ESD.69, HST.926J, HC.750 FINAL REPORT

# Predictive Modeling at Beth Israel Deaconess Medical Center

## A Short-Term Length of Stay Model of the Cardiac Ward

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## Introduction to Predictive Modeling

The issues of limited access to hospital beds and waiting times for elective surgery havebeen challenging the healthcare industry for many years.The shortage in primary care physicians andnursing staff has added another layer of complexity to this intertwined issue regarding limited healthcare resources.

In coming years, these issues are expected to worsen. Almost all developed countries andmany developing countries are facing a shift in their population structure where the proportion of elderly is increasing. According to the OECD, the greatest use of healthcare services and expenditures occur in serving elderly population[1].With this growing number of elderly citizens, shift in disease prevalence from acute infectious disease to one of chronic diseasehas been observed. As a consequence ofincreased life expectancy, the increased incidence of chronic disease observed in the aging population poses significant challengeto the healthcare system.

Healthcare workers are not an exception to this phenomenon; they too are ageing and the existing workforce is replete with baby boomers, many of whom will retire within the next several years.

There is therefore an emerging gap in the ability to supply services, both in terms of capital infrastructure and in terms of workforce, to meet the growing demand. Given this challenge, there are serious consequences in both economic resource allocation and patient health outcomes if decisions about future health service structures are incorrect.

Models can provide a simplified interpretation of reality that preserves the essential features of the situation being examined and can be used as a tool to investigate decision-making options, particularly in complex environments such as the healthcare sector. As one potential approach to facilitatedecision-making in the healthcare sector, predictive modeling can be used to model decisions about hospital bed capacity.

## Range of Approaches exists to Modeling Hospital Bed Capacity

There are multiple ways to make a predictive model, but most fit into the three following categories:

1. **Deterministic Model[2]**
   In deterministic modeling, variables are determined for a dynamic system. Parameters are often selected to build a generic model representing a specific system. Once its parameters are set, a deterministic model will produce exact values of the variables of interest and hence will not reflect the complex nature of the situation.

[1]OECD. "A Disease-Based Comparison of Health Systems – What is Best and at What Cost?", OECD Publications 2003, Paris.
[2] Marshall et al. *Length of Stay-Based Patient Flow Models: Recent Developments and Future Directions.*Health Care Management Science, 8: 213-220, 2005.

2. **Stochastic Model**

Stochastic modeling will lead to probabilistic solution, which may be less precise than a deterministic solution. Stochastic models however will consider missing and uncertain input variables and generate probability distributions of the output variables. Such distribution is often times not realistic as not all outcomes are possible or applicable in real situations.

3. **Distribution Free Model**[3]

Distribution free modeling uses statistical distribution parameters such as mean and variance to optimize a variable considering best and/or worst case scenarios. The outcomes from this model will generate more realistic distributions. However, it will require expertise to justify appropriate ranges for the most and least likely scenarios for a valid model construction.

**Problem Description**

Our particular problem was given to us by Dr. Y of Beth Israel Deaconess Medical Center. He is interested in the area of predictive modeling, specifically, he wants to be able predict how many in-patient beds Beth Israel Deaconess Medical Center would need over the next couple years. He explained that this is important to the hospital because serious problems occur both when there is too much capacity in the system as well as too little.

When all available in-patient beds are full, three things happen. One, the emergency room (ER) becomes overcrowded because patients can't be admitted into the in-patient ward. This leads to make-do solutions such as putting patients in the hallways, something so common now that they are referred to as “hallway beds”. Two, patients start to crowd the surgical recovery room, meaning that scheduled surgeries later in the day have to be canceled because there is simply no place to put them after surgery. This leads to patient frustration as well as idle surgical facilities. Finally, the intensive care unit (ICU) can't take in new critical patients because the downgraded patients can't be transferred to the in-patient wards.

On the opposite side, having empty beds is inefficient and thus costly to the hospital.

In both cases, not knowing how many beds are going to be in use makes staff scheduling difficult. Overscheduling means there are too many workers with nothing to do. Under-scheduling means too few workers, necessitating additional workers to be called in on short notice and therefore at higher cost, both in the monetary sense and in worker satisfaction.

Previous researchers have approached solving this problem in several ways. The most common method is to look at the historical in-flow of patients and how long patients stay

[3] Gallego and Moon. *The Distribution Free Newsboy Problem: Review and Extensions*. Journal of the Operational Research Society. 44: 825-834, 1998.

in the hospital and try to find trends and correlations through regression analysis. However, this analysis is complicated by such issues as changes in standards of medical care, changes in hospital partnerships and the fact of historical admittance data is saturated at the high end, meaning that when in-flow is the highest, it is not necessarily reflecting the full demand because people are being turned away to other hospitals.

**Original Problem Approach**

Working off previous research in the field[4], we designed a diagram to explain the situation (Figure 1). We identified 4 sources of in-flows into the in-patient ward; the ER, the ICU, the surgical ward and through other institutions. We planned to use multiple years of historical data to look at daily admits and discharges to find patterns with any number of variables. Previous work shows effects due to weather, day of the week,

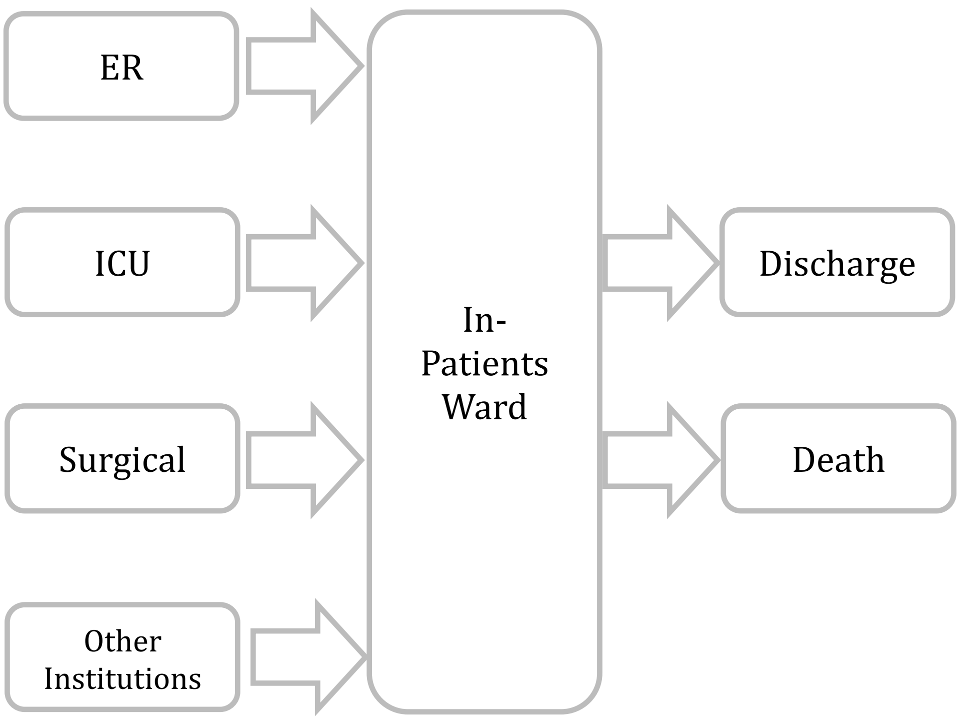


**Figure 1 - Model of Original Project Problem.**

[4] de Bruin, AM, Van Rossum, AC, Visser MC, and Koole, GM. *Modeling the emergency cardiac in-patient flow: an application of queuing theory.* Health Care Management Science 10:125–137, 2007.

holidays, and macroeconomic changes among others[5]. You would find that some of these variables affected all four of the in-flow points, albeit in different degrees, while others may just affect the ER, like flu season, or the surgical ward, which is often empty on weekends. This process is referred to as "demand forecasting".

To determine out-flow we could look at the discharges over time in the same way we looked at the admittances. However, we can also determine "predicted length of stay", which looks at the type of patient being admitted and calculates how long the likely hospital stay would be[6,7]. We requested a year of detailed individual patient data including race, age, gender, economic status (using the hospital bill payer as a proxy), discharge destination and, of course, primary and secondary diagnoses.

To simplify the analysis, we would consider all of the in-patient beds as equivalent, ignoring that patients with different diagnoses would need to be sent to different floors, each with their own bed limitations.

**Problem Modification**

The original project described above proved to require more data than the hospital was willing to release. After talking with Dr. Y, we came up with a simplified model based on the data that was available to us. First, instead of looking at long-term bed occupancy, we would examine short-term occupancy. Second, we restricted our work to a single ward, the cardiac ward, which consists of 38 beds. Third, we would look at length of stay predicting only. This means that the in-flow would be given knowledge and we would use that with our model to determine the outflow (see Figure 2).

**Given Information and Assumptions**

On what we would call "census day" at 12:01 am all the patients currently on the cardiac ward would be known along with their date of admission. They would further be categorized into one of six 'diagnoses'

1. Balloon catheterization
2. Balloon catheterization with stenting
3. Balloon catheterization with drug coated stenting

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[5] Mackey M and Lee M. *Choice of Models for the Analysis and Forecasting of Hospital Beds.*Health Care Management Science 8, 221–230, 2005.

[6]Mounsey JP, Griffith MJ, Heaviside DW, Brown AH, and Reid DS. *Determinants of the length of stay in intensive care and in hospital after coronary artery surgery*.British Heart Journal73, 92-98, 1995.

[7]Tu JV, Mazer CD, Levinton C, Armstrong PW, and Naylor CD. *A predictive index for length of stay in the intensive care unit following cardiac surgery*. Canadian Medical Association Journal 151(2), 177–185, 1994.

4. Chest pain
5. Circulatory disorders
6. Cardiac arrhythmias.

These six groups were chosen because they are the six most common reasons patients are at the Beth Israel cardiac ward.

We would also be given a list of the dates scheduled surgical patients were expected to be admitted into the ward, each identified with one of those six diagnoses. We would assume that all scheduled patients would show up and be operated on successfully and thus be admitted into the cardiac ward. These two sets of data would thus make up the in-flow into our cardiac ward.

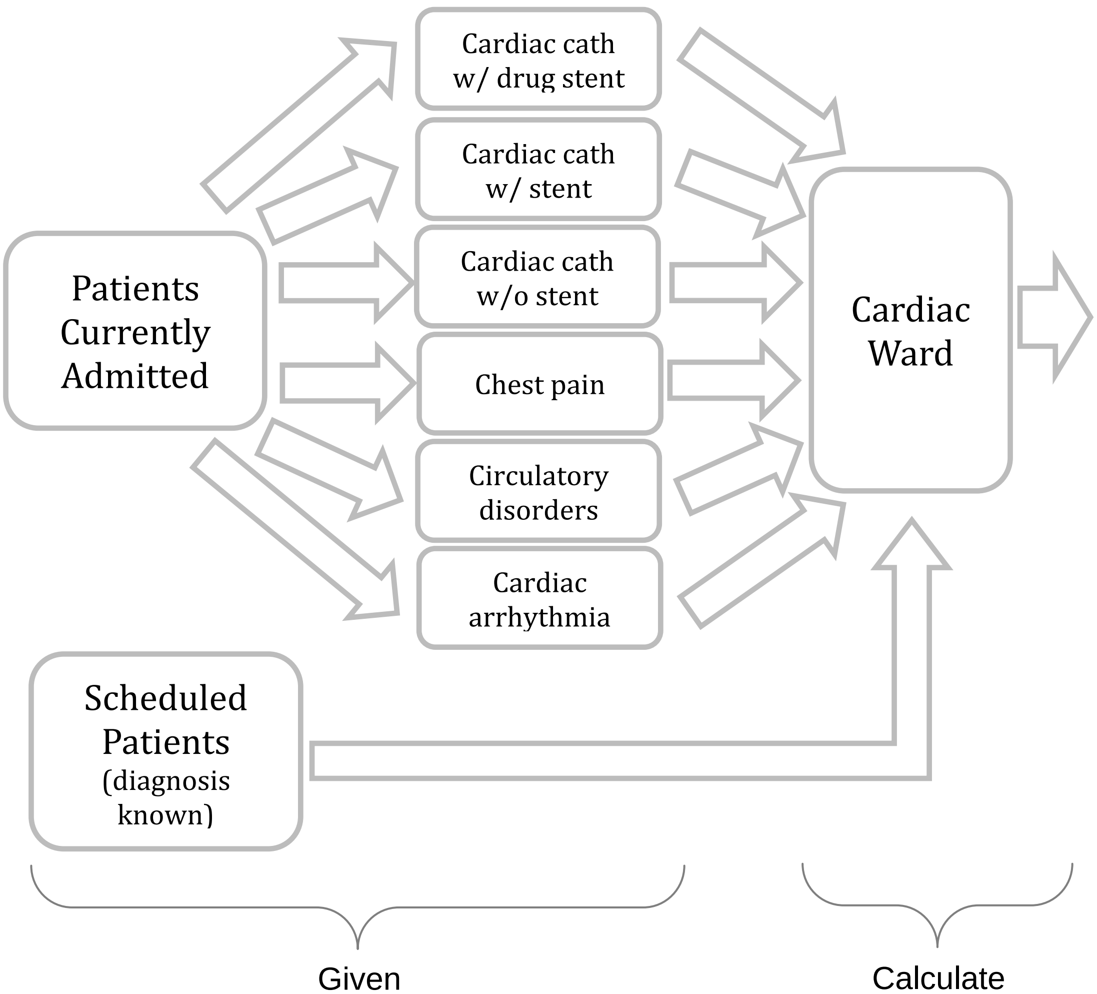


**Figure 2 - Model of Modified Project**

The data we got from hospital on which to build our model consisted of enough information to determine the mean and standard deviation of historical length of stays for people in those 6 diagnosis groups. We would need to use that to figure out what day we expected each of those patients to leave.

## Model Preparation

In thinking about the model, we felt it was important to build something that is both easy to use and widely applicable for BIDMC. The meetings with Dr. Y were used to discuss the concerns of the hospital and reveal the factors that were thought to contribute to those concerns. We understood the need for simplicity as well as the basic requirements for the various stakeholders using the model.

We conducted research and found some papers addressing similar problems. These papers included demand forecasting as well as length of stay predictions for various combinations of disease types, hospital settings, and wards within a hospital. It was difficult to evaluate how much of this previous research would be applicable to the BIDMC's cardiac ward considering characteristics such as hospital capabilities and even demographic combinations of the patients. After narrowing the project, this became even more complicated. Once it became clear that we would have access to less data than expected, we set out to build a model that could be easily modified to include more information as it is discovered.

We chose to use Excel, which is prevalent and familiar to BIDMC's staff. If the model could be accessible and understood easily, then the chances of it being used would be higher. In addition, we designed the predictive model to be easily adaptable to other wards within the hospital, though some adjustments may be necessary for the unique characteristics of each ward.

With these considerations in mind, we set the following plan. First, we'd decide on a type of probability distribution for length of stay. Then, we would apply BIDMC's data and calculate the probabilities of patients staying in the hospital for a given day. From these probabilities, we determine the predicted number of beds that the cardiac ward can expect to need on that day. Finally, we calculate a confidence interval around this expected number to account for best and worst case scenarios.

## Model Creation

From the myriad of available distributions, we decided that the lognormal distribution was most appropriate for our purposes[8]. It is commonly used in hospital length of stay models and is characterized by having a long-tail trend. We believe that it is a reasonable assumption that BIDMC's cardiac ward patients follow a similar distribution.

The data provided by Dr. Y included the lengths of stay of a sample of patients for each of six diagnosis types discussed earlier, and is displayed below in Figure 3 and detailed in Appendix I.

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[8] Harper PR and Shahani AK. *Modeling for the Planning and Management of Bed Capacities in Hospitals*. The Journal of the Operational Research Society, 53(1): 11-18, 2002.

**[Figure 3 Redacted]**

To determine the average lengths of stay and standard deviations, we calculated the weighted mean and corresponding weighted standard deviations for each diagnosis. The values computed are listed in Table 1 below.

**Table 1:** Calculated Length-of-Stay Mean and Standard Deviation by Diagnosis Type

| **Diagnosis** | **Mean** | **SD** |
|---|---|---|
| 1. Cardiac catheterization with drug-eluting stent placement | 1.60 | 1.16 |
| 2. Circulatory disorders | 2.16 | 2.71 |
| 3. Cardiac catheterization without stent placement | 1.86 | 3.06 |
| 4. Cardiac catheterization with bare metal stent placement | 1.91 | 1.60 |
| 5. Chest Pain | 1.55 | 1.57 |
| 6. Cardiac Arrhythmia | 1.90 | 1.60 |

To obtain our desired log-normal distribution, we need to calculate two parameters, μ andσ, which are derived from the expected value and variance of the dataset. (Despite the parameter symbols, μ and σ are not the mean and standard deviation in these equations.) We set E(X) to be the mean length of stay and Var(X) to be the variance and solve the equations below to find the μ and σ of each diagnosis.

$$\mathrm{E}[X] = e^{\mu+\frac{1}{2}\sigma^2},$$

*(Equation 1)*

$$\mathrm{Var}[X] = (e^{\sigma^2} - 1)e^{2\mu+\sigma^2}$$

*(Equation 2)*

$$\mathrm{s.d}[X] = \sqrt{\mathrm{Var}[X]} = e^{\mu+\frac{1}{2}\sigma^2}\sqrt{e^{\sigma^2} - 1}$$

*(Equation 3)*

**Table 2:** Calculated μ and σ values by Diagnosis Type

| **Diagnosis** | **μ** | **σ** |
|---|---|---|
| 1. Cardiac catheterization with drug-eluting stent placement | 0.2558 | 0.6504 |
| 2. Circulatory disorders | 0.2972 | 0.9726 |
| 3. Cardiac catheterization without stent placement | (0.0382) | 1.1460 |
| 4. Cardiac catheterization with bare metal stent placement | 0.3826 | 0.7293 |
| 5. Chest Pain | 0.0827 | 0.8407 |
| 6. Cardiac Arrhythmia | 0.3711 | 0.7341 |

We then apply μ and σ to the log-normal formulas below to derive the six diagnosis-specific probability distributions.

Probability Density Function:

$$f_X(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}}\, e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}, \quad x > 0$$

*(Equation 4)*

Cumulative Distribution Function:

$$F_X(x;\mu,\sigma) = \frac{1}{2}\text{erfc}\left[-\frac{\ln x - \mu}{\sigma\sqrt{2}}\right] = \Phi\left(\frac{\ln x - \mu}{\sigma}\right),$$

*(Equation 5)*

With these six probability distributions, we can determine the expected number of beds needed. We begin by looking at the individual probabilities of each patient still being at the hospital on a given day x after the 'census day'.

The probability that a patient will be in the hospital on day x after his/her admission date is $P_x$=1-F(x), where F(x) is the log-normal cumulative distribution function of the patient's indicated diagnosis. F(x) is the area under the curve for the particular diagnosis type's f(x), the log-normal probability density function derived earlier (see Equations 4 and 5).

Because patients are continuously arriving and departing the cardiac ward, each patient has a different arrival date. This means that at any given day, the patients in cardiac ward are at different days of their own length of stay time-frames. In order to capture these probabilities from a relevant perspective, we need to extract each patient's probability from his/her corresponding day since admission based on the patient's arrival date (or scheduled arrival), the census date, and the desired date. The census date is defined as the last date for whichactual and complete bed information is given. The desired date is defined as the date for which we desire to know the beds still occupied. Then, we need to consider the conditional probability of patients who have been in the hospital for more than one day already. In these cases, the probability of that patient still being in the hospital between his/her admission date and the census date is 100%. The calculations for computing patients' likelihood of being in the hospital on the desired date need to be renormalized and are, therefore, given by the conditional probability of Bayes' Theorem:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

*(Equation 6)*

We use this method to individually compute the probability of still being in the hospital on the desired date for each of the existing patients in the cardiac ward. Future scheduled patients are added into the list on the day of scheduled admittance and afterward use the same probability curves as the 'census day' patients, with no need to renormalize.

To illustrate this process, we can examine two patient examples. We hypothesize that BIDMC would like to know the likelihood that two patients will still be in the hospital three days from today. In this fictional scenario, the first patient is admitted today (census day) with a diagnosis of cardiac catheterization with a bare metal stent placement. To determine the likelihood that he will still be here in three days, we simply calculate the area under the curve of that diagnosis's log-normal probability density function for x greater than 3 (see Equations 4 and 5).

The second patient was admitted two days ago with the same diagnosis. To determine the likelihood that she will still be here in three days, we compute the conditional probability (Equation 6) that she will be here 5 or more days, given that she's already been here for 2 days. This is denoted as P(5|2) = P(2|5)*P(5)/P(2), in which P(2|5) equals 1 (the probability of being in the hospital 2 days if you are still there on day 5 is 100%). Graphically, we represent this conditional probability as the area under the log-normal curve for x greater than 5 divided by the area under the curve for x greater than 2.

In this manner, we can derive the probability of still being in the hospital for each patient. The sum of these probabilities is the total number of beds still occupied on that desired date.

**Confidence Intervals**

In addition to the predicted number derived from the model, we wanted to calculate confidence intervals around our prediction to give the hospital a more realistic range of number of occupied beds that our model expects. Because we are working with multiple different log-normal distributions (one per diagnosis), it is not immediately obvious how to calculate confidence intervals. From speaking to experts in statistics, we found that there are a couple of possible methods.

The first method uses simulation software, such as Crystal Ball. We can input the list of individual patient probabilities of being in the hospital on the desired date into the program. The program then runs thousands of simulations of possible outcomes given those probabilities. From these simulations, we can directly see where 95% of the outcomes lie. However, it turns out that this method is impractical for a couple of reasons. First, Crystal Ball requires quite a bit of manual manipulation of the data each time it is run, which is a lot of work on the hospital's end. Second, if we rely on simulation software to determine confidence intervals, then we are unrealistically asking BIDMC to purchase the Crystal Ball software and train someone on staff on how to use it. Given this, we decided it would be better to build our model entirely in Excel.

To do this, we searched for known statistical formulas that can give appropriate confidence interval estimations for log-normal distributions. We considered using Chebyshev's Inequality, but decided against this after consulting with our experts. We know we sum up PQ (probability*(1-probability)) for each individual patient probability to determine variance. If we assume the distribution in normal, the 95% confidence interval is the estimated number of beds plus or minus two times the standard deviation.

**Using the Model**

As mentioned earlier, our goal was to make the model user friendly and adaptable to other wards in the hospital and improvements in the probability distribution calculations. It provides a simple foundation on which more complexities may easily be added for improved accuracy and situational parameters by simply modifying look-up tables. But for day to day use, the excel model only requires BIDMC staff to input census day patient information and scheduled patient information. Ideally, this would be added automatically from hospital records and the staff member would just check it over for errors. The desired date of interest would also be entered. The results are automatically calculated and presented as output, as well as a chart of the estimated number of beds still occupied on the 7 days after census day. Confidence intervals are represented by error bars around the daily totals (see Figure 4 as an example of this).

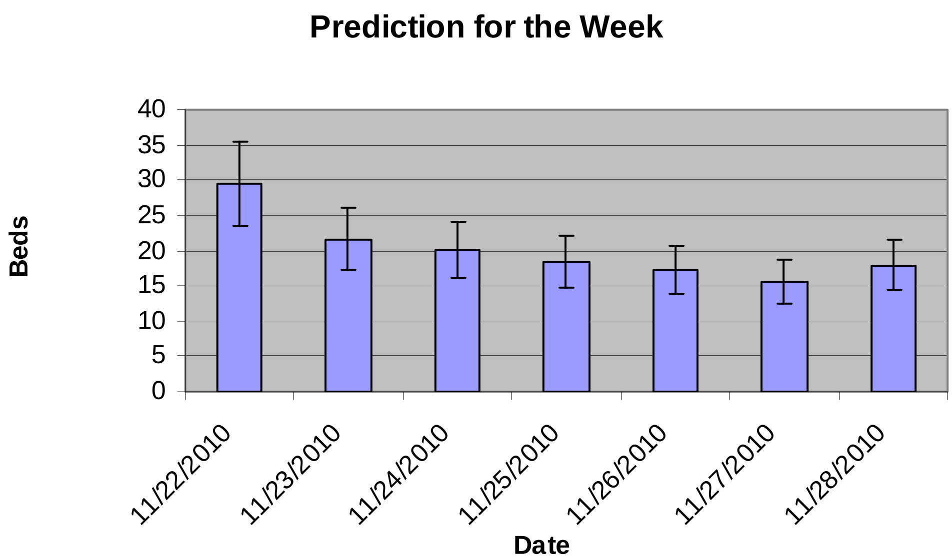


**Figure 3 - This is a chart of the expected bed occupancy for the seven days after the given census day information from 11/21/2010. The error bars represent the calculated 95% confidence intervals.**

In the excel model, the input page asks for:

- Means and Standard Deviations for each diagnosis
- Census Date
- Desired Estimation Date
- Admission Date and Indication (diagnosis) for each patient currently in the ward. For the cardiac ward, this number is limited to the maximum 38 number of beds available.
- Number of patients per indication per day scheduled to arrive after the census date.

Notice that this information can be applied to any hospital ward outside of the cardiac department as well.

The output page then immediately provides the following information:

- Expected total number of beds still occupied on the desired date
- Review of the census date and the desired date for input error-checking.
- Expected number of beds being used by the 'census day' patients

- Expected number of beds being used by the scheduled patients
- Confidence intervals for each of the three expected number calculations.

Refer to Appendix IIfor images and further explanation of the excel model.

**Limitations of the Model**

Our model is based on several assumptions and the predictability is limited by the availability of the appropriate data needed to capture relevant dynamic variables. Based on our literature review and a critical analysis of the model and the supplied data, we have identified certain limitations.

1. **Patient demographic information.**Patient specific information was not available, hence this information has not been considered as part of the model design. The relationship between the length of stay and patient attributes is very important for prediction accuracy.

2. **Random nature of ED patient flow.**ER patient flow has not been used as an input in the model. The reason for exclusion was the BIDMC data was not available to us and any literature-based patient flow information would not have the needed diagnosis type associated with the patients. The simplification of patient flow from the OR and complete absence of ER flow after the census day is a limitation of the model.

3. **Uncertainty with the patient time length of stay.**Our literature review led to the use of log-normal distributionsto calculate length of stay probabilities. This distribution was taken as a given in the model.The variability in the patient length of stay is unexplained. Since no information beyond the six 'diagnosis types' was provided, the model does not contain other variables that might influence length of stay, such as secondary diagnosis and discharge destination. More information could make the probability distribution steeper, which would lead to a more accurate model with smaller confidence intervals.

4. **Time of day patient data**.The patient data provided is based on a midnight census. This fails to capturehow the number of patients fluctuation over the course of a day. This means the model is unable to address periods of peak demand during a day, where new patients are being admitted before old patients are discharged. The staffing level and bed availability during the time of the day can be severely impacted by the patient flow above and beyond the inpatient bed capacity.

5. **Simplified aggregation of cardiac floor.** One simplification with the analysis is that all the inpatient beds are considered capable of accommodating any patient, without consideration of underlying patient condition or cardiac operation performed. This is a limitation with the model as certain beds may not be capable of handling patients with some special needs.

6. **Relationship with overall inpatient flow,** the patient inflow and occupancy at cardiac floor is considered to be independent of the overall inpatient flow and bed capacity at other floors. This simplification fails to consider the interdependencies of patient flow and time length of stay between other floors.

**Next Steps**

The limitations identified in the previous section illustrate the potential aspects of the model which can further be improved and explored. This section highlights the path forward.

1. **Obtain detailed historical data.** Detailed historical data will enable a more comprehensive predictive model depicting the actual trends at the cardiac in-patient floor. Information containing following attributes will be extremely helpful.
   - Annual, monthly or weekly tends
   - Patient specific information (age, gender, etc.)
   - Operation procedure and
   - Underlying patient health condition

2. **Modeling of random ER patient flow into the cardiac ward.**Inclusion of ER to cardiac ward patient flow will be important in improving the usefulness of our model.

3. **Modeling of uncertainty with the patient length of stay times.**The ability to explain the variability in patient stay times will be significantly important in better predictive results. Future analysis of time length of stay variation with respect to patient demographics and medical condition is expected to significantly improve the model.

4. **Use of daily patient flow information** instead of midnight census data will improve the peak demand modeling, as literature research indicates the daily patient in-flow can exceed the bed capacity at certain times of the day, before the daily out-flow of patients is completed. This trend is not captured by midnight census.

5. **Better classification of cardiacfloor beds** will improve the precision of predictive model as not all beds are capable of accommodating different patient conditions.

6. **Inclusion of overall patient inflow in the model** to capture the interdependencies of patient flow and time length of stay between cardiac and other floors.

**Summary and Conclusion**

Hospital beds are expensive resources. Adequate demand forecasting for the resource is highly linked to the even more important resource, the medical staff. An aging population, increased prevalence of chronic diseases, on-going shortages of medical staff and increased patient expectations increase pressure to the hospitals and make effective use of the bed more important than ever for hospitals. Appropriate decision-making support tools for the planning and management of bed capacity is critical to successfully address the issues that hospitals face.

Like other institutions, BIDMC is also experiencing the difficulties of hospital bed planning and management, which often leads to a crowded emergency room, surgical suites unable to be used because there is nowhere to put the patients after the surgery, and ICUs unable to take new critical patients, as well as mismatched staff scheduling. We initially intended to address the whole issues of bed management, from patient inflow demand forecasting to length of stay probability distribution for the entire in-patient ward at BIDMC. However, given the limitation of data accessibility, team modified the approach to more practical level by targeting only the cardiac ward and focusing only on length of stay analysis.

Historical data ofindividual patient length of stays with the six most common diagnoses of the BIDMC cardiac ward was used to develop a probability distribution of length of stay, which can be used for both currently admitted patients and scheduled patients. The model can capture the probability of bed occupancy within short period times and thus can support some decision-making processes of hospital.

Although the model can provide basic information for the planning and management of beds, it still has limitations mainly due to the lack of data availability. First, demand forecasting of patient inflow is missing in the model. Second, because we used aggregated averages and standard deviations of length of stay, the model does not take into account patient-level variations other than the primary diagnosis. Third, midnight census data does not account for patient flow within a day, which is critical information for staffing and other resource allocation.

Despite these limitations, we believe that our approach to predicting short-term bed occupancy at BIDMC has made a meaningful first step, and we expect further research will improve the effectiveness and efficiency of our work.

## Appendix I – Raw Patient Data

**[Redacted]**

## Appendix II – Excel Model

Excel Model "Input" Page – Sample

| LoS data per indication | | | ← Shaded cells indicate data is to be provided (Filled with dummy data for modeling purpose) |
|---|---|---|---|
| **Code** | **Mean** | **SD** | **Indication** |
| 1 | 1.60 | 1.16 | Cardiac catheterization with drug-eluting stent placement |
| 2 | 2.16 | 2.71 | Circulatory disorders |
| 3 | 1.86 | 3.06 | Cardiac catheterization without stent placement |
| 4 | 1.91 | 1.60 | Cardiac catheterization with bare metal stent placement |
| 5 | 1.55 | 1.57 | Chest pain |
| 6 | 1.90 | 1.60 | Cardiac arrhythmia |

| | | |
|---|---|---|
| **Census date** | 11/21/10 | <--assume Census at 00:00 at the date |
| **Desired estimation date** | 2 | days after Census |

**Current bed occupation**

| Bed number | Admission | Indication |
|---|---|---|
| 1 | 11/20/10 | 1 |
| 2 | 11/19/10 | 2 |
| 3 | 11/18/10 | 3 |
| 4 | 11/17/10 | 4 |
| 5 | 11/16/10 | 5 |

| **Scheduled patients** | | |
|---|---|---|
| Expected admission date | 11/21/10 | 11/22/10 |
| Indication | - | 1 |
| 1 | 1 | 2 |
| 2 | 5 | 2 |
| 3 | 2 | - |
| 4 | 3 | 2 |
| 5 | 2 | 1 |
| 6 | 2 | - |

Excel Model “LoS Prob Lognormal” Page – Sample

| **Indication** | **Mean** | **SD** | **Mu** | **Sigma** |
|---|---|---|---|---|
| 1 | 1.60 | 1.16 | 0.2558 | 0.6504 |
| 2 | 2.16 | 2.71 | 0.2972 | 0.9726 |
| 3 | 1.86 | 3.06 | (0.0382) | 1.1460 |
| 4 | 1.91 | 1.60 | 0.3826 | 0.7293 |
| 5 | 1.55 | 1.57 | 0.0827 | 0.8407 |
| 6 | 1.90 | 1.60 | 0.3711 | 0.7341 |

**Probability assuming lognormal: cumulative density function (Fx)**

| | LoS being equal or less than… | | | | |
|---|---|---|---|---|---|
| Indication | 0 | 1 | 2 | 3 | 4 |
| 1 | - | 0.3470 | 0.7494 | 0.9025 | 0.9589 |
| 2 | 0 | 0.3799 | 0.6580 | 0.7950 | 0.8686 |
| 3 | 0 | 0.5133 | 0.7383 | 0.8394 | 0.8931 |
| 4 | 0 | 0.2999 | 0.6649 | 0.8369 | 0.9156 |
| 5 | 0 | 0.4608 | 0.7661 | 0.8866 | 0.9395 |
| 6 | 0 | 0.3066 | 0.6695 | 0.8391 | 0.9166 |

**Probability assuming lognormal: 1-cumulative density function (1-Fx)**

| | LoS being more than… | | | | |
|---|---|---|---|---|---|
| Indication | 0 | 1 | 2 | 3 | 4 |
| 1 | 1.0000 | 0.6530 | 0.2506 | 0.0975 | 0.0411 |
| 2 | 1.0000 | 0.6201 | 0.3420 | 0.2050 | 0.1314 |
| 3 | 1.0000 | 0.4867 | 0.2617 | 0.1606 | 0.1069 |
| 4 | 1.0000 | 0.7001 | 0.3351 | 0.1631 | 0.0844 |
| 5 | 1.0000 | 0.5392 | 0.2339 | 0.1134 | 0.0605 |
| 6 | 1.0000 | 0.6934 | 0.3305 | 0.1609 | 0.0834 |

Excel Model “Bed Occupancy” Page - Sample

| | | | LoS to… | | | P of staying | Probability of LoS being more than X days after census | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Admission | Census | Census | Des. date | Indication | at Census | 0 | 1 | 2 | 3 |
| **Bed number** | | | | | | | | | | |
| 1 | 11/20/10 | 11/21/10 | 1 | 3 | 1 | 0.6530 | 0.6530 | 0.2506 | 0.0975 | 0.0411 |
| 2 | 11/19/10 | 11/21/10 | 2 | 4 | 2 | 0.3420 | 0.3420 | 0.2050 | 0.1314 | 0.0886 |
| 3 | 11/18/10 | 11/21/10 | 3 | 5 | 3 | 0.1606 | 0.1606 | 0.1069 | 0.0753 | 0.0552 |
| 4 | 11/17/10 | 11/21/10 | 4 | 6 | 4 | 0.0844 | 0.0844 | 0.0463 | 0.0267 | 0.0160 |

| **Newly admitted on Census or after** | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| **Probability** | | | | | |
| | Expected admission date | | | 11/21/10 | 11/22/10 |
| | Days after Census | | | - | 1 |
| Indication | Admission to desired date | | | 2 | 1 |
| 1 | | | | 0.2506 | 0.6530 |
| 2 | | | | 0.3420 | 0.6201 |
| 3 | | | | 0.2617 | 0.4867 |
| 4 | | | | 0.3351 | 0.7001 |
| 5 | | | | 0.2339 | 0.5392 |
| 6 | | | | 0.3305 | 0.6934 |

Excel Model "Output" Page – Sample

| **Summary output** | | | |
|---|---|---|---|
| Expected total bed needed, as of (desired date): | | | 11/23/2010 |
| Estimated given data as of (census date): | | | 11/21/2010 |
| Total estimated bed needs: | | | 21.6 |
| Approximate estimation of 2 standard deviation: | | | 7.2 |
| | | | |
| | | Min | Max |
| 95% confidence interval (combined): | | 14.4 | 28.9 |
| **Bed needs from existing patients only** | | | |
| Indication | Needs | | |
| 1 | 1.39 | | |
| 2 | 2.80 | | |
| 3 | 2.96 | | |
| 4 | 1.86 | | |
| 5 | 1.95 | | |
| 6 | 1.58 | | |
| Total | 12.54 | | |
| | | | |
| | Min | Max | |
| 95% confidence interval | 6.8 | 18.3 | |
| **Bed needs from scheduled patients only** | | | |
| Indication | Needs | | |
| 1 | 1.56 | | |
| 2 | 2.95 | | |
| 3 | 0.52 | | |
| 4 | 2.41 | | |
| 5 | 1.01 | | |
| 6 | 0.66 | | |
| Total | 9.10 | | |
| | | | |
| | Min | Max | |
| 95% confidence interval | 4.7 | 13.5 | |