Hospital Readmission Reduction Strategies using Probabilistic Constraints

Michelle Alvarado, Ph.D.
Assistant Professor

Behshad Lahijanian
Ph.D. Student

Industrial and Systems Engineering
University of Florida

October 1, 2018
Workshop: Risk Management Approaches in Engineering Applications

Agenda

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Introduction

- A hospital **readmission** occurs when a patient has an unplanned admission to a hospital within 30 days after discharge from hospital stay.
- Nearly 1 in 5 of hospital readmissions happen within 30 days [6] of discharge.
- Many of these readmissions are thought to be preventable through service and financing reform [4].
- The cost of hospital readmission is estimated to cost Medicare $17 to $26 billion annually [6].
- The Centers for Medicare and Medicaid Services (CMS) established the **Hospital Readmission Reduction Program (HRRP)** in 2012, in response to the increasing costs of readmissions in hospitals.

Introduction

Table: Health Conditions and Maximum Penalty by Year.

FY 2013	FY 2014	FY 2015-2016	FY 2017 - present
AMI PN HF	AMI PN HF	AMI PN HF COPD THA/TKA	AMI PN HF COPD THA/TKA CABG
1%	2%	3%	3%

- CMS considers 3 years of performance history for a hospital to compute a risk adjusted excess readmission ratio (ERR) for each condition.
- The HRRP classifies hospitals into five peer groups, and penalizes hospitals whose ERR is worse than their peer group median.
- The CMS estimates that penalties across all hospitals have increased from $428 million in FY 2015 to $528 million in FY 2017 [2].

Why is HRRP a challenge to hospitals?

- Trade-off in cost vs. readmission probability (quality of care)
- Readmission probabilities are uncertain
- Peer competition (current ranking, moving target)
- Which treatment programs are cost-effective in a treatment strategy?
- Confidence level in a treatment strategy?

Table of Contents

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Problem Statement

Need for a treatment strategy for the hospital that:

- minimizes costs

- provides a confidence level, β, that the strategy will avoid the HRRP penalty.

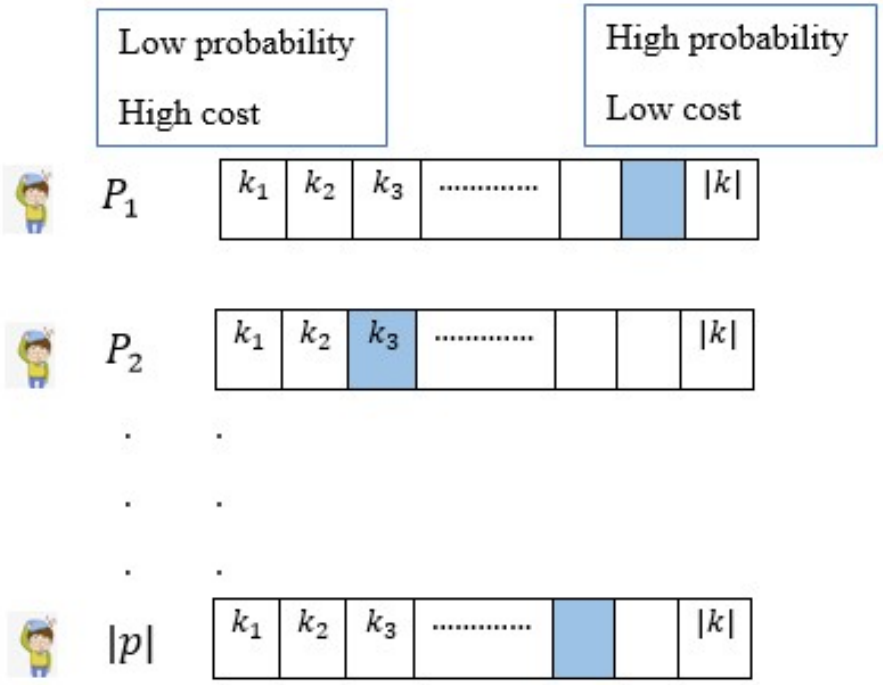


Figure: Treatment Options by Patient

Table of Contents

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Literature Review

- Zhang et al. (2016) introduced a game theoretic analysis of the HRRP penalty only mechanism. They took an operational and economical perspective to analyze the effectiveness of the HRRP policy [7].
- Hospitals are expected to respond to the financial penalties by implementing care strategies that reduce the probability of readmission such as coordinated discharge planning and follow-up [3].
- Alvarado et al. (2016) formulated a penalty-incentive model for hospital readmissions in game-theoretic setting involving an insurer and a hospital. They suggested CMS a hybrid penalty-incentive mechanism or incentive-only mechanism that is effective for both hospital and insurer [1].

Research Objectives

To *develop a decision model* that:

- Specifies a treatment strategy for the hospital over a given time period
- Balances costs with quality of care (readmission probabilities)
- Controls uncertain readmission probabilities across all patients for each condition
- Provides a confidence level, β, that the strategy will avoid the HRRP penalty

Approach: *Stochastic Programming Model with Probabilistic Constraints*

Assumptions

- Selecting a treatment strategy for a given time period (e.g. 3 months).
- Exactly one treatment plan with a known cost must be chosen for each patient.
- The probability of readmission is uncertain and follows the Normal distribution.
- Readmission probability is a good estimator of ERR.
- For readmission probability, then mean is a good estimator of the median.

Table of Contents

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Notation

- **Sets:**

  C: Set of conditions

  K: Set of treatment plans

  P^c: Set of patients with condition $c \in C$

- **Parameters:**

  β^c: Confidence level to satisfy the probability constraint for condition $c \in C$

  θ^c: Target readmission rate (e.g. mean readmission rate of the peer group) for condition $c \in C$

  a^c_{pk}: Cost of treatment plan $k \in K$ for patient $p \in P^c$ with condition $c \in C$

  μ^c_{pk}: Readmission probability of treatment plan $k \in K$ for patient $p \in P^c$ with condition $c \in C$

Notation

- **Decision variable:**

$$x_{pk}^{c} = \begin{cases} 1, & \text{Select treatment plan } k \in K \text{ for patient } p \in P^{c} \\ & \text{with condition } c \in c \\ 0, & \text{otherwise.} \end{cases}$$

Model Formulation

$$\text{Min:} \quad \sum_{p \in P} \sum_{k \in K} \sum_{c \in C} a^c_{pk} x^c_{pk} \tag{1}$$

$$\text{s.t.} \quad \sum_{k \in K} x^c_{pk} = 1, \quad \forall p \in P^c, c \in C \tag{2}$$

$$\mathbf{P}\left(\left(\frac{\sum_{p \in P} \sum_{k \in K} \mu^c_{pk} x^c_{pk}}{|P^c|} \right) \leq \theta^c \right) \geq \beta^c, \quad \forall c \in C \tag{3}$$

$$x^c_{pk} \in \{0, 1\}, \quad \forall p \in P^c, k \in K, c \in C \tag{4}$$

Solving Methodology

Since x^c_{pk} is binary, we can reformulate probabilistic constraint (3) to a deterministic equivalent [5]. When the probabilities of readmission are independent, non-identically distributed gaussian random variables with $\sim N(\mu^c_{pk}, \lambda_c \mu^c_{pk})$ for $\lambda_c > 0$:

$$\mathbf{P}\left(\frac{\sum_{p\in P^c}\sum_{k\in K}\mu^c_{pk}x^c_{pk}}{|P^c|} \leq \theta^c\right) \geq \beta^c$$

$$LHS = \mathbf{P}\left(\frac{\sum_{p\in P^c}\sum_{k\in K}\mu^c_{pk}x^c_{pk}}{|P^c|} \leq \theta^c\right) =$$

$$\mathbf{P}\left(\sum_{p\in P^c}\sum_{k\in K}\mu^c_{pk}x^c_{pk} \leq \theta^c|P^c|\right) =$$

$$= \mathbf{P}\left(N(0,1) \leq \frac{\theta^c|P^c| - \mu_c(x)}{\sqrt{\lambda_c\mu_c(x)}}\right)$$

where $\mu_c(x) = \sum_{p\in P^c}\sum_{k\in K}\mu^c_{pk}x^c_{pk}$

Solving Methodology(Cont.)

$$\mathbf{P}\left(\frac{\sum_{p\in P^c}\sum_{k\in K}\mu^c_{pk}x^c_{pk}}{|P^c|}\leq\theta^c\right)\geq\beta^c=$$

$$\iff \frac{\theta^c|P^c|-\mu_c(x)}{\sqrt{\lambda_c\mu_c(x)}}\geq\phi^{-1}(\beta^c)$$

$$\iff \mu_c(x)\leq\mu^*_c$$

where μ^*_c is the unique root of the equation

$$\theta^c|P^c|-\mu_c(x)=\sqrt{\lambda_c\mu_c(x)}*\phi^{-1}(\beta^c)$$

Solving Methodology(Cont.)

The the model has the deterministic equivalent form:

$$
\begin{aligned}
\text{Min:} \quad & \sum_{p \in P^c} \sum_{k \in K} \sum_{c \in C} a^c_{pk} x^c_{pk} \\
\text{s.t.} \quad & \sum_{k \in K} x^c_{pk} = 1, \quad \forall p \in P^c, c \in C \\
& \sum_{p \in P^c} \sum_{k \in K} \mu^c_{pk} x^c_{pk} \leq \mu^*_c, \quad \forall c \in C \\
& x^c_{pk} \in \{0, 1\}, \quad \forall p \in P^c, k \in K, c \in C
\end{aligned}
$$

Table of Contents

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Computational Example

- For the fiscal year 2018, CMS's 3-year performance history data is from July 2013 to June 2016
- 1 hospital, 6 conditions.
- 3 month decision strategy period
- Solved the model using CPLEX.

Computational Example

North Shore University Hospital (provider ID 330106) with FY2018 penalty of 1.35%. Generated 10 treatment options per patient, $\lambda_c = 0.04 \ \forall c \in C$.

Table: Hospital information.

Cond.	Readmission Prob.	Avg. in Peer Group 2	# of patients
AMI	21.21%	15.97%	52
PN	19.01%	15.37%	132
HF	22.43%	20.48%	126
HK	4.21%	8.01%	96
COPD	19.56%	18.67%	47
CABG	17.33%	15.15%	21

Computational Example

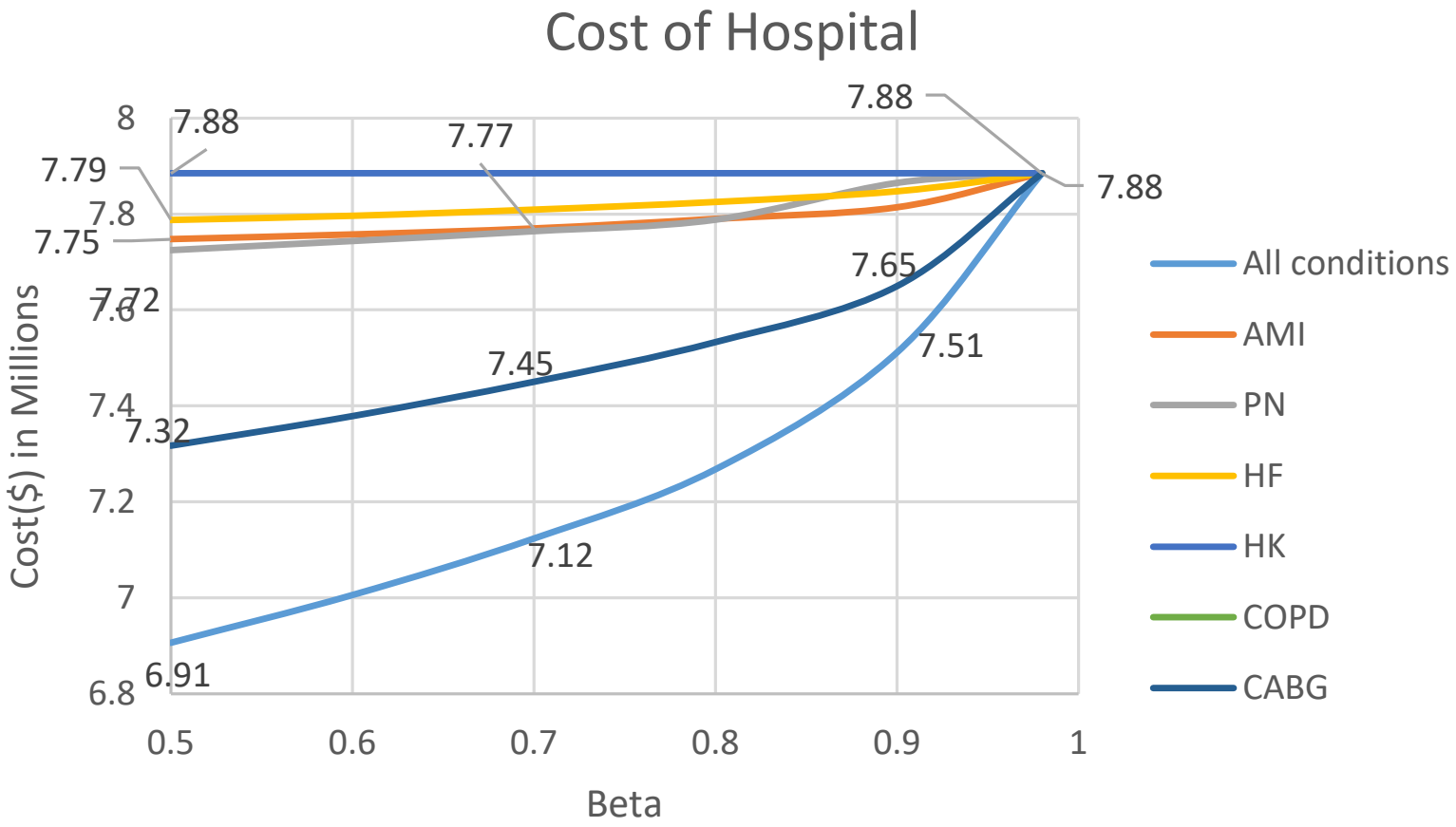
North Shore University Hospital cost data

Table: Cost of treatment plans

Condition	Penalized	Cost($) Distributions*
AMI	P	TRIA(6745, 8431, 21078)
PN	P	TRIA(6312, 7890, 19725)
HF	P	TRIA(5990,7487, 18718)
HK		TRIA(3585, 9359, 31814)
COPD	P	TRIA(6460, 8075, 20188)
CABG	P	TRIA(39864, 56297, 161385)

* Source: www.healthcarebluebook.com

Computational Example - Results



Computational Example - Results

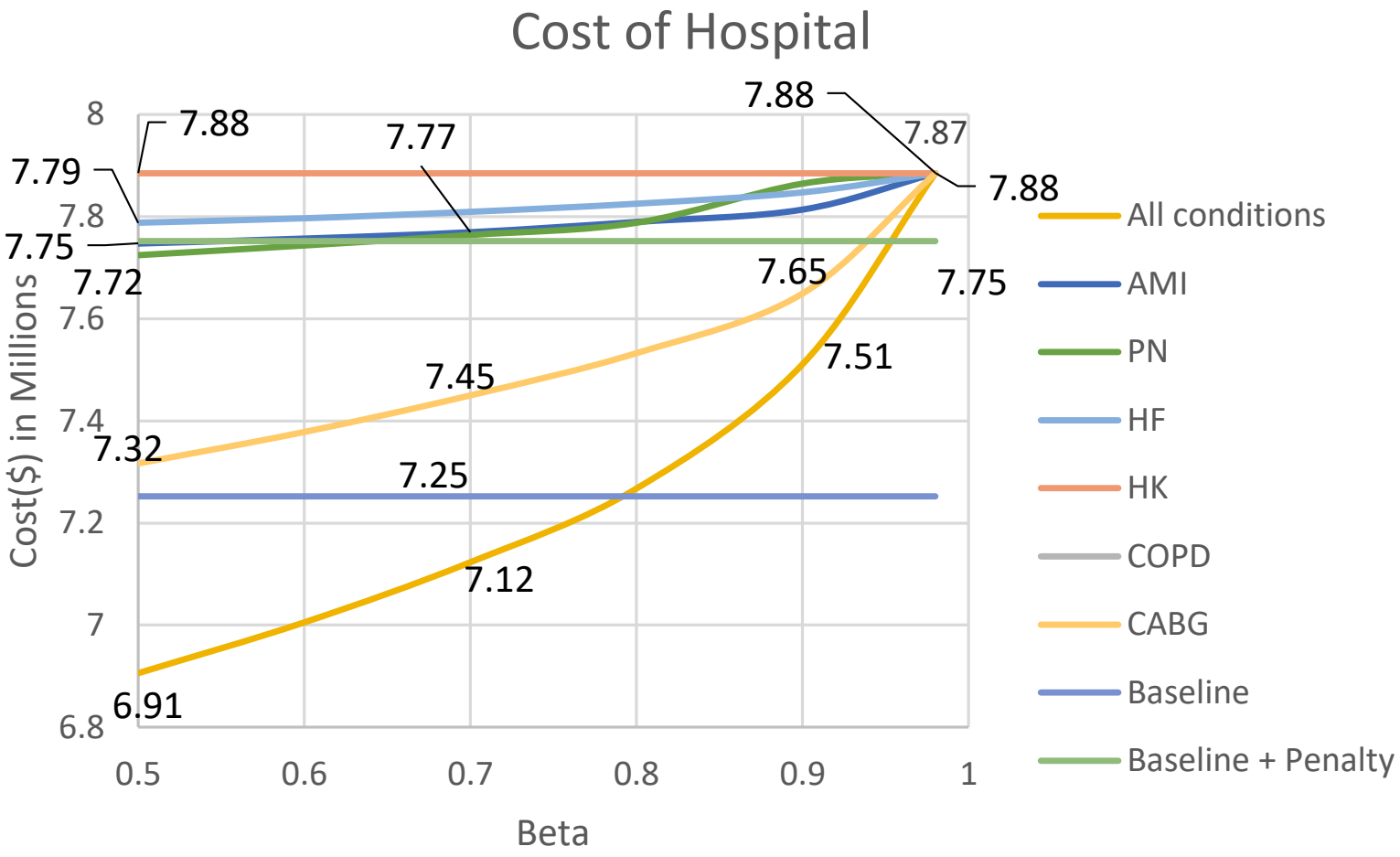


Table of Contents

Introduction

Problem Statement

Literature Review

Model Formulation

Computational Example

Conclusion

Conclusion

- Developed a stochastic model for the hospital's optimal care strategy in response to HRRP to reduce hospital readmissions.
- Introduced a probabilistic constraint to control the readmission probability across all patients for each condition.
- Explored the trade-off between cost of care, reduced readmission rates, and confidence levels for the care strategies.
- Next steps: (1) Chronic vs. Surgical patient strategies

Questions?

Thank You!

Michelle Alvarado, Ph.D.
Assistant Professor
Industrial and Systems Engineering
University of Florida
alvarado.m@ufl.edu

M Alvarado, Yi Zhang, and Mark Lawley.
Hospital readmission reduction strategies using a penalty-incentive model.
In *IISE Annual Conference and Expo, Anaheim, CA*, 2016.

C. Boccuti and G. Casillas.
Aiming for fewer hospital u-turns: The medicare hospital readmission reduction program, March 2017.
https://www.kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/.

Laura C Feemster and David H Au.
Penalizing hospitals for chronic obstructive pulmonary disease readmission.
American Journal of Respiratory and Critical Care Medicine, 189(6):634–639, 2014.

U.S. Centers for Medicare & Medicaid Services.
Readmissions reduction program (HRRP), April 2018.
https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.html.

Bernard Fortz and Michael Poss.
Easy distributions for combinatorial optimization problems with probabilistic constraints.
Operations research letters, 38(6):545–549, 2010.

Stephen F Jencks, Mark V Williams, and Eric A Coleman.
Rehospitalizations among patients in the medicare fee-for-service program.
New England Journal of Medicine, 360(14):1418–1428, 2009.

Dennis J Zhang, Itai Gurvich, Jan A Van Mieghem, Eric Park, Robert S Young, and Mark V Williams.
Hospital readmissions reduction program: An economic and operational analysis.
Management Science, 62(11):3351–3371, 2016.