A Heuristic Policy for Outpatient Surgery Appointment Sequencing: Newsvendor Ordering

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Abstract

Sequencing and scheduling the surgeries in operating rooms (ORs) can be a very important problem since (i) the duration of each surgery can be uncertain, (ii) surgeries are a great source of revenue and a huge source of cost for the hospitals because doctors, OR staff, and surgery equipment are very expensive resources, and (iii) the satisfaction of patients and minimizing their waiting time is also a very important criterion. Solving this problem can reduce the costs and increase the satisfaction of patients significantly, but at the same time it is very hard to drive the solution mathematically. Even the sequencing sub-problem can be challenging if the number of surgeries are large. There is no known tractable optimal solution to this problem and in practice, mostly a heuristic policy which orders surgeries based on increasing duration variances, i.e. the surgery with the smaller variance is scheduled earlier, is applied. We propose a simple heuristic policy for the sequencing of the surgeries based on the Newsvendor cost, and analyze it using a hospital data set as a case study. We show that this heuristic policy outperforms the ordering based on variance since it takes the asymmetry of waiting and idle costs into account. For the cases where the difference between the idle and waiting cost is large, which is the case in surgery sequencing, this approach achieves a better improvement in the total expected cost.

Keywords

Surgery sequencing, Newsvendor, Heuristic policy, outpatient appointment

1. Introduction

Scheduling and sequencing jobs with uncertain time duration of services has been a challenging problem in operation research (e.g. Wang 1997, Panwar 1999, Pinedo 2005). There are different applications for the sequencing and scheduling and one of the common applications is the surgery scheduling (e.g. Denton 2007, Weiss 1990, Denton 2003, Wachtel 2009). Operation rooms (ORs) are the main sources of revenue for the hospitals and on the other hand the main sources of costs since the surgery equipment and staffs are very expensive resources. There are two different types of surgeries, outpatient and inpatient. In the inpatient surgery case, the patient has been already hospitalized and has an assigned room to stay the night before the surgery or after the surgery for longer recovery duration. On the other hand, in the outpatient surgery case, the patient doesn't need to be hospitalized and arrives to the hospital a short time before the surgery and leaves the hospital the same day after a short recovery. Furthermore, some procedures may need a deterministic or predictable time but some may take a significantly uncertain time to be served. The scheduling of the appointments must provide both the order of the patients and the exact appointment time for each patient considering different types of cost.

Assume that we have N patients and we should assign the ordering of the patients and the appointment times for their arrival to the hospital to minimize the total expected cost. There are three different sources of the cost: (i) idle cost: it occurs when the resource, e.g., OR, is under-utilized, (ii) waiting cost: it occurs when a patient arrives on-time but the resource is still busy serving the previous patient, and (iii) overtime cost: it occurs when the resource, e.g., doctor, has to serve after the shift time. An example of surgery scheduling for $N = 3$ is shown in Fig.1.

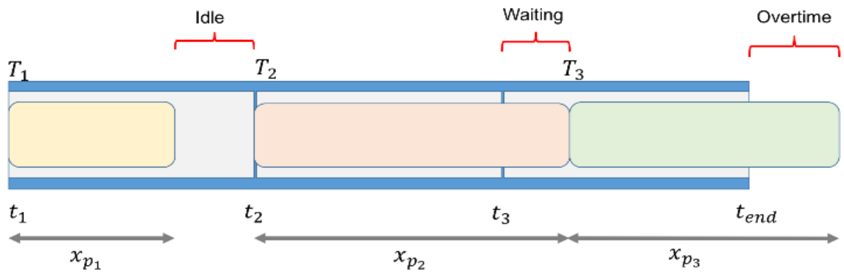


Fig. 1. Scheduling schema for an example of 3 patients; t_i: scheduled time for patient p_i, T_i: time of start surgery i, x_{p_i} : the duration of surgery for patient p_i, t_{end}: shift end time

The scheduling of surgeries can be very challenging since the uncertainty of surgery durations is significant. Even the sequencing sub-problem is challenging enough that finding the optimal sequencing for $N > 2$ surgeries with uncertain surgery durations is not known up to now. For a simpler case of $N = 2$ with zero overtime cost the optimal policy is known and special cases where some heuristics are equal to the optimal policy are given in Weiss 1990. Instead there are works in literature proposing heuristic policies on how to order the surgeries (e.g. Denton 2007). A heuristic policy based on the variance of the surgery durations is proposed in Denton 2007. In their approach, the surgery with the lower variance should be scheduled earlier (we call it VAR ordering). The authors show that this ordering can substantially reduce the total cost and illustrate this with a case study on a real data set from a hospital and comparing this heuristic approach with the actual scheduling in that hospital.

In some hospitals, another simple scheduling is applied, in which patients are asked to come in the morning and have the operations in a row (we call it No-Idle (NI) ordering). In this case, the idle costs are zero but the waiting costs are large. In this paper, we propose a different heuristic based on Newsvendor (NV) cost ordering that can outperform the VAR and NI sequencings. We illustrate this with the results of a case study that uses a hospital data (which was obtained with permission and anonymized) to compare our proposed heuristic policy with those two common heuristics. The idea of NV sequencing comes from the structure of the cost function in the surgery sequencing problem for only 2 operations which is equivalent to the Newsvendor problem which balances the trade-off between over-utilization (waiting) and under-utilization (idle) costs (e.g. Arrow 1951, Mansourifard 2017). Our NV heuristic policy is inspired by this structure and applied to more than only 2 surgeries.

Our contribution to the surgery sequencing literature is that we propose a heuristic approach which takes the asymmetry between the waiting cost and the idle cost into account in finding the orderings. For surgery sequencing application since the difference between the waiting and idle cost is noticeable, the improvement of our heuristic policy (based on the Newsvendor costs) can be significant in comparison to the variance ordering, as demonstrated with analyzing a real data set from a hospital.

2. Related Literature

In general, the sequencing of customers with uncertain time duration of services is studied in the literature (e.g. Wang 1997, Panwar 1999, Pinedo 2005). There are different applications for the sequencing and scheduling, such as scheduling arrivals of cargo ships at a seaport (Sabria 1989), the arrival of parts on the shop floor (Wang 1993), and the sequencing of the appointments in an outpatient medical center (e.g. Denton 2010, Deng 2015, Bam 2015, Riise 2016). Cardoen 2010 and Ahmadi-Javid 2017 present comprehensive surveys of different models and solution approaches in surgery planning and scheduling. Finding the optimal solution for the sequencing and scheduling of surgeries is very challenging. In Jafarnia-Jahromi 2017, it is proved that the optimal sequencing problem is non-indexable, i.e., neither the variance, nor any other such index can be used to determine the optimal sequence in which to schedule jobs. For the simple case of N = 2 and zero overtime cost the total cost can be formulated mathematically and under some conditions, the variance ordering is the optimal (Weiss 1990). But for larger number of surgeries, the problem is too complex and there are works in the literature proposing non-optimal heuristic approaches on how to order the surgeries (Denton 2007, Gul 2015). Among them, the heuristic policy based on the variance of the surgery durations proposed in Denton 2007. In Kong 2016, it is shown that the optimality of the VAR ordering depends on two important factors: (i) the number of patients in the system, and (ii) the shape of service time distributions. They exploit the insights obtained from analytical models to construct counterexamples showing that the VAR ordering is not optimal. In this paper, we also show counterexamples, but we propose a heuristic approach with a better performance, especially when idle cost and waiting cost are not balanced.

3. Problem Formulation

The surgery sequencing and scheduling problem contains two sub-problems, finding the optimal order of the surgeries (sequencing) and the optimal appointment times (scheduling). To formulate these problems, let assume, in a day, we have to schedule surgeries for N patients $i \in \{1, \dots, N\}$, and each surgery takes different duration to be done. The "actual" surgery duration of patient $i \in \{1, \dots, N\}$ is indicated by x_i which is a random variable with a distribution $f_{x_i}(x_i)$ and a surgery ordering is given by the sequence of the patients $p_1, \dots, p_N \in \{1, \dots, N\}$ where p_j is the j-th patient in the surgery order. Our goal is to minimize the total expected cost by finding the optimum schedule (time appointment of surgeries) for each of the *N! (N-factorial)* possible surgery sequences.

To solve this problem, we search for the best appointment time schedules for each surgery ordering (one of *N!* possibilities) and compute the total expected cost (including all waiting cost, idle cost and overtime cost) with the expectation over the joint probability distribution of the surgeries durations. And then, we pick the ordering which achieves the minimum cost among all possible $N!$ orderings. Assume that the j-th surgery will be scheduled for time t_j as shown in Fig.1 as an example. The actual start time of the j-th surgery (which is affected by the delays of the previous surgeries) is denoted by T_j which equals to:

$$T_j = \max(t_j, T_{j-1} + x_{pj}) \qquad (1)$$

We indicate the cost units as c_w, c_l, c_o, for the waiting cost, idle cost and overtime cost, respectively. Thus, the optimization problem is given by:

$$\min_{p_1,\dots,p_N \in \{1,\dots,N\}} \quad \min_{t_1,\dots,t_N} \mathbb{E}\left[\sum_{j=1}^{N} c_w\left(T_j + x_{p_j} - t_{j+1}\right)^+ + c_l\left(T_{j+1} - T_j - x_{p_j}\right)^+ + c_o\left(T_j + x_{p_j} - t_{end}\right)^+\right],$$

$$s.t.\, t_1 = 0, t_j \geq t_{j-1}$$

$$T_j = \max\left(t_j, T_{j-1} + x_{p_j}\right) \;\; \forall j = 2, \dots, N \qquad (2)$$

where t_{end} is the shift end time (which is usually 8 hours) and $(y)^+ = max(y, 0)$. In this equation, the first, second, and last terms correspond to the waiting, idle, and overtime cost respectively. Moreover, the inner "min" is to find the optimum schedule and the outer "min" refers to the finding the best ordering.

The problem in Eq. (2) is a stochastic mixed-integer program since finding the best order is equivalent to finding binary variables indicating which surgery must be served right after which surgery and the appointment times are real variables. If we assume that the orders are fixed priori, there are some proposed approximation algorithms to find the best time schedules (Denton 2003, Gose 2016). Now if we relax the assumption of having a fixed order a priori, we get a combination of stochastic and combinatorial variables which make the problem in Eq. (2) very difficult to solve, specially for large number of surgeries since there are $N!$ possible orders.

4. Newsvendor Cost Function

First, we consider the case of $N = 2$ surgeries with zero overtime cost. For this simple case, the optimal cost function equals to the Newsvendor cost, denoted by:

$$C_i(x_i, \tau_1) = c_w(x_i - \tau_1)^+ + c_l(\tau_1 - x_i)^+ \;, \qquad i = 1,2 \qquad (3)$$

where x_i is the actual duration of the surgery of the patient i and τ_1 is the assigned duration for this surgery which equals to the scheduled time for the second surgery minus the starting time of the first surgery which is 0. Thus, the optimal value of τ_1 can be obtained from the solution to $C_i' = min_{\tau_1}\mathbb{E}_{x_i}[C_i(x_i,\tau_1)]$ for $i = 1,2,$ and the optimal ordering p_1^*, p_2^* can be derived as p_1^*=arg $\underset{i=1,2}{min}\, C_i'$ and p_2^*=arg $max_{i=1,2}\, C_i'$. Thus, based on the Newsvendor structure of the cost functions, we find the best schedule as:

$$\tau_1^* = F_{x_{p_1^*}}^{-1}\left(\frac{c_w}{c_w + c_l}\right) \qquad (4)$$

which indicates the NV ordering is optimal for this simple case. Note that the total expected cost and the optimal ordering are dependent on only the first surgery since the only possible costs are the idle and waiting costs caused by the first surgery, thus, the second surgery will not contribute in the total expected cost. In Weiss 1990, this simple case is discussed in more detail and it is shown that when a convex ordering (Gupta 2010) exists between the distribution of the surgery durations, VAR ordering is equivalent to NV ordering.

5. Heuristic Ordering Policies

5.1 Variance (VAR) Ordering

One of the most common ordering heuristics that is used in practice is VAR ordering (Denton 2007). In this approach, the surgeries are ordered based on the lowest to highest variance of their durations. We will compare our proposed heuristic with this one.

5.2 Proposed NewsVendor (NV) Ordering

Inspired by the observations that VAR ordering doesn't take the asymmetry (un-balance) on waiting and idle cost units into account, we present a simple heuristic based on the Newsvendor cost function. In this heuristic approach, for a surgery $i\,\epsilon\{1,\dots,N\}$, we calculate the optimal expected cost for the scenario where there is only "one" other surgery to be done after that surgery. This optimal expected cost equals to:

$$\min_{\tau_i} \overline{C_i}\,(\tau_i) = \int_0^\infty C_i(x_i,\tau_i) f_{x_i}(x_i)dx_i = (c_w + c_l)\tau_i F_i(\tau_i) + c_w(m_i - \tau_i) - (c_w + c_l)\int_0^{\tau_i} x_i f_{x_i}(x_i)dx_i \qquad (5)$$

where m_i indicates the mean of the i-th patient's surgery duration and the optimal τ_i^* equals to $F_{x_i}^{-1}(\frac{c_w}{c_w+c_l})$ where $F_1^{-1}(0)$ indicates the Inverse Cumulative Distribution Function (ICDF) of the patient 1. And the optimal expected cost equals to:

$$C_i' = c_w m_i - (c_w + c_l)\int_0^{F_{x_i}^{-1}\left(\frac{c_w}{c_w+c_l}\right)} x_i f_{x_i}(x_i)dx_i \qquad (6)$$

This policy looks like a "Percentile" policy with the threshold $h = (\frac{c_w}{c_w+c_l})$ (Mansourifard 2017). Then the NV ordering heuristic policy selects the increasing order of C_i'. Intuitively, this could work better than VAR ordering since it takes the asymmetry of waiting cost and idle cost units into account in ordering and this could help reduce the total expected cost. In summary, the NV ordering heuristic of the patients is given in the Algorithm 1.

Algorithm 1 Newsvendor Ordering

1: **Given parameters** c_w, c_l, **and** f_{x_i} **for** $i = 1,\dots,N$

2: **for** $i = 1,\dots,N$ **do**

3: $\tau_i = F_i^{-1}(h)$

4: $C_i' \leftarrow \bar{C}_i(\tau_i)$

5: **end for**

6: sort the patients based on C_i': p_j has the j-th smallest element of $\{C_i', i = 1, \dots, N\}$, $i.e.$ $C_{p_1}' \le \dots \le C_{p_N}'$.

6. Numerical Results

To show that the VAR ordering may perform poorly depending on the distributions, we consider the simplest scenario in which only two cases with known distributions need to be scheduled with zero overtime cost. For this case, the NV ordering is optimal. Here we present some examples to show that the VAR ordering under-perform the optimal (NV) ordering.

In Fig. 2 (left), the orders chosen by both NV and VAR heuristics for two uniform distributions which threshold $h = 0.1$ (i.e. $c_w = 1$, $c_l = 9$, $c_o = 0$) are given. The first uniform case has mean $m_1 = 2$ and variance $\sigma_1^2 = 2$ and the figure shows the solution for different mean and variance of the second uniform case. As it is obvious from the figure, the optimal ordering chooses the case with lower variance. Thus, for this case, VAR and NV orderings are equivalent and optimal because the uniform distributions follow the convex ordering based on Weiss 1990.

Now to compare NV and VAR orderings, we use $\frac{C_{VAR}-C_{NV}}{C_{VAR}}$ as a measure for the improvement of the NV to VAR, where C_{VAR} and C_{NV} are the total expected cost corresponding to NV and VAR heuristics, respectively. In other words, the difference between two costs divided by the cost of VAR heuristics shows the cost reduction percentage if NV heuristic is applied instead of VAR policy. In the following figures, we use heat-map to compare the cost improvement of NV to VAR ordering. The red color shows the highest improvement and the white color shows the lowest improvement which is 0, i.e., the costs of two heuristics are equal in the areas with white color. In Fig. 2 (right), the orders for a scenario with two triangular distributions are shown. In some cases, for instance if $1.8 \le \sigma_2^2 < 2$ and m_2 takes any value, the improvement of NV ordering to VAR ordering is around 30%. Similarly, in Fig. 3, the orders for a scenario with one triangular and one uniform distribution are shown.

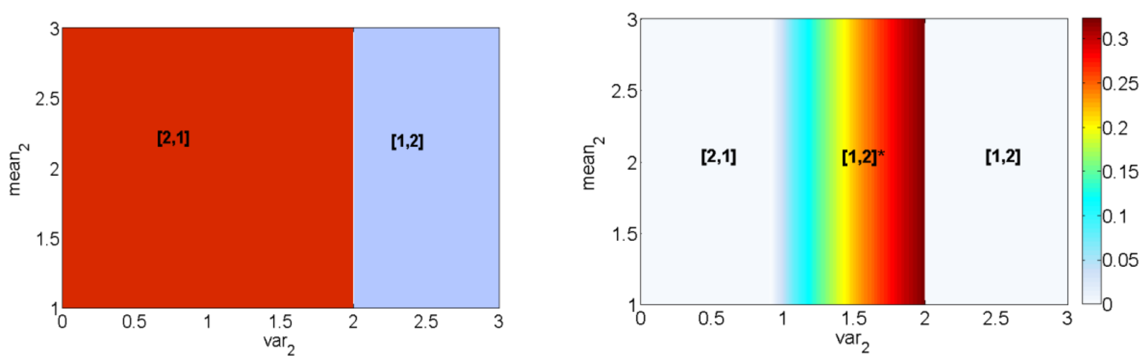


Fig. 2. Ordering chosen by NV and VAR heuristics for (left) two uniform distributions with different mean and variances, $m_1 = \sigma_1^2 = 2$; (right) for two triangular distribution with different mean and variances and the improvement of NV to VAR heuristic, $m_1 = \sigma_1^2 = 2$.

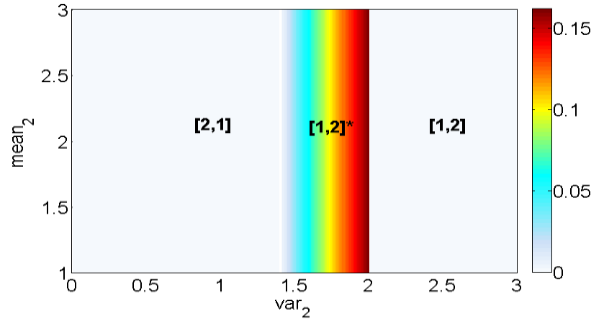


Fig. 3. Ordering chosen by NV and VAR heuristics for a triangular distribution with $m_1 = \sigma_1^2 = 2$ and a uniform distribution with given mean and variances and the improvement of NV to VAR heuristic.

In Fig. 4, scenarios with two log-normal distributions are shown where the improvement can go up to 90%. As we will see later, the log-normal is the most practical distribution for surgery duration. For instance, if $m_1 = \sigma_1^2 = 2$ and $m_2 \leq 0.1$ and $\sigma_2^2 > 1$, the NV heuristic reduces the cost up to 90% of the cost of VAR heuristic (Fig. 4 right). This result shows that even for a simple case of two surgeries without over-time cost, the VAR heuristic can perform poorly.

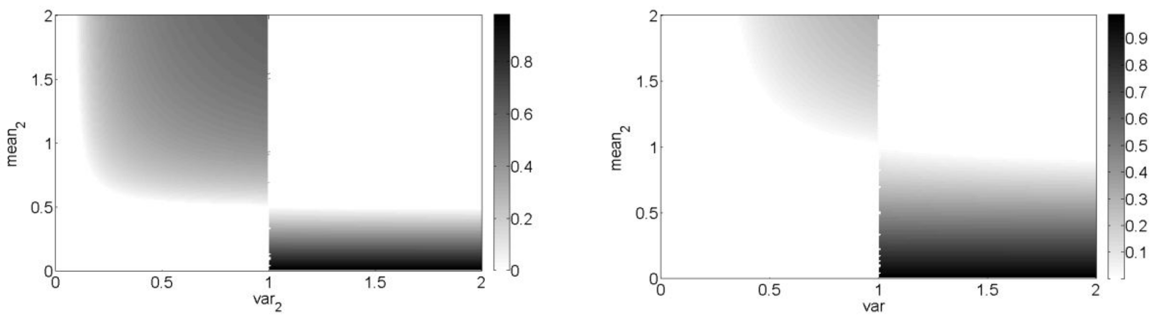


Fig. 4. The improvement of NV to VAR heuristic for two lognormal distributions, (left) first with mean=0.5, variance=1 and the second with given mean and variances; (right) first with mean=1, variance=1 and the second with given mean and variances.

Now for an example of two log-normal distributions, the improvement of NV to VAR heuristic for $c_w = 1$ is shown in Fig. 5 (right) for different values of c_l. As it is shown in this figure, for larger ratio of $\frac{c_l}{c_w}$ the NV ordering works much better than VAR ordering which is an example where VAR ordering cannot be a suitable choice for ordering. The lognormal distributions with the given mean and variances are shown in Fig. 5 (left) for $\frac{c_l}{c_w} = 3$ in which the cost improvement of NV to VAR heuristics is around 37%. For this example, the VAR heuristic will choose the red distribution which has a lower variance, but NV heuristic will choose the blue one since the percentile is very small and the chance of paying idle cost (which is the most significant one) is very low.

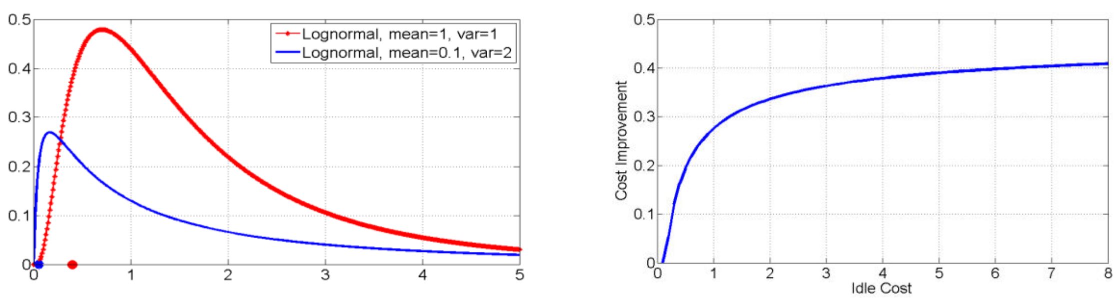


Fig. 5. (left) The two lognormal distributions, and their corresponding percentile values for $\frac{c_l}{c_w}$ =3 indicated with solid circles.; (right) The improvement of NV to VAR heuristic for two lognormal distributions, first with mean=1, variance=1 and the second with mean=0.5, variance=2.

7. Case Study: Outpatient Surgery Sequencing

In this section, we work with a real data set obtained from a hospital to compare the heuristic ordering policies mentioned in the previous section for practical and more complicated scenarios.

7.1 Characteristics of Data Set

The anonymized data set includes the surgeries in 2014-2015. For more consideration, we filtered out the data corresponding to the surgeries with frequency less than 30 since we need enough data to have a reasonable estimation about their distributions. First, we did some preprocessing on the data. For instance, we combined all surgeries related to 'left' or 'right' side of symmetric organs and substitute the title with 'any'. The histograms of these most frequent surgery types are shown in Fig. 6.

For the most frequent surgery type, 'Any eye cataract removal', we plot the histogram in Fig. 7 (left) with different distribution fits in which Log-normal distribution is the best. As given in Fig. 7 (right), the Log-normal distribution has larger Maximum Likelihood (ML) which results in a better fit compared to other distributions. This is to confirm that the most reasonable distribution for surgery duration is Log-normal (May 2000).

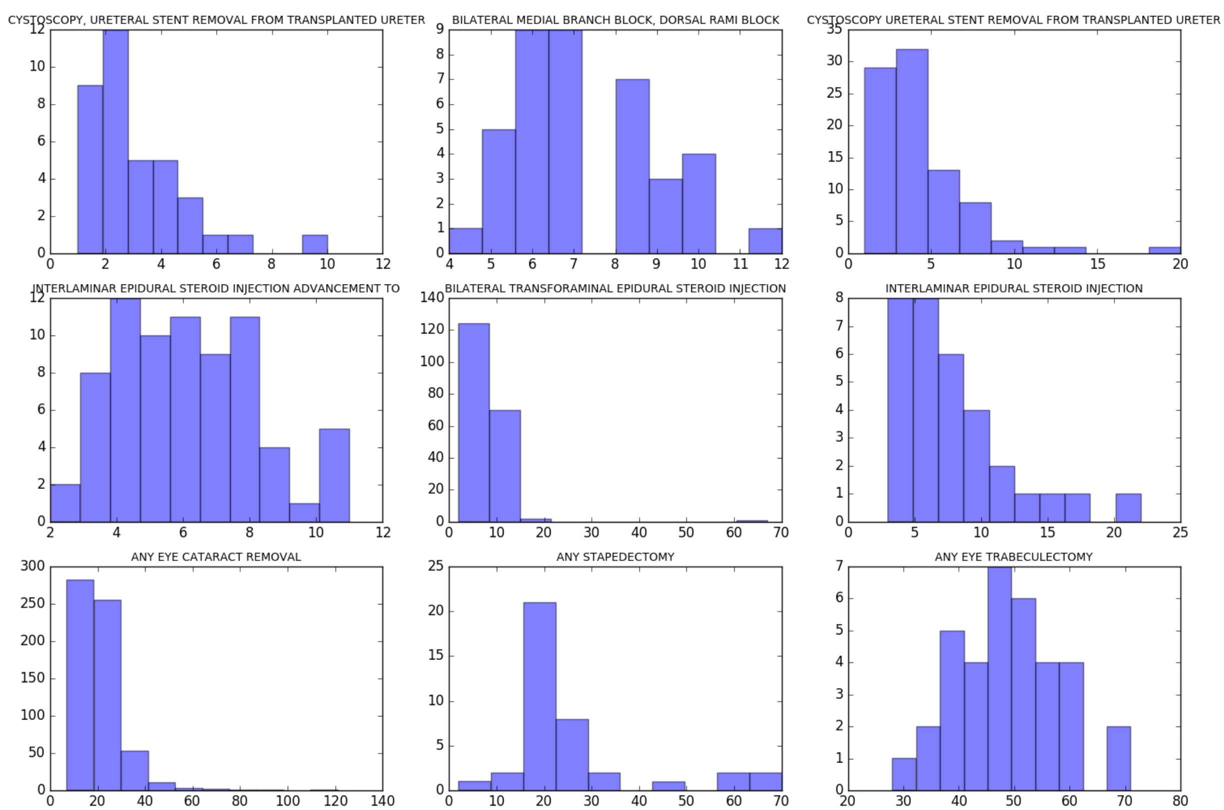
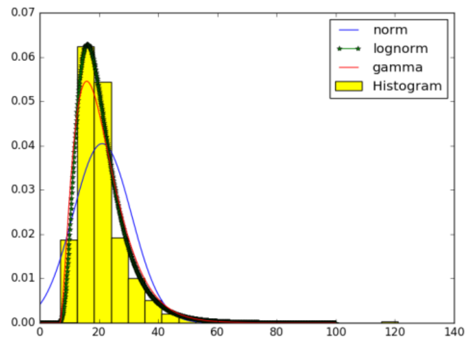


Fig. 6. The histogram of top frequent surgery types, for the Outpatient Surgery Center (durations are in minutes)



Distribution	MLE
lognormal	-2065.518577
gamma	-2085.466529
normal	-2261.298903

Fig. 7. (left) The histogram and the best distribution fit; (right) The MLE values for three distribution fits for the most common surgery type 'Any eye cataract removal"

7.2 Modified NV Ordering

The modified algorithm to use the data samples instead of distributions is given in Algorithm 2 where the set of samples for surgery i is indicated by S_i and the size of a set is denoted by $|.|$. The orders chosen by NV and VAR ordering heuristics are given in Table 1 and the surgery types with different orders in the sequence are indicated with specific colors.

Algorithm 2 Newsvendor Ordering on Samples

1: **Given parameters** $c_w, c_l,$ **and** S_i **for** $i = 1, \dots, N$

2: **for** $i = 1, \dots, N$ **do**

3: $\tau_i = min_{\tau \in [\min(S_i), \max(S_i)]} |\{s \in S_i : s \leq \tau| \geq h|S_i\}|$

4: $C_i' \leftarrow \frac{1}{|S_i|} \sum_{s \in S_i} (c_w(s - \tau_i)^+ + c_l(\tau_i - s)^+)$

5: **end for**

6: sort the patients based on C_i': p_j has the j-th smallest element of $\{C_i', i = 1, \dots, N\}, i.e. C_{p_1}' \leq \dots \leq C_{p_N}'$.

SURGERY_TYPE	nv_index	var_index
CYSTOSCOPY, URETERAL STENT REMOVAL FROM TRANSPLANTED URETER	0	1
BILATERAL MEDIAL BRANCH BLOCK, DORSAL RAMI BLOCK	1	0
CYSTOSCOPY URETERAL STENT REMOVAL FROM TRANSPLANTED URETER	2	4
ANY TRANSFORAMINAL EPIDURAL STEROID INJECTION	3	3
INTERLAMINAR EPIDURAL STEROID INJECTION ADVANCEMENT TO	4	2
BILATERAL TRANSFORAMINAL EPIDURAL STEROID INJECTION	5	6
INTERLAMINAR EPIDURAL STEROID INJECTION	6	5
ANY WRIST CARPAL TUNNEL RELEASE	7	7
ANY EYE CATARACT REMOVAL INTRAOCULAR LENS INSERTION	8	8
ANY EYE CATARACT REMOVAL	9	10
ANY STAPEDECTOMY	10	13
ANY EYE TRABECULECTOMY	11	9
SEPTOPLASTY, BILATERAL TURBINOPLASTY	12	11
ANY KNEE ARTHROSCOPY, MEDIAL MENISCECTOMY	13	12
ENDOSCOPIC SINUS SURGERY	14	14
ANY EYE AQUEOUS SHUNT	15	15
ANY TYMPANOPLASTY	16	16
ANY COCHLEAR IMPLANT	17	18
ANY EYE CORNEAL TRANSPLANT	18	17
ANY URETEROSCOPY LASER LITHOTRIPSY, ANY URETERAL STENT PLACEMENT	19	20
ANY SHOULDER TOTAL ARTHROPLASTY	20	19
ANY SHOULDER REVERSE TOTAL ARTHROPLASTY	21	21
TOTAL THYROIDECTOMY	22	22

Table 1: Orderings For $c_w = 1$, c_l=5, $c_o = 10$, (nv_index: index of the surgery type in NV ordering, var_index: index of the surgery type in VAR ordering)

7.3 Sampling and Scheduling

After fixing the orders $(p_1, \dots, p_N)$ based on any heuristic ordering policy, finding the best appointment time schedules can be formulated as a stochastic program that replaces the expectation on the distribution with the sample average. To this end, we need a discrete finite set of scenarios, $Z = \{z_k, k = 1, \dots, K\}$, that represent the uncertainty in the durations of all surgeries. If we have enough number of these scenarios, we can use averaging on the scenarios to mimic the expectation.

Note that for each scenario, we need a sample from each surgery type and since the number of data points for each surgery type varies and are not enough, thus we use statistical sampling to sample with replacement and generate enough number of scenarios (in simulation, we generate K = 10, 000 scenarios). Now, given the discrete set of scenarios we can write the appointment time scheduling sub-problem as the following sample average approximation (Kleywegt 2002):

$$\min_{t_1,\dots,t_N} \frac{1}{k} \sum_{k=1}^{K} [\sum_{j=1}^{N} c_w(T_j(z_k) + x_{p_j}(z_k) - t_{j+1}(z_k))^+ + c_l(t_{j+1}(z_k) - T_j(z_k) - x_{p_j}(z_k))^+$$

$$+c_0 \left(T_j(z_k) + x_{p_j}(z_k) - t_{end})^+\right],$$

$$s.t. \, t_1 = 0, t_j(z_k) \geq t_{j-1}(z_k)$$

$$T_j(z_k) = \max\left(t_j(z_k), T_{j-1}(z_k) + x_{p_j}(z_k)\right) \; \forall j = 2, \dots, N \qquad (7)$$

This stochastic programming can be used to compute the appointment time schedules for cases given a known sequence of surgeries (i.e. surgery orders) using the approximation algorithm proposed in Gose 2016.

A very naive heuristic for scheduling the appointment times is the one that ignores patients' waiting cost and ask all patients to be present in the morning, i.e. $t_j = 0; \; \forall i = 1, \dots, N$. Thus, the surgeries will be done in a row without any idle time in between. We call this No-Idle (NI) heuristic for scheduling. For this policy, the orders can be anything and will not affect the total expected cost because the waiting cost is the same for all patients. This could be a good heuristic to compare the scheduling for the sequence generated by our NV ordering to show the importance of the waiting cost and the patients' satisfaction even though its value is less than the idle cost of OR resources.

7.4 Performance Comparison

In this subsection, we compare the total average cost of different heuristics, NV, VAR and NI for scheduling and assume that the total shift time is 8 hours. The cost ratio of NV ordering to VAR and NI heuristics is shown in Fig. 8 (left) and (right), respectively. These ratios are plotted versus idle cost c_l and overtime cost c_o , respectively, for waiting cost $c_w = 1$. As it is obvious from Fig. 8 (left), for larger values of c_l the NV heuristic performs about 18% better than VAR heuristics and similarly for very small values of c_l , NV outperforms VAR heuristic. But for $0.2 \leq \frac{c_l}{c_w} \leq 2$, these two heuristics perform closely. The reason is that when c_w and c_l are not close to each other, the asymmetry in the cost is more significant and thus the VAR heuristic that ignores this asymmetry cannot perform well. Similarly, as shown in Fig. 8 (right), for larger c_o, the NV heuristic outperforms VAR heuristics about 19%. For $c_o = 0$, there is not much different between the cost of NV and VAR, but as c_o increases, NV will have a better performance compared to VAR since NV schedules the appointment times earlier. As shown in both figures, the NI heuristic under-perform both VAR and NV heuristics specially for large values of c_l and small values of c_o. Since NI will not cause any extra delay, it could perform better for larger values of c_o, but for $c_o = 0$ the large amount of waiting cost for all surgeries is more important and causes the under-performance of this heuristic approach compare to others. Also for larger values of c_l, NV will choose scheduled times close enough to reduce the idle cost, thus it will have the advantage of NI heuristic plus less waiting cost. And this results in outperforming NV compare to NI. But for $c_l = 0$, the NV may choose a looser schedule than NI and cause an overtime cost, thus the improvement of NV to NI is not obvious for this case.

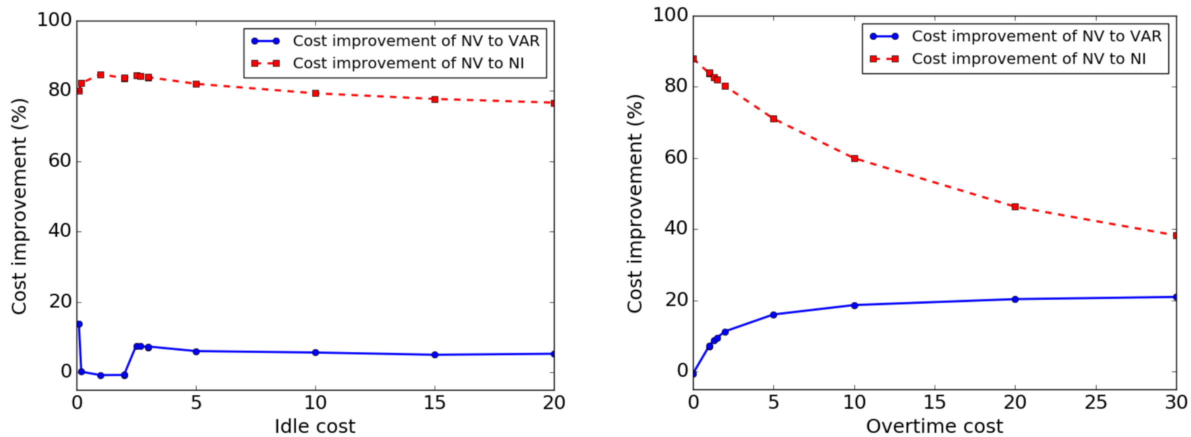


Fig. 8. (left) Cost ratio of NV to VAR and NV to NI heuristics versus c_l, for $c_w = 1$, $c_o = 5$; (right) Cost ratio of NV to VAR and NV to NI heuristics versus c_o, for $c_w = 1$, $c_o = 5$.

In Denton2007, the normalized cost units are selected as $c_w = 1$, $c_l = \frac{8}{3} = 2.67$ and $c_o = \frac{4}{3}$ =1.33 through their consultation with management engineer involved in managing the OR schedules. For their selection of cost units, we achieve the cost improvement of NV to VAR equal to 10% and NV to NI equal to 83%.

8. Conclusion

We have proposed a heuristic surgery sequencing policy based on the Newsvendor cost and compared it with the most common heuristics in practice, which order the surgeries based on the variance of surgery durations (VAR) and the one that asks all patients to be present in the morning to avoid any idle cost (NI). We have used both simulation and a hospital data to show that this proposed heuristic approach can outperform the available heuristics and have a considerable impact on the revenue of the hospitals as well as patients' satisfaction.

As a future work, it will be interesting to consider more complex scenarios in which multiple ORs are involved and the patients and doctors have time restrictions which will affect the ordering and scheduling and see how the NV heuristic can affect the cost reduction. In addition, any mathematical direction to show the optimality of NV ordering under specific conditions or deriving a performance guarantee for this scheme could be an exciting direction.

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