

EMORY UNIVERSITY HOSPITAL EMERGENCY DEPARTMENT

Georgia Tech Senior Design Final Report

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1. EXECUTIVE SUMMARY

Emory University Hospital (EUH) is a nationally ranked medical center with an Emergency Department (ED) that services over 32,000 patients annually. Our engineering team has developed a prototype model of the Operational Scheduling of Care And Resources (OSCAR) tool, to be implemented as an add-on to the current ED software.

OSCAR will predict which resources (e.g. X-Ray, EKG, MRI) a patient will require while in the ED and then schedule those resources. Predictions will be made based on patient acuity and major complaint taken upon arrival to the ED. Either a nurse or doctor will validate these tests at the bedside before they are performed. We employed statistical methodology such that the expected number of times that ED personnel will need to add a test that was not predicted would be equal to the expected number of times that they would have to delete an unnecessary test.

OSCAR schedules patient tests using an algorithm that seeks to minimize the Length of Stay (LOS) of each patient by producing near optimal schedules. Higher acuity patients are prioritized within the schedules. OSCAR will provide a scheduled start time and an expected completion time for each resource that a patient requires. OSCAR includes functionality such that patient tests can be added or deleted and that new patients can enter the system dynamically. There are also separate operational views for the doctor, nurse, patient, and radiology departments.

From test case analysis comparing historical data to ED performance using OSCAR, we estimate a 17% decrease in the Average Length of Stay (ALOS) which was extrapolated to a 4% decrease in the Longest LOS in waiting room, reducing the average NEDOC score by approximately 1.4%. The reduced NEDOC score would decrease the time spent on diversion which could lead to additional annual EMS patient volume of 24 patients valued at \$203,500 annually.

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2. OPPORTUNITY DESCRIPTION

Beginning at 11 AM, the Emory University Hospital Emergency Department (EUH ED) patient volume begins to increase, peaking at 3 PM and remains relatively high throughout the night. During this period, the ED experiences a large amount of service congestion. This service congestion causes ED patients to wait longer to receive rooms, tests, and test results. Due to the high service congestion and limited ED resources, the ED is forced to go on diversion. Further background information on the operations of EUH ED is included in Appendix 1.

Diversion occurs when the ED is forced to turn away EMS (Emergency Medical Service) patients to other EDs in the area due to overcrowding. Diversion jeopardizes critical patients' abilities to receive timely treatment. EUH ED also loses significant potential revenue due to diversion, as EMS patients typically require more treatment and admittance to the hospital, therefore accumulating more charges. EUH ED uses the National Emergency Department Overcrowding Score, or NEDOC Score, as an indicator that the ED should go on diversion. The NEDOC score is a national ED metric used to quantify the degree of crowdedness in an ED. The NEDOC score and its parameters are further discussed in later portions of this report.

We have developed the Operational Scheduling of Care and Resources tool or OSCAR tool. The OSCAR tool predicts patient resources and schedules these resources in the ED, reducing patient waiting times throughout their stay in the ED. This reduction in patient waiting periods helps to alleviate some of the ED overcrowding, reducing the NEDOC score and therefore reducing time on diversion.

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2.1. RESOURCE REQUIREMENT PROBABILITY TAXONOMY

OSCAR contains a database that houses predicted resources and respective processing times of those resources. The database is referred to as the Resource Requirement Probability Taxonomy (RRPT), and the information recorded in the RRPT was derived from ED 2009 patient data records.

2.2. PREDICTING PATIENT RESOURCES

The creation of this tool required predicting which resources a patient would require using information on the patient's acuity level and major complaint. The first part of the prediction included determining which resources a patient would need.

2.2.1. DETERMINING THE SIGNIFICANT RESOURCE REQUIREMENTS

We first determined which resources OSCAR would include. We chose the most common tests that are required by patients in the ED which include radiology tests, blood work, urine testing, and EKGs.

Radiology tests can be further broken down into the specific types. We focused on the top seven radiology tests. These tests are listed with their respective number of times performed during 2009 in Table 1 below. These seven resources represent 97% of all radiology tests performed for patients in the ED in 2009, showing that most of the radiology test volume will be represented by focusing on these frequent tests.

Table 1: 2009 Top Seven Radiology Tests

Radiology Tests	2009 Count
X-Ray	12,400
X-Ray Portable	7,400
CT w/ Contrast	4,100
CT w/o Contrast	6,500
Ultrasound	3,100
MRI	1,900
MRA	800

In addition to the radiology tests, we also chose to look at two tests performed by nurses: blood draw and urine collect. In both of these cases, patient specimens are taken by the nurse and then sent to another department in the hospital for analysis. OSCAR predicts the processing time for how long it will take the nurse to acquire these specimens. Finally, EKGs are another high volume test performed by nurse technicians in the ED, so these tests will be predicted and scheduled in OSCAR as well. The number of these tests performed in 2009 and the percent of patients that required these tests are listed in Table 2 below.

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Table 2: 2009 Top Three Most Frequent Non-Radiology Tests

Other Tests	# of Tests Performed	% of Total ED Patients
EKG	13,900	42%
Urine Collect	15,400	47%
Blood Draw	22,000	67%

2.2.2. PREDICTORS

We looked at two predictors as factors to determine whether or not a patient will require a given test during their stay in the ED: acuity level and major complaint.

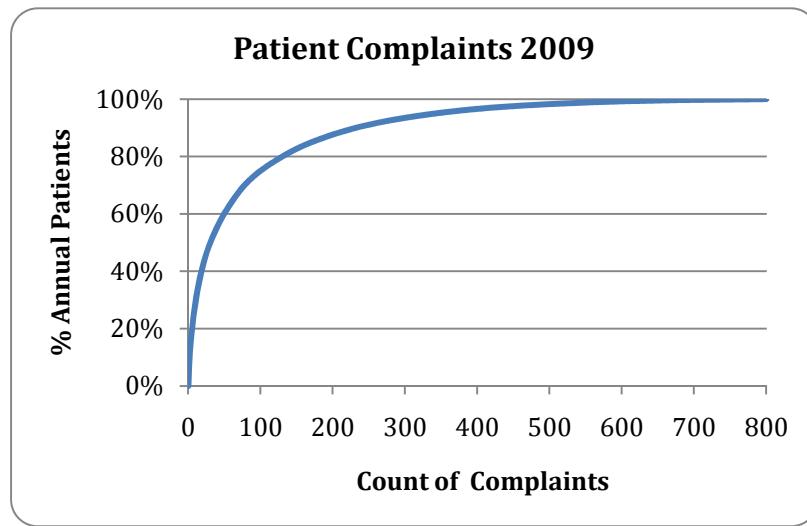
Patients are assigned an acuity level of 1-5 when they arrive at the ED. Acuity level 1 patients are the most severe, while acuity level 5 patients are the least severe. Table 3 shows the volume of patients entering the EUH ED in 2009 broken down by acuity. Most of the ED's volume is in level 2 and 3 acuity patients.

Table 3: 2009 Patient Acuity Level Distribution

Acuity	% 2009 Patient Volume
1	4%
2	39%
3	43%
4	14%
5	1%

Patients also record one major complaint when they arrive in the ED such as Chest Pain, Fever, Abdominal Pain, etc. There is a list of 801 major complaints that ED personnel currently choose from, however a small set of these complaints account for a majority of the patient volume. Figure 1 shows that 230 of these complaints make up 90% of patient volume, and that the most common 80 complaints make up 70% of volume.

Figure 1: 2009 Patient Major Complaints



2.2.3. PROBABILITIES FROM TEST FREQUENCIES

Next we determined a methodology, based on historic data, for determining how to predict whether a patient coming into the ED with a certain acuity and major complaint should be expected to require a given test.

First, we found the frequency for each combination of acuity and complaint for each of the ten tests using all patients that came to the EUH ED in 2009. A sample of the probabilities estimated from these frequencies is shown in Table 4 below. This table displays sample probabilities for the top five major complaints of patients entering the ED that will eventually require an EKG. For example, a level 2 acuity patient entering the ED with a major complaint of Chest Pain had a 0.99 estimated probability of requiring an EKG during their stay in the ED. On the other hand, a level 3 acuity patient entering the ED with a major complaint of General Abdominal Pain only had a 0.22 estimated probability of requiring an EKG.

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Table 4: Sample Selection of EKG Requirement Probability Estimations by Acuity Level and Major Complaint

Major Complaint	Acuity			
	1	2	3	4
Chest pain	1.00	0.99	0.97	0.83
Difficulty Breathing	0.97	0.90	0.67	0.40
Altered Mental Status	0.97	0.89	0.80	-
Syncope	1.00	0.97	0.90	1.00
Pain, Abdominal General	1.00	0.44	0.22	0.07

Thus, in order to decide which patients should be predicted to require certain tests, we had to determine a probability threshold. From the previous example, if the EKG threshold were to be set at 0.60, acuity level 2 patients with Chest Pain would be predicted to require an EKG since their estimated probability of 0.99 would be greater than the probably threshold. Similarly, the acuity level 3 patients with General Abdominal Pain would not be predicted to require an EKG since their estimated probability of 0.22 would be less than the probability threshold. Due to the differences in frequency and estimated probabilities among the ten tests, each test required an individual probability threshold.

2.2.4. DETERMINING A PROBABILITY THRESHOLD

Sensitivity and specificity were parameters analyzed in order to determine an appropriate probability threshold for each test.

Sensitivity is the true positive rate, or the rate at which we correctly predict that a person requires a given test.

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Specificity is the true negative rate, or the rate at which we correctly predict that a person will not require a test.

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

In order to view the tradeoff between these two metrics, we constructed Receiver Operator Characteristic (ROC) Curves¹ for each of the test. Figure 2 shows an example of the EKG ROC curve.

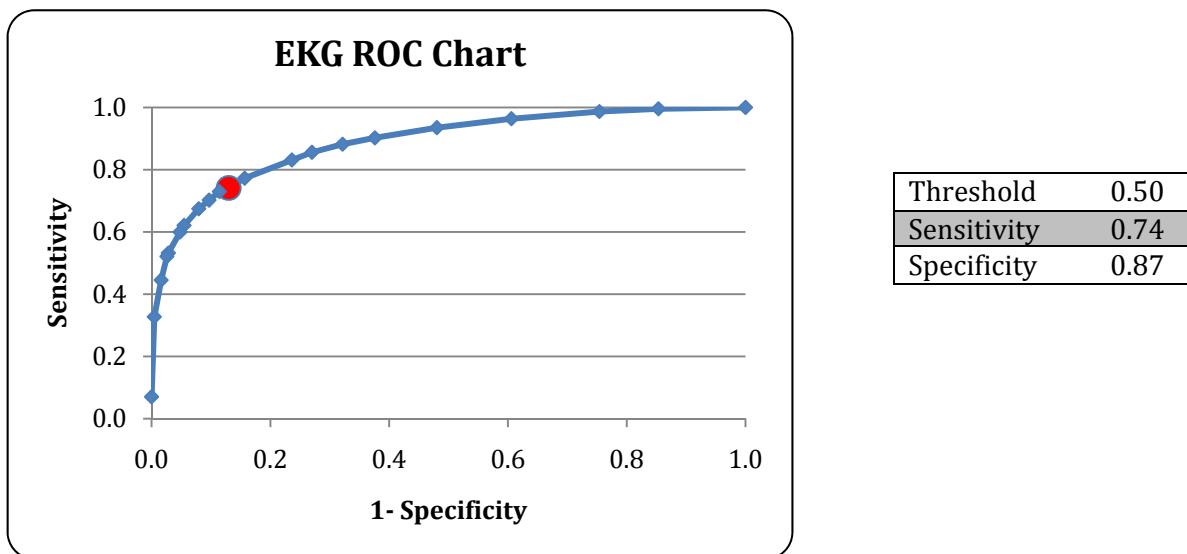
¹ Lang, Thomas , and Michelle Secic. How to Report Statistics in Medicine, 2nd Edition. American College of Physicians: 2006. 137.

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Each point on the graph corresponds to a certain probability threshold and shows the tradeoff between sensitivity and specificity at that threshold.

Figure 2: EKG ROC Chart



The resources predicted by OSCAR must be validated by a doctor or nurse before they are performed. ED personnel will have the opportunity to add tests that have not been predicted and remove unnecessary tests. After consulting with ED personnel, we determined that we would like to predict resources in such a way that the expected number of times that a test must be added is equal to the expected number of times that a test must be deleted from the initial prediction.

Thus, since the weights for specificity and sensitivity are equal, the optimal point can be found where the tangent to the slope of the ROC curve is 1. For the EKG ROC curve, the optimal threshold was 0.50. ROC curves for all of the tests as well as optimal points can be found in Appendix 2.

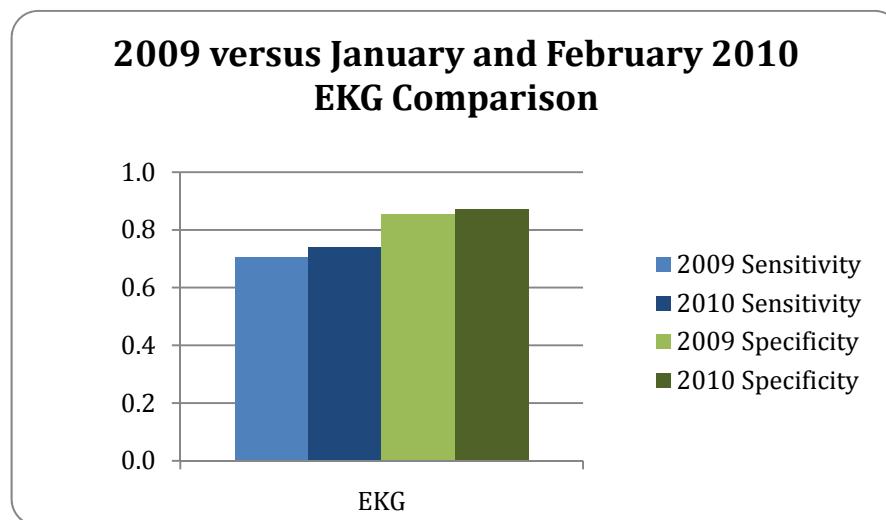
The optimal point on each curve corresponds to certain sensitivity and specificity that we expect to see at that threshold. Table 5 shows the final threshold for each test and sensitivity and specificity at each of those points.

Table 5: Resource Final Threshold Levels and Respective Sensitivity and Specificity

Test	Threshold	Sensitivity	Specificity
Blood Draw	0.70	0.84	0.77
MRA	0.05	0.73	0.82
MRI	0.10	0.59	0.82
CT w/o Contrast	0.25	0.68	0.78
CR w/ Contrast	0.15	0.76	0.59
X-Ray	0.40	0.72	0.67
X-Ray Portable	0.30	0.73	0.75
Urine Collect	0.55	0.69	0.80
Ultrasound	0.15	0.63	0.74
EKG	0.50	0.74	0.87

2.2.5. VALIDATING THRESHOLDS

Next, we conducted a study to determine the sensitivity and specificity that would have been achieved in January and February 2010 had the thresholds from 2009 been chosen. Figure 3 shows the graphical results of the EKG study. We found that sensitivity increased by 4% and specificity increased by 2% as seen in Table 6. The same analysis was performed for all ten tests and sensitivity and specificity differences along with their graphical representations can be seen in Appendix 3 and Appendix 4.

Figure 3: January, February 2010 EKG Sensitivity and Specificity Comparison

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**Table 6: January, February 2010 EKG Sensitivity and Specificity Comparison
(Threshold = 0.50)**

	Sensitivity	Specificity
Entire Year 2009	0.70	0.85
January and February 2010	0.74	0.87
Difference (2010 - 2009)	0.04	0.02

X-Ray Portable, X-Ray, MRI, MRA, CT with Contrast, and Urine Collect all saw slight decreases in sensitivity but a corresponding increase in specificity. This means that while a slightly smaller percent of people were correctly predicted to require a test, a slightly larger percent of people were correctly predicted that they would not require a test. Of these tests, only X-Ray portable showed a difference in either sensitivity or specificity greater than 10%. X-Ray Portable is a lower volume test which explains some of this variation.

Ultrasound, CT without Contrast, and Blood Draw all saw slight decreases in both sensitivity and specificity, though these differences were mostly minimal. Of these tests, only Blood Draw showed a difference greater than 10%, which was a 12% decrease in specificity. However, even with this apparent decrease in performance, the Blood Draw threshold achieved a sensitivity of 0.80 which is the highest of all tests. Thus, even though Blood Draw saw a larger decrease in specificity during testing, the threshold still correctly predicted 80% of patients that would require this test and 65% of patients that would not.

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2.3. RESOURCE PROCESSING TIMES

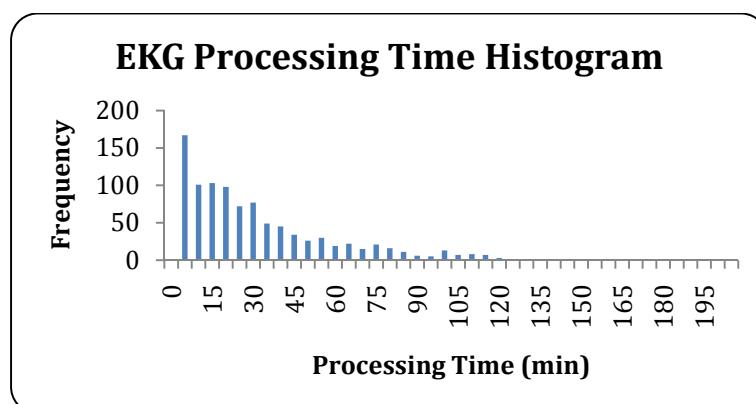
2.3.1. URINE COLLECTION AND BLOOD DRAW

The processing times for Urine Collection and Blood Draw could not be determined using historical data, as the processing times for these events were not recorded. Alternatively, through consultation with EUH ED personnel and ED shadowing, a processing time of 15 minutes for both resources across all acuity levels was determined. This processing time includes a buffer for patient to patient variation. For example, this allots time for a patient that requires the nurse to make multiple attempts to draw a blood specimen. Travel times for the patient to these resources were not incorporated into these processing times, as the patient's nurse conducts both tests and does not require the use or transportation of an additional ED resource.

2.3.2. RADIOLOGY TESTS AND EKG

The processing times for the remaining seven radiology and EKG tests scheduled by the OSCAR tool were determined through analysis of the patient ED service times in December 2009. The seven radiology tests scheduled by the OSCAR tool include: X-Ray, X-Ray Portable, CT with Contrast, CT without Contrast, MRI, MRA, and Ultrasound. It was observed that all of the resource processing time distributions had high standard deviations, reflected by the long right tails exhibited in all of the resources processing times' histograms. These long right tails are exhibited in the EKG overall histogram chart below, Figure 4. The overall processing time histograms of each of the eight resources are included in Appendix 5. Each resource's processing time was further analyzed by acuity level to determine the impact of acuity on the patient resource processing times. Each acuity level's processing time histogram also exhibited long right tails and high standard deviations. Because the acuity level did impact processing times, the 60th percentile processing times by acuity level per resource were used in OSCAR.

Figure 4: EKG Overall Processing Time Histogram



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The 60th percentile processing time was used to account for slight variations of processing times that exist between the specific procedures grouped under each resource of the ED. For example the specific processing times for a finger X-Ray versus a chest X-Ray may differ, but as OSCAR does not predict a specific test requirement, an overall processing time must be used.

The travel time per resource was also included in the processing time. Travel time is the time dedicated to either transporting the patient to and from a resource, or transporting a resource to a patient. Travel time was observed to be 15 minutes per each direction of travel. The travel time was dependent on the resource type, as some of the resources are brought directly to the patient, while other resources require the patient to come to it. Those resources that are transported to the patient include: EKG and X-Ray Portable. These resource processing times only include a one-way travel time (15 minutes). Patients are transported to and from X-Ray, MRI, MRA, Ultrasound and CT, therefore a two-way travel time (30 minutes) was included in these resource processing times.

Because many of these resources are typically utilized only by high acuity patients, minimal data exists for patients of lower acuity levels (acuity levels 4 and 5). As a result, the calculated resource processing time for the lowest acuity level with substantial data was assigned to level 4 and level 5 patients. This method was taken rather than simply using an overall mean for a given resource processing time because there are significant differences in processing time among acuity levels. The final processing times used in the tool for these resources are included in Appendix 6.

3. OSCAR: SCHEDULING TOOL

3.1. FUNCTION

OSCAR is intended to be used in the ED as a patient resource scheduling tool. It is designed to accept patient information as input and then query a database containing the results of our team's previously discussed statistical data to obtain additional parameters (predicted required resources, respective processing times). Once all of the parameters for a patient have been gathered, the patient is scheduled on ED resources.

OSCAR is designed to minimize the LOS of each patient in the ED and build a central schedule to be referenced by ED personnel in order to efficiently process patients. The schedule is built relative to a wide array of system constraints (e.g., resource availability, precedence constraints) to ensure the schedule's practicality and ease of meeting the recommended start and end times of tasks.

3.2. AUDIENCE

OSCAR is designed to deliver its schedule output to the following audiences:

- ED Personnel
 - Doctors
 - Nurses
 - Nurse Technicians
- Ancillary Resource Providers
 - Specimen testing laboratory (e.g., blood, urine)
 - Radiology (e.g., X-Ray, MRI, CT, MRA)
- Hospital Administrators
 - Operations analysts
 - Staffing and resource analysts

In order to meet the information representation needs of each audience, our team created different modes of viewing the same information. Section 6 covers these different views in more detail.

4. OPERATING CHARACTERISTICS

4.1. USER INTERFACE

OSCAR was created with the Java programming language and is comprised of a series of windows used to modify current system information (e.g., patients in the ED, amount of nurses on staff), control the Scheduler, and view schedule output in a variety of formats. For a description of how OSCAR interacts with the database and manipulates information, please refer to Appendix 7.

4.2. SCHEDULER LOGIC

Objective

OSCAR's objective is to minimize the LOS for each patient in the ED at any given time. These times are driven by processing times and resource availabilities.

Input

In order to solve this problem, OSCAR requires each patient's unique identification number (assigned externally by a Cerner² application), acuity level, and major complaint. Based on this information, OSCAR will predict required resources and associated processing times for each patient from the RRPT and use the results to generate a near-optimal schedule.

Constraints

Schedules generated by OSCAR are constrained by characteristics of the Emory ED. These constraints are modeled by the scheduler in order to generate schedules that are feasible, practical, and easy to implement. Some of these constraints are listed below:

- A patient cannot be processed by more than one resource at a given time
- A resource cannot process more than one patient at a time (unless specified otherwise)
- No previously scheduled resources for a patient may be rescheduled before a certain "Visibility" time parameter. This constraint was created to avoid confusing ED personnel by constantly making last-minute changes to the central schedule.
- Patients are weighted by their level of acuity to give priority scheduling to those with more serious complaints or degree of trauma.

² Cerner software packages are currently deployed by Emory to track data in the ED

Base Algorithm

The OSCAR tool's main decision engine is a list algorithm derived from the Longest Total Remaining Processing Time on Other Machines (LTRP-OM) dispatching rule³. Concisely, the rule does the following:

When a resource becomes available, schedule on it the patient who has the longest total remaining “processing time” on other ED resources.

For example, two patients (Patient A and Patient B) need to be scheduled for an MRI which becomes available at 11:30. Patient A still needs an X-Ray and another blood test which at a minimum would require another 60 minutes. However, Patient B does not require any more resources besides the MRI. Thus Patient A has remaining processing time of 60 minutes and Patient B has remaining processing time of 0 minutes. Thus, Patient A will be scheduled to use the MRI first.

The example may seem counter-intuitive since Patient B could take the MRI and leave the system shortly after the results of the MRI are assessed (assuming no other resources are deemed necessary). However, when put in context of a larger, realistic scenario with many more patients to be considered, the rule works towards an optimal schedule that minimizes the LOS for each patient.

Solution Topology Search

Since OSCAR employs a list algorithm, permutation of entities in each of three lists (operation, patient, resource) dictates the outcome of the LTRP-OM decision rule. To approach optimality, the application uses a greedy randomized adaptive search procedure (GRASP) by randomizing the permutation of each list before running an iteration of the base algorithm. Each base algorithm run generates a new schedule instance which has its own objective value (minimized LOS for each patient). Each new schedule is added to a Candidate Solutions Pool.

Once OSCAR has filled the Candidate Solutions Pool (a size specified by OSCAR depending on the amount of operations that need to be scheduled), the solution with the best objective value is chosen as the schedule⁴ to be published to the ED. To see how the size of the Candidate Solutions Pool affects the quality of the generated schedule, refer to Appendix 8.

³ Pinedo, M. Scheduling: Theory, Algorithms, and Systems. New Jersey: Prentice Hall, 1995.

⁴ Optimal solutions cannot be guaranteed in a practical amount of time for use in the ED because the modeled problem is NP-Hard. OSCAR's scheduling algorithm is designed to find a “good enough” solution in a short amount of runtime. To see how OSCAR's schedules compare to the true optimal schedule, please refer to Appendix 8.

5. VALIDATION OF OSCAR

OSCAR's performance was evaluated by experimenting with different values for two of four user-controlled parameters. We elected to focus on Patient Acuity/Prioritization Weight parameters and Candidate Solutions Pool size, which is the amount of random schedules OSCAR will generate before choosing the one with the best objective value (minimum sum of patient LOS's). Nurse staffing and the visibility parameter⁵ are predetermined by the discretion of ED personnel. To see the detailed results of the sensitivity analysis on the Candidate Solutions Pool size and Patient Acuity/Prioritization Weight parameters, please refer to Appendix 8.

5.1. SCHEDULER PERFORMANCE

The functionality of OSCAR's scheduling capabilities was tested through historic January 2010 patient data. In total, we scheduled 1,546 patients over 30 days, with daily arrivals between 35 and 71 patients. The patients and their respective required tests were scheduled into OSCAR using the calculated processing times and developed scheduling heuristics. ED personnel consultation time was determined by a weighted average time by acuity level of the historic data. This time was also added to the resulting length of stay by acuity level. Appendix9 displays the added ED consultation time per acuity level.

Compared to the patient's actual overall length of stay, OSCAR's schedules yielded a reduced overall patient length of stay of 2.2 hours, an overall 17% percent difference⁶. The impact of the tool by acuity level on overall length of stay and the percent difference by acuity level are included in Appendix 9. The improvements in the overall length of stay by scheduling resources and reducing waiting times indicate the significant value of scheduling resources of ED patients.

⁵ It should be noted that we did not neglect testing the effect of the visibility parameter. Rather, we did not analyze this parameter in as much detail as the effect is straightforward: as the parameter increases, schedule quality is negatively affected while runtime is positively affected.

⁶ Percent difference was calculated by subtracting the OSCAR trial LOS result from the actual data LOS and then dividing this difference by the actual data LOS statistic.

6. RECOMMENDED EXPANSION OF OSCAR

We chose to create several views for the output schedules of OSCAR in order to provide a view for each of the different positions in the ED. Each has been created to provide concise and pertinent information for the person that will be using it.

Engineer view

This view consists of a color-coded Gantt chart of the schedules of all patients currently in the ED. It is intended to be used by an engineer or high level administrator to oversee the operations of the ED. The user of this view will be able to see any trends of tardy operations and react accordingly.

Resource view

Designed to improve interdepartmental communication, this view provides the user with information on patients that require tests from the user's department. The resource view will help the departments, such as X-Ray in Radiology, increase the utilization of their resources by providing advanced notice of incoming ED patients.

Doctor view

As the results of the tests are necessary for a doctor to make an accurate diagnosis of a patient, this view will show doctors the expected completion time of their patients' tests.

Nurse view

The nurses will use this view to know which resources their patients require and their expected start times for these resources. This increased visibility of patient requirements will help to improve the efficiency of patient care provided by the nurse.

Patient view

In order to improve communication between patients and ED personnel, thereby increasing patient satisfaction, this view shows the patient a schedule of their resources.

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7. VALUE

7.1. DIVERSION AND THE NEDOC SCORE

The NEDOC score is a national capacity protocol that assesses the severity of ED overcrowding.

The level of overcrowding is defined by the five ranges shown in the table below:

Table 7: NEDOC Score Range

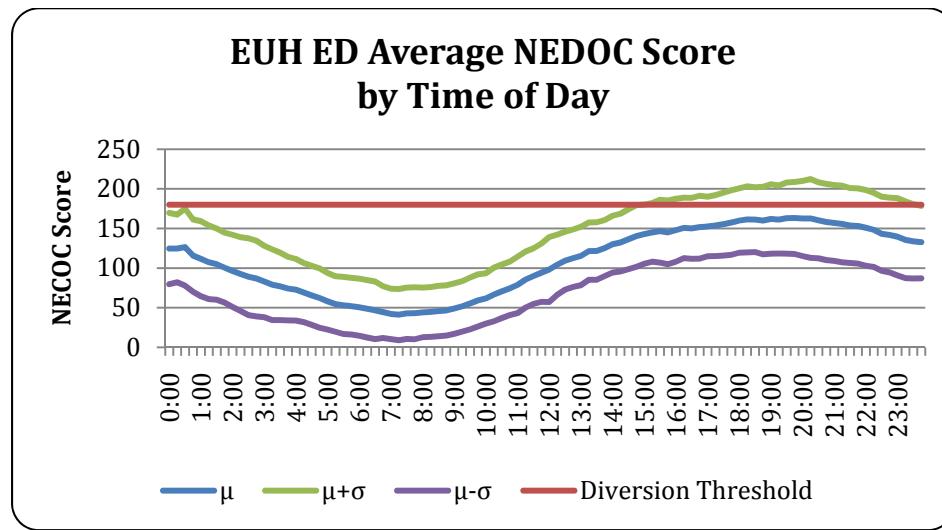
Score Range	Crowdedness Level
0-20	Not busy
21-60	Busy
61-100	Extremely busy, but not overcrowded
101-140	Overcrowded
141-180	Severely overcrowded
181-above	Dangerously overcrowded

The average NEDOC scores and one standard deviation above and below the mean for EUH ED by time of day is shown in Figure 5 below. These are average scores for the ED from January to April 2010. The NEDOC score follows the same trend of patient arrivals by time of day, with a two hour lag time. The graph showing the relationship between times of patient arrivals versus the NEDOC score is included in Appendix 11. Figure 5 below illustrates that during a portion of the peak hours (5PM – 12AM), the NEDOC score rises above 180 with a high probability, indicating that the ED is “dangerously overcrowded” during these times. For the purpose of this project, we assumed that EUH ED goes on diversion status when its score is 180 or higher. The average NEDOC score during the peak demand times was calculated to be 154, indicating that the ED is at a “severely overcrowded” level during peak times. The overall average NEDOC score for the ED was 108 (standard deviation 42), which indicates that the ED is often at an “overcrowded” level, even during non-peak hours.

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Figure 5: EUH ED Average NEDOC Score by Time of Day



EUH ED defines the parameters for calculating the NEDOC score as follows. The formula for calculating the NEDOC score is included in Appendix 12.

- Total number of patients in ED (including waiting room)
- Total number of beds in ED
- Total number of hospital beds in EUH
- Total number of acuity level 1 patients, and number of Intensive Care Unit (ICU) bed requests
- Total number of patients waiting in ED for hospital admission
- Longest waiting time in ED Waiting Room for ED bed
- Longest waiting time for hospital admission for ED patients

OSCAR's impact was quantitatively measured by its impact on the NEDOC score and therefore the diversion rate of the ED. The tool could not be analyzed for its actual impact on the total number of patients in the ED waiting room, because the number of test cases used does not accurately reflect the total number of patients in the ED, as it was developed to reduce patient waiting periods and not the overall service levels of the ED. The test cases for OSCAR could not reflect the total number of patients because the tool was validated only with patients with accurate ED records. The tool was designed to predict the top ten high volume tests, therefore it does not account for patients in ICU. The total number of ED beds and hospital beds in EUH remains constant, 21 and 487 beds respectively. Finally, the tool was created to improve ED operations and does not account for hospital bed availability. Further development of the tool by Emory, such as the expansion to

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include ICU patients and hospital operations will further impact additional parameters of the NEDOC score.

7.2. ASSESSING WAIT TIME UNTIL BED ASSIGNMENT

The NEDOC parameter used to analyze the effect of OSCAR was the longest wait period of patients waiting in the ED Waiting Room for a bed assignment in the ED. It was assumed that the other parameters were constant for calculation purposes. OSCAR's results yielded the total length of stay for each patient, so the wait times until bed assignment were calculated to analyze the tool's impact on the ED's NEDOC score. The January patient data used to develop the test cases were further analyzed to determine the percentage of their total length of stay that was spent waiting for a bed assignment in the ED. These percentages were then broken down further by acuity level to account for any waiting time differences between acuity levels. The wait times until bed assignment were then calculated for the OSCAR test results using each respective percentage by acuity level. The calculated patient waiting times for an ED bed assignment from the OSCAR tool test case output were then compared to actual patient waiting room wait times. We found that the average reduction in the patient wait time before bed assignment was 9 minutes on average, or a reduction of approximately 4%.

7.3. REDUCTION IN NEDOC SCORE

The average overall NEDOC score and average NEDOC score by time of day for EUH ED were found using historical data from January to April 2010. By holding all other NEDOC parameters constant except longest waiting time before bed assignment, the impact of the reduced ED Waiting Room waiting times on the overall NEDOC score for each day and time period from January was calculated. The average percent difference of the original NEDOC score and the reduced NEDOC score from the OSCAR tool data was determined. The results showed that the NEDOC score was reduced on average by 1.4% (1.3 NEDOC score points).

7.4. REDUCTION OF TIME ON DIVERSION

After determining the reduction in the NEDOC score from the output of the OSCAR tool, the 1.4% reduction rate was applied to the NEDOC scores for the EUH ED January NEDOC score and diversion data. This reduction was then analyzed further to determine the decrease in the number of times EUH ED was on diversion during peak demand hours in January 2010. We compared the number of instances when the NEDOC score was reduced to a score under 180 when the original score for that time was over 180, implying that EUH ED would no longer be on diversion at that time. EUH ED does not record the time the ED goes on diversion and the time the ED is relieved from diversion, so the number of instances that the ED went on diversion was used to evaluate added EMS ground patients.

According to January data, EUH ED went on diversion 25 times throughout the month. This number was reduced to 23 times during the month, showing that the OSCAR tool contributed to EUH ED being on diversion 2 less times in January, or an 8% reduction in number of times on diversion.

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7.5. ADDED EMS PATIENTS

The hospital loses a substantial amount of revenue when the ED must divert EMS patients to other hospitals. Thus, when diversion occurs at peak hours, it indicates that demand exists for additional ED services at EUH and that an increase in patient capacity will bring additional revenue for the hospital.

By analyzing historical data for January 2010, it was calculated that approximately 24% of all patients arrived to the ED by EMS transportation. The total number of patients the ED serviced in January 2010 was 2,790 patients (660 EMS patient arrivals for the month). This further shows that EUH ED services approximately 22 EMS ground patients per day, or approximately 1 EMS ground patient per hour.

A minimum of one additional EMS patient would arrive for each instance that EUH ED was originally on diversion in January but was determined to no longer be on diversion from the output of the OSCAR tool. This estimate is a lower bound assumption, as it is expected that 2 more EMS ground patients would arrive to the ED throughout the month, 24 additional EMS patients yearly.

7.6. VALUE CALCULATION

To calculate the additional revenue generated for added EMS patients, we determined the average revenue for an admitted ED patient to be \$18,000 and the average revenue for a discharged ED patient to be \$421. If a minimum of an additional 24 EMS patients were received throughout the year, it was determined that the annual impact of reducing diversion for EUH ED via the OSCAR scheduling tool is approximately \$203,500 of additional revenue per year. Further detailed calculations of this figure can be found in Appendix 13.

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8. APPENDIX

8.1. APPENDIX 1: SPONSOR DESCRIPTION

8.1.1. EMORY HEALTHCARE SYSTEM

Emory Healthcare System, with locations in Atlanta, GA, is the university affiliate of the Robert W. Woodruff Health Sciences Center of Emory University, including the Emory University School of Medicine. Emory Healthcare System encompasses more than 20 healthcare centers throughout Metro Atlanta. The Emory Healthcare System is the largest in Georgia, staffing 9,000 employees with 1,184 licensed beds⁷.

8.1.2. EMORY UNIVERSITY HOSPITAL

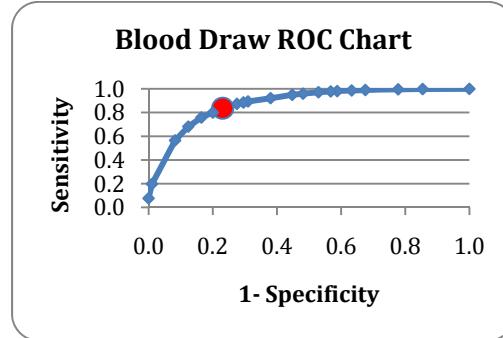
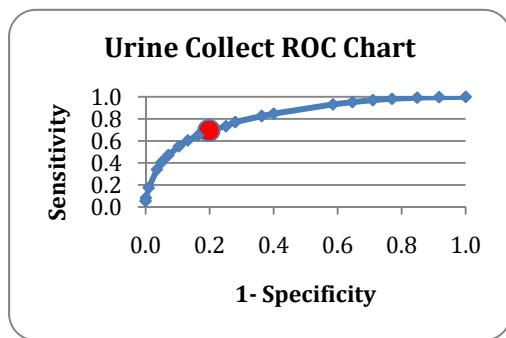
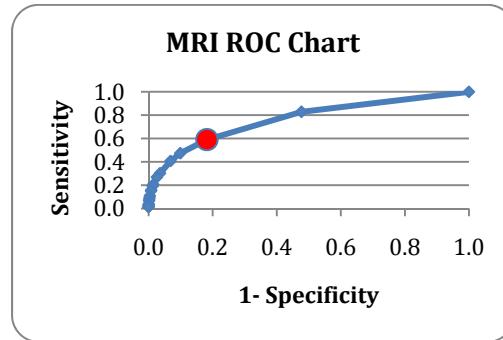
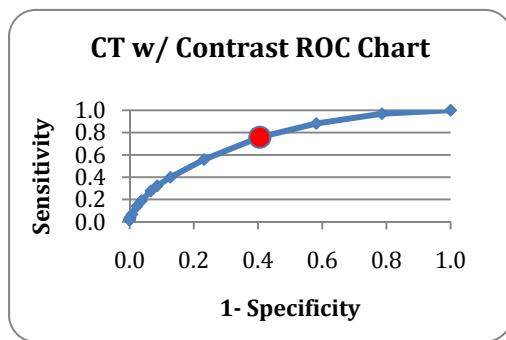
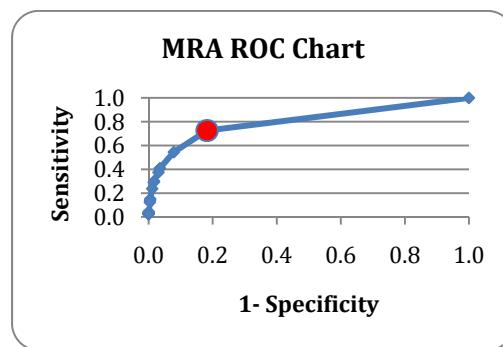
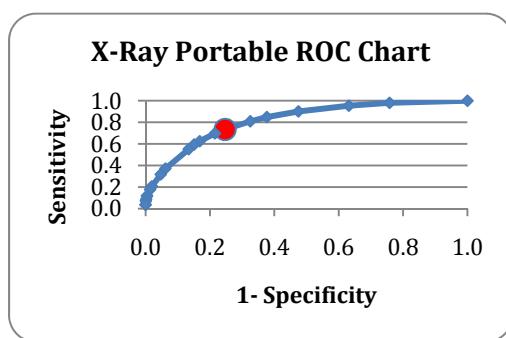
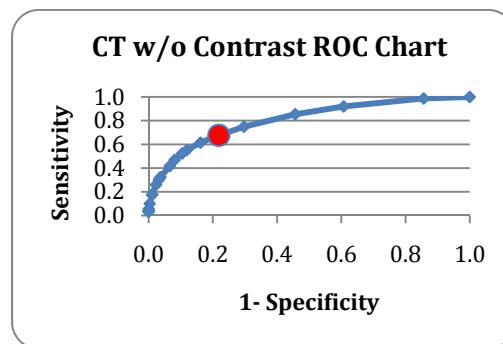
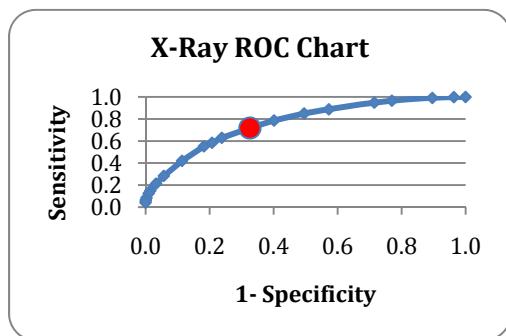
As a branch of the Emory Healthcare System, Emory University Hospital (EUH⁸) specializes in providing medical care to severely ill adults. EUH also operates as a teaching facility for Emory University and is staffed by the School of Medicine faculty who are members of The Emory Clinic. EUH serves more than 24,000 inpatients and 80,000 outpatients annually. For several years, U.S. News and World Report has ranked EUH's cardiology center as one of the top ten national centers. EUH is also recognized as a national leader in cardiology and cardiac surgery, neurology, oncology, ophthalmology, orthopedics and transplantation.

8.1.3. EMORY UNIVERSITY DEPARTMENT OF EMERGENCY MEDICINE

The Emory University Department of Emergency Medicine provides medical care to five metro Atlanta Emergency Departments, serving over 250,000 patients annually. Emory serves as the leading adult and pediatric referral center. This department strives to attain and remain the nation's dominate Department of Emergency Medicine through research, education, and healthcare.

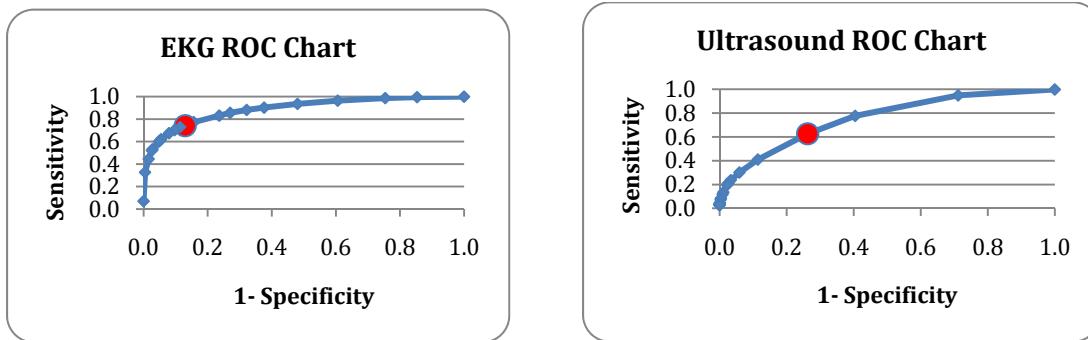
⁷ The Agency for Healthcare and Research Quality defines 'licensed beds' as "The maximum number of beds for which a hospital holds a license to operate. Many hospitals do not operate all of the beds for which they are licensed." <<http://www.ahrq.gov/research/havbed/definitions.htm>>

8.2. APPENDIX 2: ROC CURVE CHARTS



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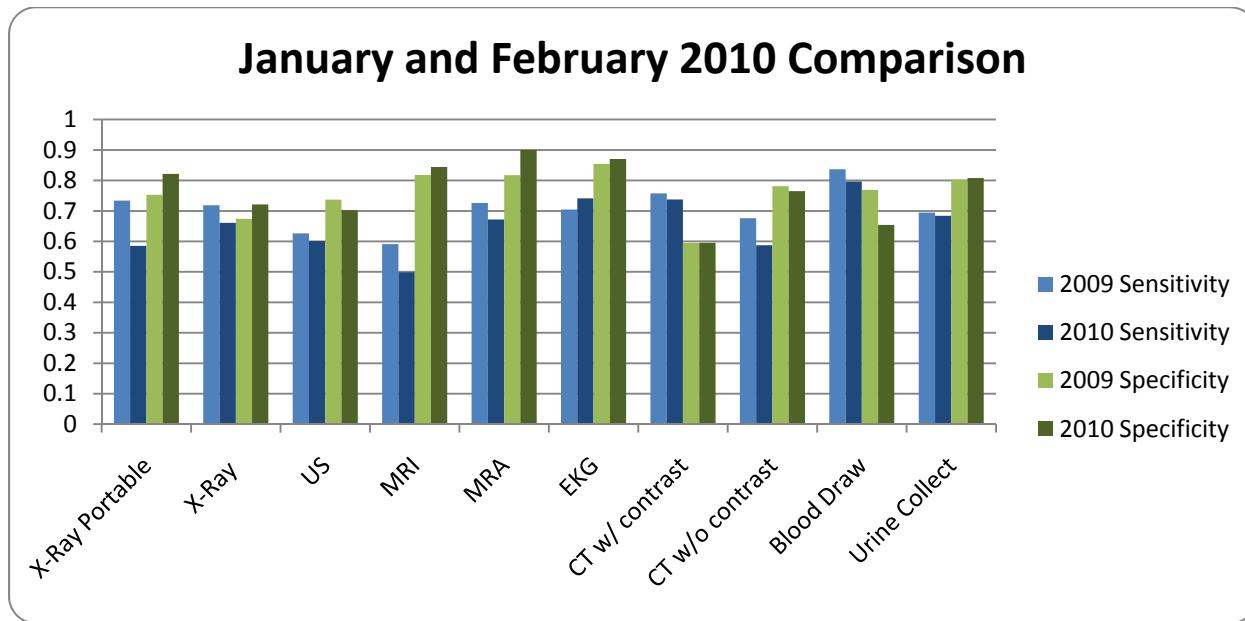


The above charts are ROC (Receiver Operating Characteristic) curve charts for each predicted test. The red point indicates the optimal threshold for each test used to determine the probabilities of requiring a resource.

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8.3. APPENDIX 3: TESTING OF 2009 THRESHOLDS ON JANUARY AND FEBRUARY 2010 DATA



The graph above compares the expected sensitivity and specificity from 2009 data to the achieved sensitivity and specificity in January and February 2010 using the determined optimal thresholds.

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8.4. APPENDIX 4: TABLE OF TESTING 2009 THRESHOLDS ON JANUARY, FEBRUARY 2010 DATA

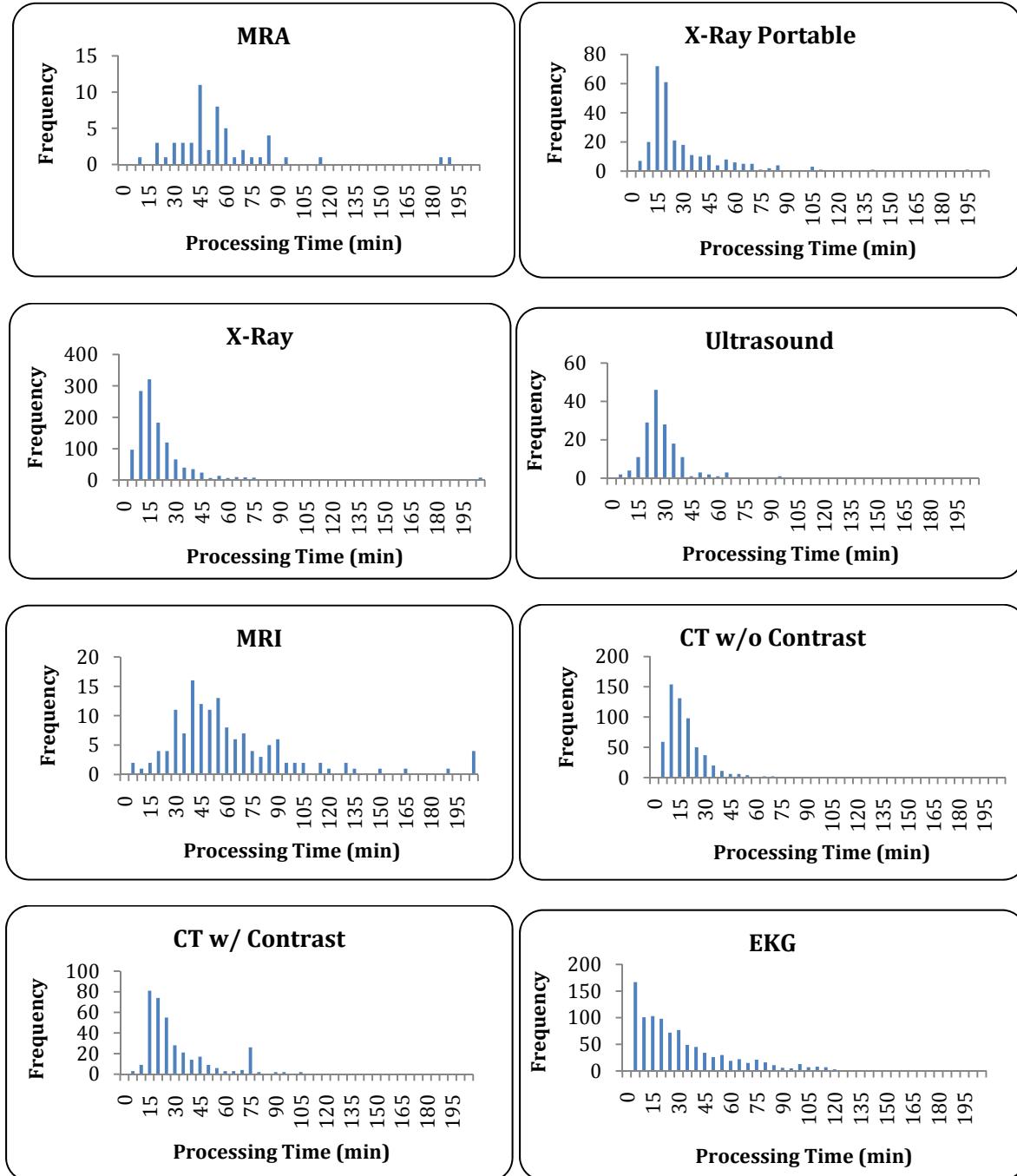
Test	Threshold	Entire Year 2009		Jan, Feb 2010		Difference (2010-2009)	
		Sens	Spec	Sens	Spec	Sens	Spec
X-Ray Portable	0.30	0.73	0.75	0.59	0.82	-0.15	0.07
X-Ray	0.40	0.72	0.67	0.66	0.72	-0.06	0.05
Ultrasound	0.15	0.63	0.74	0.60	0.70	-0.03	-0.03
MRI	0.10	0.59	0.82	0.50	0.84	-0.09	0.03
MRA	0.05	0.73	0.82	0.67	0.90	-0.05	0.08
EKG	0.00	0.70	0.85	0.74	0.87	0.04	0.02
CT w/ Contrast	0.15	0.76	0.59	0.74	0.60	-0.02	0.00
CT w/o Contrast	0.25	0.68	0.78	0.59	0.76	-0.09	-0.02
Blood Draw	0.70	0.84	0.77	0.80	0.65	-0.04	-0.12
Urine Collect	0.55	0.69	0.80	0.68	0.81	-0.01	0.01

The table above shows the expected sensitivity and specificity from 2009 data to the achieved sensitivity and specificity in January and February 2010 using the determined optimal thresholds.

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8.5. APPENDIX 5: OVERALL HISTOGRAMS OF PROCESSING TIMES BY RESOURCE



The above graphs are histograms of the processing times for the radiology resources and EKG. As noted in the paper, the 60th percentile processing times were used because of the long right tails present for all resource processing times.

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8.6. APPENDIX 6: 60TH PERCENTILE PROCESSING TIMES BY ACUITY LEVEL INCLUDING TRAVEL TIME (MINUTES)

Acuity	Test	60% + Travel	Acuity	Test	60% + Travel
1	Blood Draw	15	1	MRI	86
2	Blood Draw	15	2	MRI	83
3	Blood Draw	15	3	MRI	99
4	Blood Draw	15	4	MRI	99
5	Blood Draw	15	5	MRI	99
1	CT w/ Contrast	59	1	Urine Collect	15
2	CT w/ Contrast	53	2	Urine Collect	15
3	CT w/ Contrast	54	3	Urine Collect	15
4	CT w/ Contrast	54	4	Urine Collect	15
5	CT w/ Contrast	54	5	Urine Collect	15
1	CT w/o Contrast	41	1	Ultrasound	40
2	CT w/o Contrast	45	2	Ultrasound	40
3	CT w/o Contrast	45	3	Ultrasound	38
4	CT w/o Contrast	45	4	Ultrasound	38
5	CT w/o Contrast	45	5	Ultrasound	38
1	EKG	35	1	X-Ray	47
2	EKG	43	2	X-Ray	43
3	EKG	55	3	X-Ray	42
4	EKG	55	4	X-Ray	43
5	EKG	55	5	X-Ray	43
1	MRA	85	1	X-Ray Portable	34
2	MRA	82	2	X-Ray Portable	35
3	MRA	82	3	X-Ray Portable	45
4	MRA	82	4	X-Ray Portable	45
5	MRA	82	5	X-Ray Portable	45

The tables above display the processing times used in OSCAR for the ten scheduled and predicted resources by acuity level in minutes. These times are the 60th percentile processing times and include travel times to and from resources where applicable.

8.7. APPENDIX 7: OSCAR'S CODE ARCHITECTURE

This section is intended for computer programmers and other technical personnel that are interested in how OSCAR operates at the code level.

OSCAR was coded completely in Java Standard Edition 7. It communicates with a MySQL 5.1 Server through the JDBC and Connector/J API's. Although the Gantt chart rendering feature of OSCAR uses many classes from the open-source JFreeChart⁹ API, many of the classes were extended to meet the needs of the project.

8.7.1. DATA HANDLING

OSCAR models the ED as a collection of entities (patients, resources, and operations) with each having a unique set of attributes. Patients and resources are considered base-layer entities because they represent concrete, immutable objects in the real-world ED. The third type of entity, the operation, is considered an abstract-layer entity because its attributes are derived from the base-layer entities through a mapping function. In the case of OSCAR, the mapping “function” is actually the finite set of data contained in the database that maps resource requirement and processing times based on patient acuity and complaint. We refer to this database as the Resource Requirement Probability Taxonomy (RRPT).

Database

The OSCAR code specifies a URL for a database server that can exist on the local system or on a remote machine. The database holds all of the RRPT information as well as a static reference to base-layer entities in the ED at a given instance of time. Because of the volatility of Operation objects (i.e., many operation objects are created, modified, referenced, and de-referenced on the order of microseconds), they are not updated in the database while the scheduler is running. Instead, operations, along with other volatile information, are handled locally by OSCAR when the scheduler is running.

Local System

OSCAR maintains a local clone of each entity stored in the database. At scheduler runtime, these local objects are rapidly manipulated by the algorithm. When the scheduler ceases, a variable factory class interfaces with the database to reconcile all entity attributes. While the scheduler runs on a separate thread in the application, it ensures data integrity between the local and database entities by locking the database and only allowing modifications to the data when the scheduler is not running (i.e., modifications made to entities by the user via the UI while the scheduler is running are stored ‘in limbo’ and will not execute until the scheduler releases its lock on the database).

⁹ JFreeChart 1.0.13 is part of the JFree package of open-source API's designed for rendering charts in Java. It is available under the GNU Lesser General Public License from <http://www.jfree.org/>

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Time

Since the scheduler generates schedules detailed to the minute, the program must track three primary time location references in order to calculate time differences between currently scheduled operation start times, possible operation start times, and real-time:

- Real-time (RT) is defined as the current real-world time.
- Scheduler Run Start Time (SRST) is the time when the scheduler locks the database and begins solving for the near-optimal schedule.
- Scheduler Search Time (SST) is the time that the scheduler algorithm is currently checking to schedule operations in accordance with the LTRP-OM decision rule.

8.7.2. RESOURCE REQUIREMENT PROBABILITY TAXONOMY (RRPT) DATABASE

The database was created using MySQL. It is accessed by the Java based GUI via JDBC and Connector/J API's. The PATIENT and OPERATION tables will be updated as new patients are added to the system and schedules of operations are generated for those patients. The COMPLAINT table, RESOURCE table and TAXONOMY table are hard coded with the set data derived from our analysis.

List of all of the tables in the RRPT database:

Tables_in_rrpt
complaint
operation
patient
resource
taxonomy

Sample row from the COMPLAINT table:

complaintid	complaintname
1	Abdominal pain

Sample row from the OPERATION table:

operationid	patientid	resourceid	processingtime	starthour	endhour	startminute	endminute
1	1	1	30	5	6	30	0

This document and its contents have been created in the framework of a student design project and the Georgia Institute of Technology does not officially sanction its contents.

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Sample row from the PATIENT table:

patientid	lastname	firstname	acuity	age	sex	complaintid	isactive
1	Doe	John	2	21	1	120	1

Sample row from the RESOURCE table:

resourceid	resourcename	processetime	isscheduled
0	EKG	34	1

Sample row from the TAXONOMY table:

taxonomyid	acuity	complaintid	resourceid	processingtime
20	2	120	0	55

8.8. APPENDIX 8: PARAMETRIC SENSITIVITY ANALYSIS FOR OSCAR

OSCAR's performance can be adjusted by four different parameters that can be controlled by the user:

- *Visibility Parameter* – This parameter controls the point in time where OSCAR will begin list iteration for operation scheduling. It is simply the difference to be maintained between SST and SRST to avoid rescheduling operations already scheduled to happen with a certain time from the real time.
- *Nurse Availability* – There is one primary staffing constraint on the system: a “nurse” constraint. Resources that require a nurse (e.g., to move a patient to an X-ray operation) decrease the amount of available nurses to handle other operations at the same time. This constraint is represented as an integer variable that the scheduler must check before scheduling an operation at SST.
- *Candidate Solutions Pool Size* – Since OSCAR deals with a combinatorial optimization problem, the amount of input data to be processed has a significant impact on the performance of the Scheduler module. The value of this parameter can be controlled by the user but is preset by OSCAR to only allow the scheduler to run for one minute.
- *Patient Acuity/Prioritization Weights* – Imagine a case where the ED currently has six patients, all with an acuity 4 (i.e., relatively non-severe complaints such as a broken finger). Then, a patient with acuity 1 arrives via helicopter with catastrophic injuries. Clearly, the scheduler should give high priority to scheduling resources for the new patient. OSCAR accounts for this need by scaling a patient’s projected LOS by his or her acuity when calculating an objective value.

8.8.1. CANDIDATE SOLUTIONS POOL SIZE (RANDOM SCHEDULE GENERATIONS) PARAMETER

In order to compare OSCAR’s schedule quality relative to true optimality, our team developed an integer programming model in Xpress Mosel which is detailed in Appendix 14. Between the IP and OSCAR, we tested four scenarios of different size (9 patients, 22 operations; 13 patients, 28 operations; 17 patients, 36 operations; 21 patients, 43 operations) were examined with 10 replications each to determine the effect of the Candidate Solutions Pool size on OSCAR’s schedule quality.

The scheduler was allowed to generate 10,000 schedules but because OSCAR is designed to be agile, we wanted the scheduler to run in under one minute. Thus, OSCAR sacrifices optimality for runtime but nonetheless provides “good enough” schedules. The results of the analysis on the next page show the best objective value acquired in less than one minute of runtime. The “Best” column refers to the best objective value found at which sequential random schedule generation (“Run” column).

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Table: Candidate Solutions Pool Size (Random Schedule Generations) Test Results

Replication	0=22, P=9		0=28, P=13		0=36, P=17*		0=43, P=21	
	Best	Run	Best	Run	Best	Run	Best	Run
1	832	433	1223	1271	2094	489	3430	958
2	832	238	1221	59	2094	489	3447	85
3	832	643	1221	734	2094	489	3400	623
4	832	898	1221	1065	2094	489	3407	478
5	832	253	1221	418	2094	489	3450	1631
6	825	933	1221	719	2094	489	3504	507
7	821	842	1221	75	2094	489	3450	414
8	825	223	1221	524	2094	489	3450	2261
9	837	661	1222	643	2094	489	3450	1058
10	828	372	1221	29	2094	489	3407	2907
OSCAR Minimum	821	223	1221	29	2094	489	3400	85
OSCAR Maximum	837	933	1223	1271	2094	489	3504	2907
OSCAR Mean	829.6	549.6	1221.3	553.7	2094.0	489.0	3439.5	1092.2
IP Best (Runtime)	810	103.4s	1172	488.3s	1937	912.4s**	3080	3024.5s**
Difference (OSCAR, IP)	2.4%		4.2%		8.1%		11.7%	

*The 0=36, P=17 case found its best value at the same run iteration each time. However, the pseudorandom number generator used unique seeds for each replication. This may have been caused by a limitation of the LTRP-OM dispatching rule and may not accurately reflect a similar scenario with slight entity attribute variations.

**Xpress crashed; the best solution at the time of crash is listed.

OSCAR was rarely able to improve on the solutions in the chart above even when allowed to generate 1,000,000 schedules (requiring about four hours of runtime for each scenario).

8.8.2. PATIENT ACUITY/PRIORITIZATION WEIGHT PARAMETER

Prioritizing the scheduling of patients by their acuity ensures that patients with the most severe medical problems are scheduled on the resources they require within a relatively short interval of time after they arrive to the ED. To analyze the effects of these weights, OSCAR was given a 21-patient, 43-operation test scenario with five different types of weighting ratios (the weights are listed in brackets from acuity 1 (highest priority patient) to acuity 5 (lowest priority patient)):

1. Unweighted {1, 1, 1, 1, 1}
2. Low-Sensitivity Linear {5, 4, 3, 2, 1}
3. Low-Sensitivity Fibonacci {8, 5, 3, 2, 1}
4. Medium-Sensitivity {400, 200, 100, 50, 1}
5. High-Sensitivity {50000, 4000, 300, 20, 1}

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The weighting ratios are scalar values applied to the patient's acuity when the objective value for a schedule is calculated by OSCAR. Results for the test cases with different weight parameter values are tabulated below (patients with acuity 3 are excluded from the chart):

Acuity	Unweighted	Linear	Fibonacci	Medium-Sensitivity	High-sensitivity
1	105	165	105	120	115
1	105	225	105	60	75
2	45	30	90	45	30
2	300	349	229	206	150
2	75	225	75	223	75
4	160	55	453	447	334
4	90	153	345	405	498
5	355	306	288	294	390

The High-Sensitivity weight scalar values are the most effective at prioritizing patients by acuity. However, ultimate control of the weight parameters is left to the user via an "Edit Parameters" window accessible from the main GUI window of OSCAR. If not changed, the default values are set with the Medium-Sensitivity values listed above.

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8.9. APPENDIX 9: ED CONSULTATION TIME BY ACUITY LEVEL (MINUTES)

Acuity	Consult Time
1	107
2	117
3	108
4	79
5	62

The table above displays the time added to each patient's OSCAR length of stay in minutes per patient acuity level. These times account for any consultation time a patient receives while in the ED, including assessments from doctors, nurses, technicians, physician assistants, etc.

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8.10. APPENDIX 10: JANUARY 2010 PATIENT LENGTH OF STAY VERSUS OSCAR (HOURS)

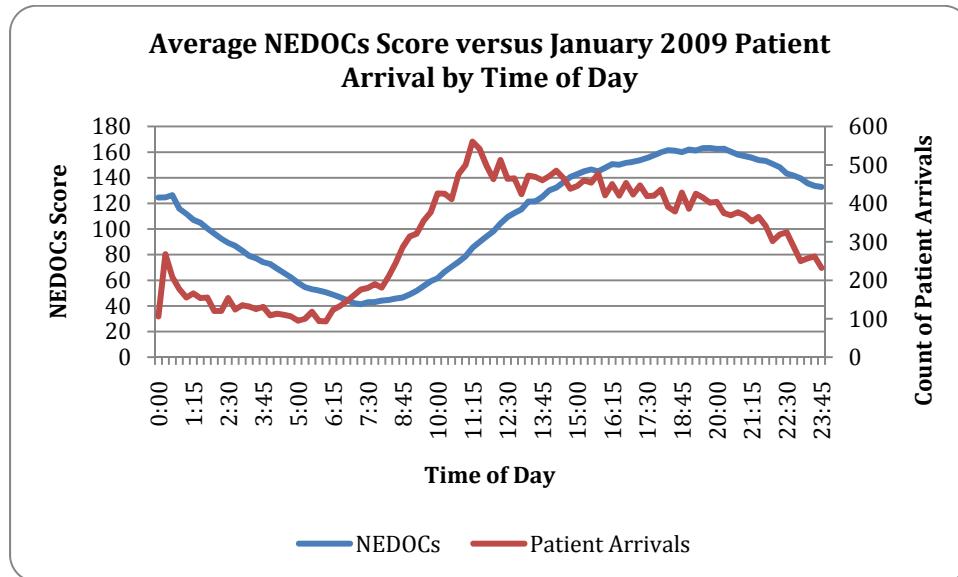
Acuity	Actual		OSCAR		% Difference
	μ	σ	μ	σ	μ
1	5.9	3.2	4.0	1.6	-13%
2	7.1	4.6	4.2	1.5	-23%
3	6.1	4.1	4.0	1.8	-18%
4	3.5	2.2	3.0	1.4	2%
5	1.3	0.1	1.2	0.1	-5%
Overall	6.1	4.2	3.9	1.7	-17%

The table above shows the improvements of the OSCAR tool versus the average patient lengths of stay overall and by acuity level. The final right column shows the average percent difference from of the OSCAR schedule versus the historic data overall and by acuity level.

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8.11. APPENDIX 11: NEDOC SCORE VERSUS PATIENT ARRIVALS BY TIME OF DAY



The above graph shows the impact of patient arrivals on the NEDOC score. The NEDOC score reflects shifts in the number of ED patients with an approximate two hour delay. This shows the impact that the number of patient arrivals has on the value of the NEDOC score.

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8.12. APPENDIX 12: NEDOC SCORE FORMULA AND PARAMETERS

$$85.8 \left(\frac{P(\text{bed})}{B(t)} \right) + 600 \left(\frac{P(\text{admit})}{B(h)} \right) + 5.64W(\text{time}) + 0.93A(\text{time}) + 13.4R(n) - 20$$

Parameter	Definition
P(bed)	Total number of patients in ED (excluding CDU locations)
B(t)	Total number of beds in ED
P(admit)	Total number of admit holds in total number of beds in ED
B(h)	Total number of hospital beds at EUH
W(time)	Longest LOS in Waiting Room
A(time)	Longest admit hold time for patient in ED
R(n)	Total number of patients level 1 acuity, any patients with an ICU bed request

The NEDOC score is a national ED metric used to measure the level of over crowdedness in the ED. EUH ED calculates its NEDOC score by the above equation using the parameters as defined above. The reduction of patient length of stay by the OSCAR tool primarily reduced W(time), the longest amount of time spent waiting for an ED bed assignment in the ED Waiting Room.

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8.13. APPENDIX 13: VALUE CALCULATIONS

Revenue Calculations for Additional EMS Patients

Item	Description	Calculation	Value
A	Total number of patient visits during January 2010		2,790
B	Number of EMS patients admitted during January 2010		308
C	Number of EMS patients discharged during January 2010		352
D	Percent of ED EMS patients admitted	B/(B+C)	47%
E	Net patient revenue per adjusted admission		\$18,000
F	Average revenue per discharged patient		\$421
G	Additional number of EMS patients per year		24
H	Additional number of EMS patients admitted per year	D*G	11
I	Additional number of EMS patients discharged per year	G-H	13
J	Yearly revenue from additional admitted EMS patients	E*H	\$198,000
K	Yearly revenue from additional discharged EMS patients	F*I	\$5,473
L	Yearly revenue from additional EMS patients	J+K	\$203,473

This table shows the calculations made by our team to determine the conservative financial impact of the OSCAR tool at EUH. These calculations were made using the ED patient demand data from January 2010 and from EUH Consolidated Income Statements, Report Cards, and Department Performance Summaries for 2008-2009. It was conservatively estimated that EUH will earn an additional yearly revenue of \$203,473.

According to the EUH Monthly Consolidated Income Statement, the “Net Patient Revenue per Adjusted Admission” is \$21,852. This revenue figure is calculated for all EUH patients, not specifically ED patients. Thus, through an interview with the head of the Department of Emergency Medicine at EUH, it was determined that the revenue generated per patient admitted to the hospital from the ED is approximately \$18,000.

Based on EUH Monthly Consolidated Income Statements, an average of 34% of patients entering the ED will be admitted to the hospital while the remaining 66% will be discharged directly from the

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ED. The table below displays the calculations performed to determine the average revenue per discharged patient of \$421. This value was used to determine the additional revenue of discharged EMS patients from the results of the OSCAR tool.

**Revenue for Discharged Patients
(Fiscal Year 2008-2009)**

Item	Description	Calculation	Value
A	Average number of monthly ED patients		2,740
B	% ED patients admitted		34%
C	Average number of monthly ED discharged patients	A*(1-B)	1,817
D	Outpatient average monthly revenue (discharged)		\$764,718
E	Average revenue per discharged patient	D/C	\$421

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8.14. APPENDIX 14: INTEGER PROGRAMMING MODEL

Indices		
$j, k \in N, N = n$		Patients j in set N containing all n patients
$i \in R, R = r$		Resource i in set R containing all r resources
Parameters		
p_{ij}		Processing time of patient j on resource i
rec_j		# of resources required by patient j (derived)
pat_i		# of patients required by resource i (derived)
$O_{ij} = \{i: j \text{ must be processed on } i\}$		Set of resources that patient j requires
$m_{ij} = \{j: i \text{ must be processed on } j\}$		Set of patients that resource i requires
Variables		
$x_{ijj'} \in \{0,1\}$		$\begin{cases} 1 & \text{if } j \text{ precedes } j' \text{ on } i \\ 0, & \text{else} \end{cases}$
$y_{iij} \in \{0,1\}$		$\begin{cases} 1 & \text{if } j \text{ is processed on } i \text{ before } i' \\ 0, & \text{else} \end{cases}$
s_{ij}		Start time of patient j on resource i
Objective		
$\min \sum_{j=1}^n s_{(r+1)j}$		$s_{(r+1)j}$ is the completion time of patient j in the system

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Constraints			
(1)	$s_{im_{ij}} + p_{im_{ij}} \leq s_{im_{ij'}} + M(1 - x_{ijj'})$	$\forall i \text{ and } j, j' \in 1 \text{ to } pat_i \text{ and } j < j'$	M is an arbitrarily large number; ensures that a resource cannot process more than one patient at a time
(2)	$s_{im_{ij'}} + p_{im_{ij'}} \leq s_{im_{ij}} + M(1 - x_{ijj'})$	$\forall i \text{ and } j, j' \in 1 \text{ to } pat_i \text{ and } j < j'$	M is an arbitrarily large number; ensures that a resource cannot process more than one patient at a time
(3)	$s_{o_{ij}j} + p_{o_{ij}j} \leq s_{o_{ij'}j} + M(1 - y_{iij'})$	$\forall j \text{ and } i, i' \in 1 \text{ to } rec_j \text{ and } i < i'$	M is an arbitrarily large number; ensures that a patient cannot be processed by more than one resource at a time
(4)	$s_{o_{ij}j} + p_{o_{ij}j} \leq s_{o_{ij}j} + M(1 - y_{iij})$	$\forall j \text{ and } i, i' \in 1 \text{ to } rec_j \text{ and } i < i'$	M is an arbitrarily large number; ensures that a patient cannot be processed by more than one resource at a time
(3)	$s_{ij} + p_{ij} \leq s_{(r+1)j}$	$\forall i, j$	Process a dummy resource last
(4)	$s_{ij}, p_{ij} \in \mathbb{Z} \geq 0$	$\forall i, j$	Non-negative integers

The objective function seeks to minimize the sum of the completion times of each patient by minimizing the start time of the last resource of each patient.

Constraints (1) and (2) work together to ensure that a resource is not processing more than one patient at any given time. They do this by making the start time plus the processing time of patient B on resource Y come before the start time of patient C on resource Y (1) and the start time of that patient B on resource Y come after the start time plus the processing time of a patient A on resource Y (2).

Constraints (3) and (4) work together to ensure that a patient is not being processed by more than one resource at any given time. They do this by making the start time plus the processing time of patient A on resource Y come before the start time of patient A on resource Z (3) and the start time of that patient A on resource Y come after the start time plus the processing time of a patient A on resource X (2).

8.15. APPENDIX 15: OSCAR USER MANUAL

OSCAR

Operational Scheduling of Care and Resources

User Manual

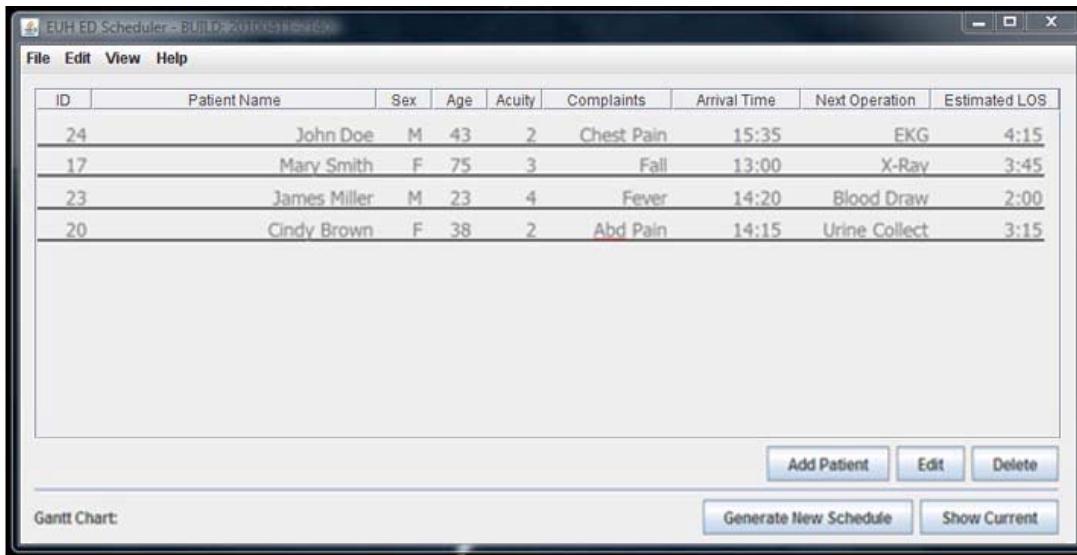
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EUH ED SCHEDULER WINDOW



After opening OSCAR, you will see the EUH ED Scheduler window. This window will display information about patients who are currently in the system.

EUH ED SCHEDULER WINDOW DISPLAY

- **ID** - a unique number assigned by OSCAR to each patient that is added to the system.
- **Patient Name** - the patient's first and last name
- **Sex** - 'M' for male and 'F' for female.
- **Age** - the patient's age.
- **Acuity** - an integer ranging from 1 to 5 indicating the severity of the patient with 1 being the most severe and 5 being the least severe.
- **Complaints** - displays the patient's major complaint.
- **Arrival Time** - the time when the patient was added to the system.
- **Next Operation** - displays which resource the patient is scheduled to be processed on next.
- **Estimated LOS** - displays the estimated length of stay for the patient in hh:mm format.

EUH ED SCHEDULER WINDOW BUTTONS

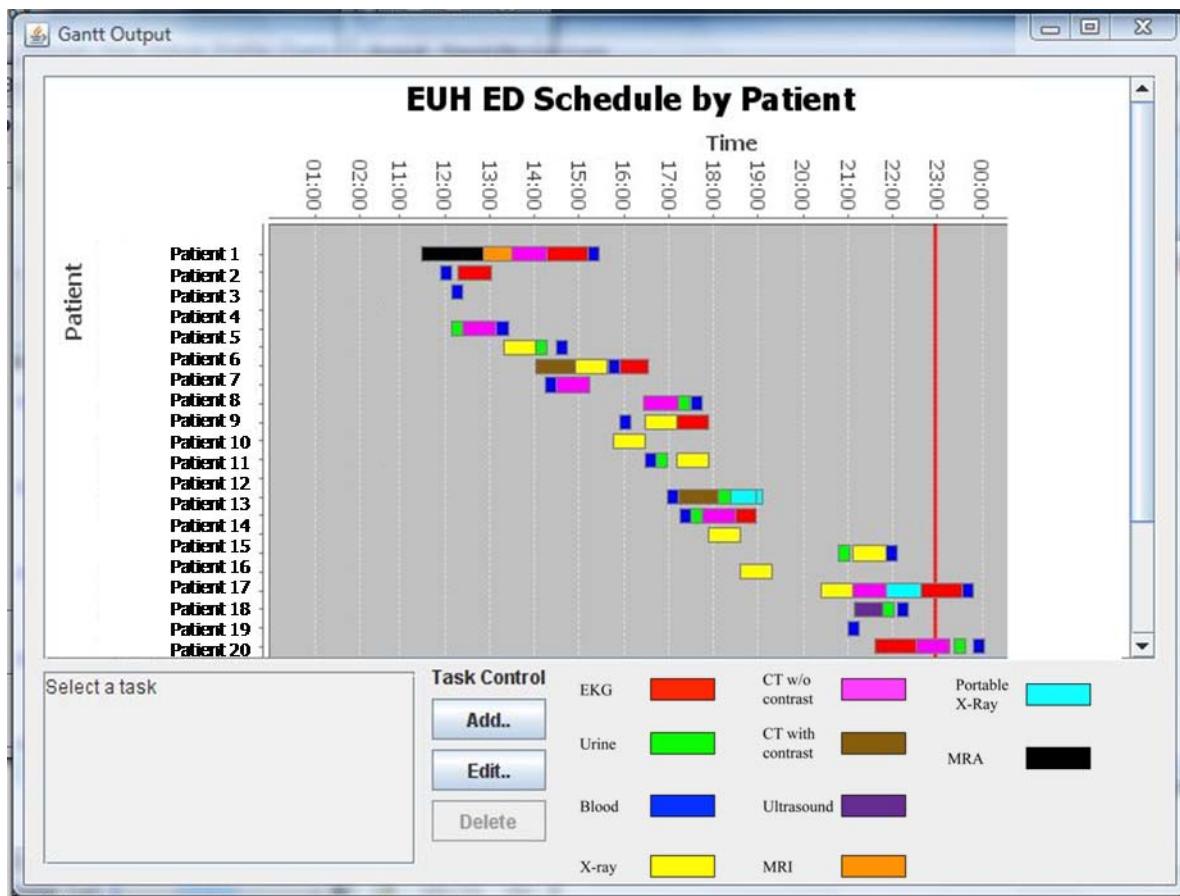
- **Add Patient** – clicking this button opens another window that allows you to input information about a patient and then add the patient to the database
- **Edit** – If a patient is selected in the table, clicking this button will open a window similar to the "Add Patient" window but will be pre-populated with the information of the selected patient. Changes to the fields in this window will update the patient's information.

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- **Delete** - If a patient is highlighted in the table, clicking this button will display a window asking to confirm a decision to remove the selected patient from the system.
- **Generate New Schedule** - Clicking this button will run OSCAR's scheduling engine on the patients entered on the main window display. When the scheduler is finished, the Gantt Output window will open and display the resulting schedule.
- **Show Current** - This button displays a Gantt chart representation of the current schedule. A schedule must first be generated before this button will work.

GANTT OUTPUT WINDOW



GANTT CHART

- Horizontal axis displays “Time” – a vertical red line indicates the current real-world time. Operations (colored blocks) on the chart will move left as time passes. Operations with end times that have elapsed more than an hour from the time indicated by the red line will disappear from the chart and are assumed to have been completed.

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- The vertical axis displays “Patients” – this is a list of patients in sorted by their arrival time.
- Each colored block on the chart represents an operation and is color-coded by resource type. A resource-color legend is displayed at the bottom right corner of the window. The horizontal length of the blocks indicates the processing time of the operation.
- Zooming In – holding the left click of your mouse and dragging it from right to left over the Gantt chart will zoom in on the area that you drag over.
- Zooming Out– holding the left click of your mouse and dragging it from left to right over the Gantt chart will zoom out to the default view.

“SELECT A TASK” DISPLAY FIELD

- When an operation represented by a color block is clicked on the chart, information for that operation will be displayed:
 - Operation ID: Unique number assigned to the operation
 - Patient ID: ID of the patient that the operation is assigned to
 - Resource ID: ID of the resource required by the operation
 - Starting Time: Starting time of the operation
 - Ending Time: Ending time of the operation

TASK CONTROL

- “Add..” Button – Clicking this will display a window to add an operation to a patient.
- “Delete” Button –This button deletes the most recently selected operation on the chart.

RESOURCE KEY

This key shows the color corresponding to each resource. The color for a resource is the color directly to the right of the resource name (e.g., a “CT without Contrast” resource is pink).

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FUNCTIONS

ADDING A PATIENT



1. From the EUH ED Scheduler window, click "Add Patient." The "Add Patient" window will display.
2. Enter the patient's information into each field.
3. Click "Add."
4. Repeat steps 1 to 3 for each new patient.

DELETING A PATIENT

From the EUH ED Scheduler window, select a patient for removal. Then click "Delete." This will pop up a confirmation window. Select "Delete." The patient will then be deleted from both the system and the database.

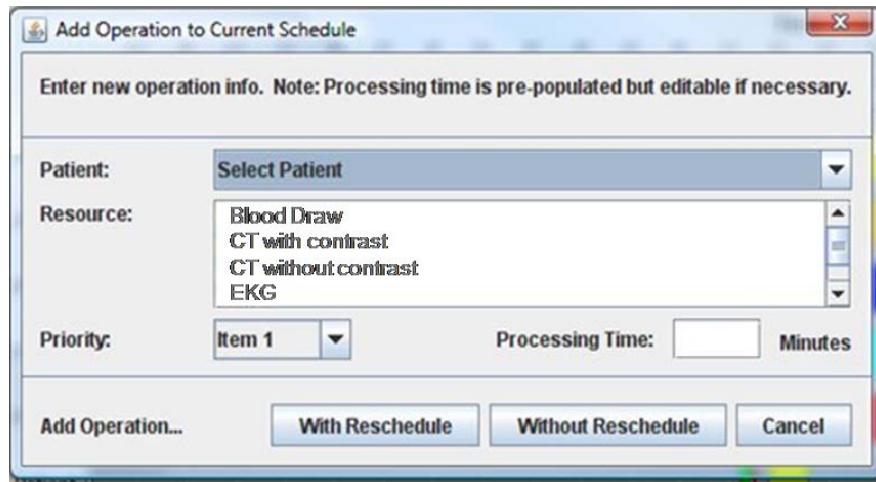
GENERATING A SCHEDULE

After at least one patient has been entered, you can generate a schedule by clicking on "Generate New Schedule". At this point a schedule will be generated and another window will open with a visual display of the schedule. The type of display is called a Gantt chart.

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ADDING AN OPERATION



1. From the Gantt Output Window, click “Add..” under the Task Control. This will open the Add Operation to Current Schedule window
2. Patient: Choose from the drop down which patient you want to add an operation to
3. Resource: Choose which resource to add to that patient
4. Priority: (Only necessary if rescheduling) Choose a level to indicate the importance of how soon the test needs to be scheduled in respect to the other patients’ scheduled on the same resource and in respect to the chosen patient’s other scheduled resources
5. Processing Time: This field will be pre-populated default processing time acquired from the RRPT database. However, entering a value will override the default processing time.
6. Choose whether to add this operation and reschedule or add this operation and not reschedule (if you choose to not reschedule, OSCAR will just add the new operation to the earliest available time slot).

DELETING AN OPERATION

From the Gantt Output Window, click the colored block in the Gantt chart that represents the operation you want to delete. Verify you have selected the correct operation by looking at the operation information in the display field at the bottom left of the Gantt Output window. Once you have confirmed you have selected the correct operation, click “Delete.” This will display a confirmation window. Select “Delete with Reschedule” or “Delete without Reschedule” based on whether you want the system to be rescheduled or not when this operation is removed. In both cases, the operation will be deleted from the system.