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Abstract

Purpose – This paper aims to identify key factors that impact operating room (OR) utilization and evaluate different scenarios on OR performance.

Design/methodology/approach – Five months of data were collected. stepwise regression and best subset models were used to select factors and generate regression model for OR utilization. We further used simulation to test the influence of case duration mean, case duration variation, scheduled utilization and first-case delay on OR utilization, OR cost inefficiency and patient wait time on the day of surgery.

Findings – The scheduled utilization, case cancellation and add-on cases were the most important factors identified in all models. The larger the case duration variation, the lower the OR cost efficiency and utilization, the longer the patient wait time. First-case delay and turnover times are not critical in OR utilization or cost efficiency.

Practical implications – OR management should focus on creating an effective way to manage case cancellation and add-on policy to tackle the change on the day of surgery. In addition, several weeks before the surgery, the management needs to consider how to schedule cases to fit the allocated OR time.

Originality/value – In complementary of current OR management, this research assists OR management by identifying the factors that would result in the most significant improvement on OR utilization.

Keywords Cost efficiency, Regression model, Best subset model, Health-care organization, OR utilization, Stepwise regression

Paper type Research paper

1. Introduction

The success of operating room (OR) management is important to a hospital in the sense that it has a high financial impact on the organization (Fei *et al.*, 2009). Currently, there are several defined measures for evaluating the performance of ORs, including staffing costs, daily OR start-time tardiness, case cancellation rate, turnover time, utilization and so on (Macario, 2006). Many health-care organizations in the USA work under a fixed budget such as the veteran affairs (VA) system and health-care systems in Europe. For such organizations, utilization needs to be maximized to maintain low cost. There are two types of utilization: raw utilization and adjusted utilization. Raw utilization is



calculated as total hours of cases performed within block time divided by allocated OR hours. The adjusted utilization takes in account setups and cleanups between cases, and it is defined as total hours of cases performed within block time plus “credit time” divided by allocated OR hours ([Dexter et al., 2003](#)). Our study is focused on OR utilization management. This typology of problem is usually tackled using Kaizen event ([Glover et al., 2011](#)) and Lean Six Sigma (LSS) projects ([Arcidiacono et al., 2012](#)).

From our previous experience, compared to other established metrics, utilization is relatively more difficult to significantly improve because of the complexity of correlations among different factors. As an effort to narrow down the factors management can focus on increasing the adjusted utilization of OR, we conducted this study.

Traditionally, OR utilization was defined as the ratio of hours the OR use to allocated OR hours ([Strum et al., 1997](#)), regardless of whether the use of the OR was outside of the allocated OR hours. However, the problem with this definition was that from a cost perspective, 10 hours used in the allocated OR hours is not the same as 10 hours used outside of the allocated OR hours because over-utilized OR time is more expensive. Observing this, [Strum et al. \(1997\)](#) proposed the concepts of under-utilized OR time and over-utilized OR time. Hours of under-utilized OR time equals the number of unused, allocated OR hours, and hours of over-utilized OR time is the number of OR hours used beyond the allocated OR hours. Utilization only gives credit to the usage within the allocated OR hours, and any over-utilized time is not counted. In the cost model developed in this paper, a minimum OR cost is achieved by balancing the costs of under-utilized and over-utilized OR time.

Based on the concept brought up in this paper, researchers proposed solutions for how to schedule cases ([Dexter and Traub, 2002](#); [Dexter et al., 1999](#)), how to release the allocated OR time ([Dexter et al., 2003](#); [Dexter and Macario, 2004](#)) and how to make decisions on the day of surgery ([Dexter et al., 2004](#); [Dexter and Traub, 2000](#)) to maximize OR cost efficiency, where cost efficiency is calculated as the summation of the cost of under-utilized OR hours plus the cost of over-utilized OR hours. In a review paper by [McIntosh et al. \(2006\)](#), several interventions were studied with respect to their impacts on efficiency. It was concluded that interventions to address either turnover or first-case delays will only result in a small reduction in OR labor costs, but the degree of reduction is highly related with OR allocation. Appropriately allocating OR hours is the most important step to maintain cost efficiency. The review paper described detailed steps for calculating the change in costs from the intervention. [Dexter and Epstein \(2009\)](#) used the same methods to propose a screening mechanism to quantify the potential savings from the reduction of tardiness at the beginning of the workday for ORs with workloads greater than 8 hours (i.e. with over-utilized OR time). By using this method, the OR team can evaluate the economic impacts of improving on-time performance of first case and determine whether focusing on starting the workday on time is the right decision economically, or whether to practice other interventions.

The first-case delays were not a strong indicator of the performance on OR cost efficiency. However, not significantly impacting the efficiency is not equivalent to not significantly impacting the utilization performance. For example, given that the ratio of under-utilized OR hours to over-utilized OR hours is 1 to 2, then for an OR allocated 8 hours (e.g. 8 a.m. to 4 p.m.), a day close at 2 p.m. (i.e. two under-utilized OR hours) is equivalent to a day close at 5 p.m. (i.e. one over-utilized OR hours). If there is a delay of

1 hour for the room closing at 2 p.m., it does not impact the overall utilization, as the delay postpones the OR closing to 3 p.m., but still, all cases can be done within the allocated OR hour. On the other hand, if a delay is observed for the latter case, then the first-case delay matters, as the delay may cause some time that could otherwise be within the allocated OR hours to become over-utilized OR time, thus decreasing the utilization. In this study, we want to test whether the first-case delay is one of the most important factors that influence utilization.

Bias in the case duration prediction distorts the operation of OR suites. Underestimation of case duration causes long wait times of sequential patients and may cause cancellations of cases scheduled at the end of day (Pandit and Carey, 2006). Surgeons may tend to underestimate surgery duration to fit cases into the allocated OR time (Dexter and Macario, 2004), (Abouleish *et al.*, 2002). Overestimation leaves OR staff idle, reducing utilization and cost efficiency. Thus, it is important to monitor bias in case duration prediction. Dexter *et al.* (2005) developed a method to assist the measure of bias. In this paper, the number of minutes of underestimated case duration per 8 hours of OR time was calculated for a four-week time interval. Although the case duration distribution has been identified as to follow log-normal distribution (Strum *et al.*, 2000; Strum *et al.*, 2003), but the average case duration underestimate follows a normal distribution (Dexter *et al.*, 2005). Thus, the lower 95 per cent confidence bound for average case duration underestimate can be calculated by using Student's *t*-distribution. Using this approach, McIntosh *et al.* (2006) studied whether some specialties have a tendency in bias case duration prediction, and it found out that the inefficiency was not due to bias in case duration prediction (because the bias was not large enough), but the workload itself. We first estimated the bias in case duration prediction using the data we collected from John D. Dingell Veteran Affairs Medical Center (VAMC) in Midtown Detroit to quantify the bias for the organization. Then, we tested the hypothesis if the case duration prediction at current biased/non-biased status impacts utilization performance.

With respect to utilization studies, there are several preceding in the literature. For example, Tyler *et al.* (2003) examined case duration, duration variability and turnover time on achieving optimal utilization by using simulation. They tested different scenarios such as higher case duration variability, longer turnover times, early start of case and combination of different cases. A higher variability of case durations results in a lower utilization. Turnover times do not impact utilization but the number of cases can. Dexter *et al.* (1999) identified factors influencing variability of day-to-day utilization. Seven summary statistics were calculated from data gathered from University of Iowa OR and ambulatory surgery centers. Structural equation modeling was used to establish relations among the statistics and related random effects, after which Monte Carlo simulation were applied to analyze the impacts of elimination of the random terms, combination of terms and allocated OR hours. The results from the analysis indicated that selecting the days to perform a procedure is the most important in the reduction of variability.

The previous studies focus on either the cost efficiency or various factors' effects on utilization. All these factors do not impact the adjusted utilization in the same way. Some are more influential than the others. Ideally, we would optimize the performance of all of them. However, given limited resources, it is beneficial to the management to identify top factors that impact utilization more than the others. In this way, resources will be

spent more productively. This is the main goal of this study, which is to pick out the most influential factors on adjusted utilization from their peers. We will use the data collected from the government health-care provider to demonstrate the methods to identify the most influential factors that impact utilization.

In the next section, we explain the data source and the methods we selected for analysis. Then, results will be shown, and discussions will be conducted for our conclusion.

2. Methods

2.1 Data

We have three sources of data; one is from the surgical package within the Veterans Health Information Systems and Technology Architecture in John D. Dingell VAMC. The second is the Computerized Patient Record System, which we used to gather the duration of cancelled cases, and the final one is the manual data sheet we designed to gather additional information on turnovers. The data we collected is from May 1, 2009 to September 30, 2009 (excluding weekends and the closings on Memorial Day on May 25 and July 3 for Independence Day). On August 26, 2009, the OR suites were closed due to water leakage. The first two working days did not have complete schedule information, so we also excluded these two days from the analysis. Thus, we have 102 days of data collected. The information technology department was able to develop a data-capturing program, so that we were able to obtain the following data fields: day of surgery, OR, specialty, patient in OR time, patient out OR time, schedule start time, schedule end time, cases cancelled and case type – i.e. elective, emergent, add-on and urgent (Figure 1). From the raw data, we are able to calculate the following variables:

- OR availability of each day (i.e. regularly staffed hours).
- OR scheduled hours of each day. One clarification that should be mentioned here is that in John D. Dingell VAMC, any case that is cancelled after 2 p.m. of the previous day is considered as a cancellation. We chose 2 p.m. as a threshold, and the scheduled hours include the performed elective cases, cancellations but not same-day add-on cases.

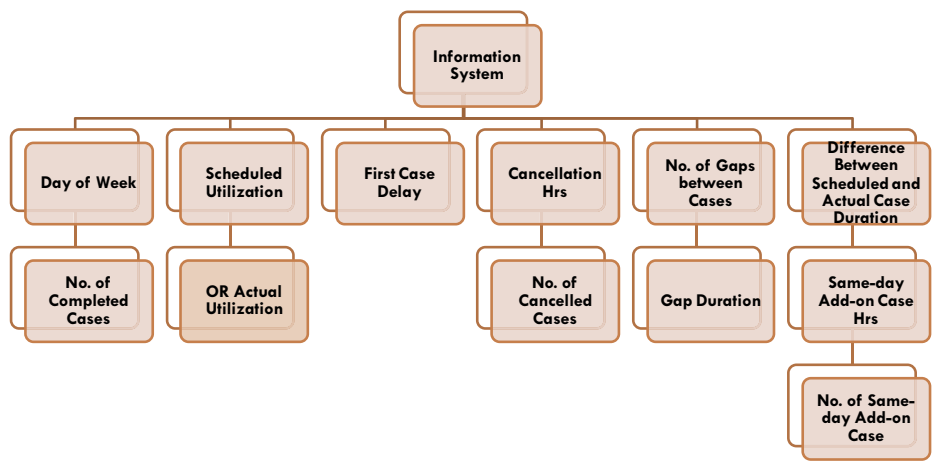


Figure 1.
Data Structure of
Our Study

- OR actual usage hours of each day. By definition of OR utilization, we only considered OR hours within regular hours. Over-utilized OR time was excluded.
- First-case delays of each day.
- Number of completed cases.
- Cancellation hours.
- Number of cancellations.
- Emergency case duration.
- Urgent case duration.
- Add-on case duration.
- Number of add-ons.
- The difference between actual case duration and scheduled case duration of performed cases.
- Scheduled utilization.
- Actual utilization.
- Number of turnovers.
- Total turnover durations.

The number of cases of each specialty is not comparable to each other. During our data collection period, general surgeons performed more cases than any other specialty, and gynecology has the fewest cases (Table I). The reason that we use data collection sheet is to identify outliers in turnovers. Delays such as equipment unavailability, pre-op not ready would add extra long time between cases; thus, for case turnovers that are longer than the average plus 15 minutes (McIntosh *et al.*, 2006), i.e. prolonged turnovers, we referred to the turnover data collection sheet and excluded the delays from turnovers. However, OR teams acted differently in the data collection efforts. Some teams were relatively more prone to providing good-quality data. Thus, it was not possible to accurately estimate the exact turnover delay times for each case. We decided to use the average of turnover times for each specialty to roughly get the turnover times for each day. Using the average turnover time to conduct the analysis is not expected to change

Specialty	No. of completed cases	No. of turnover times collected	Average turnover time
ENT	66	27	0:46
Gynecology	8	1	0:30
General	294	131	0:35
Ophthalmology	233	93	0:29
Oral	20	4	0:34
Orthopedics	150	62	0:48
Plastic	112	42	0:15
Podiatry	50	15	0:44
Thoracic	64	23	0:58
Urology	145	53	0:27
Vascular	84	34	0:50

Table I.
Case information of
each specialty

our conclusions because of the small number of turnover times and their short duration and less variability.

From the data, we identified eight potential factors that could influence the actual utilization:

- (1) *Workday of surgery*: It has been observed that the block schedule of each day is different, and the utilizations of specialties are not the same, so for each workday, the utilization is expected to be different.
- (2) *Scheduled utilization*: This is the baseline/starting point of utilization. If scheduled utilization is high, then there is a good chance that the actual utilization is also high.
- (3) *First-case delay*: If the day starts late, then there is an unutilized time period in the regular OR hour, which is expected to reduce utilization.
- (4) *Cancellation hours and number of cancellations*: They act negatively on the scheduling by reducing the OR scheduled hours. If fewer cases are scheduled, it is expected that the utilization will be lower.
- (5) *Total same-day add-on case duration and number of add-ons*: The add-on here, in our research, includes all emergent, urgent and add-on cases. They are the opposite of cancellations. If we add more cases, then the OR hours are more likely to be filled up.
- (6) *Daily difference between actual and scheduled case duration*: The bias in case duration prediction is also expected to impact the final utilization in such a way that if actual duration is less than scheduled duration, there is an unfilled hole in OR regular hours, causing utilization to go down; conversely, if the actual hours is greater than the scheduled duration, the close time of the OR will be delayed to increase the utilization when there is no overtime.
- (7) *Number of turnovers and turnover duration*: As we calculate the adjusted utilization in our study, if we have more turnovers/the turnovers take a long time, then the adjusted utilization is expected to increase.
- (8) *Number of completed cases*: The more cases we schedule, the more OR available hours are filled. It is also reasonable that when we have more cases, the case duration for each case is less, meaning the complexity of procedures are not very high; thus, the prediction of case duration is more accurate, so it is more likely to fill up the OR hours by scheduling many short cases.

2.2 Stepwise regression

From the previous section, we defined eight potential factors that can impact utilization. Among all the factors, some have greater impacts on the response than the others. It is the goal of this project to distinguish the most significant factors from the others. Stepwise regression is one of the widely used methods to identify key factors (Sarkar *et al.*, 2011; Montgomery *et al.*, 2001; Myers, 1990). This method first fits all possible one-variable models. By using the *t*-test, the independent variable with the largest *t*-value is considered as the best one-variable predictor of the response. Then, the two-variable model will be fitted by keeping the original selected predictor and selecting the second factor that has the largest *t*-value among the set of remaining factors. At this point, the model re-checks the significance of the first factor to see whether it remains

significant. If not, then this factor will be removed and another factor with the greatest absolute t -value in the presence of the second factor will be included in the model. This process continues, and more and more independent variables enter into the predictor set by adding one at a time. The process stops when no more variables yield significant t -values at a given α level (Mendenhall and Sincich, 2003; Weisberg, 1985). In their book, Mendenhall and Sincich (2003) argue that the stepwise regression is vulnerable to Type I/Type II errors due to the large amount of t -tests. However, because the studied hospital does not have patients waiting to have their surgery done, the scheduled utilization is not impacted by cancellation. Furthermore, add-on cases are primary from emergency department. They are not impacted by scheduled utilization or cancellation as well. As a result, the correlations among these factors are very limited. Thus, the potential risk of incorrect conclusion drawn from this analysis due to the correlated factors is not significant. To validate the results of stepwise regression, we apply all-possible-regressions selection procedure, which is more commonly called best subset method.

2.3 Best subset

In this approach, models with all possible combinations of independent variables are examined. For each number of included independent variables, the model with the highest R^2 value is selected. Based on the results, we select the model with relatively small mean squared error, good adjusted R^2 value and a small C_p value close to $p + 1$ (Mendenhall and Sincich, 2003).

2.4 Model validation

As with any other model, this model is useless unless validated. We applied the cross-validation method. This method split the data into two groups: a training set and a testing set. The former is used to establish the model. Using the generated model and testing it on the latter, we can check whether the model generates accurate enough predictions against observations. V-fold cross-validation indicates that the data set is split into V subsets. Each subset is used as a testing set once, and we used the remaining data as the training set to develop a model. The final model is the one that has the best performance in prediction accuracy measures. We have five months of data, and if data are collected sequentially in time, we can select a time point to divide the data (Snee, 1977). By using a four-year data set, Cady and Allen (1972) developed a corn yield prediction model. They used the first three years to build the model and tested on the last year. In the same manner, we divided our data by month. Each month's predicted values from the model derived from the other four months of data were tested against the observed values. Feng *et al.* (2005) used this best subset method combined with cross-validation to set a predictive model for honing surface roughness.

2.5 Prediction performance measures

There are a number of works of literature covering the criteria to select regression models (Montgomery *et al.*, 2001; Myers, 1990), such as R^2 , adjusted R^2 and Mallows's C_p statistics. We used the C_p value to select factors of best subset because for the best subset model, the best one should have a C_p value that is almost the same as the number of factors selected. R^2 and adjusted R^2 were also used to evaluate the goodness-of-fit of the regression model using the factors selected by best subset/stepwise regression. To select the best model, we calculated several prediction error evaluation metrics, including

prediction sum of squares (PRESS) (Miller, 1974), mean absolute deviation (MAD), mean absolute percent error (MAPE) and root mean squared errors (RMSE) (Chopra and Meindl, 2006). All these metrics present the degree of error in different perspectives. For example, PRESS is a cross-validation itself in regression. It is the sums of squares of the prediction residuals for observations not included in the model. MAD and MAPE measure the absolute and relative deviation from the observation. The model whose prediction has the least deviation from the observations was selected as the best one.

All analyses were performed on Microsoft Excel for preliminary data processing and Minitab Software for a statistical model building. The default Minitab alpha values (0.05) are used for the selection of variables.

2.6 Simulation

To have a better understanding of potential strategies to assist the facility in improving, a discrete-event simulation model was developed to evaluate what approach could be used to improve the performance with respect to utilization, cost efficiency and patient wait time on the day of surgery. The model was adopted from Tyler *et al.* (2003); however, we added first-case delay as one of the parameters in analysis to validate the results from statistical analysis. In the model, a single OR was analyzed, and it was assumed that the OR repeatedly does a single type of surgery. In a real scenario, the situation is more complex, as the cases are usually different, but it is infeasible to simulate by using real-case assignment data, as the realization of cases of each OR on each day is different. By simplifying the real scenario, our results will deviate some from practice, but the conclusions should not be influenced.

The scenarios were generated by varying parameters with respect to: case duration distribution, first-case delay and final scheduled utilization. In total, we have 72 scenarios. We first selected the most frequent case in our OR theater, eye cataract surgery for a particular surgeon, and used Arena 13, a discrete-event simulation software developed by Rockwell Automation, to fit a suitable distribution. Then, we generated hypothetically three other types of procedure duration by changing the coefficients of variation and mean. Figure 2 illustrates the types of durations. The distributions capture a large variety of case durations in the organization (the mean case duration for the hospital is 1 hour and 45 minutes, and the standard deviation of case duration is 1 hour and 24 minutes); thus, by comparing the results, our conclusions are expected to be robust enough. At present, the facility assigns 1 hour to this type of surgery; thus, the scheduled duration for Types 1 and 2 surgeries are 1 hour. As the mean durations for Types 3 and 4 are twice as those for Types 1 and 2, the scheduled duration is 2 hours.

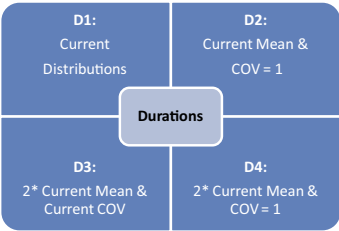


Figure 2.
Distributions of four
types of duration for
simulation

The first-case delay can be quantified by two parameters: percentage of delay and delay duration distribution. We assume that either 50 per cent of the first cases start on time or 10 per cent of the first cases start on time. If there is a delay, then the duration either follows a uniform distribution from 1 to 30 or from 1 to 60. From our observation, hardly any first cases were delayed by more than an hour (Figure 3).

We also adjusted the number of cases on the final schedule (including cancellation and add-ons). Similar to the previous work, a half-scheduled day was the baseline, and then, we added cases one by one until approximately 100 per cent scheduled. For example, as in Figure 4, if the OR is scheduled for 8 hours, and on average, the duration of the case is 1 hour, then we start by having four cases scheduled. After that, we add one case at a time, until the OR cannot fit more cases.

The turnover duration we used for our analysis is a constant 15 minutes. There is variability in turnover times, but it is very small. In addition, both our statistical analysis and some previous research (Tyler *et al.*, 2003), (Abouleish *et al.*, 2003) have excluded it as a key factor in utilization. For simplicity purposes, we used a constant. Each OR is scheduled to be open from 8 a.m. to 4 p.m., and any time beyond 4 p.m. is considered over-utilized OR time. We also assume that patients are ready for surgeries 30 minutes ahead of scheduled start time.

3. Statistical analysis: results

Table II summarizes the data fitting analysis statistics. Type I models were fitted by stepwise regression method, and Type II models were from the analysis of best subset approach. The month before the Greek number was the test data set. For example, May I refers to the model that was developed from the data set from June to September by stepwise regression, and May data were tested against the observations; September II is the model created by using data from May to August by best subset, and September was used to validate the goodness of fit. The statistics are comparable to each other. The adjusted R^2 values do not differ significantly, meaning that no method dominates the other. The R^2 values are around 0.8, indicating that our models explain a good portion of the variability of the data set, and thus, a good fit was concluded.

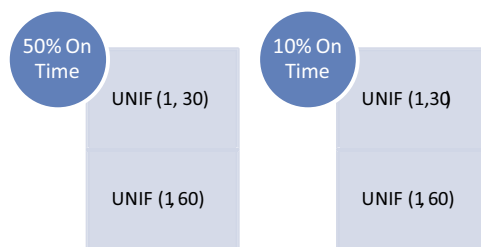


Figure 3.
First-case delay
parameters

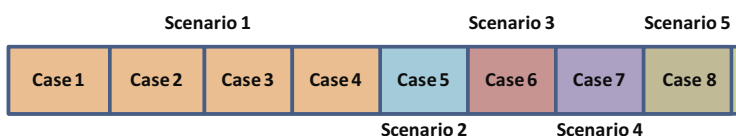


Figure 4.
Scheduling strategy
for simulation

Table II.
Stepwise regression
and best subset
model statistics

Model	S	R ²	R ² (adjusted)	PRESS	R ² (Pred)
May I	0.06490	82.04	80.62	0.422285	76.31
May II	0.06390	83.10	81.20	0.409307	77.04
June I	0.07010	81.31	80.07	0.469015	76.25
June II	0.07007	81.90	80.10	0.475155	75.94
July I	0.06920	79.35	78.00	0.488729	72.59
July II	0.06887	79.80	78.20	0.492220	72.40
August I	0.05690	85.35	84.19	0.287457	82.89
August II	0.05691	85.40	84.20	0.287457	82.89
September I	0.06650	79.76	78.71	0.412054	75.53
September II	0.06631	80.70	78.90	0.423630	74.84

Table III is the prediction performance of each model. The MAD, MAPE and RMSE do not differ a lot among the models; however, the models for June seem to have relatively small errors.

Tables IV and V summarize the most important factors identified by stepwise regression and best subset, respectively. The factors identified in the stepwise regression method include scheduled utilization, difference between actual and scheduled case durations, cancellation hours (except for August) and add-on case (except for September). The factors identified by the best subset method are scheduled utilization, difference between scheduled and actual case duration, cancellation hours (except for August) and total same-day add-on (except for September). The first-case delay, however, is not a significant factor for most Types I and II models. The number of turnovers turned out to be a significant factor in May for the Type II model but not the other models, so it could be considered as a special case.

The coefficients of all the models' variables are documented in Table AI. Positive coefficients indicate a positive relation between the independent variables and the response, and the negative ones are what we want to eliminate in practice. To have a good utilization, we want to increase the scheduled utilization by filling up the available OR hours, decrease the cancellations, have add-on cases and manage the case duration predictions (Saremi *et al.*, 2013). Given this result, we decided to fit the overall data with the generally identified top factors. The final model given by Minitab is as follows:

Table III.
Summary of model
performance

Model	MAD (%)	MAPE	RMSE
May I	5.91	7.07529	0.07450
May II	6.43	7.75652	0.08127
June I	4.29	6.00860	0.05330
June II	4.17	5.88186	0.05382
July I	4.74	5.96157	0.05808
July II	4.91	6.12778	0.06225
August I	8.99	14.19547	0.10799
August II	8.98	14.19786	0.10790
September I	6.76	9.74070	0.08110
September II	6.96	10.23544	0.08079

Model	Factors	<i>T</i>	<i>p</i>	Operating room adjusted utilization study
May I	Scheduled utilization	16.11	0.000	
	Difference (actual – scheduled)	8.07	0.000	
	Cancellation hours	–6.51	0.000	
	Total same-day add	3.33	0.001	
	First-case delay	–1.99	0.049	
June I	Scheduled utilization	16.16	0.000	121
	Difference (actual – scheduled)	8.10	0.000	
	Cancellation hours	–6.55	0.000	
	Total same-day add	3.32	0.001	
	First-case delay	–2.01	0.047	
July I	Scheduled utilization	10.05	0.000	
	Difference (actual – scheduled)	7.78	0.000	
	Cancellation hours	–5.53	0.000	
	Total same-day add	2.91	0.005	
	First-case delay	–1.94	0.056	
August I	Scheduled utilization	16.79	0.000	
	Difference (actual – scheduled)	9.12	0.000	
	Cancellation hours	–1.66	0.101	
	Total same-day add	4.57	0.000	
	First-case delay	–2.76	0.007	
September I	Cancel case	–1.76	0.083	
	Scheduled utilization	10.47	0.000	
	Difference (actual – scheduled)	6.95	0.000	
	Cancellation hours	–4.02	0.000	
	Complete cases	1.64	0.104	

Table IV.
Top factors from
stepwise regression
model result

$$\text{Act Util} = 0.143691 - 0.0163896 \text{ Cancel Hrs} + 0.019241 \text{ Total Same-dayAdd} \\ + 0.0172854 \text{ Diff (Actual - Scheduled)} + 0.807997 \text{ Sche Util}$$

By plotting the actual utilization and predicted utilization from the above formula, we found that they are highly correlated with each other (Figure 5).

3.1 First-case delays

The first-case delay does not seem to have a significant impact on the adjusted utilization. When we looked at the first-case delay statistics, we realized that for the VAMC, the first-case performance was not bad during the studied time range (Table VI). On average, during May 2009 and September 2009, there were 469 first cases, and 63 per cent of them started on time. The mean delay of first case was 13 minutes (max = 62 minutes, min = 0). The delay, compared to variability of case duration and variability in workload, can be ignored. Thus, the delay plays no critical role in the utilization.

3.2 Bias in case duration prediction

Dexter *et al.* (2005) collected three years of data to construct the confidence interval for bias. Unfortunately, our data were only available from August 1, 2008. Before August 1, 2008, there was no data-capturing mechanism for the OR suite at Detroit VAMC. We do not want to expand the date range, as the turnover of the VA surgical team is frequent,

Model	Factors	<i>T</i>	<i>p</i>
May II	Scheduled utilization	14.39	0.000
	Difference (actual – scheduled)	7.70	0.000
	Cancellation hours	–6.14	0.000
	Total same-day add	3.93	0.000
	Gap number	2.47	0.016
	First-case delay	–1.80	0.076
	WD	–1.92	0.059
June II	Scheduled utilization	13.65	0.000
	Difference (actual – scheduled)	6.61	0.000
	Cancellation hours	–5.56	0.000
	Total same-day add	3.09	0.003
	First-case delay	–1.73	0.088
July II	Scheduled utilization	14.39	0.000
	Difference (actual – scheduled)	6.97	0.000
	Cancellation hours	–5.53	0.000
	Total same-day add	2.91	0.005
	First-case delay	–1.94	0.056
August II	Scheduled utilization	16.79	0.000
	Difference (actual – scheduled)	9.12	0.000
	Total same-day add	4.57	0.000
	First-case delay	–2.76	0.007
	Cancel case	–1.76	0.083
September II	Cancellation hours	–1.66	0.101
	Scheduled utilization	10.25	0.000
	Difference (actual – scheduled)	7.09	0.000
	Cancellation hours	–4.04	0.000
	Gap time	–1.58	0.118
	Complete cases	1.40	0.166

Table V.
Top factors from
best subset model
results

Note: WD = Dday of week

and the degree of estimate bias is expected to vary depending on the surgeons. The one-year date range does not allow us to repeat the steps of the paper due to limited sample size. [Table VII](#) summarizes the average, maximum and minimum case duration estimation bias per 8 hours for the 16 4-week period for each specialty. Positive numbers are underestimations, and negative numbers are overestimations. The degree of bias varied with different services, and on average, all tended to underestimate their case duration.

3.3 Simulation analysis

The histogram of the durations of cataract surgery for a selected surgeon is given in [Figure 6](#). Arena software concluded that the best distribution is a three-parameter lognormal distribution with a mean duration of 56 minutes and variance of 16.4 minutes. The covariance of variation is approximately 0.29. From this base distribution, case duration type 2 was generated by increasing the covariance of variation (COV) to 1, case duration type 3 was of the same COV, but mean duration was increased twice as much

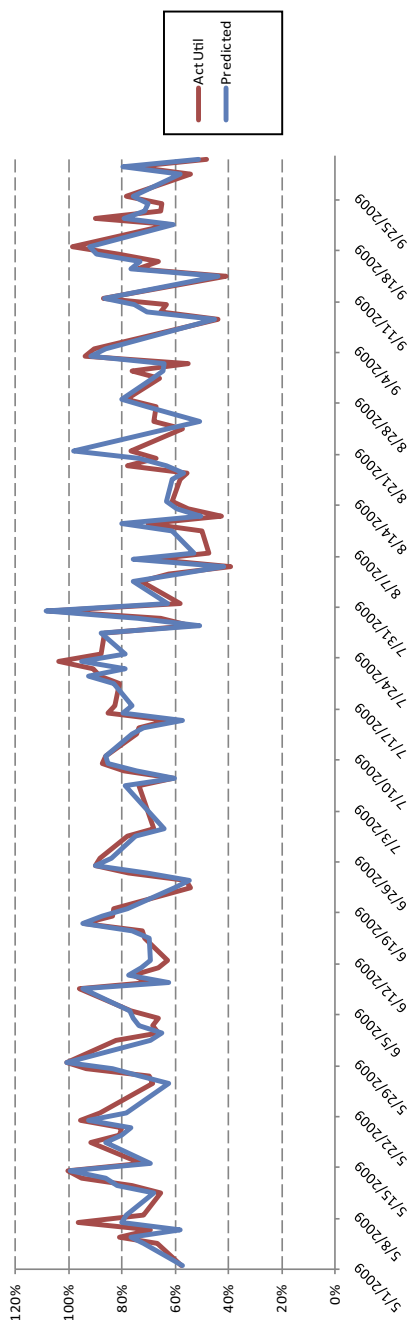


Figure 5.
Actual versus
model-predicted
utilization

as the original value (i.e. 112). Case duration type 4 has the same mean as type 3, except for the fact that the COV is 1, which is the same as case duration type 2. The simulation model provides reports on utilization, cost inefficiency and patient wait time on the day of surgery. We present the results here as pairwise comparison. Case type 1 and Case type 2 make up a pair, whereas Case type 3 and Case type 4 make up another pair. The members in each pair have the same mean case duration but different variability.

3.4 Adjusted utilization

Figures 7 and 8 plot the actual utilization versus scheduled utilization. For both pairs, the utilization increases as more and more cases are scheduled, but the higher the variability, the lower the actual utilization given the same scheduled utilization. Also, the increase in actual utilization slows down as more and more cases are scheduled, depicted by the flattened slope of the line segments toward the upper right. The first-case delays do not impact the utilization when there are fewer scheduled cases because even though there are delays at the beginning of the work day, all the cases can be done within regular OR hours. These delays will have some impact, but the difference is not significant when the day is fully scheduled. Under such circumstances, the time that would be counted as within regular hours if no delay happens would lie outside OR available hours and be considered as overtime; thus, the utilization for delayed OR is lower compared to OR with less delay.

3.5 OR efficiency

The OR inefficiency is calculated as under-utilized OR time + 1.75 over-utilized OR time. For a non-profit organization, it is extremely important to manage the costs. The OR

Table VI.
First case
performance

Date range	No. of first case	% On-time start of first cases	Mean delay
May 1, 2009 to May 31, 2009	94	65	8
June 1, 2009 to June 30, 2009	95	64	9
July 1, 2009 to July 31, 2009	103	60	15
August 1, 2009 to August 31, 2009	85	67	17
September 1, 2009 to September 30, 2009	92	58	17
Total	469	63	13

Table VII.
Case duration
prediction bias per
each specialty

Service	Average	Maximum	Minimum
ENT	76	168	-46
General	-27	124	-149
Ophthalmology	-29	84	-132
Oral	55	211	-420
Orthopedics	0	104	-196
Plastic	-111	38	-335
Podiatry	-25	120	-210
Thoracic	-38	79	-139
Urology	23	157	-179
Vascular	83	178	-134

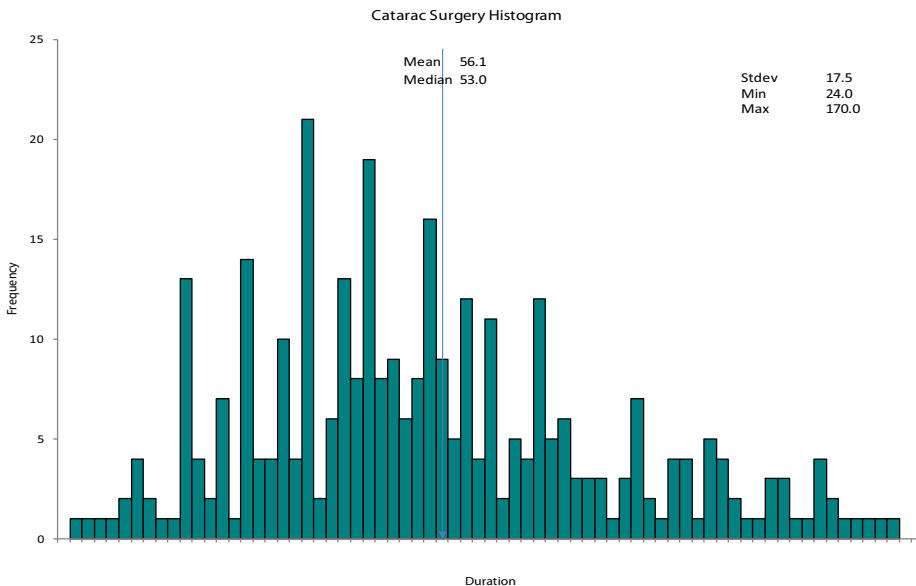


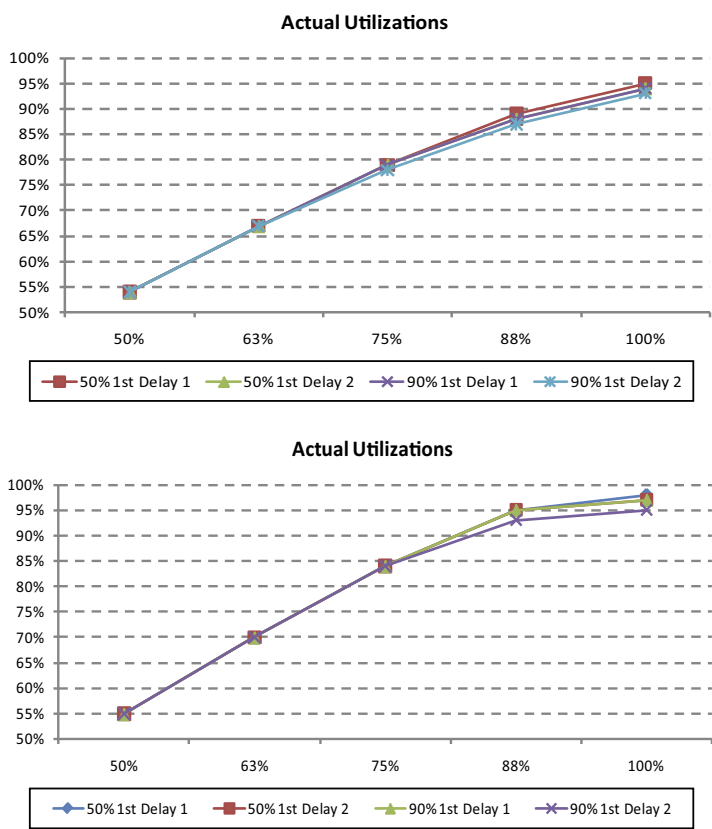
Figure 6.
Histogram of
cataract surgery

efficiency is maximized by minimizing the inefficiency. Figures 9 and 10 exhibit similar patterns. The x-axis is the scheduled utilization, and the y-axis is the inefficiency (measured in minutes). The efficiency decreases as more and more cases are scheduled until more cases are scheduled beyond the optimum point. The explanation is that when fewer cases are scheduled, under-utilized time dominates the inefficiency. As more cases are scheduled, less and less under-utilized time is expected, so the inefficiency goes down. However, the byproduct of more scheduled cases is overtime. Overtime is more expensive than under-utilized OR time, and after a certain point, the over-utilized OR time will be dominant, making the inefficiency higher. Similar to utilization, the first-case delays will not impact the efficiency until the day is more fully scheduled. The difference caused by first-case delays becomes more and more obvious.

3.6 Patient wait time on the day of surgery

The average wait time increases toward the end of the day, as the variability and uncertainty are compounded from previous cases. These results match a previous study by Wachtel and Dexter (2009); however, as we simplified our scenario and did not consider moving of cases toward the end of the day, the actual wait time for late cases was overestimated. For the same first-case delay distribution, more likely, the first cases are delayed, and more waiting time results. For the same first-case delay probability, the more variant the delay distribution, the more waiting is expected. We also saw that the behavior of the second case for case duration types 1 and 2 violates this pattern. The reason lies in the delay duration and patient wait time. For delay duration type 2, we assume that if the first case is delayed, then the duration is uniformly between 1 and 60 minutes. Thus, when the first case was delayed for more than 30 minutes, the second patient will be wheeled-in, as we assumed that each patient is ready for the surgery 30 minutes ahead of scheduled start time, decreasing the wait time. However, this does not

Figure 7.
Utilization for case
duration types 1 and
2



work for patients in case duration types 3 and 4. This situation did not apply to case duration types 3 and 4 because the scheduled case duration is 2 hours and even the first case was delayed for 1 hour, the second patient will not be ready to get in before the first patient (Figures 11 and 12).

4. Discussion

In this study, we proposed methods to pick out the top factors influencing the utilization performance and used real-data from Detroit VAMC to demonstrate how to use it. There are a couple of things worthy of mention here. First, the positive sign in the regression model before the scheduled utilization is an indication that a higher scheduled utilization results in a higher actual utilization, but we do not want to overemphasize that we should schedule as much as possible. Generally, we might not want to have a fully scheduled day. The same concern applies to the same-day add-ons. A positive relation between these and actual utilization does not mean we want to add more cases than necessary.

The positive sign before the difference between actual and scheduled case duration does not imply that we want to have surgeries run longer than expected. The delays from underestimation have other patients waiting in the pre-operating area longer and

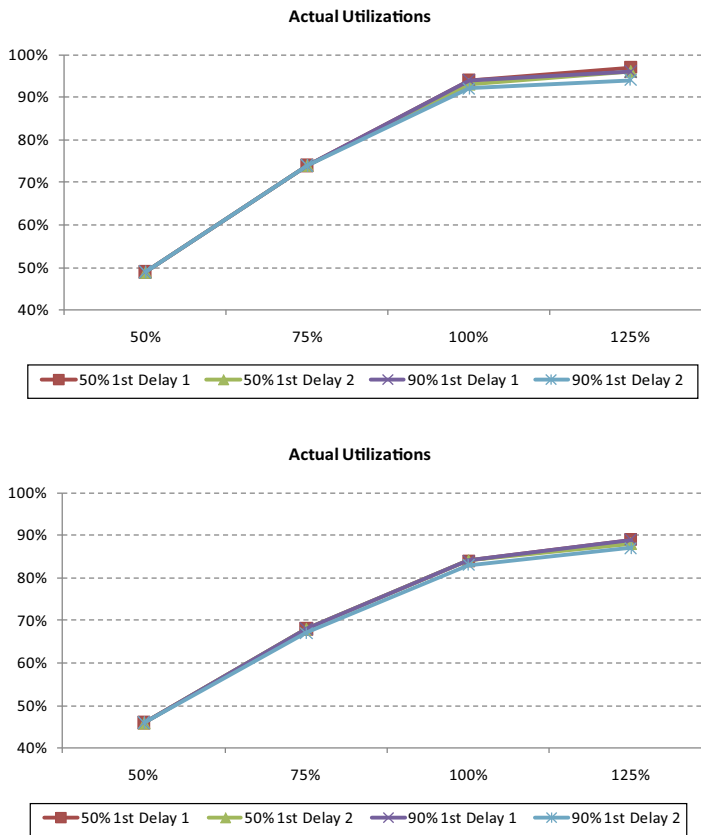


Figure 8.
Utilization for case
duration types 3 and
4

sacrifice customers' satisfaction for higher utilization. The high ranking of this factor further confirms the previous study in Detroit VAMC, which predicted that case duration predictions are not very accurate. In this facility, surgeons seem to have a tendency to underestimate the case duration, so the actual utilization usually is higher than the scheduled utilization from the performed cases. The increase in utilization from the increased underestimation is because when the previous case runs over, the OR does not need to wait for the patient because most of the time, the patient is ready for the surgery and waiting for the OR.

In addition, all these results are based on the data of a particular facility. We have a reason to believe that the situation may differ from other facilities, depending on the data set. For our facility, the case duration prediction is an important factor. But for another facility, whose surgeons have better knowledge on how long it takes to complete the procedure, the significance of this factor is expected to be reduced. For a facility that usually does smaller procedures, where duration is short and turnover time is a larger proportion of use, the turnover time may significantly impact the utilization.

In our analysis, the turnover times do not significantly impact the utilization, which matches previous research conclusions (Tyler *et al.*, 2003; Dexter *et al.*, 2003). However,

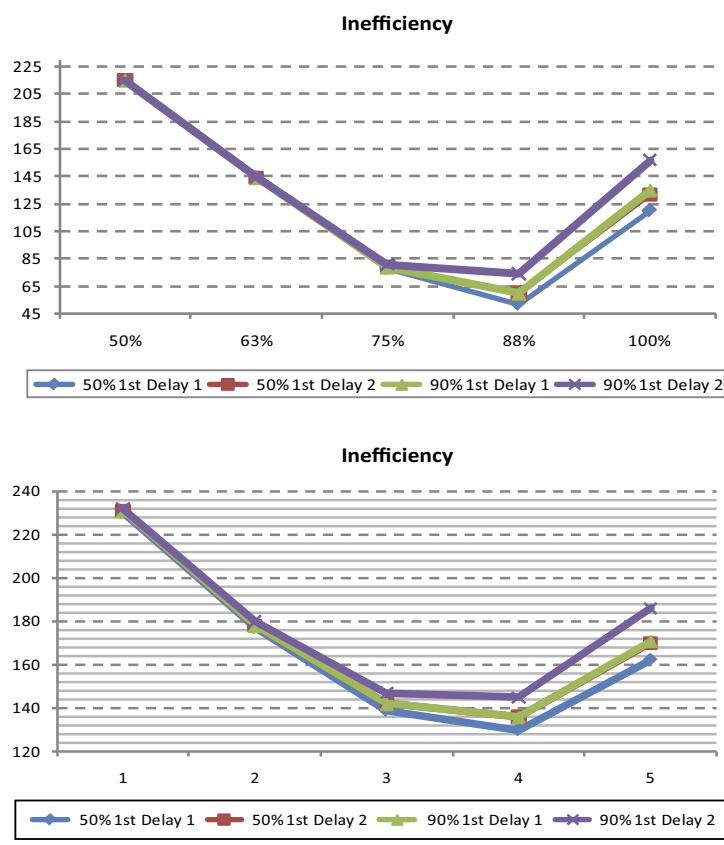


Figure 9.
Cost inefficiency for
case duration types 1
and 2

in our facility, the turnover times are observed to be longer than in some other private health-care systems. Although the utilization will not be impacted by any shortened turnover times, shorter turnover times may allow OR suites to have less overtime, so the cost efficiency will increase and patients will wait for short time to have surgeries. At the same time, we can expect a higher utilization of the expensive human resources, such as surgeons and anesthesiologists, to allow more time to perform direct patient care.

The importance of cancellations and add-on cases is an indication that the strategy to deal with cancellation and add-on case scheduling is important. If a cancellation is avoidable in advance, the management should identify it early enough, so the case on wait list can be added and the utilization can be managed as well. If a cancellation is due to unpredictable reasons, it will not adversely impact the utilization as long as we can find a case to fill the cancelled hours. It is, thus, important to establish an effective and efficient way to look for cases on the waiting list and how to manage them.

As being pointed out, the scheduling of cases is a key factor to optimize OR utilization. Queuing theory has been widely applied in different scenarios to optimize system performance. [Persson and Persson \(2010\)](#) used simulation to evaluate different queuing disciplines to achieve maximal utilization of OR and small patient wait time of an orthopedics department in Sweden by updating elective patients priority. They

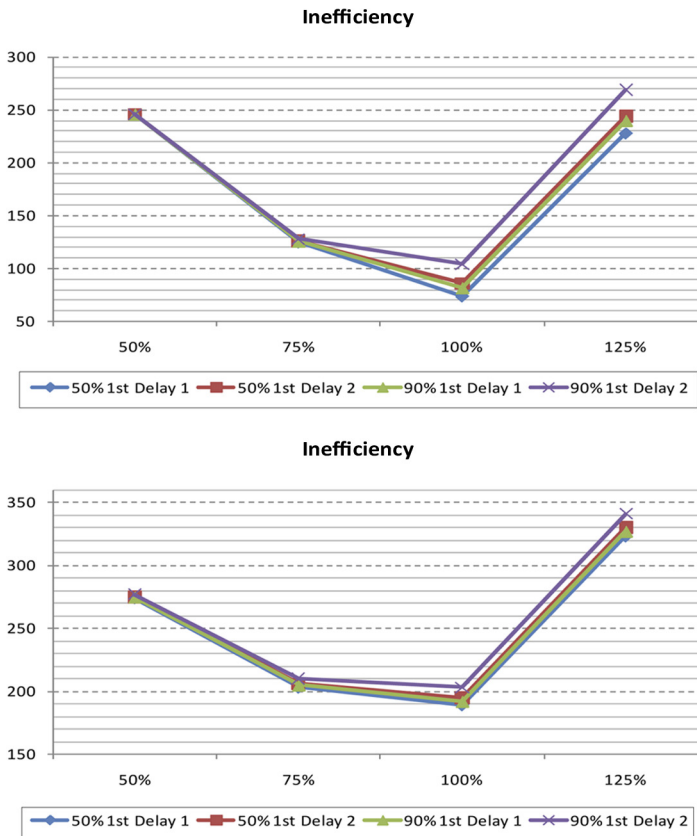


Figure 10.
Cost inefficiency for
case duration types 3
and 4

concluded that reserve OR capacity for emergency cases per different policy and increase staff in stand-by would improve performance. In their work using simulation model to study multi-OR optimization model (Denton *et al.*, 2006), they provided a single-OR optimization model using a queuing model to minimize both wait and idle time and overtime associated with surgery. Using queuing theory, Tucker *et al.* (1999) studied the probability that two or more patients will need the OR at the same time so to determine if a backup team is needed in the night shift. Combining with optimization methodology, hospitals can use such approach to determine a good case set for the OR suite on a particular to meet the performance target.

From the simulation study, we found an interesting information, that for Case duration types 1 and 2, the optimum scheduled utilization is 88 per cent, but it is 100 per cent for Case duration types 3 and 4. After investigating the reason, we figured out that the current scheduling system does not include turnovers when assigning case duration. The mean cataract surgery duration for the selected surgeon is 56 minutes. Adding 15 minutes turnover time, the actual mean duration should be 71 minutes. If we were 88 per cent scheduled, which is a seven-case day, then as a matter of fact, we schedule 71 times 7, which is 497 minutes, 17 minutes over the end time of OR, so the original 88 per cent

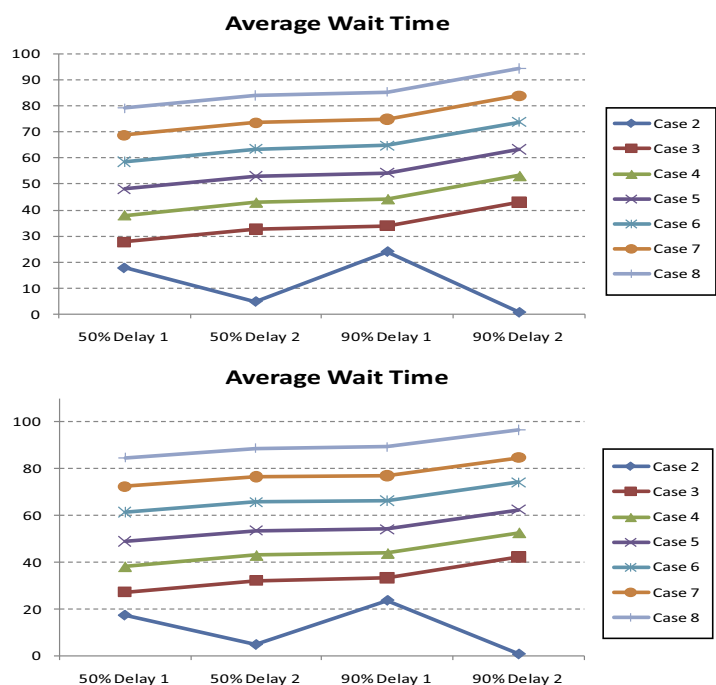


Figure 11.
Patience wait time
for case duration
types 1 and 2

scheduled utilization is actually 103 per cent scheduled utilization. This biased scheduled duration impacts not only the cost efficiency but also the patient wait time on the day of surgery. Cumulatively, the last patients on average wait longer than expected, as previous cases are more likely to run over the scheduled end time.

For the current simulation model, we assume that patients are ready 30 minutes ahead of surgery scheduled start time. We did a gap analysis between the previous patient out of OR time and the scheduled start time for the next patient. By taking the extreme condition, we considered the second and last case for case duration types 1 and 4 (i.e. duration of smallest mean and smallest variability vs duration of the largest mean and largest variability). The top two charts are for duration type 1 cases, and the bottom ones for duration type 4 cases. Toward the end of the day, the uncertainty in wait time increases as shown by the wide range of gaps. The minimum gap increases, and it is likely that a significant portion of operations has the opportunity to start earlier than 30 minutes. So, another way to increase the utilization by reducing the unutilized OR hour due to not-ready patients is to have patients ready earlier for their procedures. However, we do not want to have patients wait for 3 or 4 hours, which would also hurt the quality of service, and we may face constraints in pre-operating beds. As for when to have patients ready, a balance needs to be found between patient wait time and leaving room unoccupied (Figure 13).

We did additional simulation runs by adjusting the scheduled duration to the closest 15-minute interval to the mean case duration plus the turnovers, and having patients ready 60 minutes before the scheduled start time. The average wait time for the last case of case duration type 1 has been reduced to almost 80 minutes, and the wait for the last

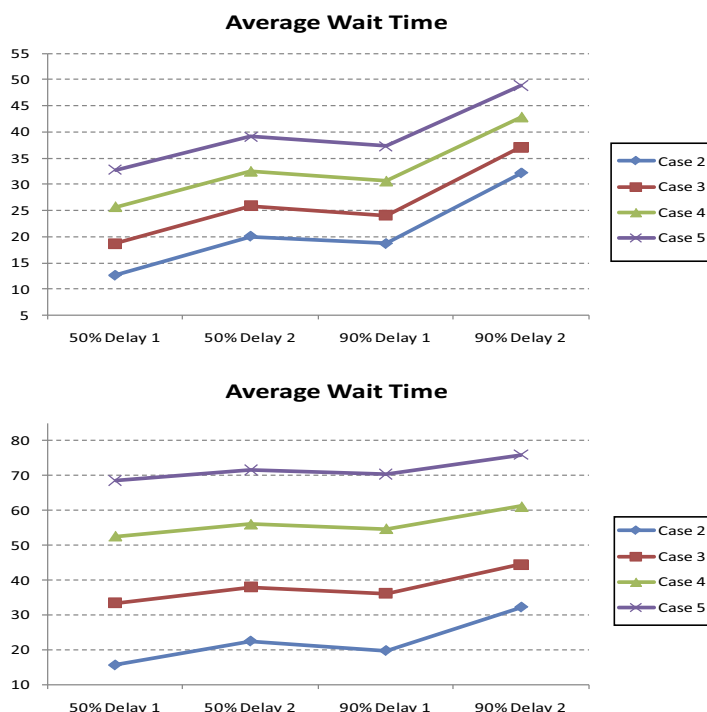


Figure 12.
Patience wait time
for case duration
types 3 and 4

case in case duration type 4 is 25 minutes. The utilization has an approximate 2 per cent increase from the adjustment.

5. Conclusions

OR utilization performance has been widely used as a measure for many health-care organizations. Given many potential factors that would impact the utilization, the identification of the most important factors that impact the utilization will assist the decision-making process of OR management.

In this research, surgical data from John D. Dingell VAMC was collected for a 5-month period. Eight factors were calculated for our study to explore the impacts of workday, scheduled utilization, first-case delay, cancellation, same-day add-on cases, difference between the actual and scheduled case duration, turnover times and the number of cases on adjusted OR utilization.

Based on the results, to increase OR utilization, the Detroit VAMC OR management should focus on the scheduling of cases, including the scheduling of add-on cases and management of cancellations.

By using the stepwise regression and best subset models, each facility can identify the critical few factors that impact utilization.

The prediction of case duration is also important in the determination of the utilization. Management is recommended to use historical data combined with adjustments for individual surgeons to better allocate case durations.

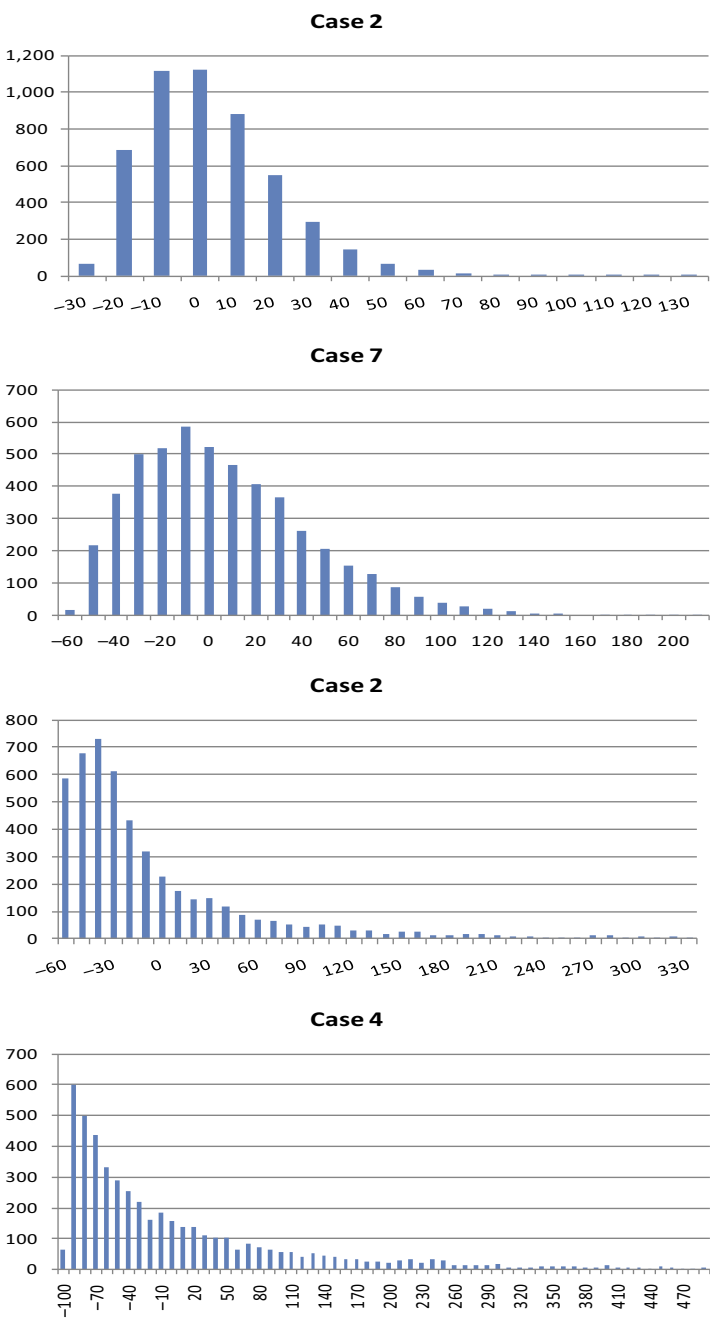


Figure 13.
Gaps between cases
(look back at
[Figure 4](#))

In addition, a 100 per cent OR utilization will sacrifice OR cost efficiency because of over-utilized OR time. Our study shows the roadmap of the typical phases in an LSS project. We first identified the issue (i.e. the improvement of OR utilization), then using data extracted from information technology system and the time collection sheet to measure the performance and values of independent variables. Later, statistics and simulation were applied to analyze the relation between different factors and OR utilization and tested different scenarios on OR performance.

This approach can be easily expanded to other LSS project to assist teams analyze complex system where many factors impose impacts on the metrics for management to tackle the key factors.

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Appendix

Table AI.
Coefficients of model
factor

Model	Factor	Coefficient
May I	Constant	0.11670
	Cancellation hours	−0.01520
	Complete cases	0.00720
	Difference (actual − scheduled)	0.01840
	First-case delay	−0.00830
	Scheduled utilization	0.69800
	Total same-day add	0.01710
	Constant	0.14708
	Cancellation hours	−0.01588
	Difference (actual − scheduled)	0.01791
	First-case delay	−0.00775
	Scheduled utilization	0.77504
	Total same-day add	0.02373
	WD	−0.01159
	Gap number	0.00865
June I	Constant	0.13350
	Cancellation hours	−0.01610
	Difference (actual − scheduled)	0.01730
	First-case delay	−0.00830
	Scheduled utilization	0.83600
	Total same-day add	0.01980
June II	Constant	0.13351
	Cancellation hours	−0.01607
	Difference (actual − scheduled)	0.01726
	First-case delay	−0.00826
	Scheduled utilization	0.83582
	Total same-day add	0.01975
July I	Constant	0.13430
	Cancellation hours	−0.01530
	Difference (actual − scheduled)	0.01810
	First-case delay	−0.00910
	Scheduled utilization	0.81800
	Total same-day add	0.01830
July II	Constant	0.13427
	Cancellation hours	−0.01531
	Difference (actual − scheduled)	0.01808
	First-case delay	−0.00906
	Scheduled utilization	0.81823
	Total same-day add	0.01830
August I	Constant	0.14440
	Cancel case	−0.02000
	Cancellation hours	−0.00930
	Difference (actual − scheduled)	0.02000
	First-case delay	−0.01820
	Scheduled utilization	0.81800
	Total same-day add	0.02630

(continued)

			Operating room adjusted utilization study
Model	Factor	Coefficient	
August II	Constant	0.14438	137
	Cancel case	−0.01977	
	Cancellation hours	−0.00932	
	Difference (actual – scheduled)	0.01999	
	First-case delay	−0.01815	
	Scheduled utilization	0.81788	
	Total same-day add	0.02632	
September I	Constant	0.13360	Table AI.
	Cancellation hours	−0.01330	
	Complete cases	0.00630	
	Difference (actual – scheduled)	0.01820	
	Scheduled utilization	0.71200	
September II	Constant	0.13935	
	Cancellation hours	−0.01335	
	Complete cases	0.00558	
	Difference (actual – scheduled)	0.01865	
	Scheduled utilization	0.70312	
	Gap number	0.00513	
	Gap time	−0.00435	

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