Collaborators

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Background

• Cancer Statistics
  – Second leading cause of death in the US
  – 1,638,910 new cases of cancer in 2012

• Outpatient Oncology
  – 29.2 million visits in the US with a primary diagnosis of cancer
  – 23 million adult patient visits for chemotherapy

• University of Michigan Comprehensive Cancer Center
  – 93,319 Outpatient Visits
  – 51,884 Infusion Treatments
Project Goals

• Improve quality of cancer care delivery in the infusion center
  – Reduce patient waiting times
  – Reduce total length of day of operations
  – Improve patient and nurse safety
Approach

Observations & Data ➔ Patient Flow Mapping ➔ Simulation Model ➔ Heuristics ➔ Optimization Model ➔ Outputs ➔ Analysis
Computer Simulation Model

University of Michigan
Comprehensive Cancer Center

Chairs
Nurse desk
Completed chemotherapy order queue
Chemotherapy orders ready for preparation
Chemotherapy orders received
Annex
Bedside
Pharmacy
Elevators
Reception A
Walking Area

Computer Simulation Model

Inputs - Outputs

**Inputs**
- Patient types
- Nurse preparation time
- Nurse discharge time
- Pharmacy preparation time
- Patient appointment schedules
  - Baseline
  - LPT heuristic
  - SPT heuristic
  - Stochastic optimization model

**Computer Simulation**

**Outputs**
- Average patient waiting times
- Hours of operation
- Chair utilization
- Average time in system
Patient wait times vs. Length of day

Start of Day

End of Day

P1  P2  P3  P4  P5

P1  P2  P3  P4  P5
Stochastic Programming Model

• Generates appointment schedule that reduces patient waiting times and total length of day of operations

• Decisions
  – Appointment times
  – Patient sequence
  – Patient-Chair assignment

• Stochasticity
  – Scenarios represent variability
  – Scenarios sample infusion, preparation, discharge, and drug mix times from distributions
Stochastic Programming Model
Variables & Parameters Explanation

Patient: $a_p, w_p, s_p, t_p, d_p$

- Nurse & chair availability
- Patient prep complete

WAIT TIME
Stochastic Programming Model
Variables & Parameters Explanation

Patient
- $a_p$
- $w_p$
- Nurse & chair availability
- Patient prep complete
- WAIT TIME
- Technician availability
- Chemo order ready
- $s_p$
- $t_p$
- $d_p$
- $R_p$
- $\text{mix}_p$

Pharmacy
Stochastic Programming Model
Variables & Parameters Explanation

- Nurse & chair availability
  - $a_p$
  - $w_p$

- Patient prep complete
  - $s_p$
  - $t_p$
  - $d_p$

- Technician availability
  - $y_p$
  - $R_p$
  - $mix_p$

- Chemo order ready
  - $p$

Patient

Pharmacy
Stochastic Programming Model
Sample Path Approximation

Decision Variables

\[ a_p \]: appointment time of patient \( p \)

\[ w_p^\omega \]: waiting time of patient \( p \) in scenario \( \omega \)

\[ R_p^\omega \]: waiting time for available technician to mix patient’s \( p \) chemo drug at the pharmacy in scenario \( \omega \)

\[ y_p^\omega \]: time patient \( p \) sits in the chair before infusion starts in scenario \( \omega \)

\[ d_p^\omega \]: exit time of patient \( p \) in scenario \( \omega \)

\[ x_{pc}^\omega \]: binary, 1 if patient \( p \) is assigned to chair \( c \) in scenario \( \omega \); 0 otherwise

\[ z_{p'p}^\omega \]: binary, 1 if patient \( p' \) is scheduled before patient \( p \); 0 otherwise

\[ L^\omega \]: end of day in scenario \( \omega \)

Parameters

\[ s_p^\omega \]: preparation time of patient \( p \) in scenario \( \omega \)

\[ t_p^\omega \]: infusion time plus discharge time of patient \( p \) in scenario \( \omega \)

\[ mix_p^\omega \]: chemo drug mix time for patient \( p \) in scenario \( \omega \)

\( m \): number of scenarios

\( \lambda \): weight in the objective function

\( M \): large number
Objective Function: Trade-off between the total expected waiting time and the expected length of day
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\min \quad & \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m} \left[ w^\omega_p + (y^\omega_p - s^\omega_p) \right] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L^\omega \\
\text{subject to} \quad & \sum_{c \in C} x^\omega_{pc} = 1 \quad \forall p \in P, \forall \omega \in \Omega
\end{align*}
\]

Each patient should be assigned to exactly one infusion chair
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\min & \quad \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m} [w_p^\omega + (y_p^\omega - s_p^\omega)] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L_\omega \\
\text{subject to} & \quad \sum_{c \in C} x_{pc}^\omega = 1 \\
& \quad a_p + w_p^\omega + y_p^\omega + t_p^\omega = d_p^\omega \\
& \quad \forall p \in P, \forall \omega \in \Omega
\end{align*}
\]

Value of exit time of patient \( p \) in each scenario
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\min \quad & \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m} [w^\omega_p + (y^\omega_p - s^\omega_p)] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L^\omega \\
\text{subject to} \quad & \sum_{c \in C} x^\omega_{pc} = 1 \\
& a_p + u^\omega_p + y^\omega_p + t^\omega_p = d^\omega_p \\
& a_p + w^\omega_p + M(3 - x^\omega_{pc} - x^\omega_{p'c} - z_{p'p}) \geq d^\omega_{p'} \\
& \forall p \in P, \forall \omega \in \Omega \\
& \forall c \in C, \forall p, p' \in P, \forall \omega \in \Omega
\end{align*}
\]

Free chair constraint: A patient can sit in a chair only if all previously sequenced patients assigned to the same chair have been discharged.
Available nurse constraint: A patient can sit in a chair if the nurse has finished preparing all previously sequenced patients
FIFO rule: A patient that arrives before another patient has to sit in an infusion chair first
Available pharmacy technician constraint: A pharmacy technician can prepare only one chemotherapy order at a time
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\min & \quad \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m} [w_p^{\omega} + (y_p^{\omega} - s_p^{\omega})] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L^{\omega} \\
\text{subject to} & \quad \sum_{c \in C} x_{pc}^{\omega} = 1 \\
& \quad a_p + w_p^{\omega} + y_p^{\omega} + t_p^{\omega} = d_p^{\omega} \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega} \quad \forall c \in C, \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega} \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + R_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega} + R_{p'}^{\omega} + \text{mix}_{p'}^{\omega} \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad L^{\omega} \geq d_p^{\omega} \quad \forall p \in P, \forall \omega \in \Omega \\
\end{align*}
\]

All patients should be discharged to end the day.
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\min & \quad \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m}[w^{\omega}_p + (y_p^{\omega} - s^{\omega}_p)] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m}L^{\omega} \\
\text{subject to} & \quad \sum_{c \in C} x_{pc}^{\omega} = 1, \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + y_p^{\omega} + t_p^{\omega} = d_p^{\omega}, \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + M(3 - x_{pc}^{\omega} - x_{p'c}^{\omega} - z_{p'p}^{\omega}) \geq d_{p'}^{\omega}, \quad \forall c \in C, \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega} + s_{p'}^{\omega}, \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega}, \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + w_p^{\omega} + R_p^{\omega} + M(1 - z_{p'p}^{\omega}) \geq a_{p'} + w_{p'}^{\omega} + R_{p'}^{\omega} + mIx_{p'}^{\omega}, \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad L^{\omega} \geq d_{p}^{\omega}, \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad (a_{p'} - a_p) + Mz_{p'p} \geq 0, \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad z_{pp'} = 1 - z_{p'p}, \quad \forall p, p' \in P
\end{align*}
\]

Definition of variable $z_{p'p}$
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\text{min} & \quad \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m} [w^\omega_p + (y^\omega_p - s^\omega_p)] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L^\omega \\
\text{subject to} & \quad \sum_{c \in C} x^\omega_{pc} = 1 \\
& \quad a_p + w^\omega_p + y^\omega_p + t^\omega_p = d^\omega_p \\
& \quad a_p + w^\omega_p + M(3 - x^\omega_{pc} - x^\omega_{p'c} - z^\omega_{p'p}) \geq d^\omega_{p'} \\
& \quad a_p + w^\omega_p + M(1 - z^\omega_{p'p}) \geq a_{p'} + w^\omega_{p'} + s^\omega_{p'} \\
& \quad a_p + w^\omega_p + M(1 - z^\omega_{p'p}) \geq a_{p'} + w^\omega_{p'} \\
& \quad a_p + w^\omega_p + R^\omega_p + M(1 - z^\omega_{p'p}) \geq a_{p'} + w^\omega_{p'} + R^\omega_{p'} + \text{mix}^\omega_{p'} \\
& \quad L^\omega \geq d^\omega_p \\
& \quad (a_{p'} - a_p) + M z^\omega_{p'p} \geq 0 \\
& \quad z^\omega_{pp'} = 1 - z^\omega_{p'p} \\
& \quad y^\omega_p \geq s^\omega_p \\
& \quad y^\omega_p \geq R^\omega_p + \text{mix}^\omega_p \\
\end{align*}
\]

Definition of variable \( y^\omega_p \)
Stochastic Programming Model
Sample Path Approximation

\[
\begin{align*}
\text{min} & \quad \lambda \sum_{p \in P} \sum_{\omega \in \Omega} \frac{1}{m}[u^\omega_p + (y^\omega_p - s^\omega_p)] + (1 - \lambda) \sum_{\omega \in \Omega} \frac{1}{m} L^\omega \\
\text{subject to} & \quad \sum_{c \in C} x^\omega_{pc} = 1 \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad a_p + u^\omega_p + y^\omega_p + t^\omega_p = d^\omega_p \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad a_p + u^\omega_p + M(3 - x^\omega_{pc} - x^\omega_{p'c} - z^\omega_{p'p}) \geq d^\omega_{p'} \quad \forall c \in C, \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + u^\omega_p + M(1 - z^\omega_{p'p}) \geq a_{p'} + u^\omega_{p'} + s^\omega_{p'} \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad a_p + u^\omega_p + R^\omega_p + M(1 - z^\omega_{p'p}) \geq a_{p'} + u^\omega_{p'} + R^\omega_{p'} + \text{mix}^\omega_{p'} \quad \forall p, p' \in P, \forall \omega \in \Omega \\
& \quad L^\omega \geq d^\omega_p \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad (a_{p'} - a_p) + M z^\omega_{p'p} \geq 0 \quad \forall p, p' \in P \\
& \quad z^\omega_{pp'} = 1 - z^\omega_{p'p} \quad \forall p, p' \in P \\
& \quad y^\omega_p \geq s^\omega_p \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad y^\omega_p \geq R^\omega_p + \text{mix}^\omega_p \quad \forall p \in P, \forall \omega \in \Omega \\
& \quad x^\omega_{pc} \in \{0, 1\} \quad \forall c \in C, \forall p \in P, \forall \omega \in \Omega \\
& \quad z^\omega_{p'p} \in \{0, 1\} \quad \forall p, p' \in P \\
& \quad a_p \geq 0 \quad \forall p \in P \\
& \quad u^\omega_p, d^\omega_p, R^\omega_p \geq 0 \quad \forall p \in P, \forall \omega \in \Omega 
\end{align*}
\]

Binary and non-negativity constraints
Stochastic Programming Model
Tractability

- Stochastic MIP model
  - Large number of constraints
  - Using big M in constraints results in weak relaxations

- Stochastic LP model assuming a fixed sequence of patients (e.g. LPT)
  - Eliminate $z_{p'p}$ and $x_{pc}^\omega$ decision variables
Results

Total time of Infusion Center operation (hrs)

Avg. waiting time for each Patient (mins)
Results
Conclusions

• Key aspects of the infusion center scheduling process can be approximated as a two stage stochastic integer program

• Fixing sequencing decisions based on LPT results in an easy to solve continuous stochastic program that performs well compared to current practice and other heuristics

• The LPT sequence is near optimal when compared to solvable instances of the MIP model for a small number of scenarios
Future Steps

• Improve stochastic MIP model
• Development of a heuristic that can be easily implemented by schedulers
• Enhancing simulation model
  – Addition of oncology clinic
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