctly classified 54 visits (81.8%). Given this decision tree, a patient visit that includes one or more Lab Test CBC, Medication Zofran, or Medication Toradol tasks will be classified as a long visit.

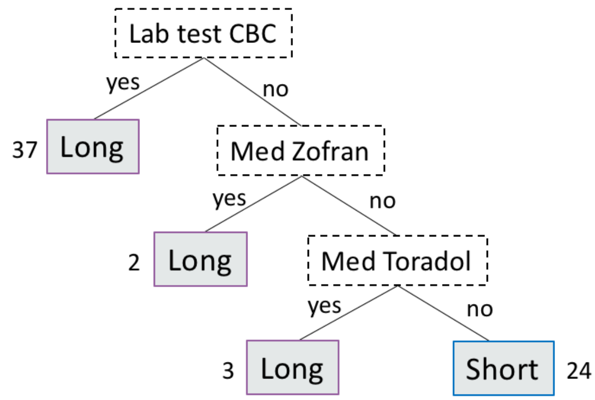


Figure 4.1: Decision tree generated with Weka using 66 patients

All of the 37 patients that required a CBC test in our training dataset were high acuity patients with ESI levels 1 or 2, and consequently have long visits. As were all of the 12 patients that have taken Zofran and Toradol medications. Zofran is used to prevent nausea and vomiting; some of the patients that have taken Zofran have also taken morphine or had CT scan of the brain. Toradol is a nonsteroidal anti-inflammatory drug and was used on patients that required a strep test or imaging tests of chest or abdomen. Clearly, patients on these medications stay in the ED for a longer period of time. It's likely that with a larger dataset these medications and the CBC test are still the common factors of long visits. But, there are probably unknown factors not present in the small acquired dataset that would come into view in a larger one.

4.3 Short-First scheduling of ED tasks

The visit classifier uses the decision tree on figure 4.1 to determine if a patient visit is short or long given that patient's previous tasks. At the beginning of an ED visit a patient is classified as a short visit patient, since no tasks have been scheduled yet. Once the next task for the patient is known, the previous task has been finished, the classifier determines if the patient continues as short visit or if the patient is changed into long visit status.

Algorithm 1 describes the procedure that is executed every time the processing of a task has been concluded, which is also the time in the execution when resources become available. The scheduler prioritizes short visits by scheduling all short visit patient's tasks that are ready to be scheduled, and then scheduling the long visit patient's tasks.

Algorithm 1: Short-First Task Scheduler

```
initialize short-visit ready queue;
initialize long-visit ready queue;
for every patient with tasks ready to be scheduled do
    classify patient visit into short or long;
    insert patient into proper ready queue;
end
while short-visit ready queue is not empty do
    p ← dequeue (longest waiting patient);
    t ← p's next task to be executed;
    if there are enough resources available to process t then
        schedule t;
    end
end
while long-visit ready queue is not empty do
    p ← dequeue (longest waiting patient);
    t ← p's next task to be executed;
    if there are enough resources available to process t then
        schedule t;
    end
end
```

4.4 Experiments and results

We ran experiments with 37 patients with a total of 403 tasks, 1/3 of the dataset, and used the patient arrival timestamp, from the dataset, as the time the first patient task is ready to be scheduled. For these experiments two scheduling policies were tested: *random* and *short-first* visit.

Random keeps a list of patients with tasks that are ready to be scheduled. Then randomly selects a patient from the list and schedules that patient's next task if there are resources available. *Short-first* uses algorithm 1.

Figure 4.2 compares the average length of stay (LOS) of the 37 patients for the two scheduling policies, *random* is used as the baseline. **Short**, **Long**, and **ALL** show the average LOS for short, for long and for all visits respectively. Short visits benefit from the *short-first* policy where patients stay in the ED 32% less time when compared to *random*, while patients with longer visits stay in the ED an additional 11% on average.

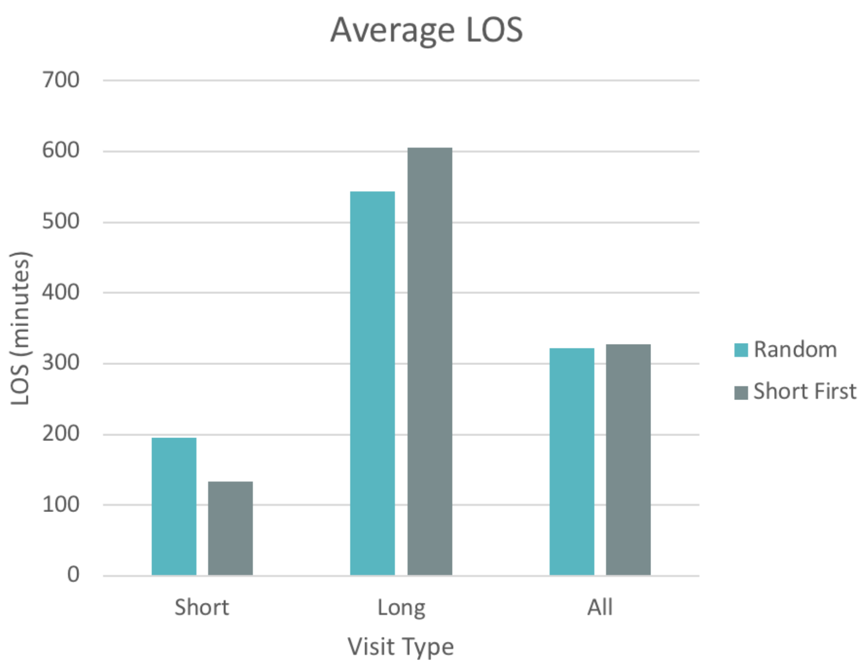


Figure 4.2: Comparison of Random and Short First scheduling policies for 37 patients

Figure 4.3 shows the *short-first* policy reordering of tasks with respect to *random*. For each task its start timestamp is plotted on the x-axis and the amount of time that same task started earlier or later is plotted at the y-axis (the difference in time between the two executions). Out of the 403 total number of tasks on the 37 patients dataset, 202 started at the same time; 83 started after and 118 started before its start time on *random*. The tasks that were pushed to a later start time, started 190 minutes later on average. While the tasks that started at an earlier start time, started 178 minutes earlier on average.

Almost 50% of the tasks had no change on their start time, those are the tasks clustered at the beginning of the execution (0 minutes difference). At that time, at the beginning of the execution, all tasks are classified as short tasks, meaning that no task has priority over the others. Moreover, this result shows that, at this time in the execution, there are enough resources to meet the demand. Later on the execution, with resource contention, there is an increase on the number of tasks that start earlier.

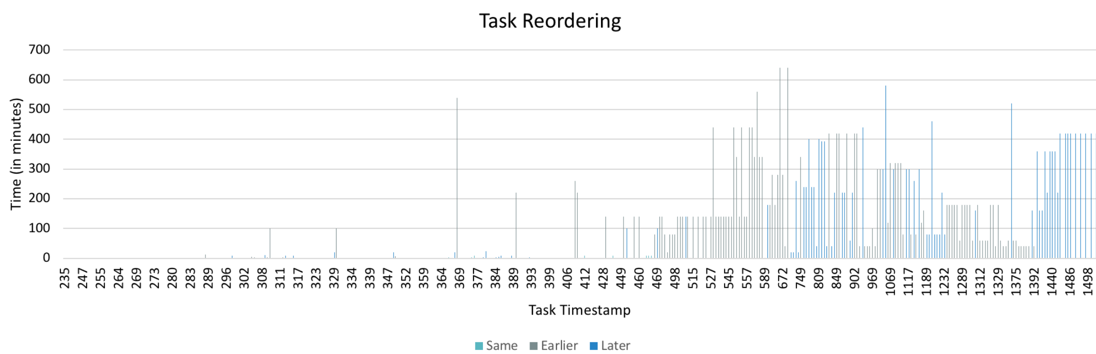


Figure 4.3: Reordering of tasks for Short First scheduling policy

Overall, *short-first* policy increases the LOS by 1% but increases the throughput 8%.

As expected, short visits benefit from the *short-first* scheduling policy which corroborates the ED administration intuition. It also corroborates our experiments on chapter 2 where we prioritized higher acuity patients which led to a decrease in the number of discharged patients (reduced throughput).

4.5 Final remarks

Given a small dataset this simple scheduling technique of prioritizing short visits resulted on 8% increase on patient throughput. This finding coupled with our findings on chapter 2 where *Shortest Distance* and *Highest Acuity* scheduling policies had a 17% difference in throughput led us to conclude that indeed providers scheduling decisions have a high impact on patient length of stay as well as patient throughput.

Without the aid of computers, providers use self-created guidelines when choosing the next patient task to process. They resort to simple decision procedures such as choosing the highest or lowest acuity patient, or the patient that is closest to them. Furthermore, given that ED visits are so random in nature, there is no single simple decision procedure (scheduling policy) that will work under all scenarios. Emergency Departments need an online system that is constantly adapting to find the optimal schedule of patient tasks to available resources. And, depending on the number of patients and their condition, the scheduling could switch from aggressively minimizing the LOS to reducing distance walked by staff in order to reduce the impacts of staff burnout.

Chapter 5

Emergency department scheduling as an optimization problem

Currently on Emergency Departments (ED), the order in which tasks are executed is chosen by providers. Without the aid of computers, providers use a set of self-created suboptimal guidelines based on their situational awareness. Examples of these self-created guidelines include choosing the patient that is closest to them, the highest acuity patient, or randomly choosing patients.

We experimentally confirmed on sections 2.3 and 4.4 that the order in which patient tasks are executed impacts the length of time patients spend in the ED. Moreover, it impacts patient throughput which translates into the ED ability to treat more or less patients during one day.

Prioritizing short visits increases patient throughput. Short visits are often lower acuity patients that require fewer resources than longer visits and therefore are over quickly. By prioritizing such visits, ED resources are freed sooner, allowing waiting patients to start their visit, which consequently increases patient throughput. But it is not realistic to prioritize short visits at all times because long visit tasks will starve from the lack of resources. Even with mechanisms to prevent task starvation, the emergency department visits are so random in nature that there is no single scheduling policy that will work under all scenarios. *Emergency Departments need an online system that is constantly adapting to find an optimal scheduling of patient tasks to available resources.*

The problem of finding an optimal scheduling of patient tasks to resources in the ED closely relates to the optimization Flexible-Job Shop Problem (FJSP). The FJSP finds the optimal solution for a static scheduling problem, that is when all the information about tasks and resource availability is known before the scheduling of tasks to resources. But, patient tasks are not known before they occur; the sequence of medical tasks a patient goes through during the ED visit is not known at patient arrival time, patient tasks are dictated by the severity of their symptoms and acuity (a measurement of the intensity of nursing care required by a patient).

We envision an online system that is constantly observing ED visits to learn the different types of patient visits (sequences of medical tasks). With the knowledge of types of patient visits and the previous tasks of a patient, the system could predict the upcoming tasks for each patient that are currently in the ED. Once the upcoming tasks for all patients currently in the ED are known the system can optimize the scheduling of tasks to the available resources given a predefined objective, such as minimizing patient length of stay or distance walked by staff.

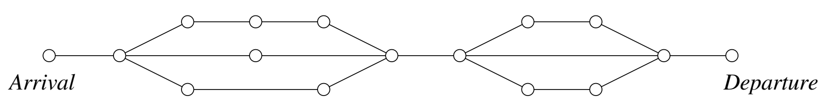
The only study, [35], to examine static scheduling in the ED also perceives the close relationship between the ED scheduling problem and the FJSP. Nevertheless, it proposes a model of the ED that does not capture the reality of ED tasks in two crucial points. The first is that in an ED a patient will be assigned the same nurse and physician throughout the visit, so every task that requires a physician will have the same physician resource assigned to it. In [35], no other resource other than a bed is assigned to the patient throughout the visit. This relaxation of the ED problem will result in shorter patient visits, since the patient can be assigned to any available provider (nurse, physician, PCA) during the visit instead of waiting for the provider that it has previously encountered. The second point is that many tasks require more than one provider. Consultation requires a physician and a nurse in addition to the bed. The study only captures tasks that require one bed and one provider which makes other resources available when they should be engaged in other tasks. By requiring less resources for a task, more resources are available in the system and therefore free to execute other patients tasks which will also shorten patients visits to the ED.

We begin our investigations towards the optimal scheduling of tasks to resources in an ED by acknowledging the difficulty of the problem since the FJSP is NP-hard. But given the current computational power, can we find an assignment of tasks to resources so that the time each patient spends in the ED is minimized? Next, we define the ED problem as a FJSP.

5.1 The emergency department scheduling problem as a flexible job shop problem

A patient visit to an ED can be seen as a sequence of tasks processed by providers (physician, nurse) and equipment (x-ray machine, bed). Starting with the initial task *Arrival*, where the patient is first seen, a set of tasks is followed by the last, the *Departure* task. Figure 5.1a is an example of a very simple visit, though the number and type of operations depend on the patient's symptoms. One patient might require extensive tests, while another might require only a consultation. Some of these tasks can be processed simultaneously, the patient could be at radiology taking X-ray images while laboratory tests are being processed. Figure 5.1b is a representation of a general patient visit. The objective of the ED is to provide care while minimizing the amount of time each patient spends in the ED, defined by visit span or length of stay (LOS).

(a) Simple Visit



(b) A general ED visit where each node represents an operation

Table 5.1: Emergency Department Visit

The JSP (Job Shop Problem) is a scheduling problem in which multiple jobs are processed on several resources. Each job consists of a sequence of operations, which must be performed in a given order, and each operation must be processed by a specific resource without preemption. The objective is to find a processing sequence for each resource that minimizes the completion time of the last operation to be processed (makespan).

The FJSP extends the JSP by allowing an operation to be processed by any resource from a given set. The objective is to assign each operation to a resource and to order the operations on the resources, so that the makespan is minimized [49].

Casting the problem of scheduling patient tasks to ED resources as a FJSP entails (1) modeling a patient visit as a job, (2) treating the providers decisions on what patient to care for as the assignment of tasks to resources, and (3) treating the providers decisions on what task to execute next, among all the ready tasks, as the sequencing of operations on a resource.

Therefore, each patient ED visit is a job consisting of operations that must be processed by resources (providers and equipment). The objective is to minimize the time spent in the ED (LOS) for every patient instead of minimizing the time of the last patient task, as in the FJSP.

We define that the Emergency Department Problem (EDP) is to assign tasks to resources and to sequence the tasks on those resources for execution, so that the LOS for each patient is minimized.

While the FJSP seeks to minimize the time of the last operation to be processed (makespan), the EDP seeks to minimize the time spent in the ED for every patient (patient span). Apart from the objective, there are two additional differences between the problems. The first is that on FJSP each operation is processed by a single resource, while on EDP, *operations may be processed by multiple resources.* An example is the Consultation operation, that requires a bed, a physician and a nurse. In which case, all resources assigned to an operation must be available at the operation's start time and cannot be preempted. The second difference is that on FJSP any resource capable of processing an operation can be assigned to it, while on EDP that is only true for the first patient operation that requires that type of resource. This is better explained with an example; once a bed is assigned to a patient, all subsequent operations for that patient, that require a bed, must also have the same bed assigned for processing. Therefore, once a resource is assigned to a patient operation, and the same type of resource is required for all forthcoming operations, *the same resource must be assigned to all operations of that same patient that require resources of that type.* These types of resources include beds, nurses, technicians, and physicians.

The travel salesman problem (TSP) is NP-hard, therefore the JSP is also NP-hard.

The TSP is a special case of the JSP with a single resource (the salesman is the resource and the cities are the jobs). Consequently, the FJSP and the EDP are also NP-hard because they are a generalization of the JSP. While NP-hard problems are intractable in the worst case, they may not be so in the case under study. Given the current computational power, can we find an assignment of tasks to resources so that the LOS is minimized for every patient? We begin our attempt to answer this question using explicit enumeration.

5.2 Explicit enumeration

The objective of the EDP is to assign each operation to a resource, and then to sequence the operations on those resources so that the time spent in the ED (LOS) is minimized for every job (patient visit). Our algorithm to enumerate all possibilities first assigns resources to tasks, then order the tasks on resources using REDSim. We use task and operation intermittently throughout the text.

5.2.1 Assigning resources to tasks

An ED job (patient visit) is a sequence of operations processed by providers and equipment (resources). Starting with the initial operation *Arrival*, where the patient is first seen, a set of operations is followed by the last, the *Departure* operation. Figure 5.1a is an example of such an ED job, where each operation requires a set of resources for execution. In this example, the *Triage* operation requires a *Triage Nurse*. Table 5.2 shows operation resource requirements along with the available resources for this example.

Operation	Resource Requirement	Available Resources
Triage	Triage Nurse	TN1, TN2
Primary Nurse	Nurse	N1, N2
Consultation	Nurse, Physician	N1, N2, P1, P2
Departure	Nurse	N1, N2

Table 5.2: Example of operation resource requirements and available levels

Consultation requires a *Nurse* and a *Physician*, so there are 4 resource combinations for *Consultation*: N1P1, N1P2, N2P1, and N2P2.

On EDP the same specific resource must be assigned to all job's operations that require resources of that same type. This applies to resources such as bed, nurse and physician. Therefore, if N1 is assigned to the *Primary Nurse* operation, then it must also be assigned to *Consultation* and *Departure*. Figure 5.1 has all eight possible operation-resource combinations for our sample visit in figure 5.1a. Each operation-resource combination or **branch** is equivalent to the same visit with a different resource assignment. Visit labeled 1A has resources TN1, N1, and P1, while visit labeled 2A has resources TN1, N1, and P2 for job A.

Suppose there is another job B in the system with the same operations as job A in figure 5.1a, so that both have the same number of possible task combinations. But, *job B*, each branch or operation combinations are labeled 1B, 2B, and so forth.

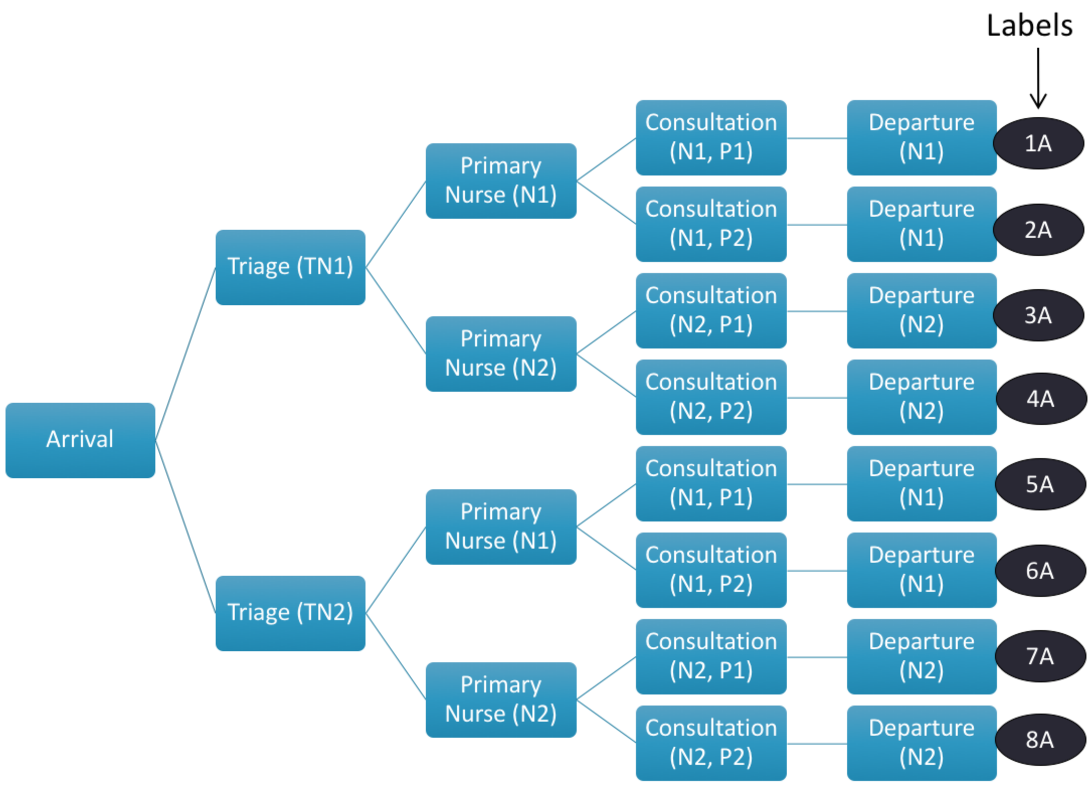


Figure 5.1: Job operation-resource assignment for one job. Each branch is one assignment of resources for the job.

Once resources are assigned for every operation, the second step is to sequence the operations on resources.

5.2.2 Sequencing operations on resources

On figure 5.1, each branch refers to one resource assignment for job A, which is the same for job B. Next, we combine all branches of both jobs to find all the possible combinations of resource assignments. The number of combinations for n jobs is $\prod_{job=1}^{n} number - of - branches_{job}$.

As an example, figure 5.2 combines branch 1 from job A (1A) with branch 3 from job B (3B). REDSim runs a simulation for each combination, to find the order of execution of the operations on the resources. Each job's operations and their resource assignment are loaded in REDSim, along with the start time of the first job operation (Arrival). The simulator then schedules each operation to be executed as soon as its previous have finished, and the resources assigned to it are available.

To find an assignment of resources to operations, such that the order that the operations are executed result in the minimum LOS for all jobs all combinations have to be executed. Next we show how the number of executions quickly grows, deeming explicit enumeration unpractical.

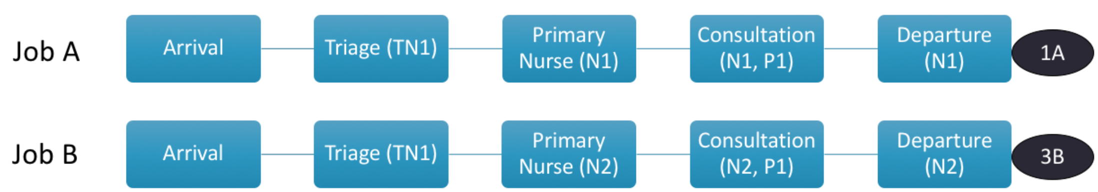


Figure 5.2

5.2.3 Problem size

The most common types of operations in the case study are listed on table 5.3a, along with its required resources for execution. The number of resources available are on table 5.3b.

Given the resources required for each operation and the number of resources available, REDSim assigns resources to operations to find all the combination branches for each job. Table 5.4 lists the number of job-resource assignment for a few types of visits.

Operation	Resources Required
Triage	Triage Nurse
Bed Assignment	Nurse
Primary Nurse	Nurse
Vital Signs	PCA
Consultation	Nurse, Physician
X-Ray	X-Ray machine, Technician
EKG	EKG machine, Nurse
Medication	Nurse
Departure	Nurse

(a) Operation resource requirement

Resource	Quantity
Triage Nurse	3
Nurse	9
PCA	6
Physician	4
X-Ray machine	2
EKG machine	4
Bed	30

(b) Number of resources

Table 5.3: Case Study

For a job with few operations there are 3240 total branches, meaning that there are 3240 different simulations or executions.

Job Operations	Branches
Arrival, Triage, Bed Assignment, Consultation, Lab Tests, Medication, Departure	3240
Arrival, Triage, Bed Assignment, Vital Signs, Consultation, Medication, Departure	19440
Arrival, Vital Signs, Triage, Bed Assignment, Consultation, Consultation, X-Ray, Medication, Vital Signs, Departure	466560
Arrival, Vital Signs, Bed Assignment, Triage, Consultation, EKG, Lab Tests, Lab Tests, Medication, X-Ray, Lab Tests, Medication, Medication, Consultation, Medication, Vital Signs, Departure	11197440

Table 5.4: Number of job-resource assignments

The number of simulations for two jobs, each with 3240 branches is listed on table 5.5. **Explicit enumeration becomes impractical with two jobs, each with 19440 branches**. The number of simulations to find the sequencing order of operations on resources is impractical. It corroborates [16] that states that FJSP is a more complex version of JSP, so that FJSP is strongly NP-hard and combinatorial, and that to solve realistic cases for more than two jobs, other approaches have to be used.

Branches per Job	Number of simulations
3240	10497600
19440	3777913600
466560	$2 * 10^{11}$

Table 5.5: Number of simulations for two jobs

We did find an assignment of operations to resources and ordered the operations on those resources using the Variable Neighborhood Search heuristic [24]. But we couldn't quantify how close the solution was to the minimum LOS for all jobs.

NP-hard problems, typically exponential in terms of time complexity and that may require exploring all possible permutations in the worst case, have a large set of tools to solve them exactly. Among the techniques available are are branch and bound, cutting planes, decomposition, Lagrangian relaxation, and column generation. In the next section we model EDP as a mixed-integer linear program (MILP) and use a solver to resolve the system of linear equations. MILP problems are generally solved using a linear programming based branch and cut algorithm, which is a combination of cutting planes with branch and bound, see [39].

5.3 Formulating EDP as a MILP problem

Mixed-integer linear programs (MILP) have been extensely used to formulate FJS problems. In this section we formulate the EDP as a system of linear equations proposed by [15] and reformulated by [42]. Then we use a MILP solver to find the optimal solution.

Branch and bound is an exact method to solve MILPs [29], and is used by most solvers. As we've seen in the previous section, explicit enumeration takes too long because the number of possible solutions explodes exponentially. Instead, branch and bound uses an enumeration tree, which is a method to enumerate all possible solutions of an integer program. The method branches on an integer variable, where on each branch, the integer variable is restricted to take certain values. Then it uses LP relaxation to bound the optimal integer solutions in a subtree of the enumeration tree. Therefore, it partially traverses the enumeration tree of all possible solutions by computing local upper bounds and global lower bounds, that are used to avoid parts of the tree that cannot produce the optimal solution.

5.3.1 FJSP mathematical formulation

First lets describe the FJSP proposed by [42]. Consider T the set of n tasks or jobs and M the set of m non-preemptive resources. Each job $i \in T$ is a sequence of n_i operations. The total number of operation is $N = \sum_{i=1}^{n} n_i$. Each operation O_i requires only one resource $k \in M$ for a processing period of $p_i > 0$.

O: set of operations of all jobs;

i, j: indices on the set O $(1 \leq i \leq N, 1 \leq j \leq N)$;

k: index on the set M $(1 \leq k \leq m)$;

O_k: the set of operations that can be processed by resource k $(O_k \subseteq O)$;

M_i: the set of resources that are able to process operation i $(M_i \subseteq M)$;

E_k: set of distinct ordered pairs of $O_k(E_k \subseteq O_k \times O_k)$;

$E = \bigcup_{k \in M} E_k$;

P: set of ordered pairs that corresponds to the precedence constraint between two operations $(P \subseteq O \times O)$. Therefore, $(i, j) \in P$ if and only if operation i precedes operation j for some job;

L: upper bound on the span of an optimal solution;

p_{ik}: processing time of operation i on machine k;

x_{ik}: binary variable that has the value of 1 if operation i is processed by machine k, 0 otherwise;

y_{ijk}: binary variable that has the value of 1 if operation i precedes j on machine k, 0 otherwise. y_{ijk} or y_{jik} can be equal to 1 if and only if both operation i and j are processed by machine k; In case $x_{ik} = 0$ or $x_{jk} = 0$ then $y_{ijk} = y_{jik} = 0$;

s_i: operation i processing start time;

p_i: processing time of operation i after a resource has been assigned to it;

C_{max}: the end time of the last job (makespan).

The objective function minimizes the *makespan*. Let $c_i = s_i + p_i$ represent the end time of operation i. Therefore, the objective is to minimize the maximum value of c_i for $i \in O$. The FJS is described by:

$$
\begin{aligned}
&Minimize \quad C_{max} && && (1)\\
&\text{Subject to} \quad \sum_{k \in M_i} x_{ik} = 1, && \forall i \in O && (2)\\
&p_i = \sum_{k \in M_i} x_{ik} . p_{ik}, && \forall i \in O && (3)\\
&s_i + p_i \leq C_{max}, && \forall i \in O_t && (4)\\
&y_{ijk} + y_{jik} = z_{ijk}, && \forall k \in M, \forall (i,j) \in E_k && (5)\\
&z_{ijk} \leq x_{ik}, && \forall k \in M, \forall (i,j) \in E_k && (6)\\
&z_{ijk} \leq x_{jk}, && \forall k \in M, \forall (i,j) \in E_k && (7)\\
&x_{ik} + x_{jk} \leq z_{ijk} + 1, && \forall k \in M, \forall (i,j) \in E_k && (8)\\
&s_i + p_i - L.(1 - y_{ijk}) \leq s_j, && \forall k \in M, \forall (i,j) \in E_k && (9)\\
&s_i + p_i \leq s_j, && \forall (i,j) \in P && (10)\\
&s_i \geq 0, && \forall i \in O && (11)\\
&x_{ik} \in \{0,1\} && \forall k \in M, \forall i \in O_k && (12)\\
&y_{ijk} \in \{0,1\} && \forall k \in M, \forall (i,j) \in E_k && (13)\\
&z_{ijk} \in \{0,1\} && \forall k \in M, \forall (i,j) \in E_k. && (14)
\end{aligned}
$$

The objective function is described by constraint (1). Constraint (2) ensures that operation i is executed by only one resource. Constraint (3) determines operation i processing time on the assigned resource. Constraint (4) ensures that the end time of every operation is less than or equal to the *makespan*. On constraint (5) $z_{ijk} = x_{ik} * x_{jk}$ meaning that if both operations i and j are processed by resource k than $z_{ijk} = 1$. The constraint ensures that if both operations are assigned to machine k only y_{ijk} or y_{jik} is equal to 1, defining the order of execution if both operations are assigned to the same resource k. Since $x_{ik} * x_{jk}$ is a non-linear value, its linearization adds constraints (6), (7), (8), and (14). Constraint (9) establishes that if two operations i and j are assigned to the same resource they cannot be processed simultaneously. Constraint (10) ensures that the order of the operations of a job is not violated. The problem variables are described by constraints (11)-(14).

The MILP model does not completely capture the EDP. EDP requires *multiple resources to process a single operation*, and requires *a single resource to process all job operations requiring its resource type* while minimizing job span for all jobs. Therefore we reduce EDP to fit into these formulations.

5.3.2 Relaxed EDP to FJSP

To reduce EDP to the FJSP formulations in section 5.3.1 we relax the objective function and the two differences between the problems. While EDP objective is to minimize *job span* for every job, FJSP objective function minimizes *makespan*. Therefore, the EDP objective is relaxed to minimize the end time of the last operation of the last patient to exit the ED (makespan). In the EDP **an operation can require multiple resources for processing**, in the FJS problem an operation is processed by exactly one resource. We relax EDP by substituting the set of resources required to process one operation in the ED as one resource in the FJS (substitute a nurse and a physician required for Consultation by one physician). Lastly, EDP requires **a single resource processes all operations of a job requiring its resource type**, which is not true for FJSP. We relax this restriction by allowing any resource that is able to process an operation to be assigned to it for processing.

JSUMC staff levels are listed on table 5.6. Since EDP is being relaxed to the current formulations of FJSP and Consultation requires a Physician and a Nurse, we considered only 6 nurses instead of 9. This relaxation is used to consider multiple resources as one, 3 nurses are combined with the 3 physicians required for the Consultation operation. Therefore, a total of 20 staff members available instead of 23. We have not yet included equipment in our experiments because it significantly increases the number of constraints generated by the model.

Resource Type	Resource k	Quantity
Greeter	1	1
Triage Nurse	2,3,4	3
Nurse	5,6,7,8,9,10	6 (9)
Physician	11, 12, 13	3
PCA	14,15,16,17,18,19	6
Lab Technician	20	1

Table 5.6: Resource Levels at JSUMC

5.3.3 Experiments and results

We used the Gurobi solver [2], version 8.01 on a 80 processor (Intel Xeon Processor Gold 6148) with 1TB of memory. Gurobi launched 32 threads to solve each instance of the problem with an imposed time limit of 1800 seconds.

Table 5.7 describes the instances of the Emergency Department dataset. Each instance is defined by its name and by the quadruple *(j, l-u, o, r)* where j represents the number of jobs (patients), l and u the minimum and the maximum number of operations per job respectively, o the total number of operations and r the number of resources available.

For each dataset we listed the number of binary and continuous variables as well as the number of constraints on the model. The completion time of the last operation is listed under C_{max} (minutes), and the average length of stay is listed under the Avg LOS column. An optimal solution was found for all instances except ED50 and ED60 that have a gap (meaning that the optimal solution was not found), and instance ED70 has reached the time limit of 1800 seconds without finding a solution (TLR: Time Limit Reached). Interestingly, the solver finds the optimal solution for ED80 and ED90 but not for ED70, which makes us wonder if the cuts implemented by Gurobi are cutting away the solution. It seems to be the case since doubling the time limit to 3600 seconds the solver does not find a solution for instance ED60 as well.

To exemplify why this model does not capture the ED problem, lets take a look at the optimal scheduling of operations found by Gurobi for instance ED2 in table 5.8. There are two jobs, job 1 has 6 operations (1-6), and job 2 has 10 operations (7-16). The first operation of each job, 1 and 7, are available for processing at $r_1 = 0$ and

Instance	Size	LP Model Size			Cmax	Gap	Avg LOS
	(j,l-u,o,r)	Binary	Continuous	Constraints			
ED2	(2,6-10,16,20)	651	33	1512	71	0%	55.5
ED3	(3,6-11,27,20)	1801	55	4305	104	0%	69.3
ED4	(4,6-11,36,20)	3404	73	8240	104	0%	68.75
ED5	(5,6-11,47,20)	5742	95	14003	123	0%	76.6
ED6	(6,6-11,58,20)	8976	117	22006	136	0%	87.8
ED7	(7,6-12,70,20)	13280	141	32673	156	0%	101.4
ED8	(8,6-12,80,20)	16860	161	41552	176	0%	105.6
ED9	(9,6-12,89,20)	21540	177	53183	176	0%	96.3
ED10	(10,6-12,96,20)	26860	193	66414	176	0%	91.4
ED20	(20,4-12,181,20)	99021	363	246204	280	0%	119.5
ED30	(30,4-12,262,20)	213717	525	532328	289	0%	117.5
ED40	(40,4-12,336,20)	354412	673	883544	308	0.9%	106.7
ED50	(50,4-12,417,20)	544326	835	1357758	414	11.3%	107.6
ED60	(60,4-12,488,20)	738753	977	1843332	473	10.1%	135.1
ED70	(70,4-12,557,20)	918157	1115	2291368	TLR	-	-
ED80	(80,3-12,601,20)	1025586	1203	2559694	596	0%	101.9
ED89	(89,1-12,628,20)	1078053	1257	2690733	669	0%	260.4

Table 5.7: Emergency department dataset and results for the relaxed EDP model

$r_7 = 2$, respectively (r_i represents the time i is ready for processing).

The arrival operation of both jobs, 1 and 7, require the same resource $k = 1$ (Greeter) for processing. Since the model's objective is to minimize the makespan, it tries minimize the end time of operation 16, which is the last operation of the longer job 2. For this reason, operation 7 is scheduled before operation 1, even though the latter is ready for processing before the former. This assignment results in job 1 span being 41 minutes ($span_{job1} = c_6 - r_1$), and job 2 span being 70 minutes ($span_2 = c_{16} - r_7$). Job span is the amount of time a job spends in the system, from the time it is ready to execute at r_i to the end time of its last operation $c_{lastOperation}$. The average length of stay (LOS) for this assignment is 55.5 minutes.

If the model's objective had been to minimize job span for all jobs, operation 1

i	s_i	p_i	k
1	6	4	1
2	10	5	3
3	15	9	7
4	24	8	13
5	32	5	11
6	37	4	10

(a) Job 1

i	s_i	p_i	k
7	2	4	1
8	6	5	3
9	11	9	7
10	20	8	12
11	28	3	9
12	31	25	14
13	56	3	19
14	59	5	6
15	64	3	5
16	67	4	8

(b) Job 2

Table 5.8: Schedule of operations for instance ED2. Operation i is scheduled to start execution at start time s_i on resource k. The length of execution is denoted by p_i.

would have been scheduled before operation 7 at $s_i = 0$, and job 1 and 2 span would be 35 and 71 minutes respectively. The span of job 2 is only increased by 2 minutes while job 1 span is reduced by 6, resulting in an average LOS of 53 minutes instead of 55.5 minutes. More importantly than reducing the average LOS, is that resources would be freed 4 minutes sooner.

Besides not minimizing the time jobs spend in the system, the model does not capture two very crucial aspects of EDP. The first is that operations of a single job require the same resource assigned for processing, for example a Physician that is assigned to all operations that require a Physician throughout the job. The second is that some operations require multiple resources for processing, in case of Consultation where a Nurse and a Physician are required. Another example is an EKG test, where a PCA technician and an EKG machine are required. In the next section we propose an MILP model that extends the current model to capture the EDP.

5.4 A MILP model for EDP

We now present an extension to the MILP model from section 5.3.1. The new model's objective function minimizes job span for all jobs while it allows multiple resources to process a single operation, and restricts a resource to process all job operations that require resources of its type. The model is an extension of the model proposed by [15] and reformulated by [42]. Next we introduce some additional notation:

B: set of resource types;

B_i: set of types of resources required for operation i's processing ($B_i \subseteq B$);

M_{ib}: set of resources of type $b \in B_i$ that can process operation i ($M_{ib} \subseteq M_i$);

O_t: set of operations of job t ($O_t \subseteq O$);

O_{tb}: set of operations of job t that require resources of type b;

n_{tb}: number of operations in set O_{tb};

v_{tk}: binary variable that has the value of 1 if all $i \in O_{tb}$ are processed by machine $k \in M_{ib}$;

Our MILP model is given by:

$$Minimize \quad 1/2\sum_{t\in T} c_{t_{nt}}^2 \tag{15}$$

$$\text{Subject to} \quad \sum_{k\in M_{ib}} x_{ik} = 1, \qquad \forall i \in O \tag{16}$$

$$p_i = \sum_{k\in M_{ib}} x_{ik}.p_{ik}, \qquad \forall i \in O \tag{17}$$

$$\sum_{i\in O_{tb}} x_{ik} = n_{tb}.v_{tk}, \qquad \forall k \in M_{ib} \tag{18}$$

$$s_i + p_i \leq C_{t_{nt}}, \qquad \forall i \in O_t, t \in T \tag{19}$$

$$y_{ijk} + y_{jik} = z_{ijk}, \qquad \forall k \in M, \forall (i,j) \in E_k \tag{20}$$

$$z_{ijk} \leq x_{ik}, \qquad \forall k \in M, \forall (i,j) \in E_k \tag{21}$$

$$z_{ijk} \leq x_{jk}, \qquad \forall k \in M, \forall (i,j) \in E_k \tag{22}$$

$$x_{ik} + x_{jk} \leq z_{ijk} + 1, \qquad \forall k \in M, \forall (i,j) \in E_k \tag{23}$$

$$s_i + p_i - L.(1 - y_{ijk}) \leq s_j, \forall k \in M, \forall (i,j) \in E_k \tag{24}$$

$$s_i + p_i \leq s_j, \qquad \forall (i,j) \in P \tag{25}$$

$$s_i \geq 0, \qquad \forall i \in O \tag{26}$$

$$x_{ik} \in \{0,1\} \qquad \forall k \in M, \forall i \in O_k \tag{27}$$

$$y_{ijk} \in \{0,1\} \qquad \forall k \in M, \forall (i,j) \in E_k \tag{28}$$

$$z_{ijk} \in \{0,1\} \qquad \forall k \in M, \forall (i,j) \in E_k \tag{29}$$

$$v_{tk} \in \{0,1\} \qquad \forall t \in T, \forall k \in M_{ib} \tag{30}$$

For a job t, its first operation is denoted by s_{t1}, while its last operation end time is denoted by $c_{t_{nt}}$, where nt is the total number of operations in the job. Therefore, the amount of time job t stays in the system is $span_t = c_{t_{nt}} - s_{t1}$. Equation 15 is the new objective function, where the Euclidean norm is used to minimize the end time of the last operation of every job, minimize $c_{t_{nt}} \forall t \in T$.

We have introduced resource type to categorize resources by type. *The categorization allows the model to specify the types of resources an operation requires, thus allowing multiple resources per operation.* Constraint 16 defines machine assignment given operation i requirements.

B	M
Physician	1, 2
Nurse	3, 4
Bed	5, 6

(a) Resources

Operation Name	t	i	B_i	M_i
Bed Assignment	1	1	Nurse, Bed	{3,4,5,6}
Consultation	1	2	Nurse, Physician, Bed	{1,2,3,4,5,6}

(b) Operations

Table 5.9: Example of one task with two operations

As an example, table 5.9 describes an ED with six resources and one job with two operations. There are two resources of each type: Physician, Nurse and Bed (5.9a). Table 5.9b describes the operations and its resource requirements. Operation 1 requires one Nurse and one Bed, therefore $M_{1Nurse} = \{3, 4\}$, $M_{1Bed} = \{5, 6\}$. Operation 2 requires a Nurse, a Physician and a Bed, therefore $M_{2Nurse} = \{3, 4\}$, $M_{2Physician} = \{1, 2\}$, $M_{2Bed} = \{5, 6\}$.

Constraint 16 forces $x_{13} = 1$ or $x_{14} = 1$, and $x_{15} = 1$ or $x_{16} = 1$, meaning that either Nurse 3 or 4 will execute operation 1 along with either Bed 5 or 6. For operation 2 either $x_{23} = 1$ or $x_{24} = 1$, either $x_{21} = 1$ or $x_{22} = 1$ and either $x_{25} = 1$ or $x_{26} = 1$, meaning that only one of each of the two Nurses, two Physicians and two Beds are assigned to it. Constraint 17 determines that the processing time for operation i on every resource is the same.

A binary variable v_{tk} is introduced to *enforce a single resource to process all job operations that requires a resource of its type.* Resource k of type b processes all operations of job t requiring resources of type b. v_{tk} has the value of 1 if all $i \in O_{tb}$ are processed by resource k. Constraint 18 forces a resource of type b, that is assigned to a job $i \in t$, to process all of t n_{tb} operations that require a resource of type b. Therefore, if $v_{13} = 1$, Nurse 3 executes operation 1 (Bed Assignment) and 2 (Consultation) consequently. Because $n_{1Nurse} = 2$, then x_{13} and x_{23} must have the value of 1.

Constraint 19 guarantees that the end time of an operation is not greater than the end time of the last job's operation. Constraints 20-25 do not differ from the model on [42].

5.4.1 Experiments and results

Gurobi version 8.01 on a 80 processor (Intel Xeon Processor Gold 6148) with 1TB of memory was used for the experiments. Gurobi launched 32 threads to solve each instance of the problem with an imposed time limit of 1800 seconds.

Table 5.10 describes the instances of the Emergency Department dataset. Each instance is defined by its name and by the quadruple *(j, l-u, o, r)* where j represents the number of jobs (patients), l and u the minimum and the maximum number of operations per job respectively, o the total number of operations and r the number of resources available. For each dataset we listed the number of binary and continuous variables as well as the number of constraints on the model. The end time of the last operation is listed under C_{max} (minutes).

Instance	Size	LP Model Size			Cmax	Gap	Avg LOS
	(j,l-u,o,r)	Binary	Continuous	Constraints			
ED2	(2,6-10,16,20)	1884	34	4430	73	0%	53
ED3	(3,6-11,27,20)	4492	57	10785	105	0%	68
ED4	(4,6-11,36,20)	8105	76	19662	105	0%	66.75
ED5	(5,6-11,47,20)	13005	99	131747	123	0%	74.8
ED6	(6,6-11,58,20)	19884	122	48772	136	0%	81.6
ED7	(7,6-12,70,20)	28565	147	70291	156	0%	89
ED8	(8,6-12,80,20)	35820	168	88282	176	0%	99.2
ED9	(9,6-12,89,20)	44379	185	109554	176	0%	90.5
ED10	(10,6-12,96,20)	53890	202	133206	176	0%	88.6
ED20	(20,4-12,181,20)	214653	382	533723	280	7.7%	84.5
ED30	(30,4-12,262,20)	45312	554	1136563	TLR	-	-
ED40	(40,4-12,336,20)	790822	712	1971570	TLR	-	-
ED50	(50,4-12,417,20)	1212963	884	3025636	TLR	-	-
ED60	(60,4-12,488,20)	1647165	1036	4110012	TLR	-	-
ED70	(70,4-12,557,20)	2035864	1184	5080760	TLR	-	-
ED80	(80,3-12,601,20)	2253879	1282	5625301	TLR	-	-
ED89	(89,1-12,628,20)	2334741	1345	5827290	TLR	-	-

Table 5.10: Emergency department dataset and results for the EDP model

This is a more complex model than the reduced ED model from section 5.3.2 because it intrinsically captures the ED. The additional complexity generates 3 times more binary variables and constraints than the previous model, see table 5.7. With a larger, more difficult problem, Gurobi only finds optimal solutions for instances of 10 jobs or less. The solver finds a solution for instance ED20, but not the optimal. All other instances have reached the time limit of 1800 seconds without a solution (TLR: Time Limit Reached).

While this model intrinsically captures the ED, it reduces the solver ability to find an optimal solution for practical size problems. There are 30 beds in JSUMC, so our goal is to find an optimal solution for at least 30 patients or jobs. Our efforts towards this goal follows in the next section. Beforehand, let us discuss the integrality gap of ED20 instance.

Given our minimization problem, the gap is the difference between the incumbent (current solution, upper bound on the optimal solution) and the best bound (obtained by taking the minimum of the optimal objective values of all of the current leaf nodes). If the gap is zero then we have the optimal solution but if the gap is greater than zero then we know that the solution cannot get better than the gap.

Table 5.11 lists the average length of stay and the gap for the ED20 instance executions with time limit of 5, 10, 20, and 30 minutes respectively. A 5 minutes execution solves the problem with 73.9% confidence, which is too far from the 7.7% gap of the 30 minutes execution. On a 10 minutes execution the gap decreases to 27%, which might prove to be close enough for a online solution.

We envision a scheduling ED online system that: (1) observes ED visits to learn the different types of patient visits (sequences of medical tasks); (2) predicts patients upcoming tasks based on their previous tasks and the learned types of patient visits; (3) optimize the scheduling of all the upcoming tasks of all patients to the available resource using our MILP model.

The following experiment, figure 5.3, showcases the modeling error of our approaches when we compare (1) *random* and *short first* policies from chapter 4; (2) the scheduling solution found by Gurobi using our MILP model (optimal); and (3) the JSUMC ED

300 secs		600 secs		1200 secs		1800 secs	
LOS	Gap	LOS	Gap	LOS	Gap	LOS	Gap
214.4	73.9%	106.1	27.5%	97.6	20%	84.5	7.7%

Table 5.11: ED20 average length of stay (LOS) and integrality gap for several time limit executions

data for a dataset of 15 patient visits.

The 15 patient visits in this experiment have more tasks per visit than the visits used on previous tests (tables 5.10 and 5.11). The dataset from JSUMC ED has every single medication as a separate task, even if the medications were administered at the same time. Previously, medication tasks with the same timestamp were grouped into one single task while, for this experiment they were kept separated. The reason is that Weka needs as much information as possible to properly build the decision tree that is used to classify patient visits into short and long visits.

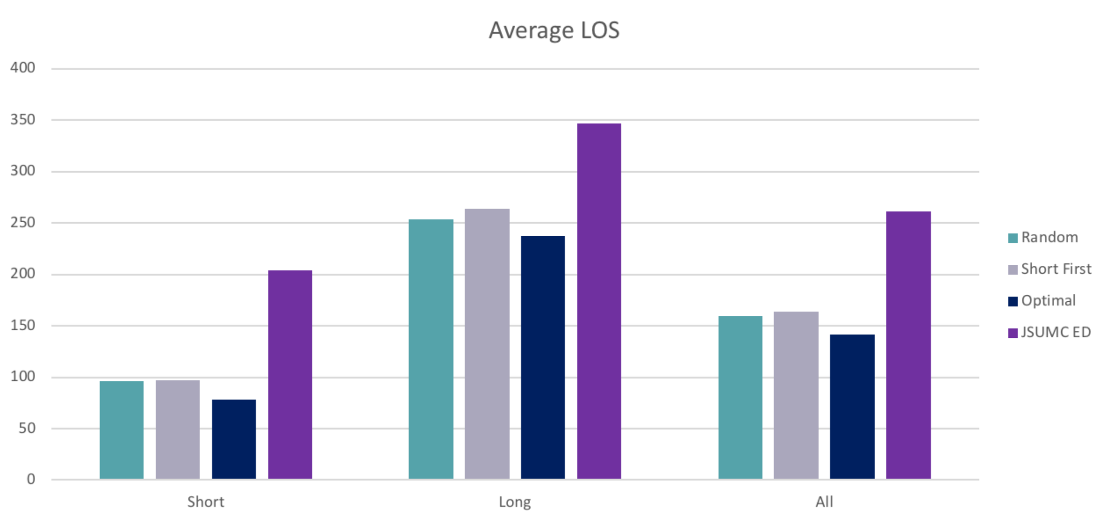


Figure 5.3: Modeling error of scheduling methods for 15 patients

Note that the JSUMC ED, which is the real dataset, has a higher LOS when compared to *Random*, *Short First*, or *Optimal*. The reason for this discrepancy is two fold. First, the **unaccounted tasks**, such as staff breaks that are not listed on the dataset, and the probably **incorrect fixed task processing time** that we used in these experiments. In reality a task processing time is likely dependent on the specific provider executing the task, since each person is likely to perform the same task in different lengths of time. Second, this result helps to add some validation to our model that, in the absence of tasks, is expected perform better than the real dataset.

The model on section 5.4 is already able to handle differing processing time (length of execution) for tasks of the same type that are executed by distinct providers (resources). Equation 17 determines operation i processing time on the assigned resource k. Had we been able to determine how long each specific provider takes to execute each type of task, the model would be able to assign processing time appropriately.

Aside from the modeling error, we can analyze *Random*, *Short First*, and *Optimal* results. Gurobi finds a solution for 15 patients with a 63% gap using our MILP model (optimal). As expected, long visits do not benefit from the *short first* policy and have a 3% increase in the average LOS when compared to Random. But for short visits, the average LOS of the *random* and the *short first* scheduling policies are equivalent.

Even though at first glance such a result might appear underwhelming because the solution is within 63% from the optimal, it is important to observe that when our model's solution is compared to the real-time scheduler using random selection, which resembles the current staff practice in EDs, it improves the overall average LOS of patients by 11%.

Furthermore, for 20 patients with simpler visits, the solver finds a solution within 73% from the optimal in 5 minutes and within only 27% from the optimal in 10 minutes. Finally, the time to find a valid solution could be significantly decreased by introducing additional constraints at runtime that would reduce the solution space.

On section 5.4.2 we look into additional valid inequalities to reduce the gap and possibly help us solve a larger instance of the ED problem.

Increasing task processing time

On the previous section we noted that JSUMC ED has a higher LOS when compared to *Random*, *Short First*, or *Optimal*. We see at least two reasons that account for the higher LOS: (a) the unaccounted staff breaks that are not present on the dataset, and (b) the incorrect task processing time used in the experiments.

In this section we explore a diversity of task processing times and the addition of break tasks for nurses and physicians. Figure 5.4 plots the JSUMC ED dataset against the optimal scheduling, for the same 15 patient visits, with varying task processing time. Optimal and JSUMC ED have the same values from Figure 5.3. Increasing task time by 50%, increases short tasks by 67%, long tasks by 40% and overall by 49%. Increasing task time by 100%, increases short tasks by 142%, long tasks by 74% and overall by 96%. When task time is increased by 100% the overall average LOS for optimal surpasses the real dataset by 7%.

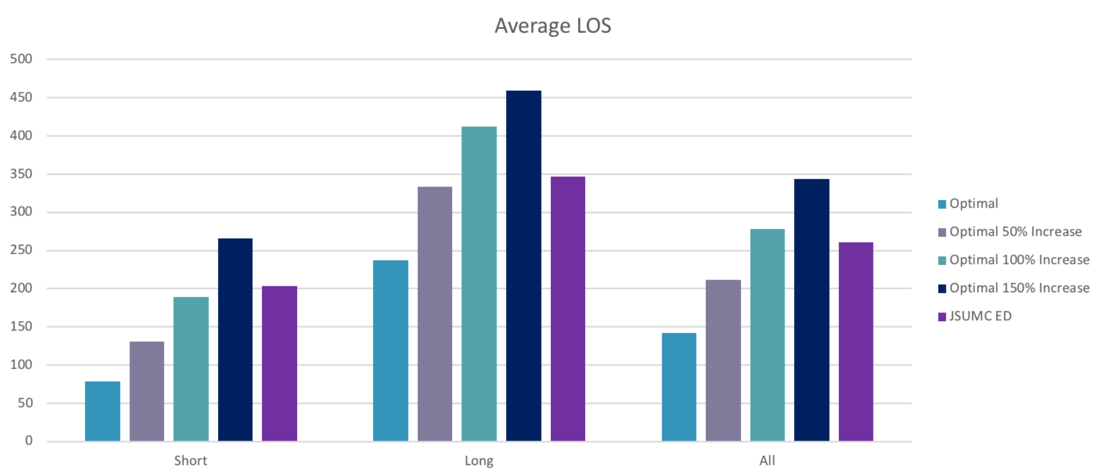


Figure 5.4: Modeling error of optimal scheduling with increased task time

Therefore, we chose to use tasks with an increased processing time of 50% which underperforms when compared with the real dataset by 18%. The increased task processing time is used in addition to two 15 minutes break tasks per patient visit. One break for nurses and another for physicians. Figure 5.5 depicts an error on overall average LOS of 6% in contrast with 45% from Figure 5.3. It's evident from these results that Electronic Health Records are not enough to capture agent based modeling accurately. A time and motion study is probably our best tool to proper supplement the EHRs.

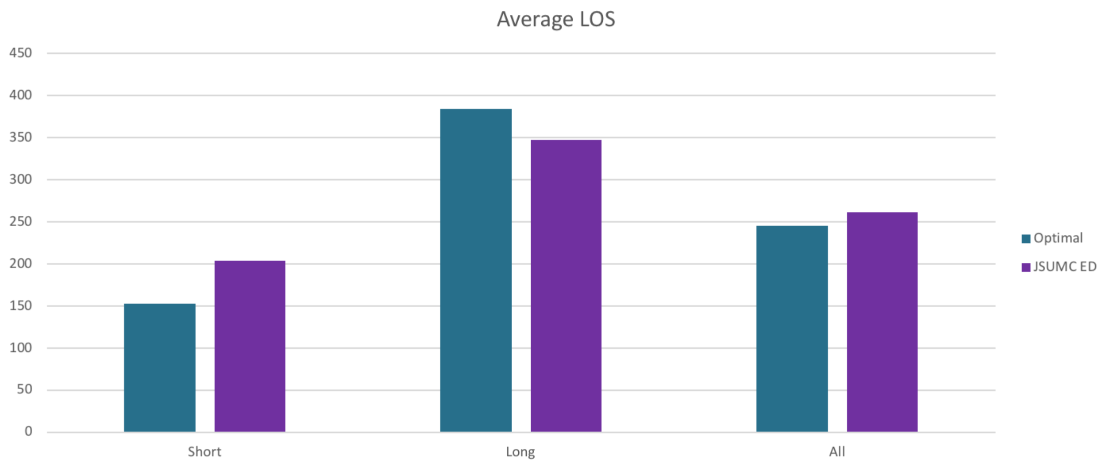


Figure 5.5: Modeling error of optimal scheduling with increased task time and added 15 minutes breaks

5.4.2 Additional valid inequalities

A linear program feasible region containing all feasible solutions can be viewed geometrically as a polyhedron, a set described by a finite number of linear equalities and inequalities constraints.

A common technique to solve mixed integer linear program is to remove the integrality constraint of each variable by relaxing the domain of the variables to be [0,1] instead of {0,1}. This technique transforms an NP-hard optimization problem into a related problem that is solvable in polynomial time. However, in this case the resulting polytope may contain points that are outside the convex hull of integral solutions, see figure 5.6.

To tighten the convex relaxation, additional constraints valid for the integral solutions can be added to the system of linear equations. These additional constraints or linear inequalities are termed cuts or cutting planes. The cutting plane method iteratively tightens the convex relaxation towards the convex hull of integral solutions.

MILP problems are generally solved using a linear programming based branch and cut algorithm, which is a combination of cutting planes with branch and bound, see [39]. MILP solvers, including Gurobi, add cutting planes to the branch and bound algorithm to refine the feasible region by removing undesirable fractional solutions. All

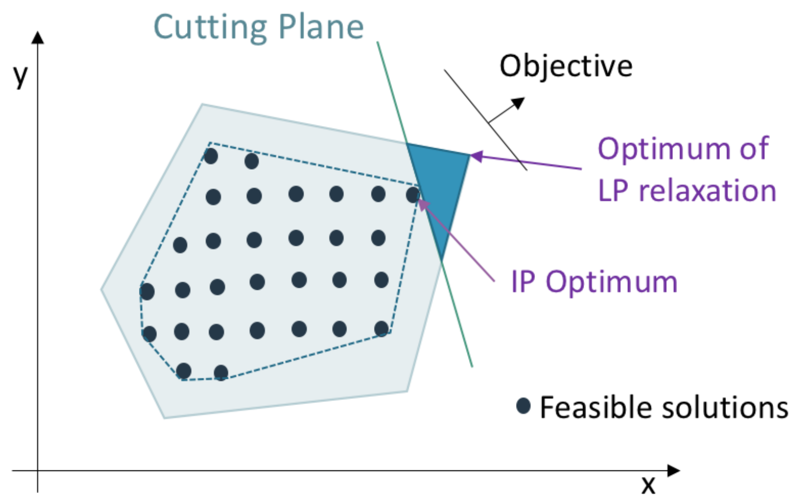


Figure 5.6: Geometric representation of a cutting plane

the results listed in this thesis have cutting planes turned on in Gurobi.

For many problems, including EDP as we've seen, the standard cuts added by the solver are not sufficient to find an integral solution. Starting with [21] a large amount of research have been done on developing methods to generate additional constraints valid for the integral solutions of the problem to tighten the convex relaxations.

The valid inequalities for the FJSP proposed by [3] were adapted to the model in section 5.3.1 by [42]. Using a Gurobi functionality that enables the user to insert additional cuts to the system of linear equations, we added the valid inequalities whenever these inequalities were violated by the integral solution. Adding these inequalities resulted in part of the feasible region to be cut away, therefore these inequalities are are not valid for EDP.

In the next sections we investigate the structure of the polyhedra in an attempt to find new linear valid inequalities to tight the bound on the feasible region.

Vertex enumeration

A polyhedron can be described by a finite number of linear inequalities (H-representation) or as a set of vertices and extreme rays (V-representation) [5]. There are programs that convert a H-representation of a polyhedron to its V-representation, and vice-versa.

Known as the vertex enumeration and convex hull problems, respectively.

The *lrs* program, based on the reverse search algorithm [4], was used to find the vertices and extreme rays given our H-representation for the ED2 instance. We were expecting the resulting vertices to give us an insight on the integral solution, but all resulting vertices were fractional.

Next we look into the lift and project method to generate additional inequalities.

Lift and project

The feasible region for a MILP problem is a polytope, that is the convex hull of the integer solutions, *integral polytope*. The set of feasible solutions of the relaxation is also a polytope, which contains the integral polytope, *relaxed polytope*.

Sherali and Adams [46], Lovász and Schrijver [34], and Lasserre [30] have proposed lift and project methods for constructing a hierarchy of sharper representations of the relaxed polytope with the final relaxation representing the convex hull of feasible integer solutions, the integral polytope. The idea is to design a relaxed polytope that is as close to the integral polytope as possible. Lift and project methods give, starting from any relaxation, a hierarchy of relaxations where the final relaxation gives the integer polytope. The caveat is that it takes exponential time to solve the final relaxation, but in-between relaxations may take somewhere between polynomial and exponential time to solve.

We tighten the EDP convex relaxation by *lifting* the problem a higher dimensional space. The lift is done by multiplying every inequality by every 0-1 variable and its complement, then linearizing the resulting system of quadratic inequalities, see [34]. With the problem in a higher dimensional space, one then has a choice between working with this tighter relaxation or projecting it back onto the original space. In the latter case, the procedure generates additional inequalities or cutting planes.

The Fourier-Motzkin elimination (FME) method allows the projection of variables from a system of linear inequalities. Very much as Gaussian elimination is for equality systems, FME is for inequality systems.

By projecting the higher dimensional problem back onto the original space using the

Fourier-Motzkin elimination method we end up with a system of inequalities that may include valid inequalities for the EDP. We have found inequality 31, where y_{ijk} is binary variable that has the value of 1 if operation i precedes j on machine k, 0 otherwise. y_{ijk} or y_{jik} can be equal to 1 if and only if both operation i and j are processed by machine k and $z_{jik} = x_{jk} * x_{ik}$ meaning that if both operations i and j are processed by resource k than $z_{jik} = 1$. The constraint ensures that if both operations are assigned to machine k only y_{ijk} or y_{jik} is equal to 1, defining the order of execution if both operations are assigned to the same resource k. Finally P is the set of ordered pairs that corresponds to the precedence constraint between two operations ($P \subseteq O \times O$). Therefore, $(i, j) \in P$ if and only if operation i precedes operation j for some job.

$$y_{ijk} - z_{jik} * y_{jik} \geq 0 \qquad \forall (i, j) \in P \tag{31}$$

If operation i precedes operation j for some job, and both operations are processed by resource k then $y_{ijk} = 1$ and $z_{jik} = 1$, forcing $y_{jik} = 0$. Consequently cutting away all solutions where $y_{jik} = 1$.

5.5 Final remarks

Our envisioned scheduling ED online system constantly observes ED visits to learn the different types of patient visits (sequences of medical tasks). Given the previous tasks of the patients currently in the ED and the learned types of visits, predicts all patients upcoming tasks. The system then, optimizes the scheduling of the upcoming tasks of all patients to the available resources using our MILP model.

For that purpose the system has to be able to solve the MILP model for practical size problems in a short amount of time. Currently, our solution is not more than 27% away from the optimal when we solve the problem with 20 patients on a 10 minutes execution.

Our MILP solution for 15 patients has a 63% gap, at most 63% away from the optimal solution, reduces the average patient LOS by roughly 18% when compared with our online scheduling *short first* and *random* policies. This important result signifies that the optimal solution might not be necessary to improve the current situation of EDs where provider use self-created suboptimal guidelines to choose the next patient to execute. Even with such a small dataset of 15 patients, the average patient LOS is reduced when compared to randomly choosing the next patient. But in order to confirm our initial findings, a larger dataset must be acquired.

The only other work that proposes a MILP model for EDs, [35], fails to capture that a patient is assigned the same physician and nurse throughout the visit. It also fails to model that some tasks require multiple providers, it only models tasks that require one bed and one provider.

Chapter 6

Related Work

6.1 ED simulation

Extensive research using simulation has been conducted on EDs to help mitigate its excessive number of patients, long waiting times, patients being treated in hallways, ambulance diversions, and patients leaving without treatment [41]. Discrete-event simulation (DES) which offers few if any insights on human actions and interactions has been widely used [27] whereas only on the past decade has agent-based simulation (ABS) been studied in the ED scope. ABS is highly attractive to model EDs not only because its entities are proactive, autonomous and intelligent but also because the simulation of the interactions of these entities create opportunities for people to better understand their nature [11].

While ABS models have the means to study provider decision making, previous works has focused only on the impact of resource changes in the number of staff, equipment, and rooms. [10] uses exhaustive search optimization to find the optimal staff configuration. [48] have studied the impact of staff experience (a senior member finishes its tasks faster than a junior member) over patient throughput and changes on the frequency of patient arrivals and staff levels. [51] combine simulation and analytical formulae to solve staff scheduling problems. REDSim can study both, the effects of *resource changes* and, in case of non-mobile resources (X-Ray) it can also analyze their *best placement into the floor plan.* REDSim enabled us to study the effects of different decisions made by the ED staff.

Sensing technology could be used for staff to make decisions based on patients location. REDSim is not the first study to simulate sensing technology on the medical field to track staff, resources, and patients. [33] used data collected by ambulance GPS system to develop a simulation model to study opportunities to minimize ambulance response time. [18] propose a system location monitoring system to enhance management of resources during catastrophic events. [38] used RFID tags to collect simulation data and demonstrate its successful use. [31] propose a system that uses location and context awareness to infer notifications for reminding physicians and nurses. But none of these studies has delved into the impact of localization awareness in the provider decision process. Furthermore, all previous studies failed to address the amount of time it takes to gather resources for a task. According to our interviews, ED staff members spend a considerable amount of time looking for misplaced resources which contributes to their frustration. REDSim models not only models movement and resource utilization but also human behavior.

Several surveys were conducted to evaluate the use of ED simulation studies. The latest [22] reviewed 154 ED simulation studies under normal and disaster conditions. It's worth to mention that only 5% of papers are about the ED operations in normal times and 95% of them simulate the behavior of EDs in disaster events. Of all the papers reviews, REDSim is the only one to investigate the effects of decisions made by the ED staff. The authors point that most of the studies focus on only one ED operation or patient flow, and do not look at the ED as part of a hospital environment where interaction with other departments within the hospital affect the ED function. One of the surveys [41] extensively examined studies from 1970 to 2006 on EDs on several areas including computer science, operations research, systems engineering and health care. [32] surveyed studies that evaluated ED waiting time reduction strategies by using queuing models. Other surveys are [37], [23], [43], [27], [22], [47], [6].

6.2 Static ED scheduling

A static scheduling environment is when all the information about tasks and resource availability is known before the scheduling of tasks to resources. It is not the case in an ED, where the sequence of patient tasks is dictated by patient's illness and the volume of patients and their arrival rate are unknown. But static scheduling is very useful to retroactively understand system bottlenecks and weaknesses, and to analyze the impact that changes have in the system as a whole. We can also statically compute the optimal scheduling solution of tasks to resources and use that lower bound to compare against other scheduling solutions. Furthermore, an optimal solution could be used to guide a dynamic scheduling algorithm.

In section 5.1 we described how EDP is analogous to the FJSP and therefore NP-hard. Due to the detail and complexity of the FJSP, the majority of studies have focused on dynamic based approaches.

The only study [35] we are aware of that seeks to statically solve the ED scheduling problem uses ILP (Integer Linear Programming) to model the ED. The model assigns the same bed to a patient throughout the ED visit but not other resources. In this model a patient will not see the same physician or nurse throughout the visit, which is not realistic. Another shortcoming is that many tasks require more than one provider, consultation requires a physician and a nurse in addition to a bed. The study only captures tasks that require one bed and one provider.The simplified model finds solutions for up to 18 patients, 12 beds and 8 other resources. The study proposes a CP (Constraint Programming) model that can solve larger problems and no attempt was made to reduce the search space of ILP model.

The flexible job shop scheduling problem (FJSP) which we were able to extend to model the emergency department problem (EDP) has more studies, but considerably less when compared to job shop problem (JSP). The FJSP extends the JSP by allowing an operation to be processed by any resource from a given set of resources. The scheduling problem of a FJSP can be decomposed into two subproblems: a routing subproblem that consists in assigning each operation to a resource out of a set of resources, and a scheduling subproblem that consists of sequencing the assigned operations on all resources in order to obtain a feasible schedule minimizing a predefined objective function. The FJSP mainly presents two difficulties. The first one is to assign each operation to a resource, and the second one is to schedule these operations in order to make a predefined objective minimal [49].

An exact model for FJSP was proposed by [15], the authors extended the definition of the FJSP to allow a job to be a set of operations with an arbitrary precedence relation instead of a linear order. The model performs better than [52]. As an extension to this model, [42] substitutes a variable to explicitly identify if an operation is preceded by another in a specific resource. This is the base model for the studies conducted in this thesis.

Studies have also developed heuristic polynomial algorithms to find an optimal solution with two jobs. [9] used two approaches to solve cases with more than two jobs: hierarchical approaches and integrated approaches. In hierarchical approaches the assignment and sequencing of operations are independent, while in integrated approaches, the assignment and sequencing are not differentiated. Hierarchical approaches decompose the problem to reduce its complexity, and [7] uses the Tabu Search heuristic [20] to tackle both of the FJSP subproblems. Also using Tabu Search, [45] presented a mathematical model that is used to find the optimal solution for small size problems, and two heuristics approaches are presented to solve real size problems. Many other studies use heuristic solutions to solve real size problems, including [13], [53], [49], [54].

6.3 Dynamic ED scheduling

In a dynamic environment resource availability is known but task information is not available until patient arrival. Actually, all patient tasks are known only at the end of the ED visit. Patient's tasks depend on test results and staff medical assessments. This factor in addition to a Poisson patient arrival rate distribution makes the ED a highly unpredictive and dynamic system.

One study [50] among the sparse literature on dynamic ED scheduling proposes an approach that combines the strength of robust incremental scheduling and genetic algorithms (GA). Robust dynamic rescheduling aims to anticipate the effects of possible disruptions while GA find a resource allocation. The rescheduling was triggered at predetermined intervals instead of being dynamically triggered by changes in the system. A priority scheduling that assigns doctors to patients to reduce the waiting time of high priority critical patients is proposed by [55]. It does not include the scheduling of other ED resources, but it does consider the doctor's load, number of patients, when during scheduling of patients to doctors.

A dynamic scheduler that first assigns patients to beds and then schedule treatment tasks for processing on ED resources is proposed by [35]. It maximizes resource efficiency and patient throughput while respecting patient priorities. The assignment and sequencing of tasks is achieved using an extended disjunctive graph. Once a feasible solution has been constructed on the extended disjunctive graph, an adaptative Tabu Search approach is applied to search for improved solutions.

An intrinsic property of EDs that is missing on these works is the fact that resources are reutilized during a visit. Any scheduling policy must account for tasks that reutilizes resources, such as physicians, beds and nurses. [35] does assign the same bed to a patient throughout the ED visit but not other resources.

Chapter 7

Conclusion and future work

In this thesis we first proposed a spatial simulation framework for Emergency Departments (EDs) that allows the ED administration to test what-if scenarios without having to resort to costly pilots and trials or probabilistic models that hide ED processes such as providers choosing their next patient. We concluded from this initial study that there is a correlation between the length of time patients stay in the ED and the scheduling decisions providers make when choosing the next patient task to execute. In the sequel, we explored the JSUMC ED administration intuition that patient throughput could be increased by prioritizing short patient visits, leading us to propose a real-time priority scheduler for ED patient tasks. Furthermore, we used our scheduler to experimentally confirm the correlation between patients LOS and provider decisions using the dataset we obtained from JSUMC ED. Finally, we observed that the ED visits are so random in nature that there is no single scheduling policy that works under all scenarios. For that reason, we concluded that *Emergency Departments need an online system that is constantly adapting to find an optimal scheduling of patient tasks to available resources.* We envision that such an online system would need make optimal decisions given the state of the ED in any point in time. As a first step towards that research avenue, we proposed a MILP model to find the optimal scheduling of patient tasks to resources. The model can be incorporated into the online system we envisioned.

An important contribution of this thesis is the conclusion that time and motion studies are needed to complement Emergency Health Records (EHR) to accurately model ED scheduling. Our results show a 45% difference in patient average LOS when EHRs are compared with the optimal solution results from our MILP model, signifying a large fraction of unaccounted time. When task processing time is adjusted and tasks, such as staff breaks, are added that difference drops to 6%.

7.1 Future work

Solving our MILP model for 10 patients finds an optimal solution in 65 seconds. When we increase the number of patients from 10 to 20, the solver finds a solution to our MILP model that is no more than 27% away from the optimal, and it does so in 10 minutes. While 10 minutes is too long for an online system, we have started to investigate additional constraints to reduce the solution search space. Given that the JSUMC ED has 30 beds, our goal is to find an optimal solution for 30 patients.

7.1.1 Our vision for an ED online scheduling system

Our vision for Emergency Departments is an online system that is constantly adapting to find an optimal scheduling of tasks to available resources using our MILP model.

These are the main points we foresee for the online ED system:

- The sequence of medical tasks patients go through when in the ED are dictated by the severity of their symptoms and acuity (a measurement of the intensity of nursing care required by a patient). A system could learn the different types of patient visits (sequences of medical tasks), even with the randomness of patients arriving at the ED, because providers follow the same procedures for a given combination of symptoms and acuity;

- With the knowledge on the types of patient visits and the previous tasks of a patient, the system could predict the upcoming tasks for each patient currently in the ED;

- The upcoming tasks of all patients are then given to our MILP model so that a solver can find the optimal global schedule of patient tasks to resources;

- Given the global optimal schedule, the online system can suggest the next task to each provider working in the ED.

7.1.2 Dataset and benchmarking

Acquiring a larger dataset of ED patient data is essential to the next steps of research. Unfortunately, IT staff refused to run our query to gather the requested 3 months of data because of the amount of time it takes to run the query.

To have a complete and accurate view of the ED process the dataset must identify the provider that executed each event and list the exact time each task was processed. If the Electronic Health Records (EHR) event timestamp cannot be trusted, because staff tend to enter tasks in bulk into the system, we can use shadow people (a person to accompany providers) to find the correct time of each event. The current medical scribe could serve this purpose. The medical scribe can be a valuable person to also identify how long each provider takes to execute different types of tasks.

If the EHRs had the exact time each event occurred and which staff member executed the event we would not only be able to identify which other tasks were waiting to be executed at the time, but we also would be able to quantify the impact in patient LOS had the staff chosen another task in a real scenario. More interesting results would come from identifying choice patterns among staff, e.g. is there medical condition staff tend to avoid? If there were patterns among classes of staff (nurses, physicians, technicians) or at a finer per person level.

A larger dataset would enable us to standardize ED testing by creating a benchmark that can be used throughout the simulation and optimization communities.

Appendix A

Electronic Health Records for Patient 23

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:21:00	PATIENT ARRIVAL		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:38	ENCOUNTER CREATION		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	EVENT TIMESTAMP CHANGE		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	HIS MERGE COMPLETE		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	PATIENT MOVE	Waiting	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:41	PATIENT VISITED		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:42	Registration	Patient Registration Page: Viewed Registration	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:49	CHIEF COMPLAINT MODIFIED		2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:55	Chart Entry Made		DD22	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:21:55	PATIENT MOVE	IT Waiting	2115D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	14:26:09	BED ASSIGNMENT	ED18	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Chart Entry Made		DD21	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	Chart Entry Made		DD21	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	PATIENT MOVE	ED18	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	RESPONSIBLE DEPT ASSIGNMENT	AUTOMATIC : MAIN ER	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	STAFF ASSIGNMENT		2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:09	STAFF ROLE ASSUMPTION		2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:26:19	PatientSummary	Patient Summary Page: Viewed Patient Summary	2030D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:26:23	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:24	STAFF ASSIGNMENT		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:28	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:34	PatientSummary	Patient Summary Page: Viewed Patient Summary	2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:26:40	CHART TEMPLATE - SELECT MANUAL		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:43	STAFF ASSIGNMENT		2062D	745106	Nurse	745106	23023	Admit

Table A.1: Raw dataset for patient 23

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:26:50	CHART STATE - ACTIVE		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:50	CHART STATE - PENDING COMPLETE		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:50	CHART TEMPLATE - SELECT MANUAL		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:50	CHART TEMPLATE - SELECT MANUAL		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:50	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:50	RECORD STATE - ACTIVE		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:26:54	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:27:04	ViewChart	View Chart: Viewed Chart	2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:09	PatientSummary	Patient Summary Page: Viewed Patient Summary	2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:14	ACUITY ASSIGNMENT	2	2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:14	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:14	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:14	TRIAGE COMPLETE		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:27:17	ViewChart	View Chart: Viewed Chart	2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:26	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:26	METHOD OF ARRIVAL CHANGED		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	CHART STATE - ACTIVE		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:28:49	RECORD STATE - ACTIVE		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	ALLERGIES MODIFIED		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	HOME MEDICATIONS MODIFIED		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	PAST MEDICAL HISTORY MODIFIED		2357W	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:29:21	PAST SURGICAL HISTORY MODIFIED		2357W	745106	Nurse	745106	23023	Admit

Table A.2: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:29:47	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:29:47	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:29:47	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:29:47	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:29:57	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:29:58	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:30:07	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:30:07	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:30:07	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:30:44	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:31:01	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:31:01	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:31:01	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:31:01	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:31:08	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:32:38	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:32:38	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:32:38	STAFF ROLE ASSUMPTION		2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:32:48	Order	Order Window: Viewed Order Page	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:33:31	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:33:31	ORDER STATE CHANGE: AUTOMATIC	I-STAT Chem 8 (14:33) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:33:31	ORDER STATE CHANGE: AUTOMATIC	I-STAT Toponin (14:33) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:33:31	ORDER STATE CHANGE: AUTOMATIC	PT W/ INR (14:33) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:33:35	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:33:36	ORDER STATE CHANGE: AUTOMATIC	PT W/ INR (14:33) - Ordered	CS02	745106		745106	23023	Admit

Table A.3: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	Blood Cultue (1 of 2) (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	Blood Cultue (2 of 2) (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	CT Head/Brain W/o Contrast (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	Foley Cathete (14:35) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	Rectal temp (14:35) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:08	ORDER STATE CHANGE: AUTOMATIC	Uine Cultue(Incl Colony Cnt) (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:10	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:10	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:10	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:10	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:10	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:14	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:35:16	ORDER STATE CHANGE: AUTOMATIC	Uine Cultue(Incl Colony Cnt) (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:35:19	ORDER STATE CHANGE: AUTOMATIC	Blood Cultue (1 of 2) (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:35:21	ORDER STATE CHANGE: AUTOMATIC	Blood Cultue (2 of 2) (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:35:22	ORDER STATE CHANGE: AUTOMATIC	CT Head/Brain W/o Contrast (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:35:26	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:26	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:27	ORDER STATE CHANGE: AUTOMATIC	Chest Potable (14:35) - Pending Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:32	PatientSummary	Patient Summary Page: Viewed Patient Summary	2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:35:35	ViewChart	View Chart: Viewed Chart	2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:35:37	ORDER STATE CHANGE: AUTOMATIC	Chest Potable (14:35) - Ordered	CS02	745106		745106	23023	Admit

Table A.4: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:35:42	ORDER STATE CHANGE: AUTOMATIC	NS 0.9% (14:35) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:44	ViewChart	View Chart: Viewed Chart	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:35:47	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:50	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:35:54	CHART TEMPLATE - SELECT MANUAL		2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:36:35	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:36:53	PatientSummary	Patient Summary Page: Viewed Patient Summary	2157D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:36:55	ViewChart	View Chart: Viewed Chart	2157D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:36:59	Vital Signs Taken			745106	PCA	745106	23023	Admit
23	2	4/13/17	14:37:11	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:37:15	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:37:26	CHART STATE - ACTIVE		2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:26	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:26	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:34	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:37:34	Order	Order Window: Viewed Order Page	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:38	CHART STATE - ACTIVE		2157D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:37:38	Chart Entry Made		DD03	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:37:38	Chart Entry Made		DD03	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:37:38	VITAL SIGNS MODIFIED		2157D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:37:39	ORDER STATE CHANGE: AUTOMATIC	Acetaminophen (14:37) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:45	Order	Order Window: Viewed Order Page	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:37:49	ORDER STATE CHANGE: AUTOMATIC	Oxygen 100% Nonebeathe (14:37) - Ordered	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:38:02	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:38:04	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:38:21	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:38:26	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:38:26	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:38:26	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:38:28	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:38:28	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:38:28	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:38:28	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit

Table A.5: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:38:28	PAST MEDICAL HISTORY MODIFIED		2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:38:28	PAST SURGICAL HISTORY MODIFIED		2062D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:38:31	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:39:18	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:39:20	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:39:20	PATIENT VISITED	Attending Physician	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:39:21	ViewChart	View Chart: Viewed Chart	2118D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:40:56	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:40:58	ViewChart	View Chart: Viewed Chart	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:41:05	Order	Order Window: Viewed Order Page	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:11	Chart Entry Made		DD02	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	14:41:16	PrintOrder	Print Order: Printed Orders of Cbc W Diff	PT W/ INR	2070D	745106	Asst. Nurse Mg.	745106	23023
23	2	4/13/17	14:41:45	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:41:47	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:42:28	PatientSummary	Patient Summary Page: Viewed Patient Summary	043D	745106	Physician Assistant	745106	23023	Admit
23	2	4/13/17	14:42:31	Order	Order Window: Viewed Order Page	043D	745106	Physician Assistant	745106	23023	Admit
23	2	4/13/17	14:42:41	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:42:41	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:42:41	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:43:00	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:45:43	PatientSummary	Patient Summary Page: Viewed Patient Summary	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:45:45	Order	Order Window: Viewed Order Page	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:34	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit

Table A.6: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:47:34	ORDER STATE CHANGE: AUTO-MATIC	Cbc W Diff (14:33) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:34	ORDER STATE CHANGE: AUTO-MATIC	I-STAT Chem 8 (14:33) - Completed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:34	ORDER STATE CHANGE: AUTO-MATIC	I-STAT Toponin (14:33) - Completed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:34	ORDER STATE CHANGE: AUTO-MATIC	PT W/ INR (14:33) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	ORDER STATE CHANGE: AUTO-MATIC	Acetaminophen (14:37) - Administeed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	ORDER STATE CHANGE: AUTO-MATIC	Blood Cultue (1 of 2) (14:35) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	ORDER STATE CHANGE: AUTO-MATIC	Blood Cultue (2 of 2) (14:35) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	ORDER STATE CHANGE: AUTO-MATIC	CT Head/Brain W/o Contrast (14:35) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:35	ORDER STATE CHANGE: AUTO-MATIC	Rectal temp (14:35) - Completed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:36	ORDER STATE CHANGE: AUTO-MATIC	Oxygen 100% Nonebeathe (14:37) - Completed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:45	ORDER STATE CHANGE: AUTO-MATIC	NS 0.9% (14:35) - Pre-pared	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:47:46	ViewChart	View Chart: Viewed Chart	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:48:16	ORDER STATE CHANGE: AUTO-MATIC	Cbc W Diff (14:33) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:48:18	ORDER STATE CHANGE: AUTO-MATIC	PT W/ INR (14:33) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:48:27	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:49:21	PatientSummary	Patient Summary Page: Viewed Patient Summary	092D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:49:23	Order	Order Window: Viewed Order Page	092D	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:49:40	ViewChart	View Chart: Viewed Chart	092D	745106	PCA	745106	23023	Admit

Table A.7: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:50:03	Chart Entry Made		DD14	745106	PCA	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:36	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:50:56	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:51:16	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:51:29	PatientSummary	Patient Summary Page: Viewed Patient Summary	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:51:32	Order	Order Window: Viewed Order Page	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:51:35	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:51:37	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:51:55	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:51:59	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	14:52:28	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:52:28	ORDER STATE CHANGE: AUTOMATIC	Chest Potable (14:35) - Sent	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	14:54:24	ORDER STATE CHANGE: AUTOMATIC	I-STAT CHEM 8 PANEL (14:39) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:54:27	ORDER STATE CHANGE: AUTOMATIC	I-STAT TROPONIN (14:41) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:54:31	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	14:54:32	ORDER STATE CHANGE: AUTOMATIC	I-STAT CHEM 8 PANEL (14:39) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:54:34	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	14:54:37	ORDER STATE CHANGE: AUTOMATIC	I-STAT TROPONIN (14:41) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:54:38	ORDER STATE CHANGE: AUTOMATIC	I-STAT CHEM 8 PANEL (14:39) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:54:42	ORDER STATE CHANGE: AUTOMATIC	I-STAT TROPONIN (14:41) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:55:34	ORDER STATE CHANGE: AUTOMATIC	CT Head/Brain W/o Contrast (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:55:35	ORDER STATE CHANGE: AUTOMATIC	CT Head/Brain W/o Contrast (14:35) - Returned	CS02	745106		745106	23023	Admit

Table A.8: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	14:56:09	ORDER STATE CHANGE: AUTOMATIC	Chest Potable (14:35) - Canceled	CS02	745106		745106	23023	Admit
23	2	4/13/17	14:56:11	ORDER STATE CHANGE: AUTOMATIC	CHEST AP (14:56) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:01:18	ViewChart	View Chart: Viewed Chart	0592D	745106	HIM	745106	23023	Admit
23	2	4/13/17	15:02:33	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:04:01	ORDER STATE CHANGE: AUTOMATIC	CHEST AP (14:56) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:04:02	ORDER STATE CHANGE: AUTOMATIC	CHEST AP (14:56) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:07:55	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:07:57	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:08:00	PatientSummary	Patient Summary Page: Viewed Patient Summary	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:08:02	Order	Order Window: Viewed Order Page	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:08:13	Chart Entry Made		DD03	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:08:13	ORDER STATE CHANGE: AUTOMATIC	NS 0.9% (14:35) - Administeed	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:08:34	PatientSummary	Patient Summary Page: Viewed Patient Summary	2027D	745106	PCA	745106	23023	Admit
23	2	4/13/17	15:08:37	ViewChart	View Chart: Viewed Chart	2027D	745106	PCA	745106	23023	Admit
23	2	4/13/17	15:09:44	Chart Entry Made		DD24	745106	PCA	745106	23023	Admit
23	2	4/13/17	15:09:44	VITAL SIGNS MODIFIED		2027D	745106	PCA	745106	23023	Admit
23	2	4/13/17	15:12:24	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:12:25	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:14:43	PatientSummary	Patient Summary Page: Viewed Patient Summary	2157D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:15:08	PatientSummary	Patient Summary Page: Viewed Patient Summary	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:15:09	Order	Order Window: Viewed Order Page	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:15:12	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit

Table A.9: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	15:15:13	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:15:15	ORDER STATE CHANGE: AUTOMATIC	Zofran (15:15) - Ordered	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:15:29	Registration	Patient Registration Page: Viewed Registration	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:15:39	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:16:06	ORDER STATE CHANGE: AUTOMATIC	PT W/ INR (14:33) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:16:48	ViewChart	View Chart: Viewed Chart	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:17:26	PatientSummary	Patient Summary Page: Viewed Patient Summary	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:17:27	Order	Order Window: Viewed Order Page	2074D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:17:50	PatientSummary	Patient Summary Page: Viewed Patient Summary	2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:17:51	Registration	Patient Registration Page: Viewed Registration	2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:17:52	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:17:53	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:17:57	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:18:29	ORDER STATE CHANGE: AUTOMATIC	CT Head/Brain W/o Contrast (14:35) - Reviewed	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:19:29	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:20:28	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:25:51	Chart Entry Made		DD02	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:00	Chart Entry Made		DD02	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:00	STAFF ASSIGNMENT		2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:00	STAFF ROLE ASSUMPTION		2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:06	FINANCIAL REGISTRATION COMPLETE		2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:06	MEDICAL EXAM		2350W	745106	Registrar	745106	23023	Admit
23	2	4/13/17	15:26:54	PatientSummary	Patient Summary Page: Viewed Patient Summary	2071D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:26:55	Order	Order Window: Viewed Order Page	2071D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:38:41	PatientSummary	Patient Summary Page: Viewed Patient Summary	2357W	745106	PCA	745106	23023	Admit

Table A.10: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	15:38:49	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:38:51	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:39:10	ORDER STATE CHANGE: AUTOMATIC	Zofran (15:15) - Administeed	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:39:11	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:41:41	ORDER STATE CHANGE: AUTOMATIC	CHEST AP (14:56) - Reviewed	CS02	745106		745106	23023	Admit
23	2	4/13/17	15:45:20	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:47:53	PatientSummary	Patient Summary Page: Viewed Patient Summary	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:47:55	Order	Order Window: Viewed Order Page	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:47:56	OrderResult	Order Result Window: Viewed Order Results	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:47:57	RESULTS VIEWED		2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:48:18	CANCELLED ORDER SIGNOFF		2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:48:18	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Reviewed	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:48:18	ORDER STATE CHANGE: AUTOMATIC	I-STAT CHEM 8 PANEL (14:39) - Reviewed	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:48:18	ORDER STATE CHANGE: AUTOMATIC	I-STAT TROPONIN (14:41) - Reviewed	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:48:19	ORDER STATE CHANGE: AUTOMATIC	PT W/ INR (14:33) - Reviewed	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:49:59	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:50:02	ViewChart	View Chart: Viewed Chart	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:50:09	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:50:28	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:50:28	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:51:00	OrderResult	Order Result Window: Viewed Order Results	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:51:01	RESULTS VIEWED		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:51:17	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:51:20	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:51:39	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:52:22	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit

Table A.11: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	15:53:14	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:53:16	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:53:18	PatientSummary	Patient Summary Page: Viewed Patient Summary	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:53:20	Order	Order Window: Viewed Order Page	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:53:26	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:53:27	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:53:28	ORDER STATE CHANGE: AUTO-MATIC	Foley Cathete (14:35) - Canceled(Othe In-tevention Used)	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	15:53:30	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:53:31	ORDER STATE CHANGE: AUTO-MATIC		2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	15:53:35	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:54:00	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	15:55:08	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:55:10	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:55:28	ORDER STATE CHANGE: AUTO-MATIC		2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:57:44	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:57:46	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:57:55	ORDER STATE CHANGE: AUTO-MATIC		2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:58:14	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	15:58:17	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:00:57	ORDER STATE CHANGE: AUTO-MATIC	Blood Cultue (1 of 2) (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:01:24	ORDER STATE CHANGE: AUTO-MATIC	Blood Cultue (2 of 2) (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:02:35	PatientSummary	Patient Summary Page: Viewed Patient Summary	2558T	745106	Scribe	745106	23023	Admit

Table A.12: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	16:02:44	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:02:52	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:15:50	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:15:55	ORDER STATE CHANGE: AUTOMATIC	Uine Cultue(Incl Colony Cnt) (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:19:06	PatientSummary	Patient Summary Page: Viewed Patient Summary	2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:19:09	Order	Order Window: Viewed Order Page	2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:19:39	CANCELLED ORDER SIGNOFF		2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:24:32	PatientSummary	Patient Summary Page: Viewed Patient Summary	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:24:34	ViewChart	View Chart: Viewed Chart	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:24:38	Order	Order Window: Viewed Order Page	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:24:50	Chart Entry Made		DD24	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:24:52	Order	Order Window: Viewed Order Page	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:24:57	PatientSummary	Patient Summary Page: Viewed Patient Summary	2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:24:59	Order	Order Window: Viewed Order Page	2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:25:18	ORDER STATE CHANGE: AUTOMATIC	Othe Nusing Order: epeat temp and heat ate please (16:25) - Ordered	2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:25:25	Chart Entry Made		DD24	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:25:31	Order	Order Window: Viewed Order Page	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:25:35	ORDER STATE CHANGE: AUTOMATIC		2169D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:25:44	Order	Order Window: Viewed Order Page	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:25:47	OrderResult	Order Result Window: Viewed Order Results	2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:25:48	RESULTS VIEWED		2074D	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:26:32	Chart Entry Made		DD24	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:30:46	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:30:48	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:31:28	OrderResult	Order Result Window: Viewed Order Results	2554T	745106	Scribe	745106	23023	Admit

Table A.13: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	16:31:29	RESULTS VIEWED		2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:32:39	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:33:02	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:33:04	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:33:14	ORDER STATE CHANGE: AUTO-MATIC		2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:33:54	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:33:59	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:35:57	ORDER STATE CHANGE: AUTO-MATIC	URINE MICRO-SCOPIC (14:35) - Ordered	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:36:00	ORDER STATE CHANGE: AUTO-MATIC	UA (14:35) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:36:02	ORDER STATE CHANGE: AUTO-MATIC	URINE MICRO-SCOPIC (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:38:19	PatientSummary	Patient Summary Page: Viewed Patient Summary	DCVMVXP04-563	745106	Resident	745106	23023	Admit
23	2	4/13/17	16:40:00	Vital Signs Taken			745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:44:54	PatientSummary	Patient Summary Page: Viewed Patient Summary	2155D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:44:56	Order	Order Window: Viewed Order Page	2155D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:45:03	ViewChart	View Chart: Viewed Chart	2155D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:48:11	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:48:14	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:48:37	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:48:39	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:53:00	PatientSummary	Patient Summary Page: Viewed Patient Summary	2071D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:56:19	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:56:22	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:56:26	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit

Table A.14: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	16:56:52	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:56:54	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:56:57	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:57:43	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - In Process Unspecified	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:57:48	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:57:49	ORDER STATE CHANGE: AUTOMATIC	URINE MICROSCOPIC (14:35) - Returned	CS02	745106		745106	23023	Admit
23	2	4/13/17	16:58:49	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	16:59:19	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:59:21	Order	Order Window: Viewed Order Page	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:59:28	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:59:30	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	16:59:54	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:59:55	ORDER STATE CHANGE: AUTOMATIC	Miscellaneous Medication - Non Fomulay (16:59) - Ordered	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:59:57	OrderResult	Order Result Window: Viewed Order Results	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	16:59:58	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	16:59:58	RESULTS VIEWED		2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:00:09	ORDER STATE CHANGE: AUTOMATIC	Cbc W Diff (14:33) - Reviewed	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:00:09	ORDER STATE CHANGE: AUTOMATIC	UA (14:35) - Reviewed	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:00:09	ORDER STATE CHANGE: AUTOMATIC	URINE MICROSCOPIC (14:35) - Reviewed	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:00:26	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:00:27	ViewChart	View Chart: Viewed Chart	2554T	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:01:14	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit

Table A.15: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	17:01:18	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:01:49	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:01:54	PatientSummary	Patient Summary Page: Viewed Patient Summary	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:01:56	Order	Order Window: Viewed Order Page	1518D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:02:50	ORDER STATE CHANGE: AUTO-MATIC	Othe Nusing Order: epeat temp and heat ate please (16:25) - Completed	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:02:56	ViewChart	View Chart: Viewed Chart	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:03:01	Vital Signs Taken			745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:03:21	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:03:21	VITAL SIGNS MODI-FIED		2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:04:27	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:04:29	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:04:38	PrintOrder		2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:04:41	ORDER STATE CHANGE: AUTO-MATIC	Miscellaneous Medi-cation - Non Fomulay (16:59) - Pepaed	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:05:53	PatientSummary	Patient Summary Page: Viewed Patient Summary	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:05:55	Order	Order Window: Viewed Order Page	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:06:22	ORDER STATE CHANGE: AUTO-MATIC	NS 0.9% (17:06) - Or-dered	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:06:23	ORDER STATE CHANGE: AUTO-MATIC	NS 0.9% (17:06) - Or-dered	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:07:14	OrderrResult	Order Result Window: Viewed Order Results	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:07:14	RESULTS VIEWED		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:07:57	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:08:01	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:08:45	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:09:03	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:11:16	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:11:18	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit

Table A.16: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	17:11:56	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:11:58	Order	Order Window: Viewed Order Page	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:12:09	ORDER STATE CHANGE: AUTO-MATIC		2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:16:15	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:16:18	Order	Order Window: Viewed Order Page	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:17:01	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:17:03	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:18:04	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:18:04	ORDER STATE CHANGE: AUTO-MATIC	NS 0.9% (17:06) - Ad-ministeed	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:18:04	ORDER STATE CHANGE: AUTO-MATIC	NS 0.9% (17:06) - Pre-pared	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:19:24	PatientSummary	Patient Summary Page: Viewed Patient Summary	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:22:11	PatientSummary	Patient Summary Page: Viewed Patient Summary	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:22:14	Admit	Admit Window: Se-lected Admit	2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:22:21	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:22:21	STAFF ASSIGN-MENT		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:22:21	STAFF ROLE AS-SUMPTION		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	ADMIT ORDERED		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	ADMITTING PHYSI-CIAN ENTERED		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	CHART STATE - PENDING COM-PLETE		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	CLINICAL SETTING		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	DI DOCUMENT ADDED		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	DIAGNOSIS MODI-FIED		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	DISPOSITION CON-DITION SET		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:02	ER CARE COM-PLETE		2098D	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:06	ViewChart	View Chart: Viewed Chart	2098D	745106	E.D. Physician	745106	23023	Admit

Table A.17: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	17:23:53	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:53	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:23:53	Chart Entry Made		DD14	745106	E.D. Physician	745106	23023	Admit
23	2	4/13/17	17:26:51	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:26:53	Order	Order Window: Viewed Order Page	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:27:02	PatientSummary	Patient Summary Page: Viewed Patient Summary	2060D	745106	Resident	745106	23023	Admit
23	2	4/13/17	17:27:10	ViewChart	View Chart: Viewed Chart	2060D	745106	Resident	745106	23023	Admit
23	2	4/13/17	17:27:16	PrintOrder		2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:28:24	ViewChart	View Chart: Viewed Chart	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:30:49	PatientSummary	Patient Summary Page: Viewed Patient Summary	2068D	745106	Resident	745106	23023	Admit
23	2	4/13/17	17:30:52	ViewChart	View Chart: Viewed Chart	2068D	745106	Resident	745106	23023	Admit
23	2	4/13/17	17:35:25	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:37:38	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:37:46	Registration	Patient Registration Page: Viewed Registration	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	17:41:16	PatientSummary	Patient Summary Page: Viewed Patient Summary	2771D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	17:41:18	Registration	Patient Registration Page: Viewed Registration	2771D	745106	Registrar	745106	23023	Admit
23	2	4/13/17	17:42:12	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:42:14	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:42:38	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:43:16	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:43:18	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:43:39	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:43:44	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	17:55:27	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:55:30	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:55:34	ViewChart	View Chart: Viewed Chart	2073D	745106	Nurse	745106	23023	Admit

Table A.18: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	17:57:11	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:57:11	VITAL SIGNS MODIFIED		2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	17:59:14	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:01:06	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:01:06	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:01:06	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:01:58	PatientSummary	Patient Summary Page: Viewed Patient Summary	2060D	745106	Resident	745106	23023	Admit
23	2	4/13/17	18:02:00	ViewChart	View Chart: Viewed Chart	2060D	745106	Resident	745106	23023	Admit
23	2	4/13/17	18:02:35	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:02:36	Order	Order Window: Viewed Order Page	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:02:48	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:02:51	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:03:32	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	18:03:38	Registration	Patient Registration Page: Viewed Registration	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	18:05:09	PatientSummary	Patient Summary Page: Viewed Patient Summary	2068D	745106	Resident	745106	23023	Admit
23	2	4/13/17	18:05:14	ViewChart	View Chart: Viewed Chart	2068D	745106	Resident	745106	23023	Admit
23	2	4/13/17	18:06:51	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:08:28	ViewChart	View Chart: Viewed Chart	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:10:10	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:13:22	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:13:25	ViewChart	View Chart: Viewed Chart	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:14:17	PatientSummary	Patient Summary Page: Viewed Patient Summary	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	18:14:24	ViewChart	View Chart: Viewed Chart	2554T	745106	Scribe	745106	23023	Admit
23	2	4/13/17	18:14:31	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:14:32	Order	Order Window: Viewed Order Page	2554T	745106	Scribe	745106	23023	Admit

Table A.19: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	18:14:56	Chart Entry Made		DD16	745106	Scribe	745106	23023	Admit
23	2	4/13/17	18:15:33	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:15:35	Order	Order Window: Viewed Order Page	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:15:43	PrintOrder		2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:16:08	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:16:22	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:16:24	Order	Order Window: Viewed Order Page	2070D	745106	Asst. Nurse Mg.	745106	23023	Admit
23	2	4/13/17	18:24:31	Vital Signs Taken			745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:13	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:13	VITAL SIGNS MODIFIED		2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:35	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:38	Order	Order Window: Viewed Order Page	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:51	ORDER STATE CHANGE: AUTOMATIC	Miscellaneous Medication - Non Fomulay (16:59) - Administeed	2073D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	18:25:52	Chart Entry Made		DD20	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:17:19	PatientSummary	Patient Summary Page: Viewed Patient Summary	2088D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:17:29	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:17:32	ViewChart	View Chart: Viewed Chart	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:17:43	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:19:55	Order	Order Window: Viewed Order Page	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:20:23	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:20:23	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:20:39	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:20:39	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:21:22	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:21:22	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:21:30	PatientSummary	Patient Summary Page: Viewed Patient Summary	2056D	745106	PCA	745106	23023	Admit
23	2	4/13/17	19:21:48	Order	Order Window: Viewed Order Page	2056D	745106	PCA	745106	23023	Admit
23	2	4/13/17	19:22:25	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:22:25	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:24:16	PatientSummary	Patient Summary Page: Viewed Patient Summary	0103D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:43:24	PatientSummary	Patient Summary Page: Viewed Patient Summary	2155D	745106	PCA	745106	23023	Admit

Table A.20: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	19:43:27	Order	Order Window: Viewed Order Page	2155D	745106	PCA	745106	23023	Admit
23	2	4/13/17	19:43:36	PatientSummary	Patient Summary Page: Viewed Patient Summary	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:43:38	ViewChart	View Chart: Viewed Chart	2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:43:42	Vital Signs Taken			745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:44:15	Chart Entry Made		DD02	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:44:15	VITAL SIGNS MODIFIED		2118D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:46:11	PatientSummary	Patient Summary Page: Viewed Patient Summary	0104D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:50:51	PatientSummary	Patient Summary Page: Viewed Patient Summary	2083D	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	19:51:21	Chart Entry Made		DD14	745106	Unit Secetay	745106	23023	Admit
23	2	4/13/17	19:58:44	PatientSummary	Patient Summary Page: Viewed Patient Summary	0104D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:58:52	CHART STATE - PENDING COMPLETE		0104D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:58:52	CLINICAL SETTING		0104D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:58:52	Chart Entry Made		DD16	745106	Nurse	745106	23023	Admit
23	2	4/13/17	19:58:52	SPECIFIC LOCATION ENTERED		0104D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:24:39	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:25:06	ViewChart	View Chart: Viewed Chart	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:25:36	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:25:40	OrderResult	Order Result Window: Viewed Order Results	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:25:41	RESULTS VIEWED		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:27:18	PatientSummary	Patient Summary Page: Viewed Patient Summary	2073D	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:27:20	ViewChart	View Chart: Viewed Chart	2073D	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:27:42	Chart Entry Made		DD10	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:34:38	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:34:57	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:34:59	ViewChart	View Chart: Viewed Chart	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit

Table A.21: Raw dataset for patient 23 cont.

Name	Acuity	Date	Time	Event	Event Description	Station	ENID	Staff	ENID	Patient ID	Outcome
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:04	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:16	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:25	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:37:27	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:38:24	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:40:44	PatientSummary	Patient Summary Page: Viewed Patient Summary	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:40:48	ViewChart	View Chart: Viewed Chart	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:41:00	PrintChart		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:41:01	PrintChart		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:41:01	PrintChart		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:41:02	PrintChart		2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:49:03	Order	Order Window: Viewed Order Page	2116D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:49:18	Chart Entry Made		DD15	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:49:18	Med Followup			745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:50:45	PatientSummary	Patient Summary Page: Viewed Patient Summary	2155D	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:50:49	Order	Order Window: Viewed Order Page	2155D	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:50:53	ViewChart	View Chart: Viewed Chart	2155D	745106	PCA	745106	23023	Admit
23	2	4/13/17	20:50:56	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:50:57	ViewChart	View Chart: Viewed Chart	2070D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	20:51:07	Chart Entry Made		DD11	745106	PCA	745106	23023	Admit
23	2	4/13/17	21:05:38	PatientSummary	Patient Summary Page: Viewed Patient Summary	0198D	745106	PCA	745106	23023	Admit
23	2	4/13/17	21:11:01	PatientSummary	Patient Summary Page: Viewed Patient Summary	2070D	745106	Nurse	745106	23023	Admit
23	2	4/13/17	21:11:06	Chart Entry Made		DD21	745106	Nurse	745106	23023	Admit
23	2	4/13/17	21:11:06	Chart Entry Made		DD21	745106	Nurse	745106	23023	Admit
23	2	4/13/17	21:11:06	DEPARTURE	1	2070D	745106	Nurse	745106	23023	Admit

Table A.22: Raw dataset for patient 23 cont.

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