SUNY PLATTSBURGH

Optimization and Simulation Models

MSA 560 - Final Report

Assignment Model for Substance Abuse and Mental Health Patients

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1 Introduction and Problem Description

The problem we are focusing on stems from the imbalance between the demand and supply of mental health and substance abuse treatment in the United States. Nearly one in five adults deal with some form of mental illness in the United States, but according to the National Institution of Mental Health, less than half of those with a mental illness get treatment. A study published in the journal Psychiatric Services [1] estimate that 3.4 percent of the U.S. population, or more than 8 million Americans, suffer from serious psychological distress (SPD) — a term that describe feelings of sadness, worthlessness, and restlessness that are hazardous enough to impair physical well being[2]. SPD isn't a medical diagnosis, but it's a good measure of community mental health that overlaps substantially with conditions like depression and anxiety. A 2017 report by the Center for Disease Control (CDC) shows in 2017, there were 47,173 reported suicide deaths with a rate of 14.5 per 100,000 students.[3] The severe shortage of inpatient care for people with mental illness causes a public health crisis, as the number of individuals struggling with a range of psychiatric problems continues to rise. A study by the American Medical Association shows roughly 50 percent of individuals with severe mental disorders are affected by substance abuse. In addition, 37 percent of alcohol abusers and 53 percent of drug abusers also have at least one serious mental illness[]. While we recognize that there is a lot that goes into the treatment of getting help for such disorders, we would like to address the allocation of resources to the patients to potentially reduce the suicide rate. Specifically, how the patients who are seeking treatment are being sent to different facilities. The facilities that offer treatment have limited capacities, which makes it harder for patients to access the help that they need. For our project, we focused on maximizing the capacity of these facilities to optimize the allocation of patients to treatment facilities. The users of this model could be healthcare workers, specifically hospitals and doctors offices. Individuals working in these places could run the model as often as they would like, but for our formulation we are going to assume they run it every 3 days. The model could be run at the end of every week, taking into account all the patients that came in during the past week who were seeking or needed treatment for these disorders.

Research Questions

1. Optimization
Our goal is to minimize the waiting time of patients by deciding the type of facility they are going to, and/or the location of these facilities based on the treatment they require and the availability at the facilities.

2. Simulation
How does the Optimization model react when the data is simulated and tested for uncertainty?

2 Data Preparation and Cleaning

Our data originated from two different surveys conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA)[4] [6]. Two data sets contains information about individual patients and the other is focused at facilities. For the patient information, we have a data set focused on the admission and another focused on the discharge of the patient[5]. Since the data is coming from surveys, both of the data sets contained all categorical variables representing different ranges, diagnosis, values, etc. For example, the variable DAYWAIT has 5 levels, with 0 representing that the patient waited no days to get into a facility, 1 representing they waited anywhere between 1 to 7 days and so on. Since our data was given in this form, there were a lot of variables that we could ignore since they did not have anything to do with our projects objective. The format of our data set also brought about the issue that we do not know individual information for patients or facilities. As a group, we decided it would be best to "simulate" our data by assigning random numbers to the observations within the range that the variable gives us. So for example, if a patient had a DAYWAIT value of 1, we would assign that patient a random whole number between 1 and 7. That way, we can actually pull numbers from our data set to formulate our model.

After cleaning and figuring out what to do with our binary variables, we took a closer look at patients diagnosis and facility types. In total there were 18 diagnosis in the data set that a patient could be given. From the 18 diagnosis, we reduced them down to two distinct categories (or types): Mental health diagnosis and substance abuse diagnosis. We also had a variable in our data set that indicated whether the patient had both a mental health issue and a substance abuse issue. Using this variable, we created a third type of diagnosis for patients who experience both. The grouping of facilities was less complex, since we have a variable that tells us the focus of the facility with 4 levels: Mental health treatment, a mix of mental health treatment and substance abuse treatment, general health care, and other. To get the types of facilities, we looked at the facility focus in the data set, as well as a few other variables to determine what types of services the facility offers. We created a new variable based on what the facility offers and came up with 3 different types of facilities: Mental health facilities, substance abuse facilities, and facilities that cater to either mental health and/or substance abuse. Lastly, we filtered our data set to focus only on one specific state, Arkansas. The reason we did this was simply because we figured that most healthcare professionals would not send patients out of state for treatment, and most patients would not seek help outside of their home state. At this time in our analysis, Arkansas had the most data available and we felt that we best for our models moving forward. After all the filtering and cleaning, we ended up with 219 facilities and 12,013 patients for our analysis.

In addition, we didn't want to assume that every patient with the same diagnosis is the same. Mental health and substance abuse issues are not a one size fits all problem, and therefore that would be a huge assumption to make. Therefore, We decided that to assign our patients individually. Since we decided to do this, we needed to create a way to prioritize certain patients. We created a severity index for each type of diagnosis using Principal component analysis (PCA), so that patients with a higher severity index will get assigned first. PCA is an unsupervised technique which gives a "best fitting" line that can be defined as one that minimizes the average squared distance from a point to the line. The weights generated from PCA were multiplied by the diagnostic information of the patients to generate a severity for patients with both, Mental health and Substance Abuse issues. For substance abuse, we used the information about the frequency of drug use to calculate the severity index. Moreover, for only Mental Health patients, we created a logical statement so that any time a person is diagnosed with Type 3, the index is the difference of the Type 3 and Type 2, otherwise, the index would be the same as Type 3. This was done to ensure that not all severity's are high at a time and properly divided for all three types.

3 Preliminary Analysis

Facility Type Along With Patient Diagnosis: The chart on your left represents the number of facilities that offer mental health and/or substance abuse treatment. The chart on your right represents the number of patients diagnosed with either mental health, substance abuse or both.

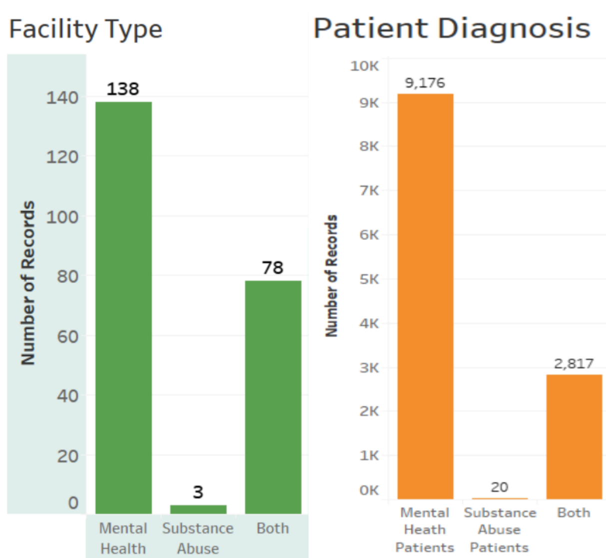


Figure 1: Facility Type and Patient Diagnosis

Patients Waiting To Enter Treatment in Days: Figure 2 below provides us with an understanding of the number of days a patient would wait to receive treatment for both mental health and substance abuse.

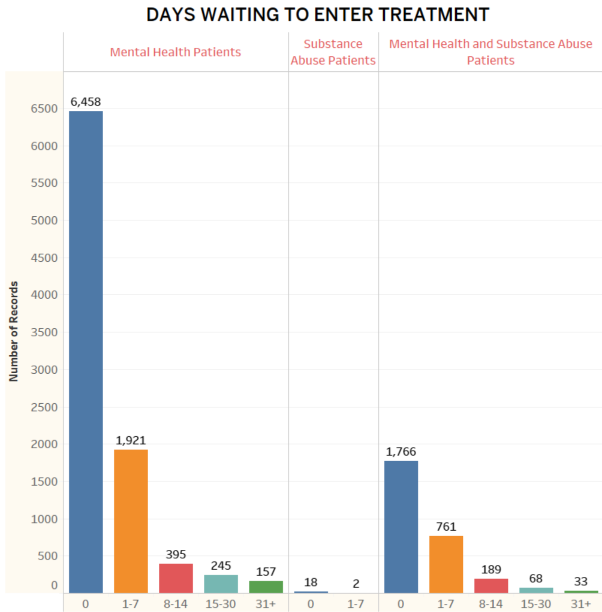
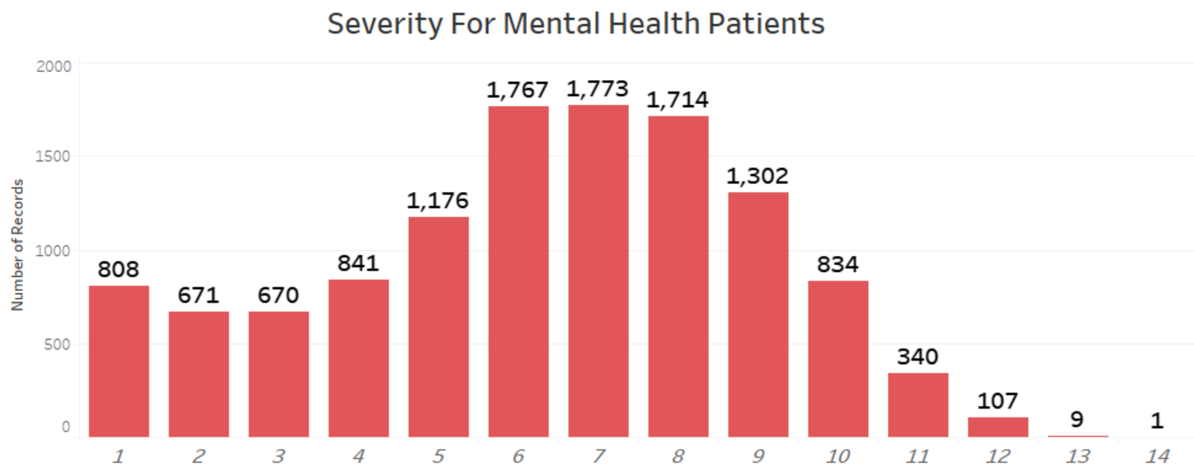
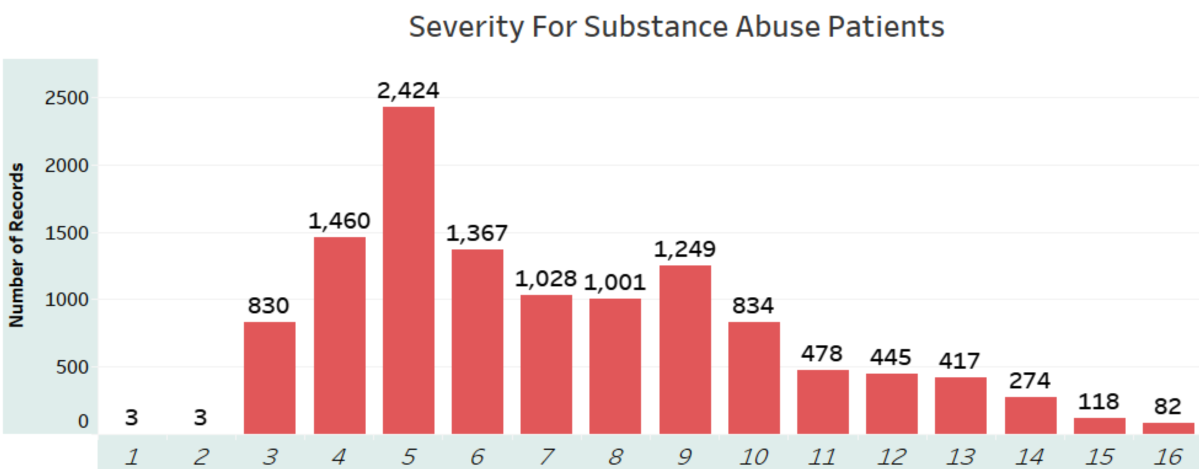
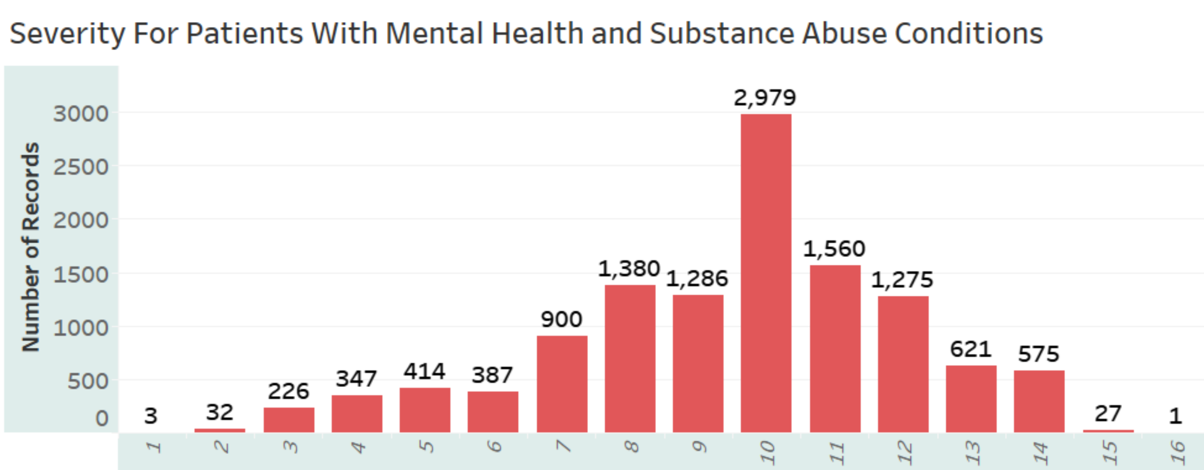


Figure 2: Facility Type and Patient Diagnosis

Severity Graphs: The charts below represent the severity of all three patient types. Severity is calculated for each patient by performing principal component analysis on patient diagnosis information. As you can see, severity ranges between one to sixteen for patients diagnosed with mental health illness, but the highest severity we encountered was fourteen. Severity for patients that have been diagnosed with substance abuse as well as mental health illness ranges between one and sixteen. The higher the number, the higher the severity and vice versa.







4 Model Formulation

We decided to go with a binary integer programming model for patient assignment. Xik will be our decision variables, with i representing the number of patients and k representing the number of facilities. Ji will represent the diagnosis for an individual patient, 1, 2, or 3 and Si will represent the severity of each patient. P is the penalty term for how long a patient will have to wait if they are not assigned immediately. In our case, we are assuming the model is being run every 3 days so if a patient is not assigned right away, that patient will have to wait another 3 days or longer. Our objective function is minimizing the waiting time and contains a reward and a penalty term. The model is rewarded by assigned patients with a higher severity first, and it penalized when an assignment does not occur. The penalty portion of our model takes into account the penalty term as well as the severity of the patient. For our constraints, we needed to limit the number of assignments to every facility. Our first constraint takes into account the fact that the number of patients assigned to a facility cannot exceed the capacity of that facility. This constraint is run for every facility in our data set, so 219 times. The next constraint says that one patient can only be assigned to one facility. Since we have a limitation of where certain patients can get treatment, we need to ensure that the patients are not only going to the correct facilities, but are only being assigned once. So for every patient, the summation of all its possible combination of assignments must be less than or equal to 1. This a patient to either be assigned to 1 facility or no facility at all.

MODEL PARAMETERS

Xik = 1 if patient i goes to facility k, 0 if otherwise
  i = 1 to n (n being the number of patients)
k = 1 to n (n being the number of facilities)
Ji = Diagnosis Type for patient i
  J1 = 1: Patient diagnosed with Mental Health Issues
  J2 = 2: Patient diagnosed with Substance Abuse
  J3 = 3: Patient diagnosed with Both
Si = Severity for patient i
P = Time frame of how often the model will be run (3 in this case)

OBJECTIVE FUNCTION

$$MINz = \sum_{i=1}^{n}(1 - Xik) \sum_{K=k}^{n} PSij - \sum_{i=1}^{n} \sum_{K=k}^{n} PSij(Xik)$$

where k $\in FacType[Ji](1)$

SUBJECT TO:

Capacity Constraint

$$\sum_{i=1}^{n} \sum_{k=1}^{n} Xik <= Capk \forall k \tag{2}$$

Only one patient can go to one facility

$$\sum_{k=FacType[J=1]}^{3} Xik <= 1 \forall i \tag{3}$$

Data Input

Paitient ID	Diagnosis
1	1
2	1
3	1
4	3
5	1
6	3
7	3
8	3
9	3
10	3

Figure 3: Patient Diagnosis

	Diagnosis Type		
Paitient ID	1	2	3
1	7	4	10
2	5	6	10
3	3	8	10
4	8	4	11
5	5	6	10
6	4	8	11
7	2	8	9
8	9	4	12
9	5	6	10
10	9	4	12

Figure 4: Patient Severity for each Diagnosis

4.1 Numerical Results

Since we simulated part of our data set, we ran the model using CPLEX 15 times to not only make sure that our model is consistent in its findings, but also to get a better understanding of the accuracy. Overall, the average optimal value from the 20 runs of the model was -13,310. The maximum optimal solution was -15,134 and the minimum was -11,924. Our model is optimized to achieve a minimum total waiting time by assigning patients with a high severity and is rewarded a negative penalty term for that. On the other hand, if the model fails to assign a patient with a high severity, it is penalized with a positive penalty term. Therefore, a negative outcome is desired in our model as it reflects that the model is able to optimize patient assignment with least penalty. We also verified that our model was correctly assigning patients by randomly checking the output. For example, in one of our instances we found that patient 952 was being assigned to facility 84. When we checked these values in the data set, we found that patient 952 had a diagnosis type 1 and was being assigned to a facility type 1. Our model seems to correctly assigning patients and consistently giving a negative result around the same range for the optimal solution. Another way we verified that our

Facility ID	Facility Type	RCBEDS
1	1	1
2	1	1
3	1	2
4	3	-2
5	1	2
6	3	3
7	3	-2
8	3	-2
9	1	-2
10	1	-2

Value	Label
1	1 to 10
2	11 to 20
3	21 to 30
4	31 to 40
5	41 to 50
6	51 to 75
7	76 to 100
8	101 to 250
9	More than 250
-1	Missing
-2	Logical skip

Figure 5: Facilities Data Set

model is working correctly is changing the penalty term. Originally, we were penalizing by 7 days, but due to the fact that we were getting a negative outcome we changed it to 3 days to see if it would make a difference. While it didn't make our models result positive, it did change the objective value from around the range of -40,000 to the values we specified above.

4.2 Limitations

However, due to the fact that our data is partially simulated, our model results do come with limitations. One of the biggest factors in our model is the capacity of the facilities, as this affects both patient assignment and the overall objective outcome. The majority of the capacity values in the data set were missing, therefore the simulated values do not show an accurate picture of which facility a particular patient in the state of Arkansas should be assigned to as the actual capacity for that facility may differ. Therefore, the objective value does not reflect the actual wait time.

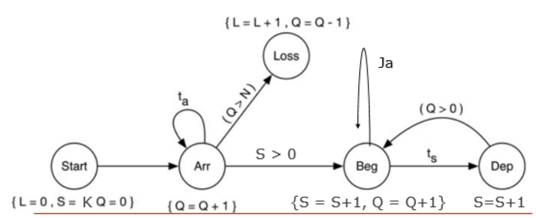


Figure 6: Multi-Server System with Limited Queue

Our simulation model is a multi server model with a limited queue. The number of servers in our simulation, which is actually the number of beds in the facility, is 100. So in our simulation model, we are dealing with one facility that has multiple beds (severs) available for the patients. We are assuming that the facility is only allowed to have 5 patients on the wait list at a time, due to high treatment time for all the diagnosis. We assumed 1000 for our simulated number of patients. In our simulation event graph, we have the state variables S, K, Q, N, and L.
S=If the facility is occupied
K=The number of beds
Q=Number of patients on the wait list
N=Maximum wait list size
L=Loss event
Ja=Severity index

When an arrival event occurs, the patient will be treated as long as there is at least one bed available in the facility. This condition is indicated by S¿0. The value of S will be decreased by 1 when a bed is occupied upon the beginning of treatment, and increased by 1 when a patient departs after their treatment. When an arrival event occurs and all servers are busy, the wait list is updated (Q+1). If when the queue is updated, it is greater than the maximum queue capacity (N) then a loss event occurs (L). When this happens, the queue size is decreased by 1 (since it was updated upon arrival) and then the loss event state variable (L) is updated to show the loss. If when the queue is updated and the maximum queue capacity is not reached, the patients severity index is checked (Ja) and then they are prioritized based on that for receiving treatment.

5 Simulation

In order to test for uncertainty such as facility capacity, patient severity, patient arrival, patient diagnosis and service time, we created a simulation model with multiple servers which in our case were the limited number of beds with a limited queue capacity of 5 patients. The arrival process is a Poisson process with an average inter-arrival time of 6 hours. The departure process is also a Poisson process where the average service time is different for each patient diagnoses type.

Each patient is diagnosed for one of the three types; Mental Health (Type 1), Substance Abuse (Type 2), or both (Type 3). Based on the discharge data set, we observe that each of the diagnoses has a different service time. The data shows that patients diagnosed with Mental Health Issues, stay on Average 45 days in the facility. On the other hand, Type 2 patients stay 75 days on average and Type 3 patients stay 48 days on average. However, there were a lot of Null values when we merged the discharge data set with the patients data set. Therefore, we assigned a random value for those null values for simulation purposes and took an average for all three types. The average service time for data for Type 1, Type 2 and Type 3 used in the model were 25 days, 50 days and 75 days respectively. In addition, we added a severity factor to prioritize the patients waiting in the queue with high severity. The simulation was done for a total of 1000 patients. The model keeps track of key performance matrices such as blocked customers, delay data, time spent in the server, no. of patients waiting in the system.

Average Inter Arrival Time: 0.25 days
Average Service Time:
Mental Health Patients (Type 1): 25 days
Substance Abuse Patients (Type 2): 50 days
Mental Health and Substance Abuse Patients (Type 3): 75 days
Number of Servers (k): 100 beds
Queue Limit: 5 patients

5.1 Simulation Results

The model was simulated 1000 times and key performance matrices were recorded. The results do vary each time the simulation is run, however, as the simulation was done 1000 times, the results on average stay relatively the same. Following are the results for different performance matrices:

Average Waiting Time: 6.25 days
Average Service Time: 52.37 days
Average Time in the System: 58.60 days
Portion of Lost Customers: 38.2 percent
Average Server Utilization: 99 percent
Average Number of Patients waiting: 4.67
We observe that 38 percent of patients are lost due to limited queue and low bed capacity. We simulated with different values to see what one thing a facility could do that would reduce the number of patients lost. First, we simulated with a 25 percent increase in capacity to 125 beds. We observe that the portion of customers lost drops significantly to 26 percent showing a 12 percent improvement in the patient lost matrix. This also improves the average wait time from 6 days to only one day. Meanwhile, rest of the

matrices stay almost the same. Second, we increased the queue limit by 25 percent as well to 8 patients while keeping the server capacity to 125. Interestingly, we found that the portion of lost patients did not improve and the average wait time increased to 2 days. Furthermore, we simulated with beds back to 100 and queue limit at 8. The portion o percent if patients lost was at 36 percent which is only a 2 percent improvement.

6 Conclusion

The simulation model shows that an increase in the capacity of the beds has a huge impact on the portion of patients lost. The consequences of not getting help at the time when its needed could be drastic the patient. A higher allocation of funding towards mental health and substance abuse facility could save many lives as they will be treated in a timely manner.

Our optimization model, while it had some limitations, is assigning patients consistently and correctly. It is important to note that this is a very simplified version of the way patient assignment actually works. It does not take into account police or government involvement, which occurs very frequently in the real world. Due to the fact that our model does not take into account the involvement from these agencies, we are also neglecting the fact that a lot of the times people in mental health and/or substance abuse crisis are being admitted into treatment due to an emergency. If you are an emergency situation, you typically skip the real life "wait list" and can get admitted to a facility much faster. We do have a factor to take into account the severity of a patient, however this is not a one size fits all problem and an emergency can occur at any severity level. Regardless of this limitation with our model, we do believe that it is general enough to have the correct state specific information applied into it and allow the users of our model to assign patients in a more efficient way.

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