

Optimization of Health Care Delivery Systems

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Summary

□ Health Care Operations:

- Planning and scheduling of appointment-based service systems
- Stochastic Programming and Robust Optimization

□ Medical Decision Making:

- Screening and treatment decisions for chronic diseases
- Markov decision processes (MDPs) and Partially observable MDPs



Appointment-Based Service Systems



Collaborators

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Summary

- ❑ Optimization models for appointment based stochastic service systems
 - Single server scheduling
 - Multiple server scheduling
 - Dynamic scheduling
 - Bi-criteria scheduling
 - Scheduled service networks

Surgery

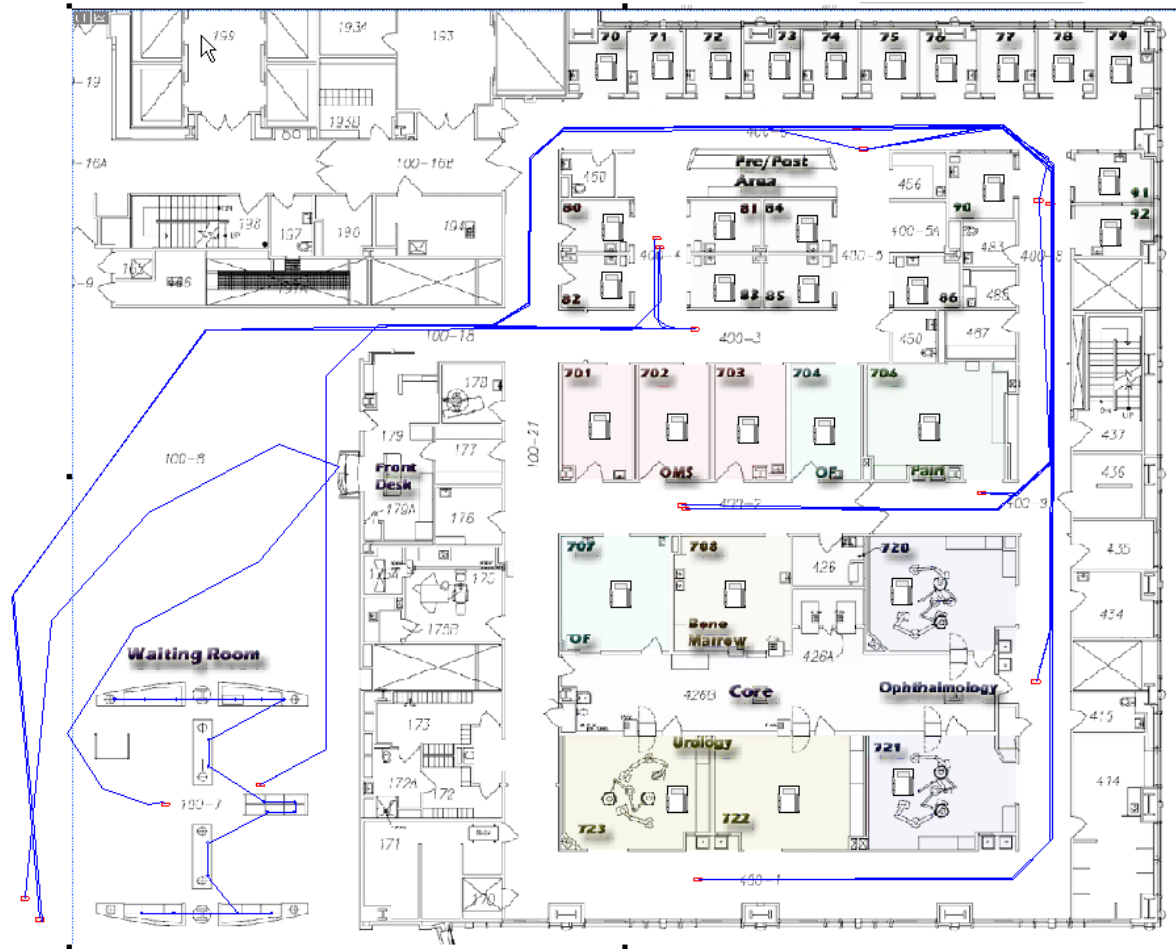
- ❑ Patient Intake: administrative activities, pre-surgery exam, gowning, site prep, anesthetic
- ❑ Surgery: incision, one or multiple procedures, pathology, closing
- ❑ Recovery: post-anesthesia care unit (PACU), ICU, hospital bed



Complicating Factors

- ❑ Multiple expensive resources
- ❑ Large number of activities to be completed in a fixed period of time
- ❑ Uncertainty in duration of activities
- ❑ Many competing criteria

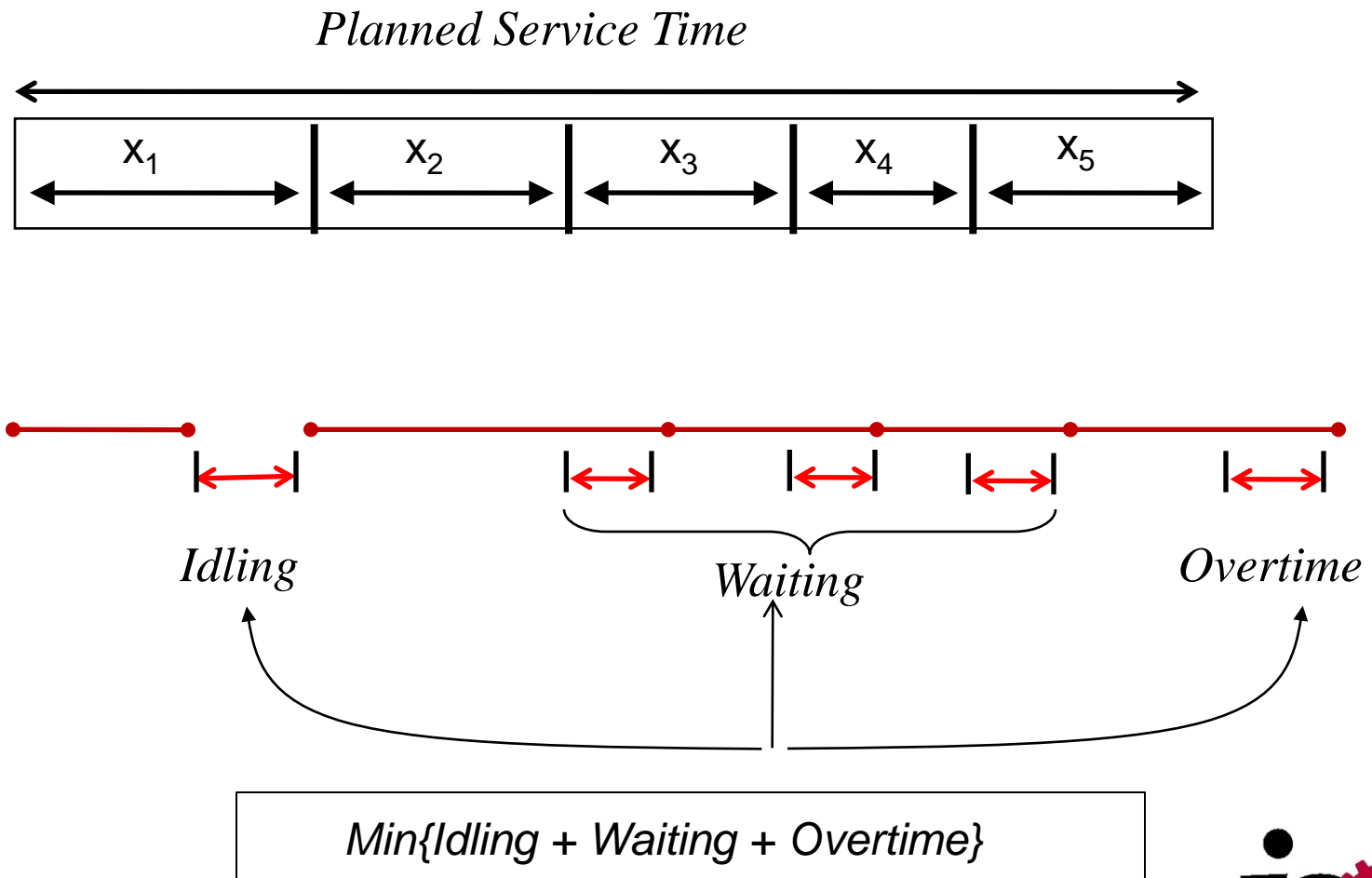
Outpatient Procedure Center



Single Server Scheduling



Single OR Scheduling ($S(n)/G(n)/1$)



Stochastic Optimization Model

$$\min \left\{ \overbrace{\sum_{i=1}^n c_i^w E_Z[w_i]}^{\text{Cost of Waiting}} + \overbrace{\sum_{i=1}^n c^s E_Z[s_i]}^{\text{Cost of Idling}} + \overbrace{c^L E_Z[l]}^{\text{Cost of Overtime}} \right\}$$

$$w_i = \max(w_{i-1} + Z_{i-1} - x_{i-1}, 0), \quad i = 1, \dots, n-1$$

$$s_i = \max(-w_{i-1} - Z_{i-1} + x_{i-1}, 0), \quad i = 1, \dots, n-1$$

$$l = \max(w_n + Z_n + \sum_{i=1}^{n-1} x_i - d, 0)$$



Stochastic Linear Program

$$\min \{ E_Z [\sum_{i=2}^n c_i^w w_i + \sum_{i=2}^n c^s s_i + c^L l] \}$$

$$\begin{aligned} \text{s.t.} \quad & w_2 - s_2 = Z_1 - x_1 \\ & -w_2 + w_3 - s_3 = Z_2 - x_2 \\ & \quad \quad \quad \vdots \\ & \quad \quad \quad -w_n - s_n + l - g = Z_n - d + \sum_{j=1}^{n-1} x_j \end{aligned}$$

$$x_i \geq 0, w_i \geq 0, s_i \geq 0, i = 1, \dots, n, \quad l, g \geq 0$$

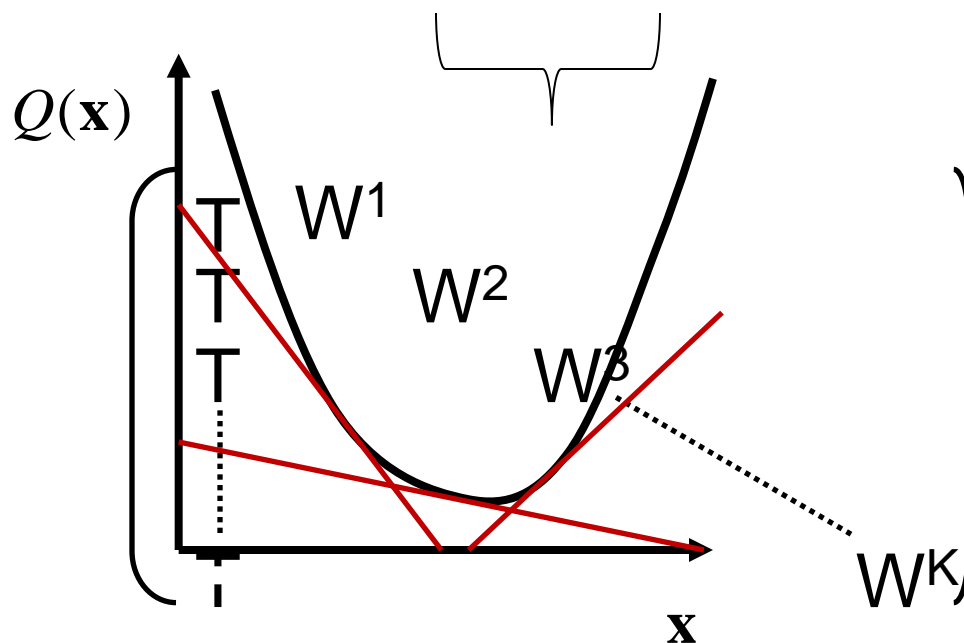


Two Stage Recourse Problem

Initial Decision (\mathbf{x}) \rightarrow Uncertainty Resolved (\mathbf{Z}) \rightarrow Recourse (\mathbf{y})

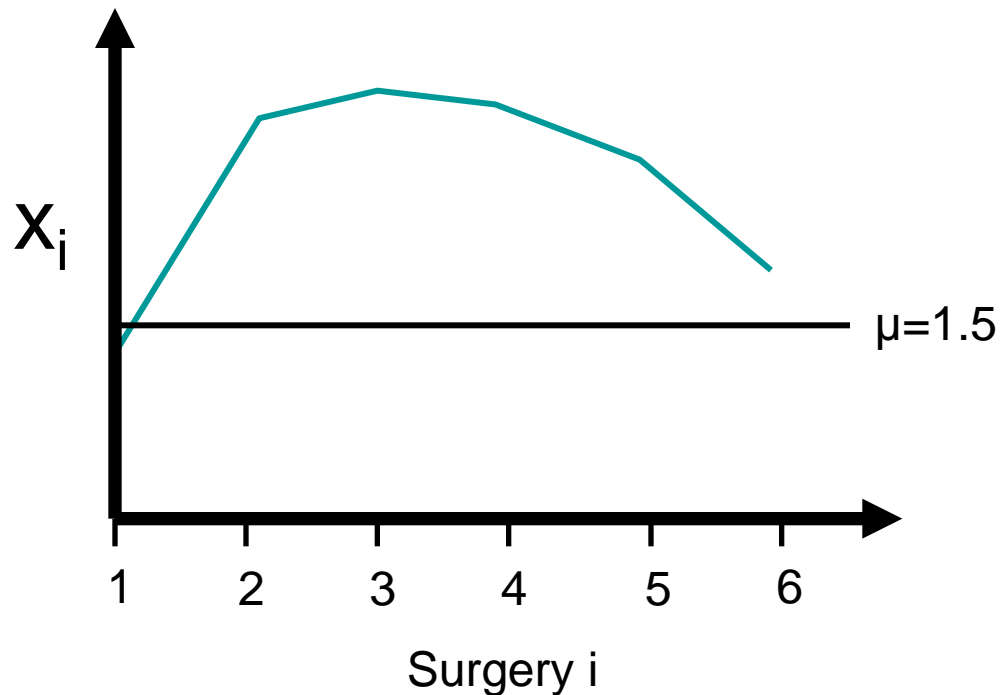
$$\min \{ Q(\mathbf{x}) = E_{\mathbf{Z}}[Q(\mathbf{x}, \mathbf{Z})] \}$$

$$Q(\mathbf{x}, \mathbf{Z}^k) = \min \{ \mathbf{c} \cdot \mathbf{y}^k \mid T \mathbf{x} + W \mathbf{y}^k = \mathbf{Z}^k, \mathbf{y}^k \geq 0 \}$$



Example

- Schedule for $n=7$ with i.i.d. distributions with $U(1,2)$:



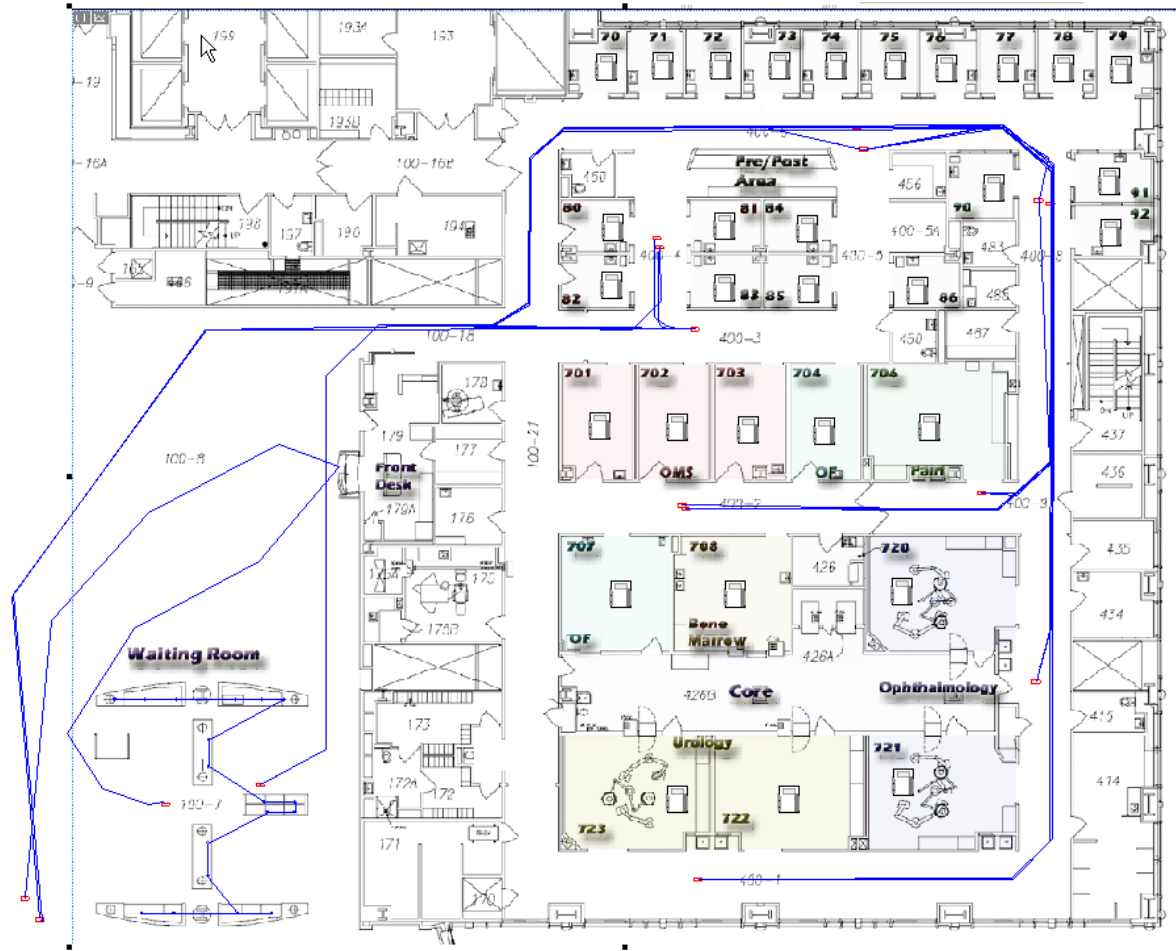
Denton, B.T., Gupta, D., "A Sequential Bounding Approach for Optimal Appointment Scheduling," *IIE Transactions*, 35, 1003-1016, 2003

Denton, B.T., Viapiano, J, Vogl, A., "Optimization of Surgery Sequencing and Scheduling Decisions Under Uncertainty," *Health Care Management Science*, 10(1), 13-24, 2007

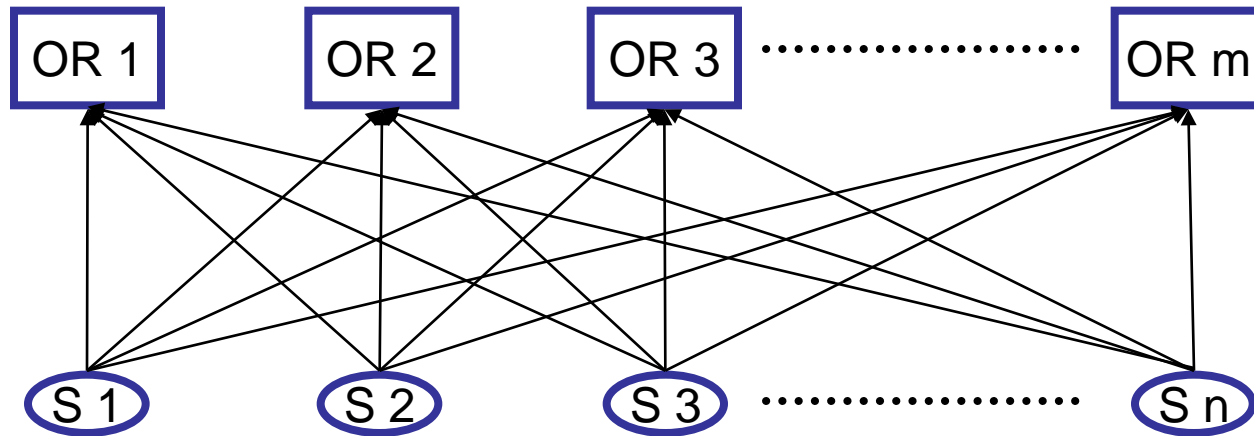
Multi-OR Surgery Allocation



Outpatient Procedure Center



Multi-OR Room Scheduling



Performance Measures:

- Cost of opening ORs
- Overtime costs

Decisions:

- How many ORs to open?
- Which OR to schedule each surgery block?

Extensible Bin Packing

$$x_j = \begin{cases} 1 & \text{if OR } j \text{ open} \\ 0 & \text{if OR } j \text{ closed} \end{cases} \quad y_{ij} = \begin{cases} 1 & \text{if Surgery } i \text{ assigned to OR } j \\ 0 & \text{Otherwise} \end{cases}$$

$$Z = \min \left\{ \sum_{j=1}^m c^f x_j + c^v o_j \right\}$$

$$s.t. \quad y_{ij} \leq x_j \quad \forall (i, j)$$

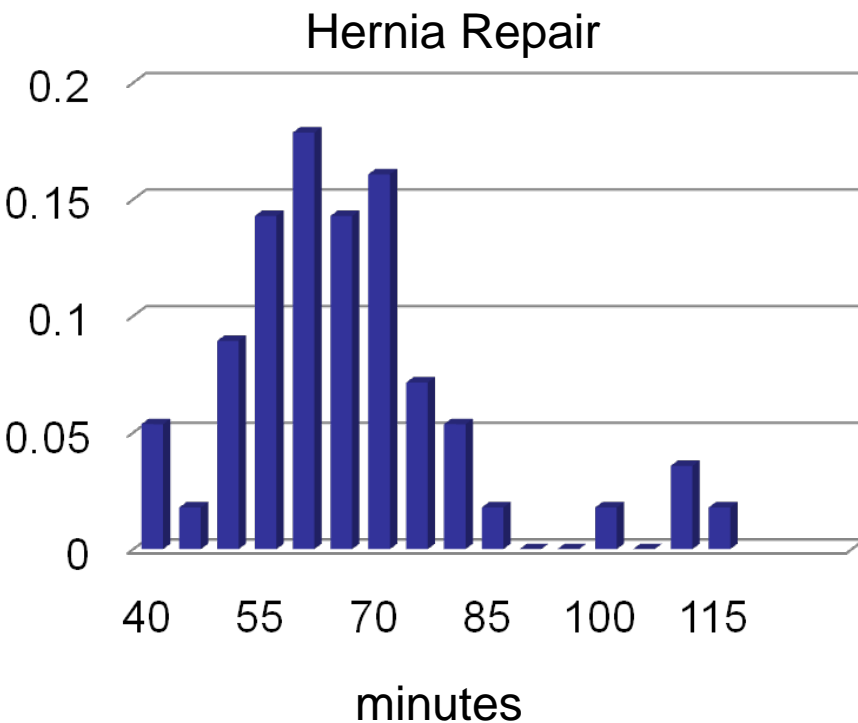
$$\sum_{j=1}^m y_{ij} = 1 \quad \forall (i)$$

$$\sum_{i=1}^n b_i y_{ij} - o_j \leq d_j x_j \quad \forall (i, j)$$

$$y_{ij}, x_j \in \{0,1\}, \quad o_j \geq 0$$



Two-Stage Stochastic MIP



$$Q(\mathbf{x}) = \min \left\{ \sum_{j=1}^m c^f x_j + c^v E_{\omega} [o_j(\omega)] \right\}$$

$$s.t. \quad y_{ij} \leq x_j \quad \forall (i, j)$$

$$\sum_{j=1}^m y_{ij} = 1 \quad \forall (i)$$

$$\sum_{i=1}^n b_i(\omega) y_{ij} - o_j(\omega) \leq d_j x_j \quad \forall (i, j, \omega)$$

$$y_{ij}, x_j \in \{0, 1\}, \quad o_j(\omega) \geq 0, \forall \omega$$

General Insights

- ❑ New upper and lower bounds on the extensible bin-packing problem
- ❑ Valid inequalities to reduce the impact of symmetry
- ❑ Decomposition based solution methods
- ❑ New Robust MIP formulation

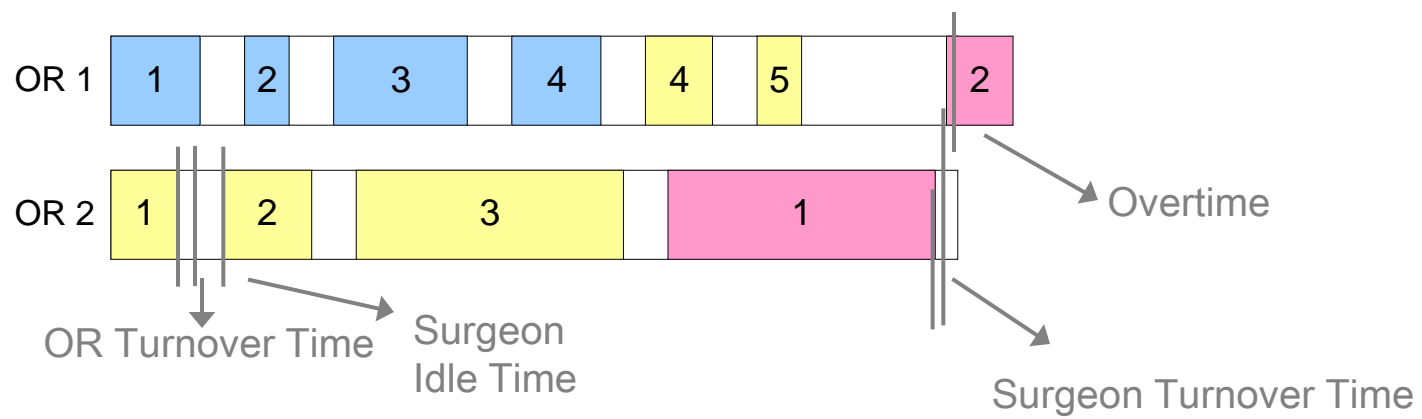
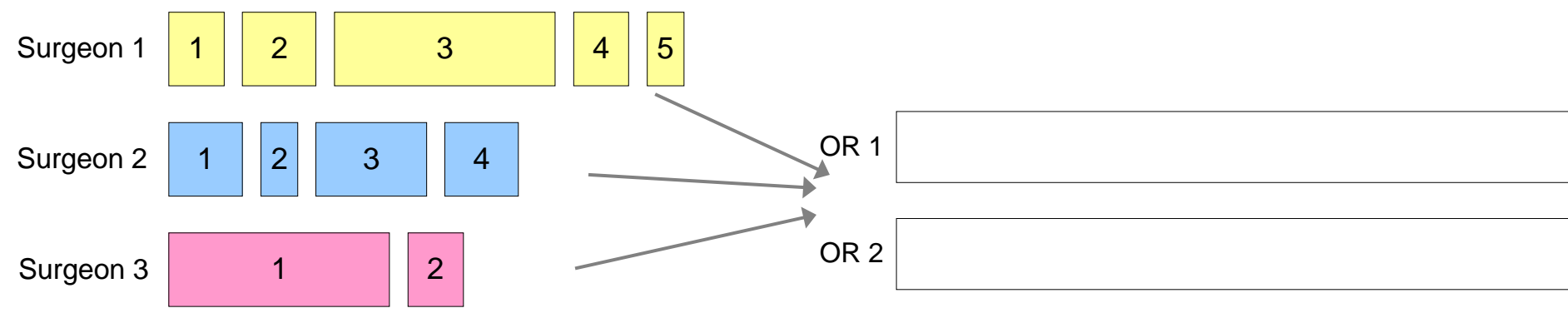
Denton, B.T., Miller, A., Balasubramanian, H., Huschka, T.,
“Optimal Surgery Block Allocation Under Uncertainty,”
Operations Research (in press), 2009



Other Research Directions



Pooling OR Capacity

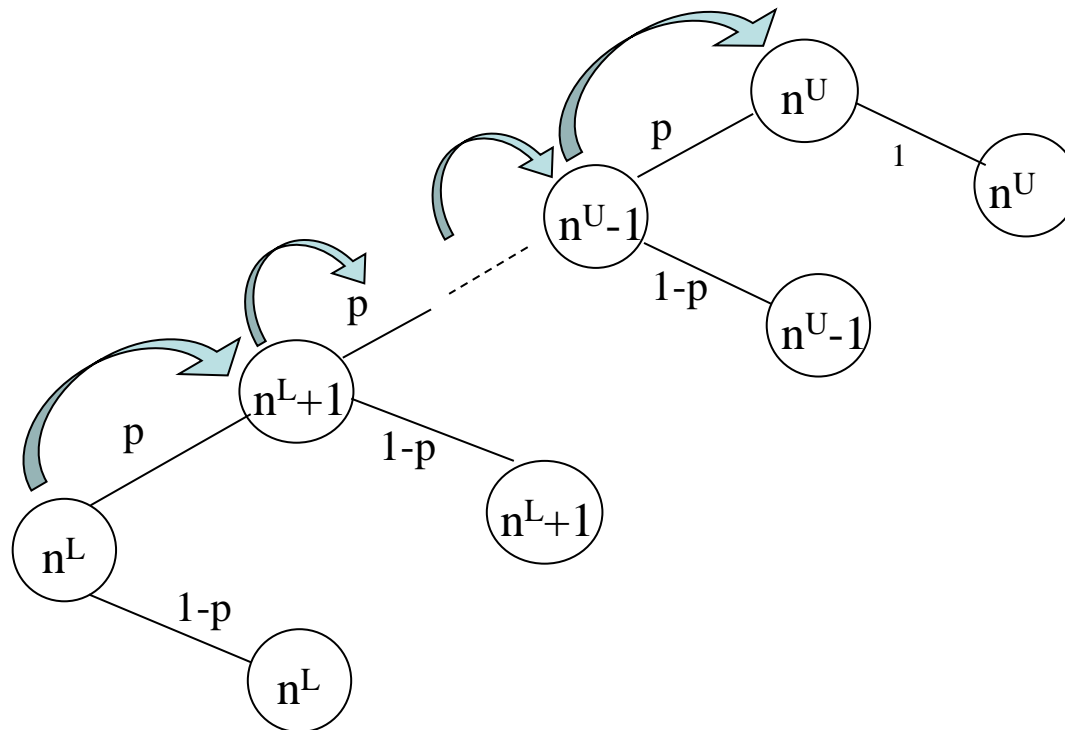


Batun, S., Denton, B.T., Huschka, T.R., Schaefer, A.J., "The Benefit of Pooling Operating Rooms Under Uncertainty," Working Paper, 2009

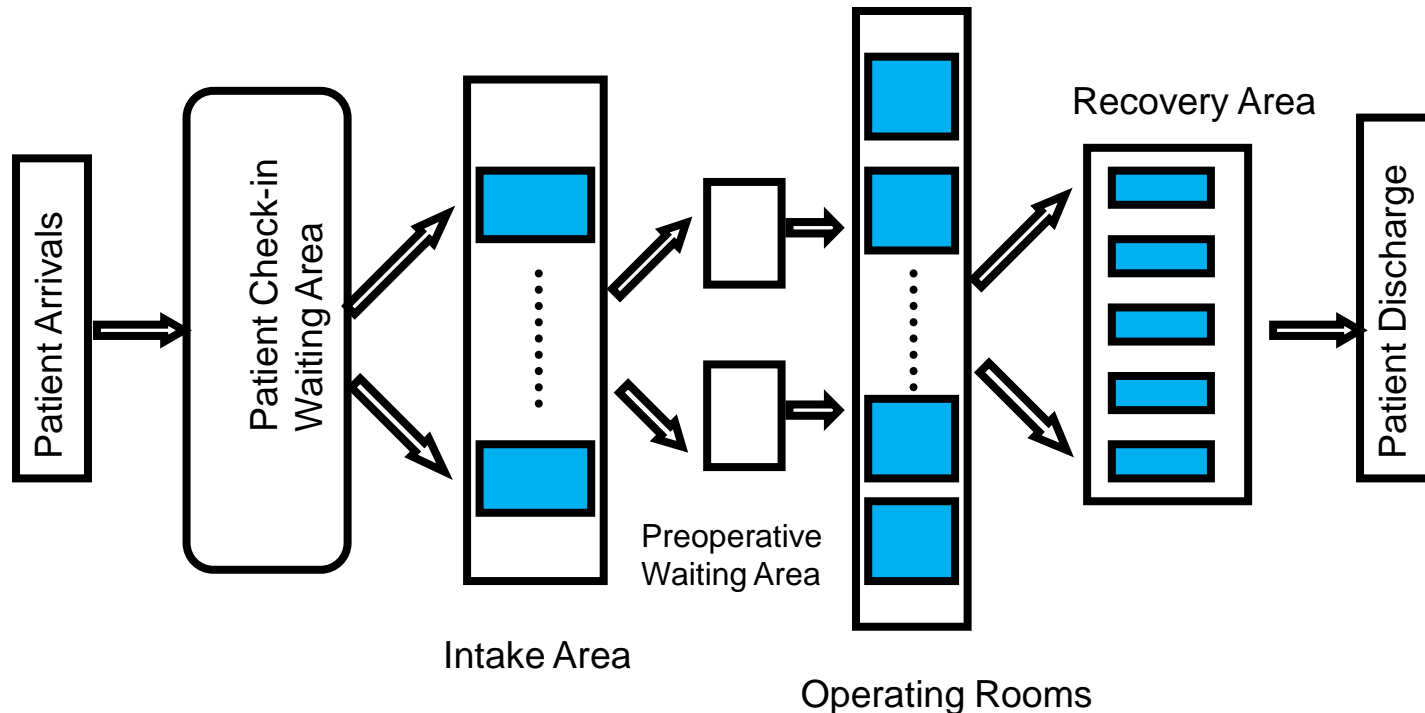


Dynamic Appointment Scheduling

- Patients request appointments stochastically
- Appointment decisions are made one at a time
- Multistage stochastic linear program



Surgical Suite Scheduling

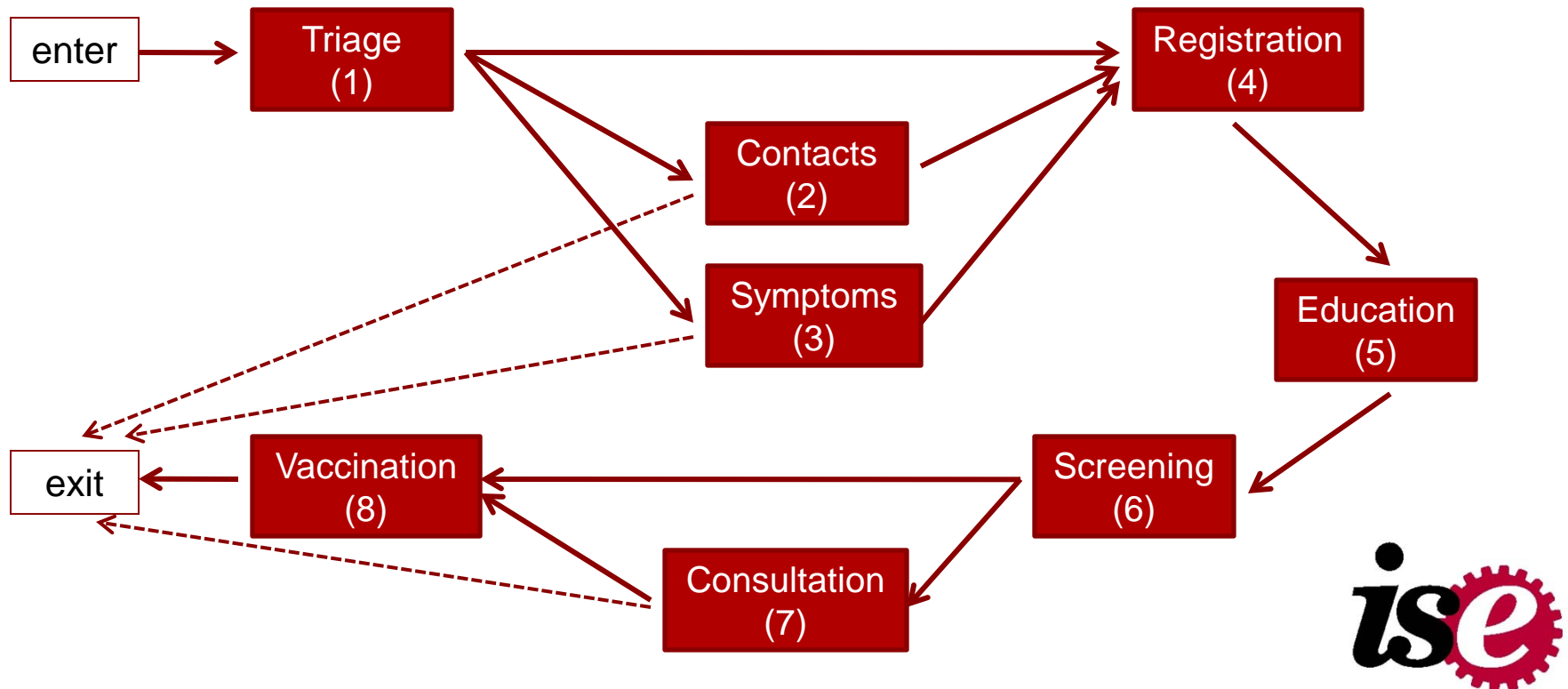


Berg, B., Denton, B.T., Nelson, H., Balasubramanian, B., Rahman, A., Bailey, A., Lindor, K., "A Computer Simulation Model to Evaluate Operational Performance of a Colonoscopy Suite," *Medical Decision Making* (in press), 2009

Gul, S., Denton, B.T., Huschka, T., Fowler, J.R., "Bi-criteria Evaluation of an Out Patient Surgery Clinic via Simulation," submitted to *POM*, December 2008

POD Scheduling

- POD Design from Aaby, et al. Montgomery County's Public Health Service Uses Operations Research to Plan Emergency Mass Dispensing and Vaccination Clinics. *Interfaces*, 36(6), pp. 569–579, 2006.



Chronic Disease Screening and Treatment



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Summary

- ❑ Disease screening under imperfect information
 - Biopsy referral decisions
 - National screening policies

- ❑ Optimal timing of medical treatment decisions
 - Treatment optimization
 - Adherence control



Disease Test Beds

- ❑ Type 2 Diabetes:
 - Mayo Clinic DEMS
 - Ingenix Inc.
- ❑ Prostate Cancer:
 - Olmsted county medical record
 - Mayo Clinic radical prostatectomy database
- ❑ Bladder cancer
 - UNC Medical Record
 - SEER



Diabetes

- ❑ There are more than 23 million people in the U.S. who have diabetes
 - 8% of the U.S. population
 - 90% have type 2 diabetes

- ❑ Two out of three people with diabetes will die from either stroke or coronary heart disease (CHD)

Statins



CRESTOR
rosuvastatin calcium

- About CRESTOR
- About cholesterol
- Diet
- Exercise
- Tools for success
- Important safety information

Down with the bad cholesterol.

CRESTOR[®] 10 mg, along with diet, can lower bad cholesterol by up to 52% (vs 7% placebo). It can also raise your good cholesterol by up to 14% (vs 3% placebo). Your results may vary.

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Cost of Statins

- ❑ More than \$20 billion dollars are spent annually in the U.S. alone
- ❑ Side effects including liver failure, muscle pain, dizziness, nausea, headaches...
- ❑ Currently there is broad disagreement about the best policy for statin treatment



CHD & Stroke Risks

□ What other factors affect CHD and Stroke risk?

- Age
- Gender
- Ethnicity
- Smoking
- Blood Pressure
- Hemoglobin A1c
- Exercise & Diet
- Body Mass Index

□ In recent years several risk models have been developed to calculate the risk of CHD & Stroke:

- UKPDS
- Framingham
- Archimedes

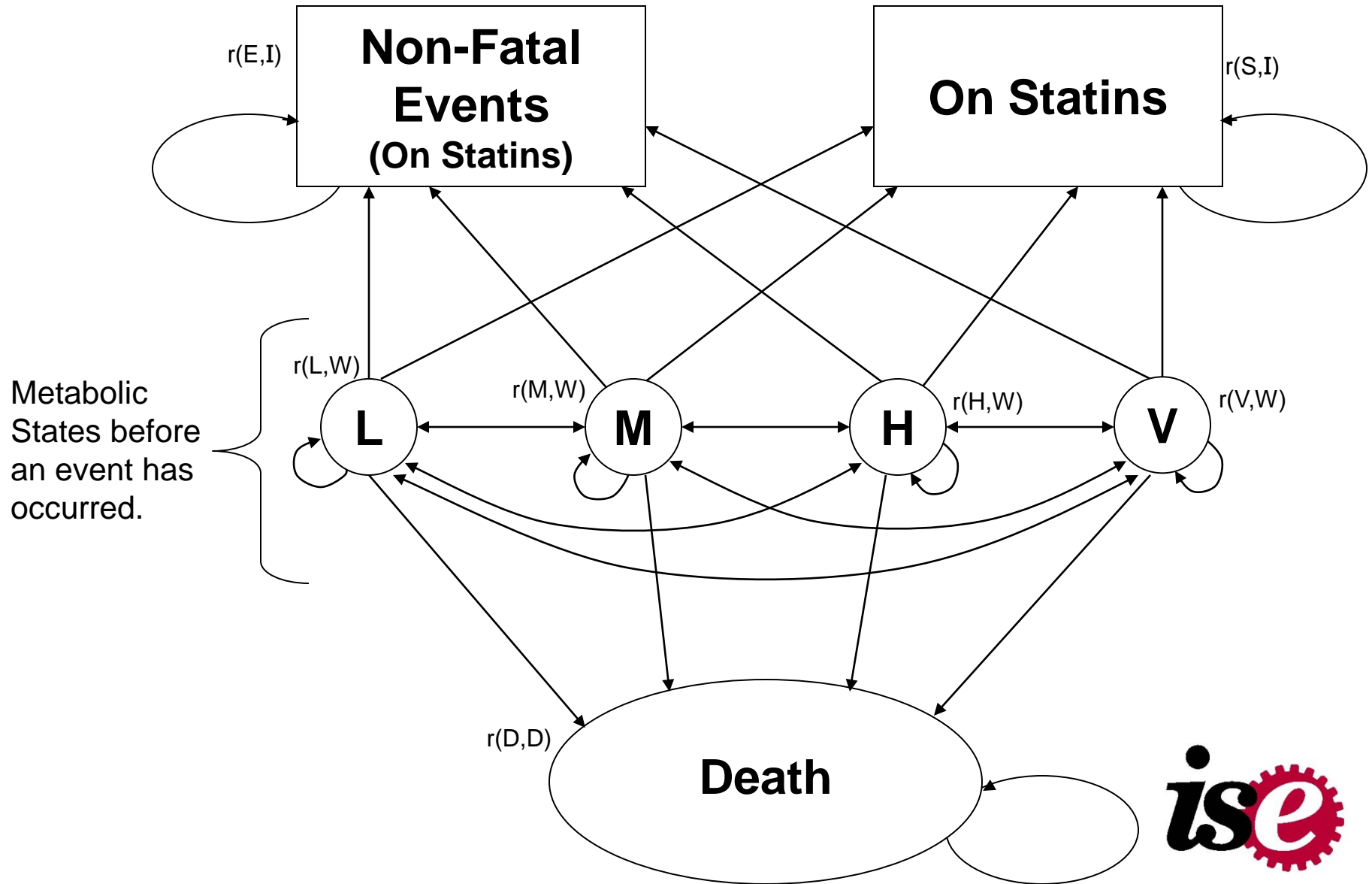


Markov Decision Process Model

- Stages:
 - Time horizon: Ages 40-100
 - Annual decision epochs
- Decision:
 - **Initiate** or **delay** statin treatment
- States:
 - Metabolic: Total cholesterol and HDL (each can be L, M, H, V), Blood pressure, HbA1c
 - Demographic: Gender, Race, BMI, smoking status, medical history



State Transition Diagram



Optimal Treatment Policy

□ Society

- Maximize a weighted combination of patient rewards for life years minus costs of treatment and health services

□ Patient

- Maximize rewards for quality adjusted life years

□ Third-party Payer

- Minimize costs of treatment and health services

Denton, B.T., Kurt, M., Shah, N.D., Bryant, S.C., Smith, S.A., “A Markov Decision Process for Optimizing the Start Time of Statin Therapy for Patients with Diabetes,” *Medical Decision Making*, 29(3), 351-367, 2009



Model Formulation

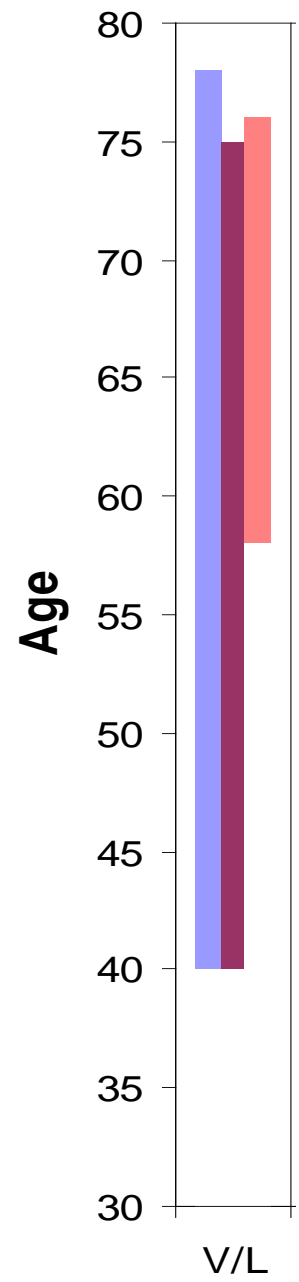
- ❑ Decision epochs: $t \in T = \{1, 2, 3, \dots, N\}$
- ❑ Health States: $s_t \in S = \{1, 2, 3, \dots, L, L + 1\}$
- ❑ Treatment Status: $m \in \{0, 1\}$
- ❑ Action: $a_t(s_t) = \begin{cases} I, W & \text{if } m = 0 \\ W & \text{if } m = 1 \end{cases}$

Optimality Equations:

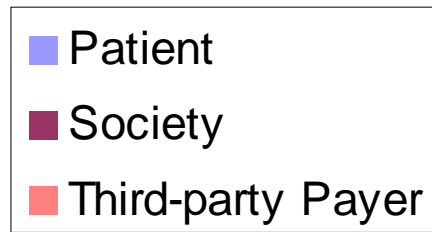
$$v_t(s_t, m) = \max \left[\underbrace{r(s_t, m)}_{\text{Reward for living to current epoch}} + \lambda \underbrace{\sum_{\forall s_{t+1}} p(s_t', m' | s_t, m) v_t(s_t', m)}_{\text{Transition probabilities}} \right]_{\text{Expected Future Reward}}$$



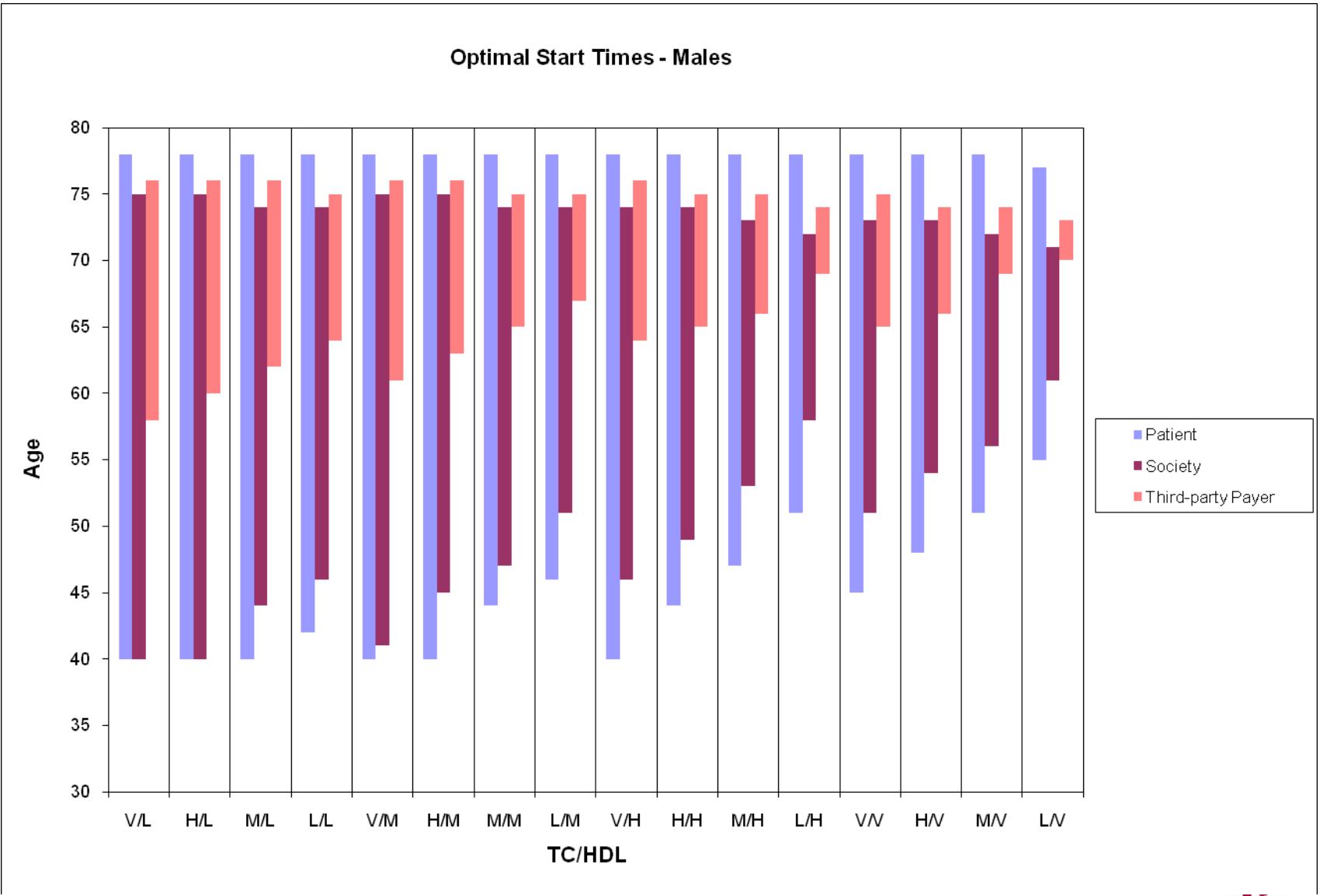
Example



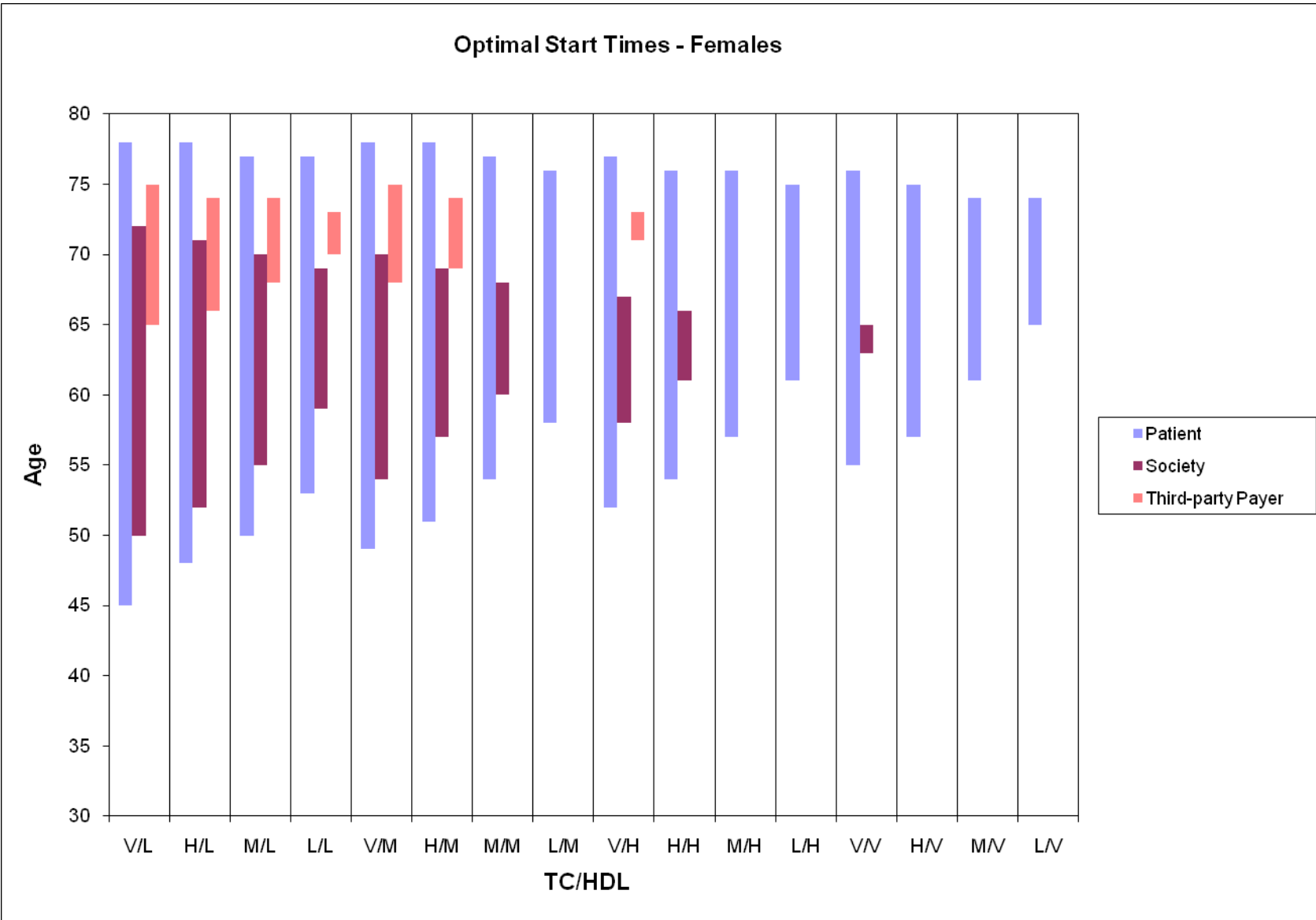
Optimal Start Times for Males with very high total cholesterol and low HDL.



Numerical Results



Numerical Results



Primary Prevention

- ❑ Define $\mu_t(s_t)$ to be the patients expected quality adjusted time to first event if treatment is initiated in state S_t
- ❑ States: defined by *lipid ratio*
- ❑ Objective: maximize time to first event ($r(s_t, m) = 1 - m\sigma$)
- ❑ Optimality equations:

$$v_t(s_t) = \max \left\{ r(s_t, 0) + \lambda \sum_{\forall s_{t+1}} p(s_{t+1}', 0 | s_t, 0) v_t(s_{t+1}'), \mu_t(s_t) \right\}$$

Theoretical Insights

Theorem 1: *If the transition probability matrix is IFR then the optimal policy has the control limit property such that for some lipid ratio $z_t^* \in S'$:*

$$a_t(s_t) = \begin{cases} 1 & \text{for } s_t \geq z_t^* \\ 0 & \text{for } s_t < z_t^* \end{cases}$$

Theorem 2: *If the expected benefit loss is nondecreasing in age then the optimal threshold is nonincreasing in age.*

Kurt, M., Denton, B.T., Schaefer, A., Shah, N., Smith, S., “At What Lipid Ratio Should a Patient with Type 2 Diabetes Initiate Statins”, submitted to *Management Science*



Other Research Directions



Treatment Optimization

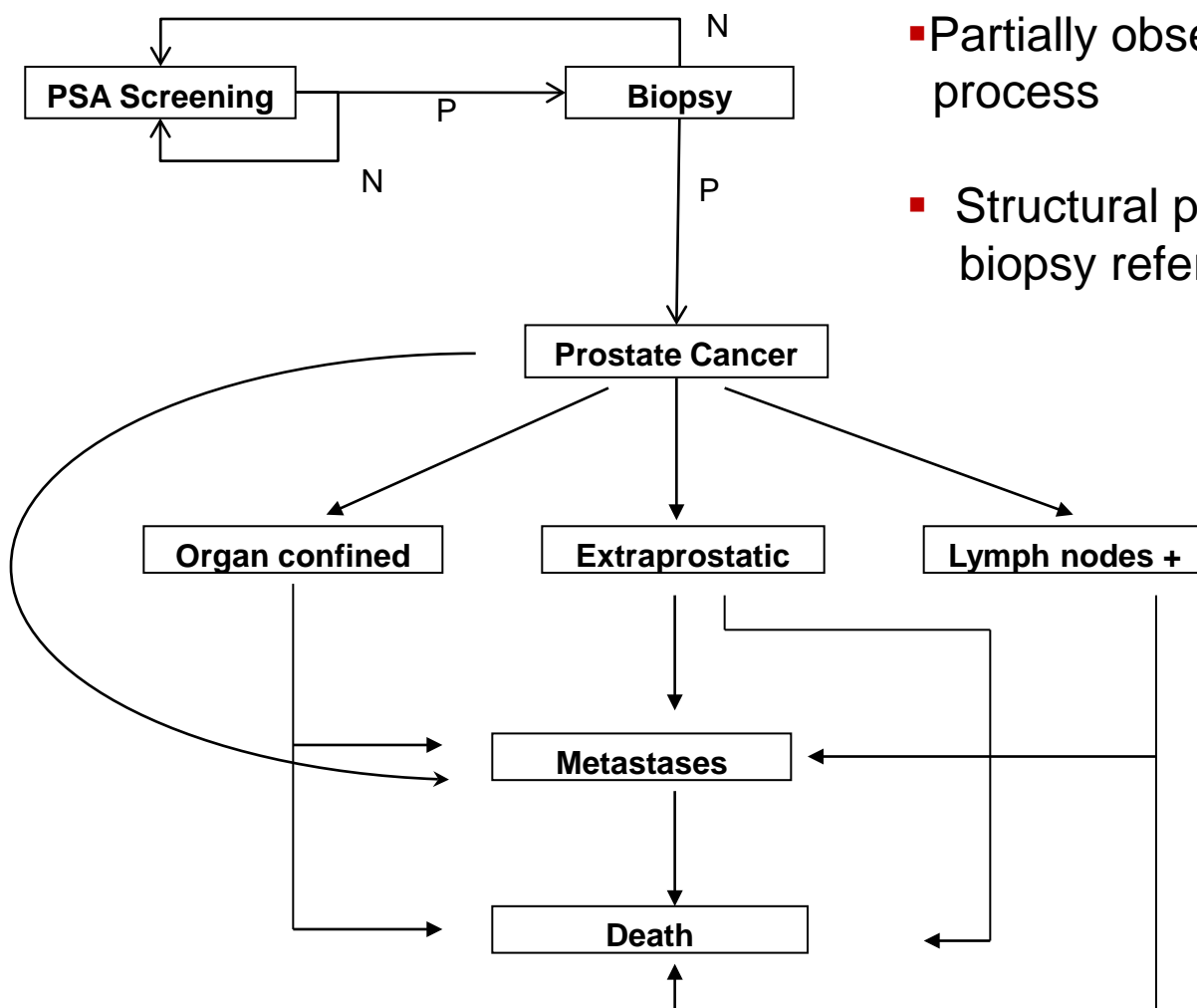
- ❑ Optimal sequencing and timing of treatment options for control of:
 - ❑ Cholesterol
 - ❑ Blood pressure
 - ❑ HbA1c

- ❑ Barriers to treatment:
 - ❑ Adherence monitoring and control

Mason, J.E., England, D., Denton, B.T., Smith, S.A., Shah, N.D., "The Effect of Adherence on the Optimal Start Time for Statins," Working Paper, 2009



Prostate Cancer Screening

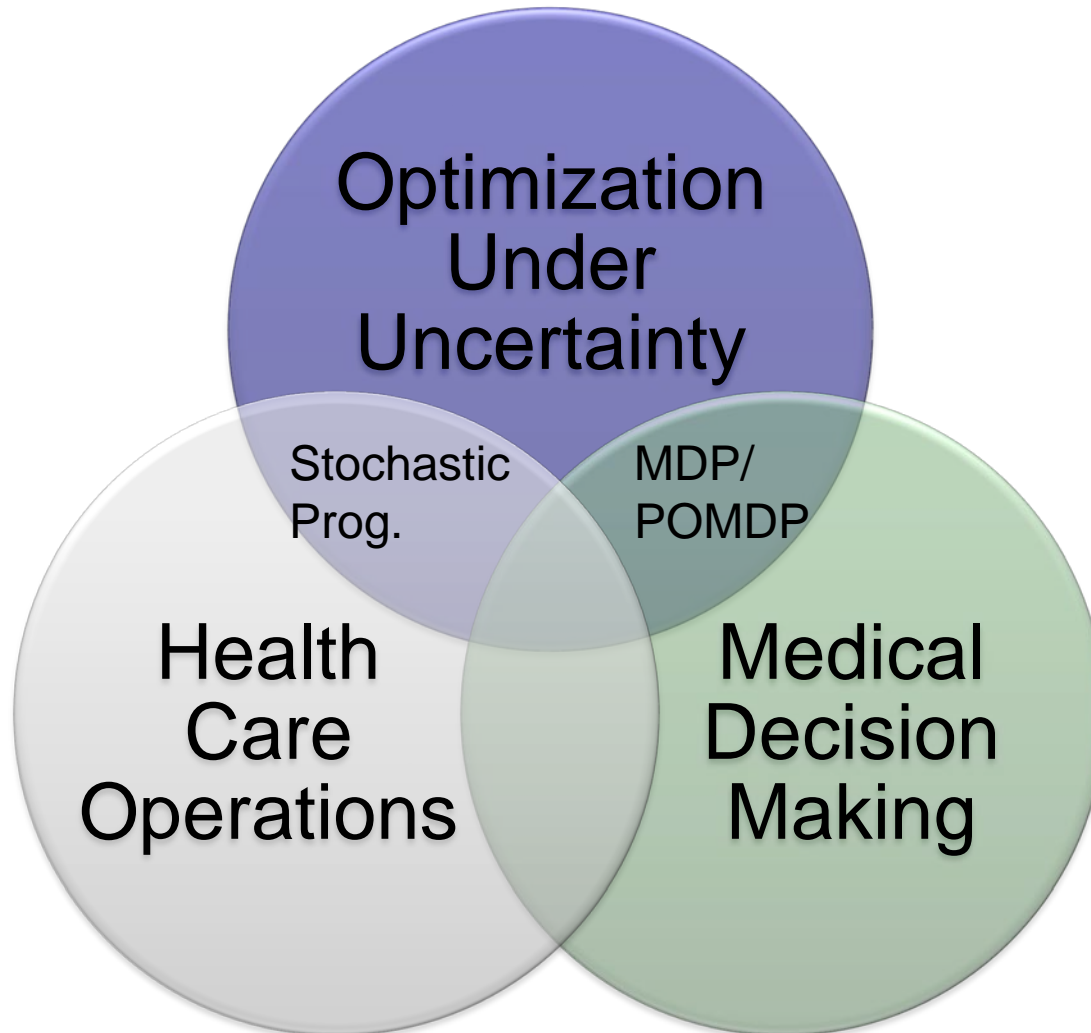


- Partially observable Markov decision process
- Structural properties of the optimal biopsy referral policy

▪ Zhang, J., Denton, B.T., Balasubramanian, H., Inman, B., Shah, N., "Optimization of Prostate Biopsy Decisions," Working Paper, 2009



Future Opportunities



Questions?

