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A SIMULATION STUDY OF OUTPATIENT SURGERY CLINIC WITH STOCHASTIC PATIENT RE-ENTRANCE

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ABSTRACT

This study investigates how the variability of different stochastic elements affects the performance of operations at a Mohs Micrographic Surgery (MMS) clinic. MMS is a popular procedure to treat non-melanoma skin cancers. In MMS, the surgeon performs skin layer excisions on the patient one at a time, and the removed layer is then examined. If cancerous cells remain during examination, another excision will be conducted; otherwise the patient goes through wound repair before being discharged. Such repetitive excisions of thin layers lead to low re-occurrence rates and impressive post-surgery cosmetic results, but it requires uncertain amount of same-day surgeries which may lead to long patient waiting times and clinic overtime. We develop a simulation model to study the operational performance of an MMS clinic with a given appointment schedule used in practice. Our study reveals how the waiting time and clinic overtime is affected by different stochastic factors.

1 INTRODUCTION

Skin cancers are the most common type of cancer (American Cancer Society 2020). More than 3.3 million people are diagnosed with non-melanoma skin cancers (NMSC) in the United States each year (American Cancer Society 2020). The NMSC's basal cell carcinoma and squamous cell carcinoma skin cancers are the first and second most common tumors treated with Mohs Micrographic Surgery (MMS). MMS is an iterative procedure that removes the skin cancer by layer and examines the tissue for any malignancies and is repeated until the area is cancer-free. Although the procedure is the most effective technique for removing the cancers while saving the most amount of healthy tissue, the procedure is known for being time consuming due to the same-day repetitive excisions (Garcia et al. 2005), and thus it often leads to long patient waiting times and sometimes clinic overtime.

There are three sources of uncertainty associated with the MMS clinic processes. First, the show-up probability can range from 70-90% at MMS clinics. No-shows are a common problem in many healthcare settings (Daggy et al. 2010) and the likelihood of no-shows has been linked to patient age, marital status, gender, ethnicity, insurance coverage, co-morbidity, previous no-show behavior, and mental health, among others. In MMS, this problem is compounded because it is a surgical procedure that attracts patients from a larger region, thus patients have challenges with travel and transportation. Second, service times are also stochastic, which is also very common in many industries (Alvarado et al. 2018; Ejaz et al. 2019; Rosenberger et al. 2002), and serves as a motivating factor for using simulation modeling. However, the most unique part of MMS procedures is the stochastic re-entrance probability. *Patient re-entrance* refers to the event in which patients repeat upstream processes; *stochastic patient re-entrance* implies that the number of times patients will repeat the upstream processes is also unknown. In MMS, re-entrance can occur at the end of the pathology stage if the cancer has not been eradicated, which causes the patient to have another skin layer removed and wait for another pathology result. Each re-entrance adds at least 45 minutes and up to 3 or more hours to a patient's cycle time. The impact is greater if this event occurs for patients scheduled earlier in the day because there is more competition for clinic resources than a comparable re-entrance later in the day. Although historical data allows us to characterize the underlying distribution for this stochastic re-entrance, no studies have truly investigated the impact of this stochastic event in the MMS clinic.

Other studies have used discrete event simulation (DES) to model outpatient clinics (Rohleder et al. 2011; Al-Araidah et al. 2012). There are reviews of simulation modeling in healthcare settings (Günal and Pidd 2010; Jacobson et al. 2006; Zhang 2018) and studies that use DES models to measure performance and aid the decision-making processes of their respective setting (Alvarado and Ntaimo 2018; Ahmed 2011; Weerawat et al. 1970). In fact, patient appointment scheduling has been studied extensively in the literature, using techniques such as dynamic programming (Erdogan and Denton 2013), stochastic programming (Castaing et al. 2016), and stochastic processes (Muthuraman and Lawley 2008). However, none of them are directly applicable to the setting of patient re-entrance, nor have they used DES to understand how stochastic re-entrance impacts the clinic's operations.

In this paper, we develop a discrete-event simulation of an MMS clinic with a fixed appointment schedule. The model simulates the patient arrival process and the MMS procedure which includes layer excision, pathology, wound repair, and discharge. We calculate two performance measures: patient waiting time and clinic overtime. The goal of the project is to understand how the stochastic factors of show-up probability, service time, and re-entrance probability affect the respective performance measures. That is to say that we do not look at a single objective that combines the performance measures into a weighted sum, rather we look at them individually.

2 SIMULATION MODEL

In this section, we develop a DES model that can closely capture the operations of MMS clinics.

2.1 Patient arrivals

The patient appointments for MMS are scheduled in advance. Therefore, walk-in or open access, which are sometimes considered in outpatient scheduling literature (Cayirli and Gunes 2014; Robinson and Chen 2010; Chen and Robinson 2014), is not applicable here. The schedule used in this study is from a typical MMS clinic, and the details of the schedule will be provided in Section 3.1 where the experimental design is discussed. Note that while last minute walk-ins are not allowed in the MMS setting, last minute cancellations do happen in practice, and thus are considered part of the patient no-show rates in our model. Patient unpunctuality, on the other hand, is not commonly seen in MMS clinics, and is therefore not considered in this study. The detailed modeling of probabilistic no-show is explained in subsection 2.3, which describes the uncertainties considered.

2.2 Patient Flow and Clinic Resources

Next, we describe the flow of each patient (or the corresponding entity to be processed, such as the removed tissue) together with the main resources involved in the whole process. Figure 1 depicts patient flow in the clinic. In the model, the patient shows up to the surgery appointment and waits for the availability of the surgeon. The surgeon then has a conversation with the patient regarding risk and consent, and then performs the initial excision. This service is modeled as a timeout before releasing the surgeon. The excised tissues will then be made into slides by an available histo-technician for examination, and this corresponds to the pathology stage in the figure. After some time, the pathology result is available and re-entrance happens when the result indicates an *unclear margin* (remaining cancer tissues); otherwise, the patient is ready for wound repair by the surgeon or a resident. After wound repair, the patient is discharged and leaves the

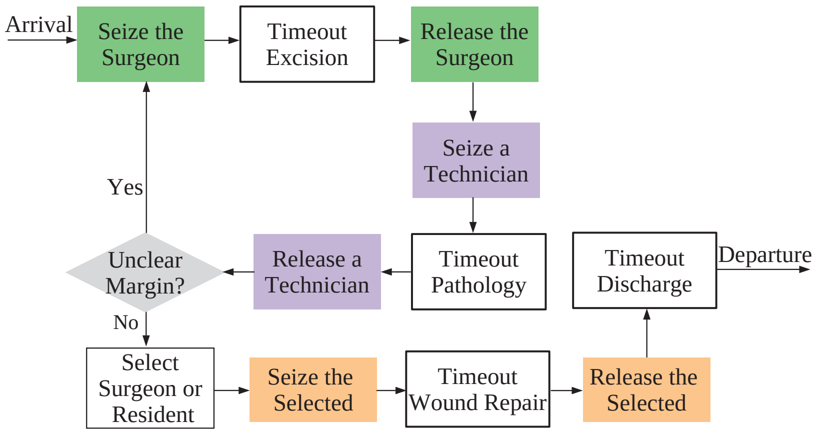

Figure 1: The patient flow in the MMS clinic.

system. We consider the single-surgeon setting because in practice each patient will only be treated by a single surgeon throughout his/her MMS. Next, we make a few remarks regarding the model.

(1) Each 'timeout' represents some service conducted in the system. In general, the duration is modeled by a random variable following some distribution. **(2)** Three types of resources are considered: *surgeon*, *histo-technician*, and *resident*. Whenever there is an attempt to seize a resource, waiting in queue is incurred if the resource is not available at the moment. **(3)** For wound repair, the system only attempts to seize the surgeon if the resident is unavailable. This selection is represented by the box 'select surgeon or resident' in Figure 1. This is because the surgeon is the most critical resource since it is the only one that can perform the skin layer excision. **(4)** The discharge stage is modeled as a 'delay' without consuming any critical resource of the system since most of the discharging period is carried out by a nurse and there are typically several nurses in the clinic. **(5)** The most unique feature of the problem is patient re-entrance, which occurs when an unclear margin is found during the pathology stage. With some probability, an excision does not result in complete removal of the cancer tissue and, in that case, pathology will detect the unclear margin, requiring another excision on the same day. The chance of an incomplete removal decreases with the number of excisions that have already been performed on the patient, and the modeling of such effect will be explained in Section 2.3. Other non-critical and less constrained resources in MMS (such as waiting rooms and procedure room) are not explicitly included.

2.3 Model Randomness

Several elements in the simulation model involve some form of randomness, and we now provide detailed explanations for them.

Patient no-show. Each patient's show or no-show is an independent event modeled by a Bernoulli random variable with parameter p. Therefore, each patient scheduled will show-up to their appointment punctually with probability p, and will turn out to be no-show with probability $1-p$.

Service time distributions. Each type of service has its own service time distribution modeled by a gamma distribution. The gamma distribution is a popular choice for modeling physician service time, since it has shape and scale parameters that can be used to make it a good approximation of many complex distributions (Chakraborty et al. 2010). Specifically there are five different types of service:

- The initial excision for each patient.
- Follow-up excision(s) for a re-entering patient due to the unclear margin of the last excision. This type of excisions is sometimes called the *secondary excision*. Both the literature and the practitioners confirm that the initial excision on average takes a longer service time than the secondary excisions.
- The pathology of the excised tissue.

- The wound repair process.
- The discharge process.

Each of these processes has its own service time distribution modeled by a gamma distribution with different shape and scale parameters. The mean value of the service times are taken from the literature, and various values of coefficient variation (CV) are used to explore how the variability of these services affect the operational performance. The mean and the CV together determine the values of the shape and scale parameters of the corresponding gamma distributions used in the simulation.

Re-entrance. As has been explained in Section 2.2, with some probability, an excision does not completely remove the cancer tissue, in which case the pathology will detect the unclear margin. Such an event leads to a re-entrance. The probability of such an event is denoted $p_r = p_r(n)$ given that the tissue just examined is from the n^{th} excision on the patient. Intuitively, the chance of having cancer tissue remaining after the 3^{rd} excision is smaller than its 1^{st} excision counterpart, e.g. $p_r(3) \leq p_r(1)$. The re-entrance probability in this study is modeled using equation (1), where β is a problem parameter that could be estimated from data.

$$p_r(n) = \beta^n \tag{1}$$

Note that this is used to model the conditional probability of re-entrance with the condition that n excisions have occurred. Denote the total number of excisions needed for a patient by the random variable N. According to (1) the probability that a patient needs exactly n excisions to completely remove the cancer tissue is given by:

$$P(N = n) = \begin{cases} 1 - p_r(1) = 1 - \beta & \text{if } n = 1 \\ (1 - p_r(n)) \cdot \Pi_{k=1}^{n-1} p_r(k) = (1 - \beta^n) \cdot \Pi_{k=1}^{n-1} \beta^k & \text{if } n > 1. \end{cases} \tag{2}$$

From the data, one can estimate $E[N]$, the expected number of N, and the value of β can be numerically determined using the re-entrance probability model (1)–(2).

3 SIMULATION EXPERIMENT DESIGN AND RESULTS

In the previous section, we provided the description of the discrete event simulation (DES) model developed in this study. In this section, we provide the specific values of the input parameters as well as the experimental environment.

3.1 Simulation Experimental Design

In this subsection, we define the values for the model input parameters.

The schedule. We consider the current practice adopted by an MMS clinic in Florida, USA. A clinic session is a four-hour period in the morning, which is considered the regular hours for MMS. Any operation exceeding the regular hours is considered overtime. Table 1 is the base schedule of patient arrivals for the daily MMS clinic session:

Table 1: The main schedule of patient arrivals to the daily MMS clinic session.

Arrival Time	8am	8:10am	8:20am	8:30am	...	9:30am	9:40am	9:50am	10am
Patient ID	1	2	3	4		5	6	7	8

We mainly use this scheme to schedule patient arrivals. Each patient in the schedule will show-up punctually to their appointment time with probability p. The show or no-show events are independent, and we set $p = 0.8$ as the base value. Other values of p such as 0.7 and 0.9 will also be considered for sensitivity analysis.

The resources. In this simulation setting, we have one surgeon, two histo-technicians and one resident as our main resources in the MMS process. This is consistent with the practice explained in Section 2.2.

The service time distributions. As has been mentioned in Section 2.3, each type of service has its own service time distribution modeled by a gamma distribution, and we assume independence among service times. Their mean values are specified in Table 2.

Table 2: The mean value of the service times (in minutes) used in this study.

Service	Mean value used	Mean value from literature
Initial Excision	17	16.9 (Loven Dermatology 2020; Bhardwaj 2014)
Follow-up Excision	8.5	1/2 of initial excision (clinic observation)
Pathology	29	28.7 (Rajadhyaksha et al. 2001; Cunha et al. 2011)
Wound Repair	21	About 21 (Rogers et al. 2010)
Discharge	10	9.7 (Ahmad et al. 2017)

A gamma distribution has two parameters–shape (a) and scale (b), and its density function (for $a > 0$, $b > 0$) is

$$f(x|a,b) = \frac{1}{\Gamma(a) \cdot b^a} x^{a-1} e^{-x/b},\ 0 < x < \infty.$$

The corresponding mean value μ is equal to $a \cdot b$, while the standard deviation σ is equal $\sqrt{a} \cdot b$ (Casella and Berger 2002). The coefficient of variation (CV) by definition is equal to σ/μ, therefore, a and b of the gamma distribution can be determined once the mean and the CV are given. Specifically, we have

$$a = (\frac{1}{CV})^2, \quad b = \mu \cdot (CV)^2.$$

In this study, the CV for each of the service times listed in Table 2 takes values from {0, 0.5, 1}, representing no variability (i.e. deterministic), medium variability, and high variability of service time, respectively. In addition, the CV of follow-up excision time is set to be equal to that of the initial excision.

The re-entrance probability. After the n^{th} excision, the patient needs another excision with probability $p_r(n)$ according to equation (1). The value of β can be determined once the expected number of excisions, $E[N]$, is specified. Different values of $E[N]$ are reported in literature. According to Rogers et al. (2010) $E[N] = 1.4$, and $E[N] = 2$ is reported in Batra and Kelley (2002). Both numbers will be considered in our study. $E[N] = 1.4$ yields $\beta = 0.35379$ while $E[N] = 2$ yields $\beta = 0.64523$ numerically.

In summary, eight patients are scheduled according to Table 1, each with probability p to show-up. The value of p has three levels: {0.7, 0.8, 0.9}, and $p = 0.8$ is the base case. The mean value of service time distribution for each service is provided in Table 2, and the CV of each service time takes one of the three values: {0, 0.5, 0.1}. The mean and CV together determine the gamma distribution used. The expected number of excisions is $E[N] \in \{1.4, 2\}$. Each instance is simulated for 1,000 replications using a simulation program coded in R (R Core Team 2019) together with the package DES (Matloff 2017) which is a discrete-event simulation library for R. For each replication, three values are recorded, namely the number of patients showing up, the waiting time per patient, and the overtime exceeding the regular clinic session (e.g. beyond four hours). Time is measured in minutes. The sample averages and standard errors, are computed for all three outputs. Point estimations and confidence intervals are then computed.

3.2 Results and Discussion

Before we discuss the results, we provide the general description of how to interpret the graphical results. Table 3 provides the meaning of the notation regarding CV used in the figures. The sample average of waiting time per patient (wait-per-patient) and session overtime (overtime) are used as point estimators of the corresponding mean value. In addition, the 95% confidence intervals are also presented using straight lines extending to the end points of the intervals. When both the x and y coordinates are simulated quantities, the confidence intervals of both coordinates are presented as ‘crosses’ with the center being the sample average of both quantities and the horizontal/vertical straight lines being the corresponding confidence intervals.

Table 3: The notation of CV used in figures.

	CV.E	CV.P	CV.R	CV.D
Meaning	Excisions	Pathology	Repair	Discharge

Figure 2 is the results when CV.D = 0.5 and $p = 0.8$ while all other parameters are ranging over all levels considered. First, we present the results regarding the impact of the CV of excisions, pathology and wound repair while keeping CV of discharge at 0.5. In each subplot of Figure 2, results with different CV.P values are encoded in different colors, and size of markers is used to represent the value of CV.E. In addition, the points corresponding to different CV.E values are connected with lines to better visualize the trend. Next we describe a few observations for each service time variable.

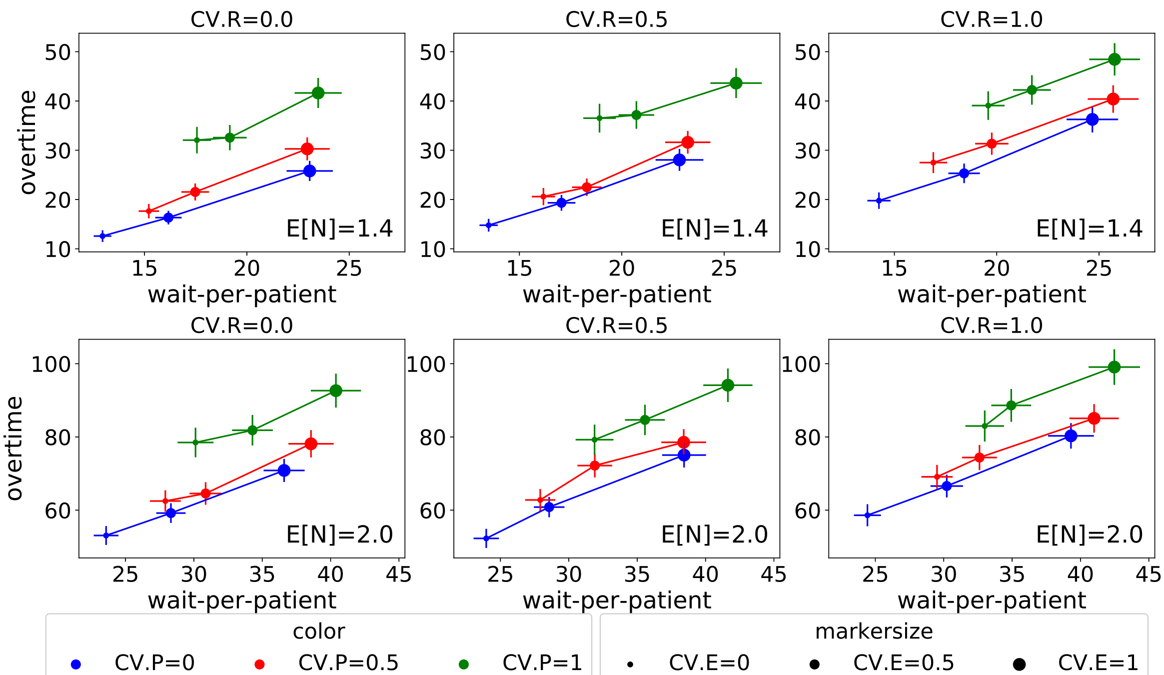

Figure 2: $p = 0.8$ and CV.D = 0.5 with $E[N] = 1.4$ vs $E[N] = 2$.

Excision. a) In general, larger variability in excision service time (CV.E, coded by the size of markers in the graph) leads to longer wait-per-patient and overtime; b) The monotonic trend in waiting time is statistically significant. In fact, within each subplot for each level of CV.P, the corresponding 95% confidence intervals of wait-per-patient generally do not overlap when CV.E changes from a smaller value to a larger one. The only exception is seen in the last subplot. c) The monotonic trend in overtime, on the other hand, is less significant, since there are several cases where the confidence intervals in the vertical direction overlaps when CV.E changes from 0 to 0.5.

Pathology. The effect of the service time variability in pathology (CV.P, coded in color) also shows a clear pattern. In general, a larger CV.P value leads to longer waiting times and overtime. Additionally, it also plays a role in how CV.E affects overtime. When CV.P is of a lower level, confidence intervals of overtime with different CV.E do not overlap. This is more prominent in blue lines (CV.P = 0). The intuition is that when pathology service time is more predictable, the CV.E has a strong effect on overtime.

Repair. The service time variability in wound repair (CV.R) will also affect waiting and overtime monotonically.

E[N]. The value of E[N] also plays a role. When $E[N] = 2$ and CV.R = CV.P = 1, neither waiting nor overtime exhibit a statistically significant difference when the excision service time changes from deterministic to moderately stochastic (i.e. CV.E = 0.5). This is the only case out of 18 curves in Figure 2 regarding the monotonicity of waiting with respect to CV.E. An intuitive explanation is that the sum of total service time of excisions becomes more stable when there are more excisions needed.

An interesting pattern shared by both pathology and excision is that, the marginal effect of CV on system performance seems to be increasing. Taking pathology for example, the blue curves (CV.P = 0) and the red ones (CV.P = 0.5) are closer to each other, while the green one (CV.P = 1) is far away from the red one. This means, changing from a deterministic service time of pathology to a moderately stochastic one does not impact the system performance too much, while going from the moderate to high level of variability significantly worsens the system performance.

Another interesting finding is that, the effect of the variability in discharge service time is different from all other CV's. A closer examination of the MMS process (Figure 1) reveals that the discharge service does not affect patient waiting at all. In addition, discharge can be conducted simultaneously (by nurses) without seizing the critical resources, and its mean service time is much smaller than that of (total) excision, pathology or wound repair. These all together make the effect of CV.D on overtime negligible. As can been seen from Figure 3, overtime demonstrates a marginally monotonic pattern with respect to CV.D only when CV.E = CV.P = 0. We examined the cases of $p = 0.7$ and 0.9 to confirm that similar conclusion regarding CV.D holds. Additional figures that confirm these conclusions are not included in the paper (due to limited space) but are available upon request.

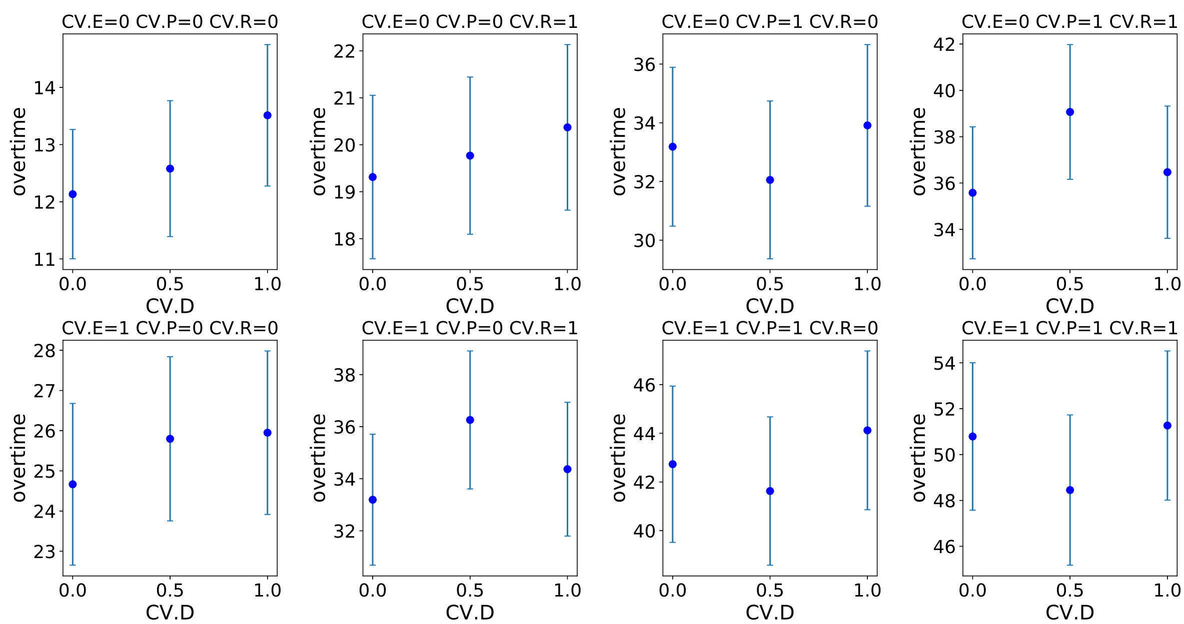

Figure 3: CV.D values and overtime when $p = 0.8$ and $E[N] = 1.4$.

We have also examined the $p = 0.7$ and 0.9 counterpart of Figure 2, and qualitatively the observations based on $p = 0.8$ still apply to the cases with different values of p. Again, due to space restrictions, the figures for $p = 0.7$ and 0.9 are not included in the paper but are available upon request. Instead, the general effect of p is presented in Figure 4, which shows that the waiting and overtime increase with p. This is very intuitive since the overall workload increases with p. Therefore, for large p, the schedule is too crowded. We examine alternative schedules in the next section to deal with this issue.

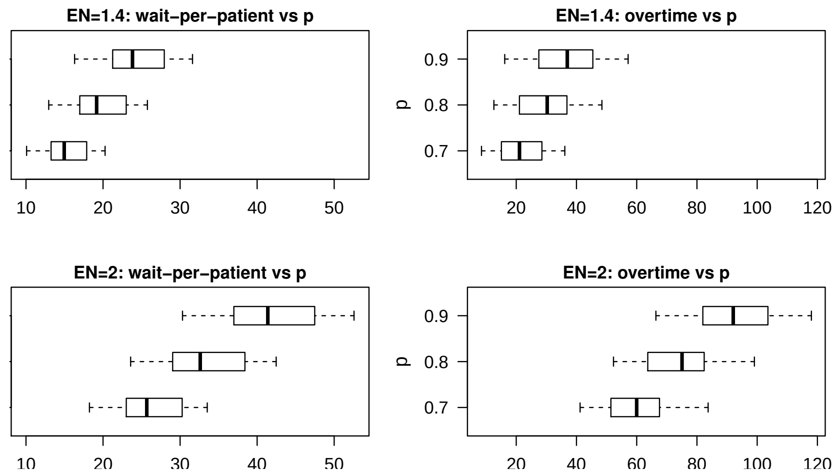

Figure 4: Boxplot of mean wait-per-patient and overtime for different p.

3.2.1 Dropping One Patient from the Schedule when Show-up Probability is High

The schedule given in Table 1 has a fixed number of appointments. When $p = 0.8$, such schedule has, on average, 6.4 patients showing up, and the number becomes 7.2 if $p = 0.9$. More patients showing up inevitably causes more waiting and clinic overtime. Clinics with higher show-up rates of 0.9, may consider scheduling seven patients so that the average number of patients showing up remains close to 6.4. An obvious question is, which one to drop? In this subsection, we investigate such a scenario to see how dropping different appointments impacts the waiting time and overtime. Trivially, the earliest appointment in the session should be kept, and we derive a set of schedules denoted Xi for $i = 2,...,8$ where patient i is dropped from the schedule in Table 1.

Figure 5 provides the waiting time and overtime for different policies together with the base of $p = 0.8$ as the benchmark. CV.P and CV.D are fixed at medium variability of 0.5. As is always the case in appointment scheduling studies, different preferences of patient waiting time and overtime will lead to favoring different policies, a few observations from Figure 5 is worth mentioning:

- Dropping the 8^{th} appointment (X8) yields largest reduction in the amount overtime, as is expected.
- Much less expected is that X7 performs almost as well as X8 does in terms of overtime, especially when CV.E is at low or moderate level. Similar comments also hold for X6.
- X6 has the best performance in terms of patient waiting among X6, X7 and X8 when CV.E is small.

These observations suggest that, X6 may be a good candidate when considering a seven-appointment clinic session in the environment of high patient show-up rate. X6 remains to be a favorable candidate when $E[N]$ is higher, as can be seen in Figure 6. It almost always outperforms the benchmark scenario–eight-patient schedules with $p = 0.8$.

Figure 7 places the waiting and overtime in x and y coordinates, respectively for each of schedule Xi when $E[N] = 1.4$ and $p = 0.9$. Both the point estimations and 95% confidence intervals are reported, and the number i on the upper-right of the cross identifies the corresponding policy Xi, $2 \leq i \leq 8$. The general trend is that, all policies are impacted by the CV.E (coded in color) significantly–the more volatile the excision service time, the longer the waiting and overtime will be. This confirms the previous findings since both initial excision and the follow-up one due to re-entrance will be impacted by CV.E. Another interesting finding regarding excision service time is that, changing from deterministic (CV.E = 0) to moderately stochastic (CV.E = 0.5) has less impact on waiting or overtime, compared to its counterpart of changing CV.E from 0.5 to 1. This can also been seen from Figure 5 and Figure 6 where the red points and the blue ones are close to each other compared to the green points.

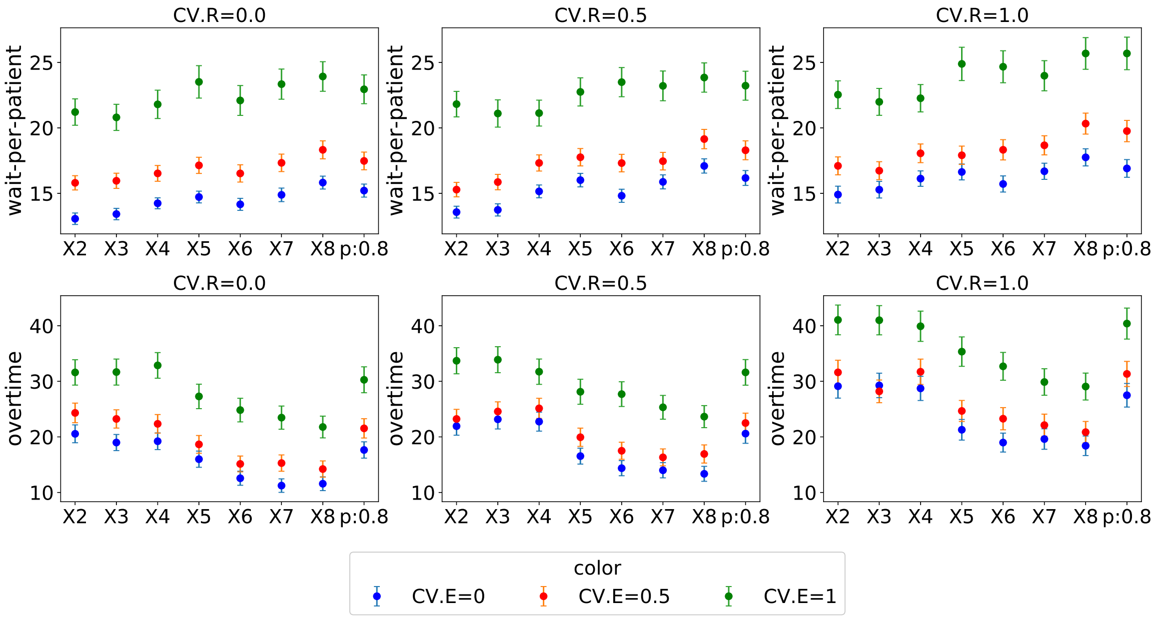

Figure 5: $E[N] = 1.4$, CV.P = CV.D = 0.5. Different schedules of 7 appointments with $p = 0.9$ vs the one of 8 patients with $p = 0.8$ as benchmark.

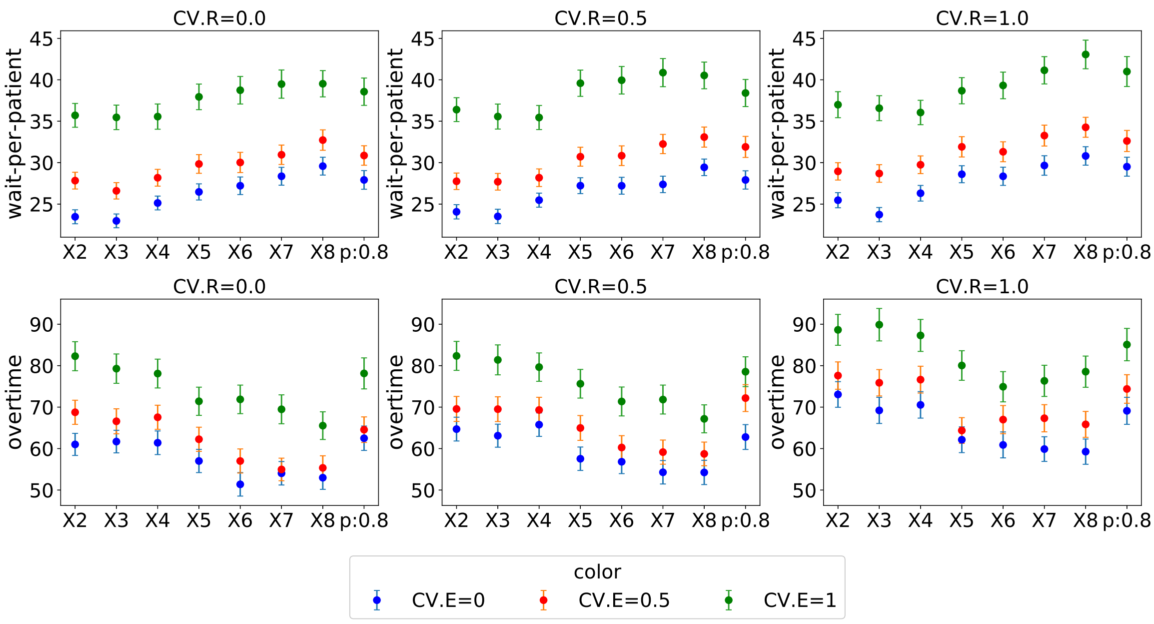

Figure 6: $E[N] = 2$, CV.P = CV.D = 0.5. Different schedules of 7 appointments with $p = 0.9$ vs the one of 8 patients with $p = 0.8$ as benchmark.

Figure 7 also shows that when the wound repair service time changes from deterministic to moderately random, the system performance remains largely unchanged. When CV.R becomes 1, it does increase overtime moderately, but waiting time remains largely unchanged. Waiting and overtime will moderately increase as CV.P increases. When examining individual policies, there is no policy that always outperforms

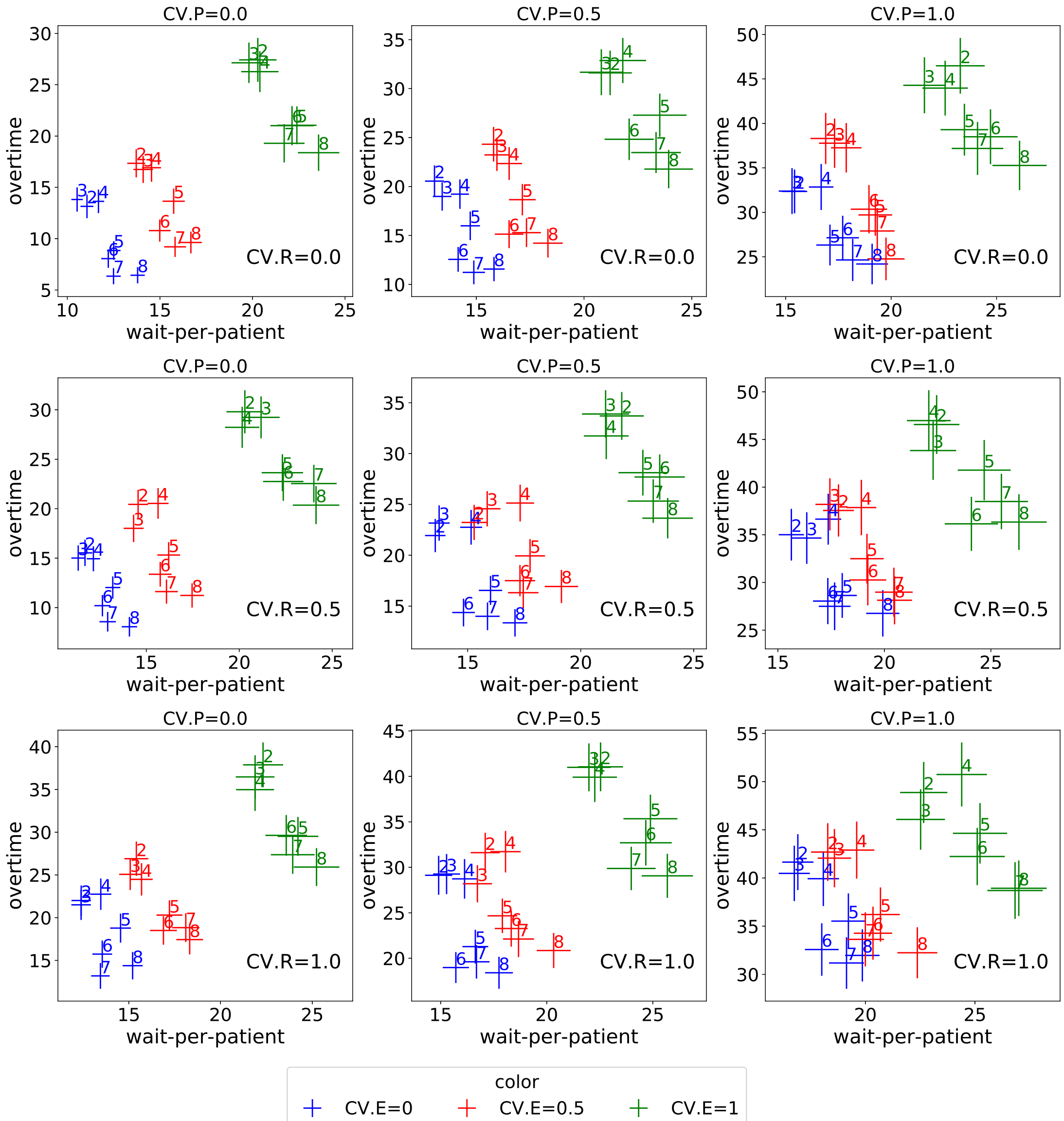

Figure 7: $E[N] = 1.4$, $p = 0.9$, CV.D = 0.5, waiting and overtime of schedules with 7 appointments.

others, since different preferences of waiting over overtime may lead to different winners. However, some polices are dominated by others in some cases. For example, when CV.R = 1 and CV.P = 0 (the lower left subplot of Figure 7) X7 dominates X5 when CV.E = 0. And for all cases where CV.P < 1, CV.E = 0, X7 seem to have comparable or better waiting time than X5 while its overtime is uniformly better than X5 (most cases with statistically significant difference in overtime). Overall, X6 consistently demonstrates good performance in both waiting and overtime. Similar observations are found when $E[N] = 2$, and the corresponding figure is omitted due to limited space (and is available upon request). In all cases, dropping a patient from the second wave is preferred to dropping a patient from the first wave. In many cases, either the X6 or X7 schedule is dominating. These results indicate that you want to have more patients arrive early to get the MMS processes started and avoid idle resources, so patient should not be dropped from the first wave (do not select X2-X4). Among the second wave, you want to keep the 1st person (so do not select X5), but X6-X8 are all reasonable choices.

4 CONCLUDING REMARKS

Like many outpatient clinics, MMS has many stochastic processes and limiting resources. One unique aspect of MMS is the stochastic patient re-entrant process that can impact the expected number of layers removed per patient. In this paper, we used discrete-event simulation to investigate the impact of uncertainty on the patient waiting time and overtime at a MMS clinic. The increased variability for service times generally lead to longer patient waiting time and clinic overtime; this is especially true for the excision and pathology time in MMS clinics. The effect of the variability for service time of discharge, on the other hand, is negligible. In addition, we considered the case of high show-up probability (e.g. 90%) and investigated schedules with fewer patients. Specifically, this paper focused on dropping one patient among the original eight slots and found that patients should not be dropped from the earlier waves, nor from the beginning of the last wave. In this case, dropping one of the last three patients from the scheduling template yielded the best results for minimizing clinic overtime and patient waiting time. However, results are limited to the assumed scheduling template. A systematic study on optimizing the MMS appointment scheduling that properly incorporates same-day stochastic re-entrants is needed and is left for future research.

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