## Optimization of Surgery Delivery Systems

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June 2, 2009

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Supported by National Science Foundation - DMI 0620573

## Summary

- Optimization models for surgery planning and scheduling
- Stochastic Programming:
- Problem 1: Single OR scheduling
- Problem 2: Multi-OR Surgery Allocation
- Simulation Optimization:
- Problem 3: Bi-criteria patient appointment scheduling
- Future research


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## Surgery Process

- 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

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## Outpatient Procedure Center


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## Complicating Factors

- Many types of resources to be scheduled: OR team, equipment, materials
- High cost of resources and fixed time to complete activities
- Large number of activities to be coordinated in a highly constrained environment
- Uncertainty in duration of activities
- Many competing criteria


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## Intake, Surgery, and Recovery



# Problem 1: Single OR Scheduling 

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## Single OR Scheduling - $\mathrm{S}(\mathrm{n}) / \mathrm{G}(\mathrm{n}) / 1$

Planned OR Time


Min\{ Idling + Waiting + Overtime\}

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## Stochastic Optimization Model



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## Stochastic Linear Program

$$
\min \left\{E_{Z}\left[\sum_{i=2}^{n} c_{i}^{w} w_{i}+\sum_{i=2}^{n} c^{s} s_{i}+c^{L} l\right]\right\}
$$

$$
\begin{aligned}
& \text { s.t. } w_{2}-s_{2} \\
& =Z_{1}-x_{1} \\
& -w_{2}+w_{3} \quad-s_{3} \quad=Z_{2}-x_{2} \\
& \begin{array}{lll}
\ddots & \ddots & \\
& \ddots & \ddots \\
& \\
& -w_{n} & -s_{n}+l-g=Z_{n}-d+\sum_{j=1}^{n-1} x_{i}
\end{array} \\
& x_{i} \geq 0, w_{i} \geq 0, s_{i} \geq 0, i=1, \ldots, n, \quad l, g \geq 0
\end{aligned}
$$

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## Two Stage Recourse Problem

Initial Decision (x) Uncertainty Resolved Recourse (y)

$$
\begin{aligned}
& \min \left\{Q(\mathbf{x})=E_{\mathbf{Z}}[Q(\mathbf{x}, \mathbf{Z})]\right\} \\
& \left.Q\left(\mathbf{x}, \mathbf{Z}^{k}\right)=\min \boldsymbol{\phi} \cdot \mathbf{y}^{k} \mid T \mathbf{x}+W \mathbf{y}^{k}=\mathbf{h}^{k}, \mathbf{y}^{k} \geq 0\right\} \\
& \left(\begin{array}{llllll}
T & W^{1} & & & \\
T & W^{2} & & & \\
T & & W^{3} & & \\
& & & & & \\
\\
T & & & & & \\
\hline
\end{array}\right.
\end{aligned}
$$

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## Example

- Comparison of surgery allocations for $n=3$, 5,7 with i.i.d. distributions with $U(1,2)$ :

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## Surgical Suite Decisions

- How to design the suite (intake rooms, recovery rooms, ORs)
- Number of cases to schedule
- Number of ORs and staff to activate each day
- Surgery-to-OR assignment decisions
- Scheduling patients arrivals



# Problem 2: Multi-OR Surgery Allocation 

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## Multi-Operating Room Scheduling



Decisions:
-How many operating rooms (ORs) to open?
-Which OR to schedule each surgery in?
Performance Measures:
-Cost of operating rooms opened

- Overtime costs for operating rooms


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## Extensible Bin Packing

$$
x_{j}=\left\{\begin{array}{l}
1 \text { if OR } j \text { open } \\
0 \text { if OR } j \text { closed }
\end{array} \quad y_{i j}=\left\{\begin{array}{l}
1 \text { if Surgery i assigned to OR } j \\
0 \text { Otherwise }
\end{array}\right.\right.
$$

$$
\begin{array}{ll}
Z=\min \left\{\sum_{j=1}^{m} c^{f} x_{j}+c^{v} o_{j}\right\} \\
\text { s.t. } \quad y_{i j} \leq x_{j} \quad \forall(i, j) \\
& \sum_{j=1}^{m} y_{i j}=1 \quad \forall(i) \\
& \sum_{i=1}^{n} d_{i} y_{i j}-o_{j} \leq T_{j} x_{j} \quad \forall(i, j) \\
& y_{i j}, x_{j} \in\{0,1\}, \quad o_{j} \geq 0
\end{array}
$$

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## Symmetry

- m! optimal solutions:

- Anti-symmetry constraints:

| $x_{1} \geq x_{2}$ |  |
| :---: | :---: |
| $x_{2} \geq x_{3} \quad$ OR Ordering |  |
| $\vdots$ |  |
| $x_{m} \geq x_{m-1}$ |  |

$$
\begin{array}{ll}
\hline y_{11}=1 & \\
y_{21}+y_{22}=1 & \text { Surgery } \\
\vdots & \text { Assignment } \\
\sum_{j=1}^{m} y_{m j}=1 &
\end{array}
$$

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## Two-Stage Stochastic MIP



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## Integer L-Shaped Method



Master Problem:
$Z=\min \left\{\sum_{j=1}^{m} c^{f} x_{j}+\Theta\right\}$

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

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

$$
y_{i j}, x_{j} \in\{0,1\}, \Theta \geq 0
$$

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## Heuristic and Bounds

Dell'Ollmo (1998) - 13/12 approximation algorithm for bin packing with extensible bins

EBP Heuristic:
$n \leftarrow L B ;$
repeat;
$L B=\left[\frac{\sum_{i=1}^{n} d_{i}}{T\left(1+\frac{c^{f}}{c^{v} T}\right)}\right\rceil$

$$
\begin{aligned}
& \text { LPT }(n) ; \quad \longrightarrow \begin{array}{l}
\begin{array}{l}
\text { sSort surgeries from longest } \\
\text { to shortest } \\
\text { sSequentially apply } \\
\text { surgeries to emptiest room }
\end{array} \\
\text { if }\left(o_{j}=0, \forall j\right) \text { Stop } ; \\
n \leftarrow n+1 ;
\end{array}
\end{aligned}
$$

end(repeat);

## Robust Formulation

$$
\left.\begin{array}{c}
Z=\min \left\{\sum_{j=1}^{m} c^{f} x_{j}+F(x, y)\right\} \\
\text { s.t. } \quad y_{i j} \leq x_{j} \quad \forall(i, j) \\
\sum_{j=1}^{m} y_{i j}=1 \forall(i) \\
y_{i j}, x_{j} \in\{0,1\} \geq 0
\end{array}\right\}\left\{\begin{array}{c}
\max _{\delta}\left\{\sum_{j=1}^{m} \eta_{j}\right\} \\
F(x, y)=\left\{\begin{array}{c}
\eta_{j}=c_{j}^{v} \max \left\{0, \sum_{i: y_{j}=1}^{m} \delta_{i j} y_{i j}-T_{j} x\right. \\
\sum_{(i, j): y_{j}=1}^{m} \frac{\delta_{i j}-\underline{d}_{i}}{d_{i}-\underline{d}_{i}} y_{i j} \leq \tau \\
\underline{d}_{i} \leq \delta_{i j} \leq \bar{d}_{i}, \forall(i, j): y_{i j}=1
\end{array}\right.
\end{array}\right.
$$

|  | 15 surgery instances |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Variable Cost $=0.033$ |  |  |  |  | Variable Cost $=0.0083$ |  |  |  |  |
|  |  |  | Robust 1 P |  |  |  |  | Robust P |  |  |
| Instance | MV_P | LPT_Heu | Taul2 | TauF 4 | TauF | MN_P | LPT_Heu | Tau=2 | Taul | Tau=6 |
| 1 | 0.808 | 0.806 | 0.892 | 0.906 | 0.933 | 0.999 | 0.998 | 0.880 | 0.948 | 0.948 |
| 2 | 0.953 | 0.966 | 0.898 | 0.896 | 0.970 | 0.999 | 0.999 | 0.999 | 0.999 | 0.980 |
| 3 | 0.854 | 0.852 | 0.936 | 0.937 | 0.970 | 0.999 | 0.999 | 0.929 | 0.952 | 0.94 |
| 4 | 0.925 | 0.972 | 0.911 | 0.971 | 0.917 | 0.999 | 0.998 | 0.930 | 0.930 | 0.929 |
| 5 | 0.896 | 0.946 | 0.831 | 0.916 | 0.892 | 0.990 | 0.996 | 0.932 | 0.938 | 0.924 |
| 6 | 0.862 | 0.853 | 0.923 | 0.931 | 0.938 | 0.989 | 0.990 | 0.886 | 0.881 | 0.881 |
| 7 | 0.930 | 0.936 | 0.810 | 0.930 | 0.817 | 0.973 | 0.993 | 0.84 | 0.974 | 0.927 |
| 8 | 0.888 | 0.966 | 0.876 | 0.903 | 0.904 | 0.966 | 0.966 | 0.966 | 0.987 | 0.939 |
| 9 | 0.962 | 0.966 | 0.964 | 0.969 | 0.964 | 0.975 | 0.993 | 0.847 | 0.960 | 0.95 |
| 10 | 0.860 | 0.924 | 0.910 | 0.893 | 0.918 | 0.997 | 0.996 | 0.900 | 0.901 | 0.903 |
| average | 0.894 | 0.919 | 0.895 | 0.925 | 0.922 | 0.988 | 0.993 | 0.916 | 0.951 | 0.933 |
| stidev | 0.046 | 0.057 | 0.047 | 0.028 | 0.046 | 0.013 | 0.010 | 0.059 | 0.045 | 0.028 |
| max | 0.962 | 0.972 | 0.964 | 0.971 | 0.970 | 0.999 | 0.999 | 1.042 | 1.040 | 0.980 |
| min | 0.808 | 0.806 | 0.810 | 0.893 | 0.817 | 0.966 | 0.966 | 0.84 | 0.881 | 0.881 |

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## General Insights

- The fast LPT based heuristic works (fairly) well on a large number of instances
- LPT works very well when overtime costs are low
- LPT is better (and easier) than solving MV problem in most cases
- Robust IP is better than LPT but worse than Stochastic IP


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## Current Research: Setups and Parallel Processing



## Problem 3: Patient Arrival Scheduling

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## Endoscopy Suite



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## Simulation-optimization Summary

- Decision variables: scheduled start times to be assigned to $n$ patients each day
- Goal: Generate the set of non-dominated schedules to understand tradeoffs between waiting and session length
- Schedules generated using a genetic algorithm (GA)
- Non-dominated sorting used to identify the Pareto set and feedback into GA


## Pareto Set

- Non-dominated sorting genetic algorithm of Deb et al.(2000) is used for ranking



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## Selection Procedure

- Sequential two stage indifference zone ranking and selection procedure of Rinott (1978) is used to compute the number of runs sufficient to determine whether a solution $i$ "dominates" $j$
- Solution $i$ "dominates" $j$ if:

$$
E\left[W_{i}\right]<E\left[W_{j}\right] \text { and } E\left[L_{i}\right]<E\left[L_{j}\right]
$$

## Genetic Algorithm

- Main features of the GA:
- Randomly generated initial population of schedules
- Single point crossover:

- Mutation
- Selection based on 1) ranks and 2) crowding distance


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## Example

Solutions in Criteria Space


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## Numerical Results



## Current and Future Research

- Investigating new stochastic programming and robust optimization formulations and methods
- Dynamic (online) scheduling problems
- Surgical suite design and re-configuration


## Questions?

