Development of a Bed Management System to Improve Patient Access to Care

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Introduction

- Bed management can be used to improve performance and reduce costs to both hospital and patients
- Access to health care services is necessary for providing quality service to patients
- Timely access to healthcare can reduce preventable death, increase quality of life, increase life expectancy, and prevent the spread of diseases

Introduction

- Lack of available beds and increased waiting times lead to patient dissatisfaction, increase in patients leaving without being seen, and prolonged delays in care
- Variety of measures for access of care; most common:
  - Reduction of waiting times
  - Effective use of bed management policies

Introduction

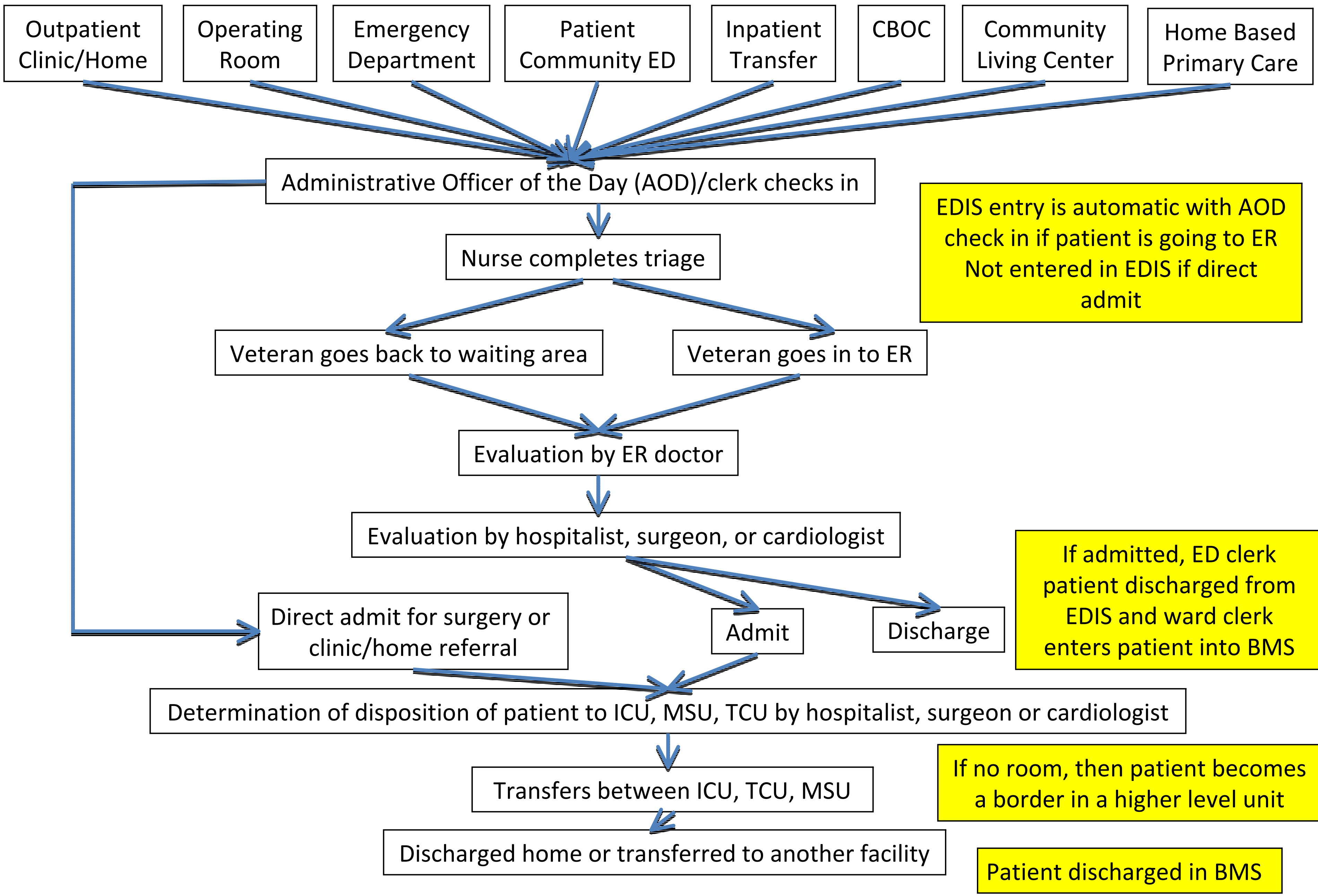
- Wait times increase risk and affects the quality of care
- A patient waiting also leads to increased costs, complications, suffering, and reduced efficiency
- Healthcare processes can be improved by determining the bottlenecks in the system and facilitating patient flow within the hospital units at all levels of acuity

Objective

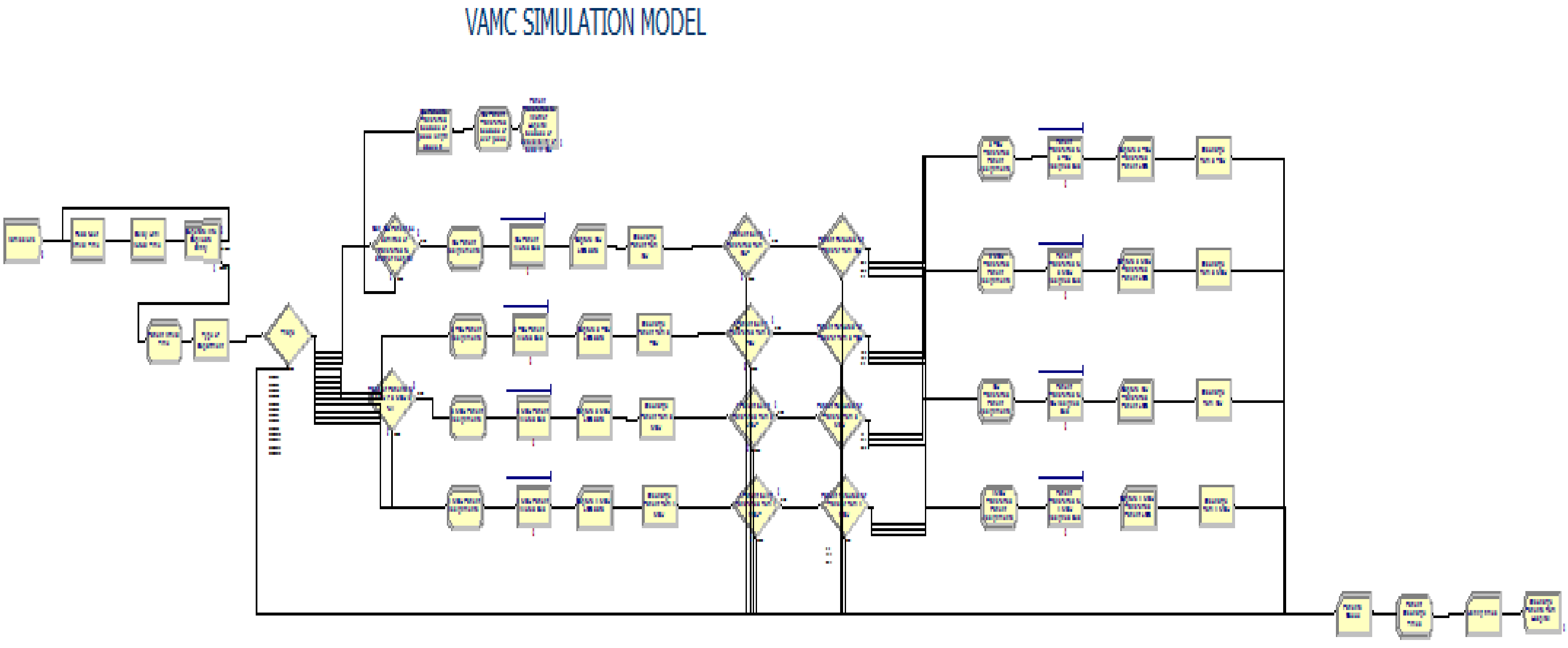
- This complex problem can be solved using integer programming, goal programming, stochastic process, queuing theory, simulation, etc., and various combinations of methods.
- Organizations are rapidly utilizing these techniques within health care systems to allow the free flow of patients.
- Develop a model that is capable to characterize individual department operations and relationships between departments in a hospital to increase patients access to care.

Simulation Model Analysis of Historical Data

- Data was collected from the Sacramento VAMC, on patient movements throughout the hospital.
- The data spans across all the major units in the hospital and provides details on admissions and transfers proportions.
- The admissions data spanned from January 1, 2009 through December 31, 2014, which consisted of 23,019 patients
- The transfers data spanned from April 2014 to March 2015, which consisted of 1,129 patients


Outpatient Clinic/Home
Operating Room
Emergency Department
Patient Community ED
Inpatient Transfer
CBOC
Community Living Center
Home Based Primary Care
Administrative Officer of the Day (AOD)/clerk checks in
EDIS entry is automatic with AOD check in if patient is going to ER Not entered in EDIS if direct admit
Nurse completes triage
Veteran goes back to waiting area
Veteran goes in to ER
Evaluation by ER doctor
Evaluation by hospitalist, surgeon, or cardiologist
If admitted, ED clerk patient discharged from EDIS and ward clerk enters patient into BMS
Direct admit for surgery or clinic/home referral
Admit
Discharge
Determination of disposition of patient to ICU, MSU, TCU by hospitalist, surgeon or cardiologist
Transfers between ICU, TCU, MSU
If no room, then patient becomes a border in a higher level unit
Discharged home or transferred to another facility
Patient discharged in BMS

Simulation Layout

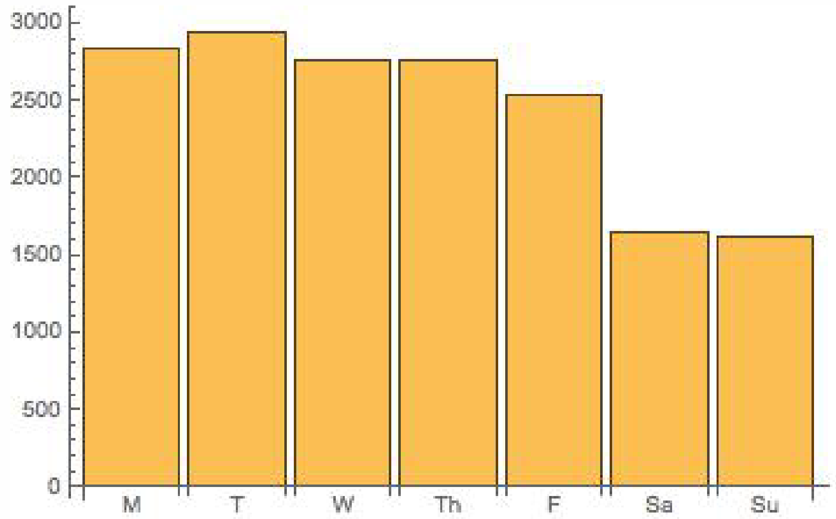


Understanding Variance at VAMC-Sacramento

- Determine key theoretical characteristics of demand (number of admissions and discharged)
  - Admissions Process and Discharge Process
- Assure key assumptions
  - The statistical distribution of number of admissions follows a Poisson Distribution
  - Perform statistical tests and other tests to assure theoretical foundation is solid
- Determine LOS statistical characteristics
  - Determine and remove outliers from the data
  - Determine what is a short-term stay and long term stay
  - Determine number of phases to incorporate into the analytical model.
- Develop equations and begin to determine parameters through optimization techniques and tools.

Total Data

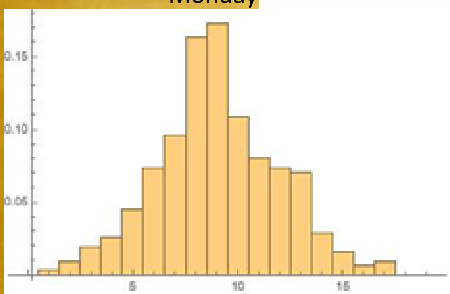
- Data ranges: 1/1/2009 to 12/31/2014
- There were a total of 31,183 instances of data
- Admissions and discharge data totaled: 23,019
- Removal of all possible artificial data resulted in 17,082 total instances of data
- Entire admissions are not stationary- this means that entire week or month or year can not be explained through one statistical distribution, variance changes daily, weekly and monthly.



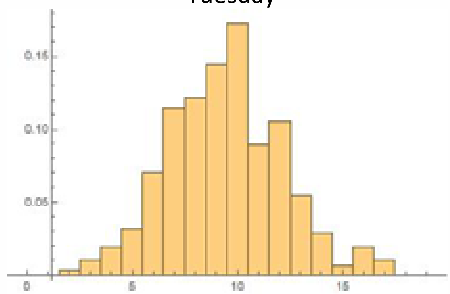
Daily Distribution of Arrivals

- Each day has a unique number of arrivals
- More importantly, each day has a different variance. However, if each day follows a Poisson distribution then each day is stable and the variance will also be stable.
- Making prediction possible.

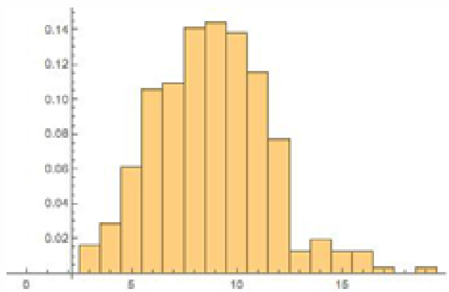
Monday



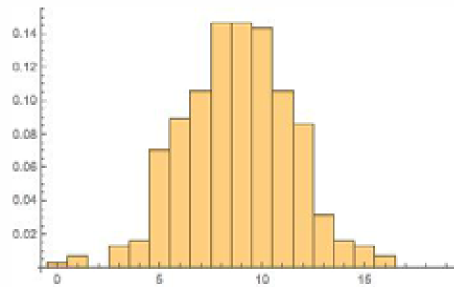
Tuesday



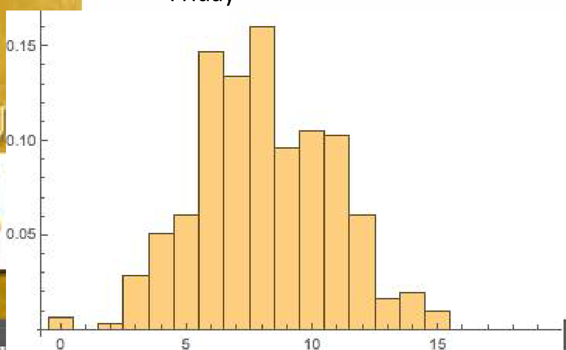
Wednesday



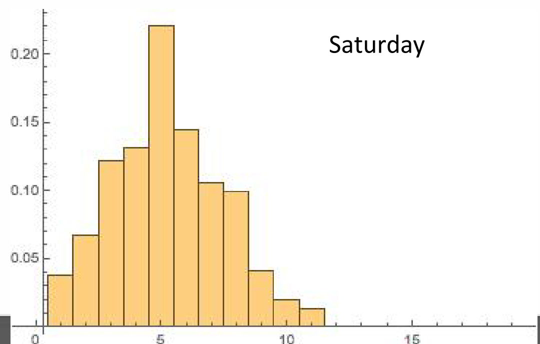
Thursday



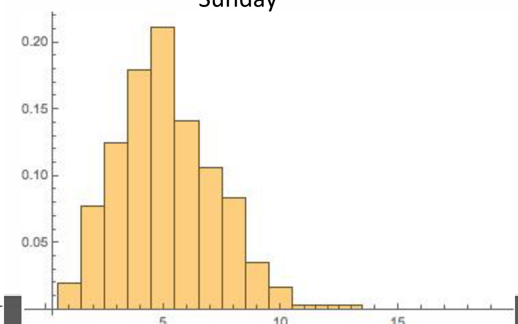
Friday



Saturday

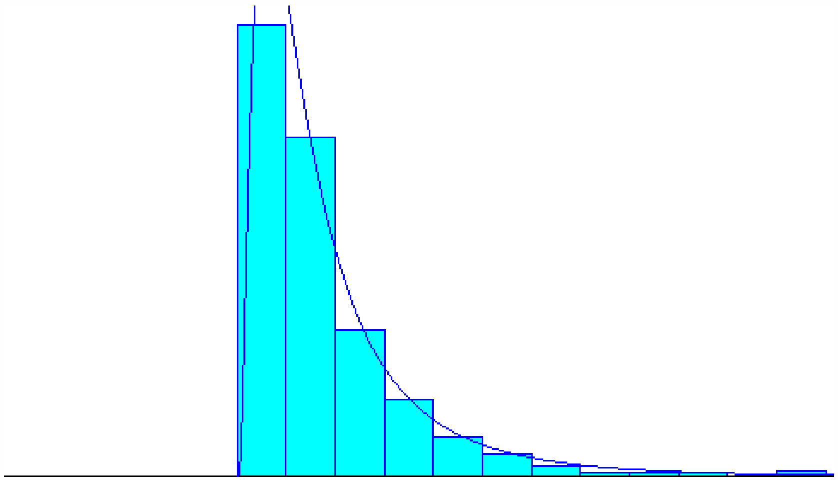


Sunday



Length Of Stay (LOS)

- Length of stay for a patient is given as an distribution in the process module



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        Distribution Summary

Distribution:   Lognormal
Expression:     LOGN(63.1, 68.5)
Square Error:   0.000701
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“What If” Scenarios

$H1_0$: There is no statistical difference between the simulated LOS and actual LOS values.

$H1_A$: There is a statistical difference between simulated LOS and actual LOS values.

$H2_0$: A change in bed turnover time does not reduce the number of people waiting in queue.

$H2_A$: A change in bed turnover time reduces the number of people waiting in queue.

$H3_0$: A reduction in LOS does not reduce the number of patients waiting in queue.

$H3_1$: A reduction in LOS reduces the number of patients waiting in queue.

“What If” Scenario Results

Hypothesis 1

Test	Hypothesis 1	P-value
Wilcoxon test	There is no statistical difference between the ICU simulated LOS and actual LOS values.	0.64
Wilcoxon test	There is no statistical difference between the 3 TCU simulated LOS and actual LOS values.	0.15
Wilcoxon test	There is no statistical difference between the 3 MSU simulated LOS and actual LOS values.	0.09
Wilcoxon test	There is no statistical difference between the 4 MSU simulated LOS and actual LOS values.	0.40
Wilcoxon test	There is no statistical difference between the transfers to ICU simulated LOS and actual LOS values.	0.87
Wilcoxon test	There is no statistical difference between the transfers to 3 TCU simulated LOS and actual LOS values.	0.25
Wilcoxon test	There is no statistical difference between the transfers to 3 MSU simulated LOS and actual LOS values.	0.06
Wilcoxon test	There is no statistical difference between the transfers to 4 MSU simulated LOS and actual LOS values.	0.10

“What If” Scenarios Results

Hypothesis 2

Test	Hypothesis 2	P value
Wilcoxon test	A change in bed turnover time does not reduce the number of people waiting in queue	<0.001

Hypothesis 3

Test	Hypothesis 3	P value
Wilcoxon test	A reduction in LOS does not reduce the number of patients waiting in queue	<0.001

“What if” Scenarios

Scenario 1: Reduction of bed turnover time

•Bed turnover time indicates the time elapsed between a discharged patient and another admission.

•When this 2 hours → 1 hour.

- Average Wq : 7.95 hours → 6.1 hours
- Average Nq: 2.93 → 2.33

Scenario 2: Reduction in LOS

•A reduction in LOS by 10 hours is simulated to know its effects on waiting time and queue length of patients.

•When the patients LOS is reduced by 10 hours:

- Average Wq : 7.95 hours to 2.07 hours.
- Average Nq : 2.93 → 0.8

“What If” Scenarios

Scenario 3: Addition of 4 beds to 3 TCU and 2 beds to 4 MSU.

•From the results obtained, it is found that 3 TCU and 4 MSU departments have long waiting times for patients.

•This can be reduced by addition of beds to these departments so 4 beds have been added to 3 TCU and 2 beds have been added to 4 MSU.

3 TCU	Average Waiting Time (hours)	Average Number of Patients in Queue	Average Length of Stay (hours)
16 Beds	8.95	1.57	71.78
20 Beds	0.40	0.07	62.92

4 MSU	Average Waiting Time (hours)	Average Number of Patients in Queue	Average Length of Stay (hours)
5 Beds	13.10	0.37	52.15
7 Beds	2.77	0.1	42.18

Prediction Model

The model is comprised of estimating the Ni(t,s), which is the number of patients in stage i who on day t have been in the hospital for s number of days.

This will be obtained from the *occupation profile.*

The overall goal is to determine the probability of remaining in the hospital one more day, given that the patient has been in the hospital s days:

$P(1|s)=N(t+1,s+1)/N(t,s)$

Basically, determine from the data for example that of all patients in the hospital how many will stay an extra day.

$$\begin{bmatrix} N_1(t+1,s+1) \\ N_2(t+1,s+1) \\ N_3(t+1,s+1) \end{bmatrix} = \begin{bmatrix} 1-v_1-r_1 & 0 & 0 \\ 0 & 1-v_2-r_2 & 0 \\ 0 & v_2 & 1-r_3 \end{bmatrix} \begin{bmatrix} N_1(t,s) \\ N_2(t,s) \\ N_3(t,s) \end{bmatrix}$$

- To determine the number of patients in each stage and their rates of leaving and entering the hospital. These rates are to be determined by running optimization
- Specifically, estimates for v and r are necessary as they determine the fraction of patients that will enter and leave the hospital, which gives us a prediction of the hospital's census during a given day to try to predict the census for the next day.
- Code was developed so that from an occupancy profile these rate can be estimated

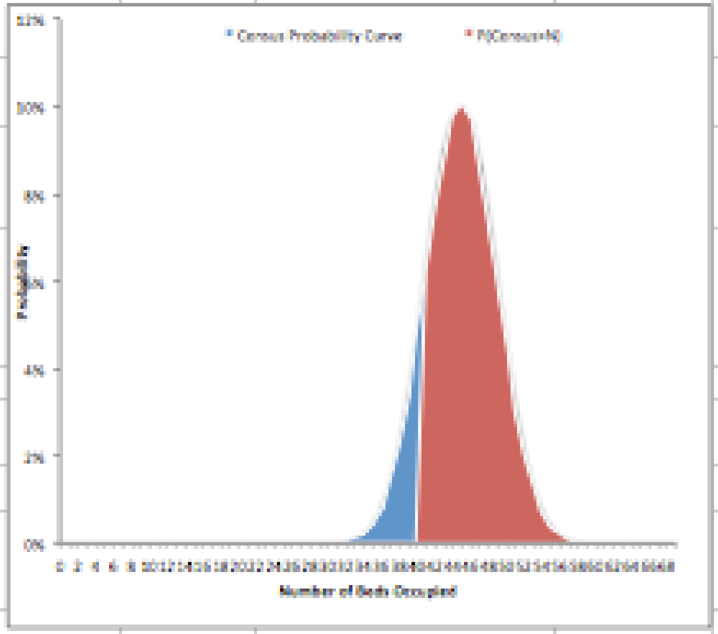
Current Conditions	
Today's date	10/27/15 11:25
Tomorrow's date	10/28/15 11:25
Today's Day of the Week	Tuesday
Tomorrow's Day of the Week	Wednesday
Current Beds In use	36
Current Number of Empty Beds	14
Current Utilization	72%

Prediction of Discharges (next 24 hrs)	
Average Number of Discharges in the next 24 hrs	3.66
Standard Deviation of Discharges	1.79
Lower 95% confidence Interval in the Number of Dicharges in the next 24 hrs.	0.14
Upper 95% Confidence Interval in the number of Discharges in the next 24 hours	7.17

Prediction of Arrivals	
Average number of Arrivals on Wednesday	12.55
Standard Deviation of Arrivals	3.54
Lower 95% Confidence Interval in the Number of Arrivals in the next 24 hrs.	5.61
Upper 95% Confidence Interval in the number of Arrivals in the next 24 hours	19.50

Next Day (tomorrow's) Census	
Lower 95% Confidence Limit:	37.11075788
Upper 95% Confidence Limit:	52.6756007
Probability of Census>45 beds (90%)	44%
Probability of Census>40 beds (80%)	87%
Probability Census>40	87%
Please enter the number of beds below to find the Pr(#beds >N)	
Enter Number of Beds (N)	40
Most probable census	45

The cells to the right allow for a user to enter information to determine any desired N.



Conclusions

- Health care systems are complex.

- Simulation can be utilized with other quality analysis tools to determine the impact of changes without disrupting normal operations.

Acknowledgment

- This work was supported by the Veteran Health Administration (VHA).

Thank you!