7-7-2017

Maximizing Operating Room Performance Using Portfolio Selection

Vivek Reddy Gunna
University of Kentucky, vivekreddy.gunna@uky.edu

Amin Abedini
University of Kentucky, a.abedini@uky.edu

Wei Li
University of Kentucky, wei.mike.li@uky.edu

Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 10 (2017) 83 – 91

Procedia MANUFACTURING

45th SME North American Manufacturing Research Conference, NAMRC 45, LA, USA

Maximizing operating room performance using portfolio selection

Vivek reddy Gunna[a], Amin Abedini[a] and Wei Li[a*]

[a]Department of Mechanical Engineering, University of Kentucky, Lexington, KY, 40506, USA

Abstract

The operating room (OR) is responsible for most hospital admissions and is one of the most cost and work intensive areas in the hospital. From recent trends, we observe an ironic parallel increase among expenditure and waiting time. Therefore, improving OR scheduling has become obligatory, particularly in terms of patient flow and benefit. Most of the hospitals rely on average patient arrivals and processing times in OR planning. But in practice, variations in arrivals and processing times causes high instability in OR performance. Our model of optimization provides OR schedules maximizing patient flow and benefit at a fixed level of risk using portfolio selection. The simulation results show that the performance of the OR has a direct relationship with the risk.

Peer-review under responsibility of the organizing committee of the 45th SME North American Manufacturing Research Conference

Keywords: operating room; scheduling; patient flow; benefit; risk;

1. Introduction

Operating room (OR) scheduling is important because of rising demand, increasing healthcare costs and waiting lists. U. S. healthcare expenditure was increased by $ 0.2 trillion in years 2014-15 [1] and waiting time is increasing every year [2]. Ironically, in spite of increasing expenditure, hospitals are unable to reduce the waiting time. The OR is one of the most cost and work intensive areas of a hospital. The ORs are the primary reason for almost 70% of all hospital admissions [3] and account for more than 40% of a hospital's total revenue [4, 5]. Therefore, one way to decrease the expenditure and waiting time is to improve the OR scheduling. Consequently, OR managers are urged to develop an efficient OR schedule in order to increase the patient flow (number of patients served) and to maximize benefits (revenue minus cost).

There are three main phases of OR scheduling; planning in long term, sequencing in short term, and adaptive control in real time. OR planning deals with the allocation of surgical services to OR block times and relative resources, such as human resources, facilities, and equipment. Sequencing mainly deals with the order of cases to be served. Adaptive control is about resource re-allocation and re-sequencing resulting from dynamic disturbances in

Peer-review under responsibility of the organizing committee of the 45th SME North American Manufacturing Research Conference
doi:10.1016/j.promfg.2017.07.028

healthcare systems, such as variations in processing times, and fluctuations in patient arrivals, e.g., no shows, cancellations and/or emergencies. As the other two phases down the line are directly impacted by the planning phase, it is inevitable to focus on OR planning. However, variations in patient arrivals and processing times always makes it difficult to realize the actual OR plan.

The common practice in hospitals is to use mean arrival and processing times for OR planning [6]. However, in a highly stochastic health care system, it is necessary to account for variations in patient arrivals and processing times [7]. In this paper, to deal with the dynamics in processing times and patient arrivals, we propose an optimization model for OR block scheduling by using the portfolio selection (PS) technique to maximize patient flow and benefit.

The rest of this paper is organized as follows. Section 2 provides a brief literature review on OR block scheduling. Section 3 presents our PS model for OR block scheduling. Section 4 explains the case studies, and Section 5 draws conclusion and future work.

2. Literature review

Investors who invest in stock markets usually use mean-variance portfolio theory [8] to create their portfolio. Portfolio is a combination of stocks with different weightages. Using historical data, Stocks are selected based on both expected return and standard deviations of expected return. Portfolio selection is the process of choosing a portfolio by gauging various portfolios with different weightage for stocks in terms of risk and reward. The rewards are the expected returns from the portfolio, and the risk is the standard deviation of expected return (fluctuation). The objective of portfolio selection is to maximize the reward at fixed risk level, or to minimize the risk at a fixed reward level.

We can draw an analogy between choosing different stocks with weightages in a portfolio to choosing a case mix for OR planning. Case mix specifies the number of patients to be served of each surgical service. Finding the case mix has been studied by researchers, Wagner et al. [9], discussed the possibility of formulating the hospital case mix selection problem (HCMSP) as a product-mix problem. Blake et al. [10], proposed a goal programming approach to solve the HCMSP from cost and volume perspectives at the planning phase. However, these case mixes are mainly formulated based on deterministic data, thus are given little significance for the variations in arrival and processing times. Dexter et al. [11], Dexter et al. [12], and Cardeon et al. [13], discussed that OR utilization is highly unstable under the presence of high variations in processing times and patient arrivals. Therefore, variations in processing times and arrivals should be taken into account during the OR block scheduling.

Regarding the application of portfolio selection in the healthcare systems, Van Houdenhoven et al. [14] used portfolio effect and mathematical algorithms to reduce the total required OR times. Hans et al. [15], proposed a concept of planned slack time to maximize utilization and minimize the risk of overtime, under the presence of variations in processing times. Dexter et al. [16] addressed the problem of OR capacity expansion using mean-variance analysis for a portfolio of surgeons, according to their contribution margin per OR hour. Dental et al [17] used stochastic programming to find the lower/upper bounds of the number ORs to be opened to minimize the amount of overtime. Erdogan et al [18] presented an extensive review on the current trends and challenges in health care management system Most of the researches, only considered the variations in the processing time to achieve different objectives, such as maximizing utilization, benefit, and number of patient served, while few considered the variation in patient arrivals. We propose a PS model that takes variations in both arrival and processing time into account, in order to maximize patient flow and benefit.

3. Optimization model for block scheduling

Two steps are involved in our PS model of OR block scheduling. First, using portfolio selection and historical data, we find the optimal case mix. Second, we formulate an optimization model to generate the OR block schedules on the weekly time horizon.

Nomenclature

g	Index of groups $g \in \{1,2,..,\mathrm{G}\}$

d	Index of Days $d \in \{1,2,..,\mathrm{D}\}$
o	Index of operating room number $o \in \{1,2,..,\mathrm{O}\}$
w	Index of week $w \in \{1,2,..,\mathrm{W}\}$
n	Number of weeks
X	$1\times g$ Weightage matrix of cases for group g in the case mix: $[w_1 \quad w_2 \quad \cdots \quad w_g]$
$\bar{S}_g$	Average number of cases served for group g from historical data
S	$g\times 1$ matrix with average number of cases served for group g:$[\overline{S_1} \quad \overline{S_2} \quad \ldots \quad \overline{S_g}]^T$
$S_{g,w}$	Number of cases served for group g in a week w
$S^*_{g,w}$	Deviation of Number of cases served for group g in a week w from mean
σ_g	Standard deviation of number of cases served for group g in a week
s	$g\times g$ Variance covariance matrix for case mix
σ	Fixed limit of risk
E	Expected reward
$N_{d,o,g}$	Number of cases of group g in OR number o on day d
$Y_{d,o}$	$1\times g$ matrix of Number of cases of groups g in OR number o on day d; $[N_{d,o,1} \quad N_{d,o2} \quad \cdots \quad N_{d,o,g}]$
R_g	Revenue generated by one case of group g
$B_{d,o}$	Block time on day d and OR number o
C	Regular operating cost per minute within block time
$O_{d,o}$	Expected Overtime on day d in OR number o
Z	Overtime operating cost per minute beyond block time
$T_{d,o}$	Maximum permissible overtime in OR o on day d
q	the variance covariance matrix for the processing times of groups
$t_{g,w}$	Average processing time for surgical group g in week w
$\overline{t_g}$	Overall average processing time for group g
T	$g\times 1$ matrix with Overall average processing time for group g:$[\overline{t_1} \quad \overline{t_2} \quad \ldots \quad \overline{t_g}]^T$
$t^*_{g,w}$	Deviation of processing time for surgical group g in week w from mean
p_g	Standard deviation of processing time of group g
V	Total budget available for the week

The input variables of our optimization model are the average number of cases served $\overline{S_g}$ for each group obtained by dividing the total number of cases served by the number of weeks, variance covariance matrix of the case mix *s*, standard deviation of cases served, overall average processing time$\overline{t_g}$, variance covariance matrix of processing times *q*, standard deviation of processing times p_g which are derived from the historical data. Revenue generated from serving one case of each group R_g , budget, and limits on costs and total permissible over time are the constants. Our decision variables are the weightage matrix *X*, block times of ORs on each day $B_{d,o}$, expected overtime $O_{d,o}$ on day d in OR number o and the matrix of Number of cases of groups g in OR number o on day d: $Y_{d,o}$.

3.1. Step 1: To find the optimal case mix

Using the historical data: it constitutes the information about the number of cases served, processing times in OR of each surgical service in a week over a period of one year we grouped various surgical services into groups as suggested in [19] to allow flexibility at the adaptive control phase, and to reduce the computational complexity. Surgery services are grouped based on similar characteristics, such as required equipment and resources, arrival rate, processing times, historic service data etc. To demonstrate our model, we grouped surgical services into group's g relying on the average number of cases served per week $\overline{S_g}$ (1).

$$\bar{S}_g = \frac{\sum_{w=1}^{W} S_{g,w}}{n} \quad \forall g = \{1, 2\ldots, G\} \tag{1}$$

$$S_{g,w}^{*} = S_{g,w} - \overline{S_g} \tag{2}$$

$$s = \frac{1}{n}\begin{bmatrix} S_{1,1}^{*} & S_{2,1}^{*} & \cdots & S_{g,1}^{*} \\ S_{1,2}^{*} & S_{2,2}^{*} & & S_{g,2}^{*} \\ \vdots & & \ddots & \vdots \\ S_{1,w}^{*} & S_{2,w}^{*} & \cdots & S_{g,w}^{*} \end{bmatrix}^{T} \begin{bmatrix} S_{1,1}^{*} & S_{2,1}^{*} & \cdots & S_{g,1}^{*} \\ S_{1,2}^{*} & S_{2,2}^{*} & & S_{g,2}^{*} \\ \vdots & & \ddots & \vdots \\ S_{1,w}^{*} & S_{2,w}^{*} & \cdots & S_{g,w}^{*} \end{bmatrix} \tag{3}$$

From the historical data, we derive average number of case served $\overline{S_g}$ for each group variance covariance matrix of the served cases s is given by equation (3). Our PS optimization model is given by equations (4-8). The output of this model is the case mixes with their respective risks and rewards.

$$\text{Maximize: } E = XS \tag{4}$$

Subject to:

$$\sum_{g=1}^{G} w_g = 1 \tag{5}$$

$$\left(\frac{\overline{S_g}}{\sum \overline{S_g}} - 3\left(\frac{\sigma_g}{\sum \overline{S_g}}\right)\right) \leq w_g \leq \left(\frac{\overline{S_g}}{\sum \overline{S_g}} + 3\left(\frac{\sigma_g}{\sum \overline{S_g}}\right)\right) \tag{6}$$

$$\sqrt{XsX^{T}} \leq \sigma \tag{7}$$

$$w_g \geq 0 \tag{8}$$

The objective function (4) maximizes the expected reward (represents the value of expected patient flow in a week). Constraint (5) imposes that the sum of the weightages should be equal to one. In constraint (6) we assume that the weightage of cases for a group g varies within three standard deviations i.e. in range of 95% confidence interval. Constraint (7) ensures that the risk of the case mix is less than or equal to the fixed risk limit σ (standard deviation of expected reward). Constraint (8) ensures that the weightage of each surgical group is greater than or equal to zero.

3.2. Step 2: To generate OR block scheduling

This step is to allocate OR block times to case mixes with the objective of maximizing benefit. To alleviate the impact of variations in processing times, we used the concept of planned slack as proposed by Hans et al. [14]. Planned slack is an additional block time provided in the OR block to prevent processing times from exceeding the regular OR block time, thus avoiding the overtime costs. A typical OR block consists of cases of services, planned slacks, idle time and overtime. For example, in Fig. 1, an OR has two cases, where t_1 and t_2 are mean processing times, with planned slack (allocated to absorb variation in t_1 and t_2 in real time), idle time and over time.

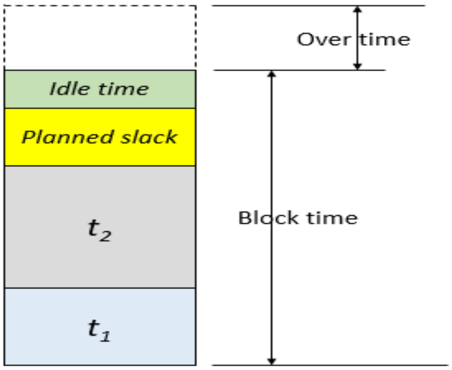

Figure 1: A typical OR block

Planned slack is calculated by substituting variance covariance matrix of processing times q (10) in equation (11).

$$t^*_{g,w} = t_{g,w} - \overline{t_g} \tag{9}$$

$$q = \frac{1}{n}\begin{bmatrix} t^*_{1,1} & t^*_{2,1} & \cdots & t^*_{g,1} \\ t^*_{1,2} & t^*_{2,2} & & t^*_{g,2} \\ \vdots & & \ddots & \vdots \\ t^*_{1,w} & t^*_{2,w} & \cdots & t^*_{g,w} \end{bmatrix}^T \begin{bmatrix} t^*_{1,1} & t^*_{2,1} & \cdots & t^*_{g,1} \\ t^*_{1,2} & t^*_{2,2} & & t^*_{g,2} \\ \vdots & & \ddots & \vdots \\ t^*_{1,w} & t^*_{2,w} & \cdots & t^*_{g,w} \end{bmatrix} \tag{10}$$

$$Planned\ slack = \sqrt{Y_{d,o}\, q\, Y^T_{d,o}} \quad \forall\ d = 1, 2...D,\ o = 1, 2....\ O \tag{11}$$

Our optimization model is presented by equations (12-18), where weekly budget, block times, operating costs, ordinary operating cost, over time operating cost and case mix are input to determine the weekly block schedule.

$$maximize: \left(\sum_{d=1}^{D}\sum_{o=1}^{O}\sum_{g=1}^{G} N_{d,o,g}\, R_g\right) - \left[\left(\sum_{d=1}^{D}\sum_{o=1}^{O} B_{d,o}\, C\right) + \left(\sum_{d=1}^{D}\sum_{o=1}^{O}(O_{d,o})\, Z\right)\right] \tag{12}$$

Subject to:

$$\left[\left(Y_{d,o}T + \sqrt{Y_{d,o}\, q\, Y^T_{d,o}}\right)\right] \le [B_{d,o}] + O_{d,o} \quad \forall\ d = 1, 2...D,\ o = 1, 2....\ O \tag{13}$$

$$\left(\textstyle\sum_{d=1}^{D}\sum_{o=1}^{O} N_{d,o,g}\right) \ge w_g \textstyle\sum_{g=1}^{G} \overline{S_g} \tag{14}$$

$$O_{d,o} \le T_{d,o} \tag{15}$$

$$\left[\left(\textstyle\sum_{d=1}^{D}\sum_{o=1}^{O} B_{d,o}\, C\right) + \left(\textstyle\sum_{d=1}^{D}\sum_{o=1}^{O}(O_{d,o})\, Z\right)\right] \le V \tag{16}$$

$$N_{d,o,g} \ge 0 \text{ and are integers} \tag{17}$$

$$O_{d,o} \ge 0 \tag{18}$$

Objective function (12) maximizes the benefit (revenue minus cost). Equation (13) ensures that the sum of processing times of cases and planned slacks doesn't exceed the sum of block time and expected overtime. If the processing time of the cases allocated to an OR exceeds the block time, then it is considered as over time. In order to avoid the instances of overtime occurring, we allocate planned slack to absorb variation in processing times. Equation (14) sets a limit on the minimum number of patients to be served for each group g, in which wg is a weightage. Equation (15) ensures that the expected overtime does not exceed a predetermined limit based on management's preference. Equation (16) imposes that the sum of regular and overtime costs doesn't exceed the available budget. Equation (17) imposes that the number of cases processed in ORs must be a positive integer. Equation (18) ensures that overtimes are non-negative.

This is a mixed integer nonlinear programming because of a nonlinear constraint (13). Therefore, it takes more time to find the optimal solution. Hence, we converted this constraint to a linear constraint by approximating the planned slack to be the sum products of safety factor β and standard deviations of processing times, as suggested in [14]. The high parameter value of β reduces the risk of overtime. It ensures that more block time is allocated for the cases in an OR to avoid the risk of over time. For example, if the value of β is 2 then each case is packed into an OR with its mean processing time plus two times their standard deviation, thus avoiding risk the overtime due to the variation.

$$\left[\left(Y_{d,o}T + \sum_{g=1}^{G} N_{d,o,g}\, \beta p_g\right) - O_{d,o}\right] \leq \left[B_{d,o}\right] \quad (19)$$

$$\forall\ d = 1, 2... D,\ o = 1, 2.... O$$

In summary of our model, we have accounted for variation in patient arrival using the portfolio selection in step one. To absorb the variation of processing times, planned slack is allocated in ORs thus avoiding the risk of overtime. Though this model of optimization is explicitly dealing with generating the OR block scheduling for a week, it can also be extended to any time horizon depending on the historical data available and the ability to afford the computational expenditure.

4. Case study

University of Kentucky Health Care (UKHC) served almost 30,000 patients from 2013-14, which is approximately 500 cases in a week, excluding weekends and holidays. Patient flow and benefit are significant performance indicators at UKHC. Therefore, we intend to study the performance of OR in terms of patient flow and benefit for different case mixes generated using portfolio selection technique at their respective risk levels.

From the historical data, we have the number of cases of each surgical group served and processing times over a period of one year. There is an assumption behind the portfolio selection theory, which implies that the input data must follow normal distribution [8]. We grouped surgery services based on average number of served cases. To ensure the normality of input data, we use central limit theory (CLT), which states that when independent random variable are added, their sum tends towards normal distribution, even if the original variables themselves are not normally distributed. We grouped surgery services into three groups (large, medium, small). Data analysis showed that these groups followed normal distribution in terms of both number of cases processed per week and processing times, with a confidence interval greater than 95%.

By inputting the average number of cases served for group *g* in a week *Sg* and variance- covariance matrix of case mix into PS model, we get various case mixes with their respective risks and rewards. To observe the relationship between the risk and reward, we found different case mixes within ten equal intervals of risk.

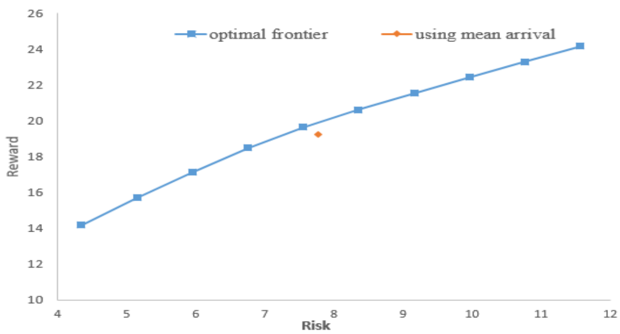

Figure 2: Reward by Risk

From Fig. 2, we observe that the graph is similar to the efficient frontier of portfolios in portfolio analysis; risk is directly proportional to the expected reward. This curve represents the optimal frontier of case mixes. We also observe that the Case mix generated using only the average arrival rates is below the optimal frontier, which means that there are other case mixes which can provide the same reward, but at a lower risk. We input case mixes from this optimal frontier in step two in order to obtain optimal resource allocation for each case mix.

We have evaluated the performance of each allocation in terms of patient flow and benefit in a week. We ran a simulation over the course of two hundred weeks with normally distributed random arrival rates and processing times for each group. These randomly generated inputs are plugged into each of the OR block schedules generated from the optimization model. Performance measures; patient flow and benefit are recorded for all two hundred weeks and average patient flow and average benefit are calculated. Along with average patient flow and benefit, the standard deviations and the control limits of fluctuation are compared at different risk levels.

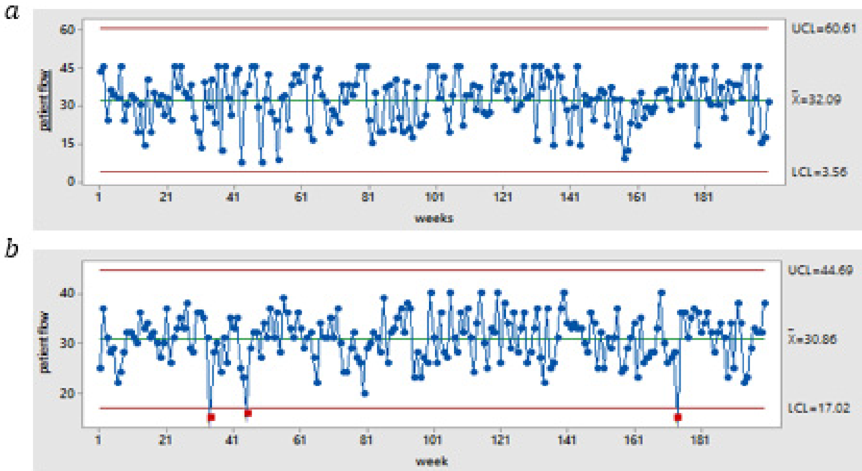

Figure 3: Simulation results of patient flow:(a) patient flow at highest risk for each week; (b) patient flow at lowest risk for each week

The range (UCL-LCL) represent the magnitude of fluctuation and the centre line represents the mean performance. Comparing the highest risk and lowest risk levels using Figures 3(a) and 3(b) shows that the average patient flow decreases from 32.09 to 30.86 and the range of fluctuation decreases from 57.05 to 27.67.

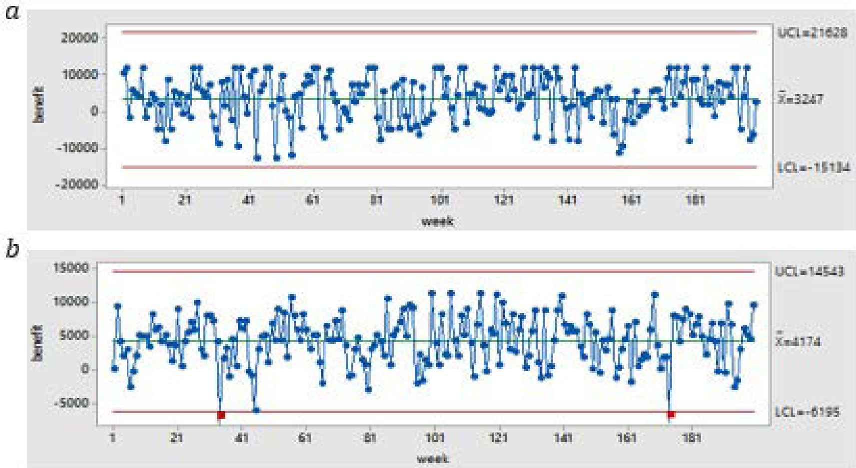

Figure 4: Simulation results of benefit: (a) benefit at the highest risk for each week;

(b) benefit at the lowest risk for each week

Comparing the highest risk and lowest risk levels using Figures 4(a) and 4(b) shows that the average benefit increase from 3247 to 4174, and the range of fluctuation decreases from $36762 to $20738.

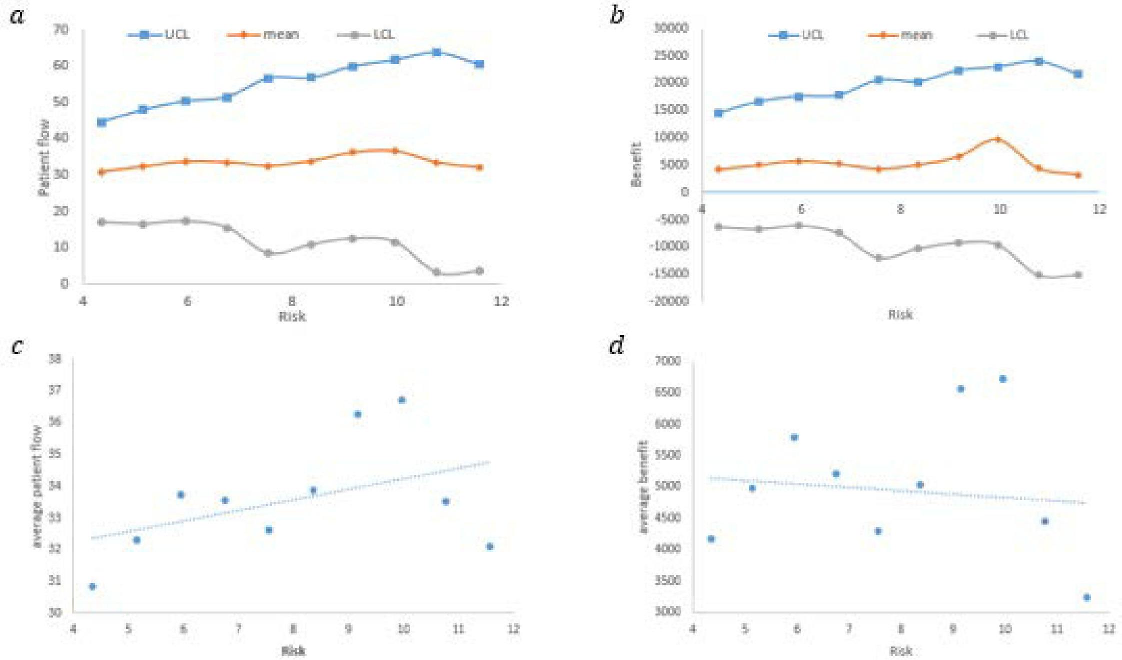

Figure 5: Simulation results of (a) Patient flow by risk; (b) Benefit by risk; (c)Average patient flow by risk; (d)Average benefit by risk

From simulation results in Fig. 5(a) and 5(b) we observe the behaviour of upper control limits (UCL), mean and lower control limit (LCL) of patient flow and benefit with respect to risk. We can observe that the fluctuation is directly proportional to the risk both in terms of patient flow and benefit. The mean patient flow is observed to be directly proportional to the risk which means that when we choose a case mix with high risk, we get higher mean patient flow with higher fluctuation and vice versa. However, the expected benefit is observed to be showing a reverse trend when compared to the patient flow. From Fig. 5(c) we observe the average patient flow is increasing with increasing risk and in Fig. 5(d) average benefit is decreasing with increasing risk.

Simulation results presents that there is no direct positive correlation between the patient flow and benefit, implying a trade-off between the objectives. In order to address this trade-off between the objectives, benefit should also be considered as an objective along with patient flow in generating the efficient frontier for the case mix. However, this model of optimization presents and proves a series of optimal decision for case mixes, which a hospital can adapt according to their appetite for risks and rewards.

5. Conclusion

OR scheduling is important, because of the rising demands, increasing expenditure and waiting times. ORs are liable for major proportion of admissions, therefore are the most work intensive and cost consuming area of hospitals. Most of the hospitals rely on average arrivals and processing times to carry out OR scheduling. However, variations in patient arrival and processing times makes the performance of OR schedule highly unstable in terms of patient flow and benefit. Hence, it is necessary to consider variations along with averages of patient arrivals and processing times at the OR planning phase.

In this paper, we proposed a model, which provides optimal OR schedules by taking average and variations of patient arrivals and processing times into consideration. Our model of optimization takes variations into account and maximizes patient flow and benefit at fixed level of risk. In the cases study, we found OR schedules to maximize patient flow and benefit at ten equal intervals of risk. Simulation results showed that the performance of OR schedules are proportional to the risk. Therefore, with the help of our model, hospital can take a qualitative decision in choosing the optimal OR schedule by gauging the risk and reward beforehand. Our future work will focus on developing the OR schedule with multiple objectives like minimizing waiting time, maximizing patient flow and benefit.

Acknowledgements

This project was supported by grant number R03HS024633 from the Agency for Healthcare Research and Quality. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Agency for Healthcare Research and Quality. We also appreciate the support from Department of Mechanical Engineering at University of Kentucky.

References

[1] Forbes. 2015. U.S. Healthcare Spending on Track to Hit $10,000 Per Person This Year. http://www.forbes.com/sites/danmunro/2015/01/04/u-s-healthcare-spending-on-track-to-hit-10000-per-person-this-year/#68cb103b294c, (2016).
[2] N. Viberg, B. C. Forsberg, M. Borowitz, R. Molin, International comparisons of waiting times in health care–Limitations and prospects. Health Policy, 112(1), (2013) 53-61.
[3] J. M. Ehrenfeld, F. Dexter, B. S. Rothman, B. S. Minton, D. Johnson, et al., Lack of utility of a decision support system to mitigate delays in admission from the operating room to the post anesthesia care unit. Anesthesia & Analgesia, 117(6), (2013) 1444-52.
[4] A. Peltokorpi, How do strategic decisions and operative practices affect operating room productivity? Health care management science, 14(4), (2011) 370-82.
[5] A. Abedini, H. Ye, W. Li, Operating Room Planning under Surgery Type and Priority Constraints. Procedia Manufacturing, 5, (2016) 15-25.
[6] F. Dexter, A. Macario, F. Qian, R. D. Traub, Forcasting surgical groups' total hours of elective cases for allocation of block time Application of time series analysis to operating room management. The Journal of the American Society of Anesthesiologists, 91(5), (1999) 1501-.
[7] D. Masursky, F. Dexter, C. E. O'Leary, C. Applegeet, N. A. Nussmeier, Long-term forecasting of anesthesia workload in operating rooms from changes in a hospital's local population can be inaccurate. Anesthesia & Analgesia, 106(4), (2008) 1223-31.
[8] Markowitz. H. M., 1991. Portfolio selection. Malden, M. A. John Wiley & Sons, Inc.
[9] H. M. Wagner, Principles of operations research: with applications to managerial decisions. In Principles of operations research: with applications to managerial decisions, (1969).
[10] J. T. Blake, M. W Carter, A goal programming approach to strategic resource allocation in acute care hospitals. European Journal of Operational Research, 140(3), (2002) 541-61.
[11] F. Dexter, R. D. Traub, How to schedule elective surgical cases into specific operating rooms to maximize the efficiency of use of operating room time. Anesthesia & Analgesia, 94(4), (2002) 933-42.
[12] F. Dexter, Operating room utilization: information management systems. Current Opinion in Anesthesiology, 16(6), (2003) 619-22.
[13] B. Cardoen, E. Demeulemeester, J. Beliën, Operating room planning and scheduling: A literature review. European journal of operational research, 201(3), (2010) 921-32.
[14] M. Van Houdenhoven, J. M. van Oostrum, E. W. Hans, G. Wullink, G. Kazemier, Improving operating room efficiency by applying bin-packing and portfolio techniques to surgical case scheduling. Anesthesia & Analgesia, 105(3), (2007) 707-14.
[15]E. Hans, G. Wullink, M. Van Houdenhoven, G. Kazemier, Robust surgery loading. European Journal of Operational Research,185(3), (2008) 1038-50.
[16] F. Dexter, J. Ledolter. Managing risk and expected financial return from selective expansion of operating room capacity: Mean-variance analysis of a hospital's portfolio of surgeons. Anesthesia & Analgesia, 97(1), (2003) 190-5.
[17]B. T. Denton, A. J. Miller, H. J. Balasubramanian, T. R. Huschka, Optimal allocation of surgery blocks to operating rooms under uncertainty. Operations research, 58(4-part-1), (2010) 802-16.
[18] S. A. Erdogan, B. T. Denton, J. J. Cochran, L. A. Cox, P. Keskinocak, et al., Surgery planning and scheduling. Wiley Encyclopedia of operations research and management science, (2011).
[19] C. Price, B. Golden, M. Harrington, R. Konewko, E. Wasil, et al., Reducing Boarding in a Post-Anesthesia Care Unit. Production and Operations Management, 20(3), (2011) 431-41.