Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds

A USER-FRIENDLY EXCEL SIMULATION FOR SCHEDULING IN PRIMARY CARE PRACTICES

Hyun Jung Alvarez Oh
Ana Muriel
Hari Balasubramanian

Mechanical and Industrial Engineering
University of Massachusetts, Amherst
160 Governors Drive
Amherst, MA 01003, USA

ABSTRACT

The purpose of this study is to provide a user-friendly Excel simulation tool for primary care practices to manage appointment schedules which accommodate multiple patient types and stochastic service times for the nurse and provider steps in patient flow. The key features of the Excel tool are: a color-coded schedule of each provider; a Gantt chart as a visual aid for schedulers; dynamic tests of different patient mix, sequence and start time combinations; and performance measures that include average and key percentiles of wait time, idle time and session completion time. The Excel tool can be easily modified by practices to incorporate their own data and needs. In our case study, we quantify the impact of flexible nurses and/or providers to satisfy patient demands for multiple providers.

1 INTRODUCTION

Primary care practices play a vital role in healthcare delivery since they provide health prevention, counseling, education, diagnosis and treatment. Anderson et al. (2007) and Camacho et al. (2006) find that the combination of short service time and long wait time is the most detrimental to patient satisfaction. This is more likely to happen when providers fall behind in their schedules. To prevent this situation, a practice needs an effective appointment scheduling policy. However, primary care faces a complex scheduling problem because of the variety of patient conditions, the mix of appointment types (physicals, follow-ups, and urgent), and the uncertain service time with providers and nurses/medical assistants, which all compound into a very variable and unpredictable schedule.

In order to improve scheduling in healthcare, many papers use simulation since it can accommodate complex queuing systems and environmental factors (Cayirli and Veral 2003). We review a few relevant papers which consider patient flow using simulation in advanced software tools. Hashimoto and Bell (1996) first conduct a time-motion study of the patient flow in an internal medicine academic practice. They use simulation, coded in Turbo Pascal, to observe the impact of increases in human resources and task variables such as appointment intervals, no-shows, and provider service time. Based on the time study and the simulation results, clinic managers made operational changes. Gul et al. (2011) consider multiple patient flow steps in outpatient procedure centers.

They use discrete event simulation and develop a genetic algorithm with the goal of minimizing the expected patient wait time and practice overtime. They found that the shortest processing time rule performs the best among heuristics. Harper and Gamlin (2003) develop a simulation model in the Simul8 package which interfaces with Excel for an ENT (Ear, Nose, and Throat) clinic in a hospital in the United Kingdom. They collect arrival and service time data and also different human resources depending on the clinic session. They test a number of different schedules while considering three performance measures: 1) average wait time in the lobby, 2) percentage of patients who wait more than half an hour in the lobby, and 3) average total time patient spent at the practice. They find that the most significant factor is whether the clinic is able to start its day on time. If the start time is delayed, spreading out the appointments in the session, instead of scheduling patients at the beginning of the session, is a more effective policy.

Unfortunately, these simulation tools are not easy to access for small primary care practices. According to National Ambulatory Medical Care Survey 2010, about 32% visits are to single physician practices. For small practices, it may be effective to use something as widely available as Excel. We review a few papers that have used Excel. Rojas et al. (2011) use LpSolve in Excel to allocate medical staff to consulting rooms for the public hospital in Bogota, Colombia. They formulate a mixed integer linear program and solve it in two stages: the first stage to minimize the number of consulting rooms and the second stage to allocate related specialty physicians. Bagust et al. (1999) use an Excel spreadsheet simulation in order to examine the relationship between the stochastic patient admission demand and available inpatient bed capacity.

The objective of our study is to provide a user-friendly Excel simulation tool for schedulers to manage appointment schedules which accommodate multiple steps in the patient flow process: wait time in the lobby, service time with nurse, wait time in the exam room, service time with provider, and total time patient spent at the practice. Additionally, we also allow for three well-differentiated patient classes which categorize various patient conditions and appointment types typically seen in the practices. More details on using the Excel simulation tool is provided in section 3. This tool can be easily modified to include more human resources, patient types, and performance measures.

In our case study, we use the Excel tool to compare the performance of dedicated versus flexible nurses using schedules from our previous work, Oh et al. (2013). We discuss more details in the next section.

2 PREVIOUS WORK

This paper builds upon our previous work, Oh et al. (2013). We analyze empirical data collected from a family medicine practice in Amherst, Massachusetts, on 9 workdays. We construct the chronology of patient flow to identify factors which cause high variability in the schedule, and propose a new easy-to-identify patient classification based on the length of the appointment: prescheduled high complexity (HC), prescheduled low complexity (LC), and same-day (SD) appointment types. The HC consists of the six conditions: routine physical exam; well child check-ups; diabetes and chronic condition management; new patient visits; procedures; and migraines and headaches. The LC includes relatively low complexity patient conditions. The SD consists of patients scheduled over the day, on short notice. In addition, we model a stochastic integer program that accommodates the coordination of service times with both nurse and provider. The model optimizes schedules and sequences of appointments in a session broken into 15-min. appointment slots with the objective of minimizing a weighted combination of provider idle time and patient wait time. Our computational work allows us to identify scheduling guidelines which can be easily applied in the practice. Also, we propose easy-to-implement heuristic schedules that take into account patient time-of-day preferences and help the practice stay financially viable. We alternate patient types in the following sequences: 1) SD/LC/HC, 2) LC/SD/HC, 3) SD/SD/HC followed by LC/LC/HC, and 4) LC/LC/HC followed by SD/SD/HC. For example, 1) SD/LC/HC sequence books a same-day appointment first followed by a low-complexity and then a high-complexity appointment. Given these sequences, we optimize the appointment times. The integer program always suggests that slack (an empty appointment slot) should be scheduled after a block of 3 appointments - we call this the three appointments an hour (3AH) rule since each appointment and the slack take up a 15-min. appointment slot.

3 EXCEL SIMULATION TOOL: MOTIVATION AND KEY FEATURES

In our previous study, we focus on practices where one nurse and one provider work as a medical team. We refer to such practices as *dedicated nurse practices* since a nurse exclusively takes care of patients in the panel of the particular provider. In practice, however, we have often observed two nurses flexibly sharing the patients of a two-provider team; we call these *flexible nurse practices*. Each provider still keeps her/his own panel of appointments and can choose to see her/his patients according to the original appointment schedule or, more commonly, in the order in which they complete the nurse step (that is, *allowing patient schedule crossover*). In our study, therefore, we consider three cases: 1) dedicated nurses, 2) flexible nurses, and 3) flexible nurses & crossover. Therefore, we account for the following factors in an Excel simulation tool: 1) patient classification into three well-differentiated patient types; 2) stochastic service times for both nurse and provider; 3) potential patient sharing by nurses; and 4) no sharing of appointments between providers.

Our goal is to provide an Excel simulation tool that allows the scheduler in the practice to explore the performance of different schedules in real time. The stochastic performance of the schedule can be thus assessed dynamically as patients requests arise. As a case-study, we compare the performance of *dedicated* versus *flexible nurse practices* in a primary care setting with two providers and two nurses. We use actual schedules observed in practice, optimal schedules, and heuristic schedules from Oh et al. (2013). A preliminary version of the Excel simulation tool is available at "UMass blog by Oh"

The Excel tool contains five different spreadsheets: nurse time, provider time, deterministic, stochastic, and schedule. We describe them in detail below. Figure 1 shows the snap shot of the Excel simulation tool.

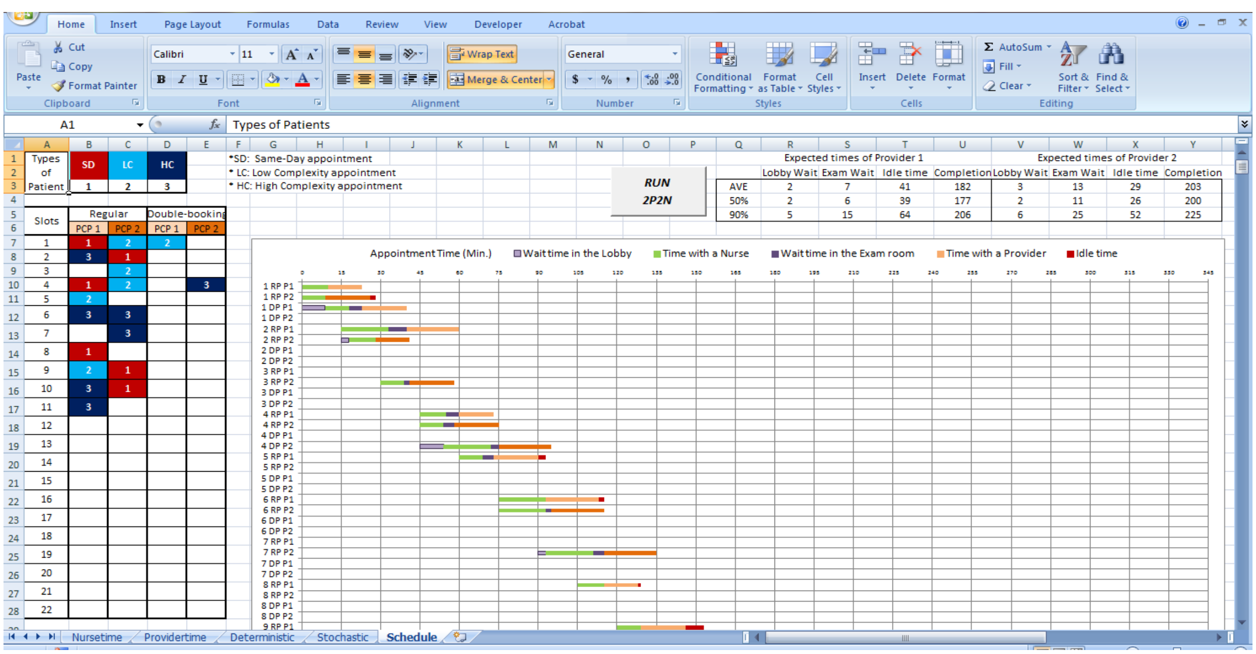

Figure 1: Snap shot of Excel simulation tool. On the left, colored slots indicate provider calendars. A Gantt chart on the right indicates how the schedule will play out in practice; this is intended as a visual aid to the scheduler.

The *nurse time* spreadsheet includes 1000 scenarios of service time with a nurse for each patient type, randomly sampled from the empirical study. The *provider time* spreadsheet includes 1000 scenarios of service time with each provider for each patient type, randomly sampled from the empirical study.

The *deterministic* spreadsheet contains the average service times of nurse and provider steps for the different patient types. This information is linked to the Gantt chart in the *schedule* spreadsheet, which shows the scheduler how the schedule would fare under average service times. The s*tochastic* spreadsheet uses service time data from the *nurse time* and *provider time* spreadsheets. All patient flow indicators are calculated by algorithms coded in visual basic for applications (VBA) in EXCEL 2007.

The algorithms in VBA are based on the stochastic integer programming model in Oh et al. (2013). We use the appointment time, start time with nurse/provider, and finish time with nurse/provider for each patient to calculate wait time in the lobby (start time with nurse minus appointment time), wait time in the exam room (start time with provider minus finish time with nurse), and idle time (session completion time minus service time of all patients with a provider). The appointment times are given in 15 min. slots, as is the case in the family care practice that inspired this study. This is a trivial calculation in the case of dedicated nurses. In the case of flexible nurse practices, patients see the nurse that first becomes available. The time when a nurse becomes available for patient i can be calculated recursively as the second largest value of the finish times of earlier patients, 1 to i-1, with the nurses. Similarly, providers will see the patient from their panel that finishes the nurse step earlier. The time at which the provider's n^{th} patient is ready can again be calculated recursively, using the second largest logic (now applied to the finish times with nurses of the earlier patients).

In addition, the *stochastic* spreadsheet links to the performance table in the *schedule* spreadsheet.

The scheduler needs to use the *schedule* spreadsheet to input the desired schedule and click the run box button to get the associated performance estimates. A *schedule* spreadsheet consists of three parts:

1) Schedule management: consisting of two columns for each provider to input both regular booking and double booking appointments with the three easy-to-identify appointment types proposed in Oh et al. (2013). The appointment types are denoted by different numbers and colors: same-day (*SD*) appointment – 1 and red; Low Complexity (*LC*) appointment – 2 and light blue; and High Complexity (*HC*) appointment – 3 and dark blue. If an additional patient needs to be assigned to an appointment slot already filled, double-booking occurs and the patient types can be scheduled in the double booking columns.

2) Gantt chart: allowing the scheduler to visualize how the appointments are staggered. The Gantt chart provides six indicators of patient flow with different color codes (assuming 15 min. slot length): wait time in the lobby - light purple; time with nurse - green; wait time in the exam room - dark purple; time with provider - orange; and idle time - red.

3) Performance: including the average, 50^{th} and 90^{th} percentiles of lobby wait, exam wait, idle time and completion time derived using the results of a simulation of 1000 scenarios from the *stochastic* spreadsheet. Note that when the scheduler plugs number indicators of appointment types in the schedule management columns, the *stochastic* spreadsheet populates the appropriate data from the *nurse time* and *provider time* data spreadsheets.

4 CASE STUDY

To illustrate the use of the Excel tool, we use schedules studied in Oh et al. (2013): schedules observed in the practice, optimal schedules generated by the Deterministic Integer Program (DIP) and the Stochastic Integer Program (SIP), and heuristic schedules. While we use these as examples, note that a practice can choose to evaluate any schedule it likes. We run all possible combinations; for example, one provider uses one of the heuristic schedules, 1) SD/LC/HC schedule, and another provider employs the DIP optimal schedule: 1 + DIP shown in Figure 2. We consider ten patients (3 SD patients, 3 LC patients, and 4 HC patients) for provider 1 and nine patients (just one less HC patients than provider 1) for provider 2. We empirically observed this appointment mix in practice.

1) SD/LC/HC Optimal schedule by DIP

Appointment Slots	Provider 1 Regular booking	Provider 1 Double booking	Provider 2 Regular booking	Provider 2 Double booking
1	1	2	2	
2	3		1	
3			2	
4	1		2	3
5	2			
6	3		3	
7			3	
8	1			
9	2		1	
10	3		1	
11	3			

Figure 2: An example of schedule combination: 1) SD/LC/HC and optimal schedule by DIP.

Figure 3 compares the performance of a variety of schedule combinations under dedicated and flexible nurse settings. The performance is measured by the weighed combination of provider idle time and patient wait time; the weight on idle time is 0.8 and wait time is 0.2. This weight combination was shown to be appropriate in our previous work. Again, a practice is free to use weights that are better suited to its operations.

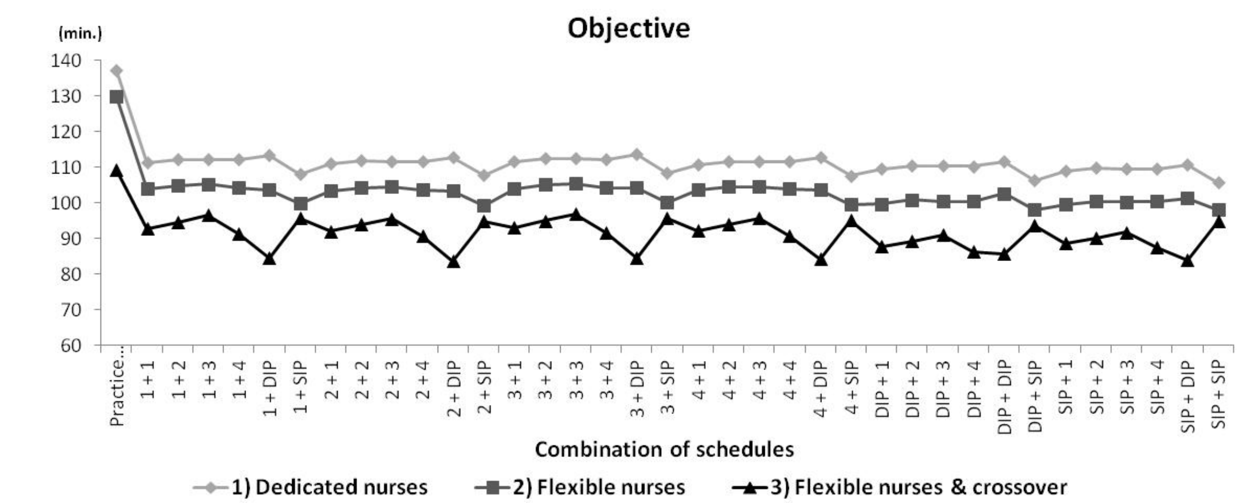

Figure 3: Objective performances among practice schedule and combinations of optimal and heuristic schedules between 1) dedicated nurses, 2) flexible nurses, and 3) flexible nurses & crossover.

As shown in Figure 3, each flexible practice yields an 8% and 18% improvement in performance relative to the dedicated practice, respectively. Observe that schedules that use SIP for at least one provider tend to outperform the others in 1) dedicated nurses and 2) flexible nurses. However, when we account for crossover with flexible nurses, DIP schedule provides better performance. The performance of the combinations of optimal and heuristic schedules we generated with single provider is 19%, 21%, and 16% better on average than that of the practice schedule in dedicated and flexible practice settings, respectively. To provide more details, Figure 4 illustrates average performance of each component of patient flow: wait time in the lobby per patient, wait time in the exam room per patient, and average idle time of both providers.

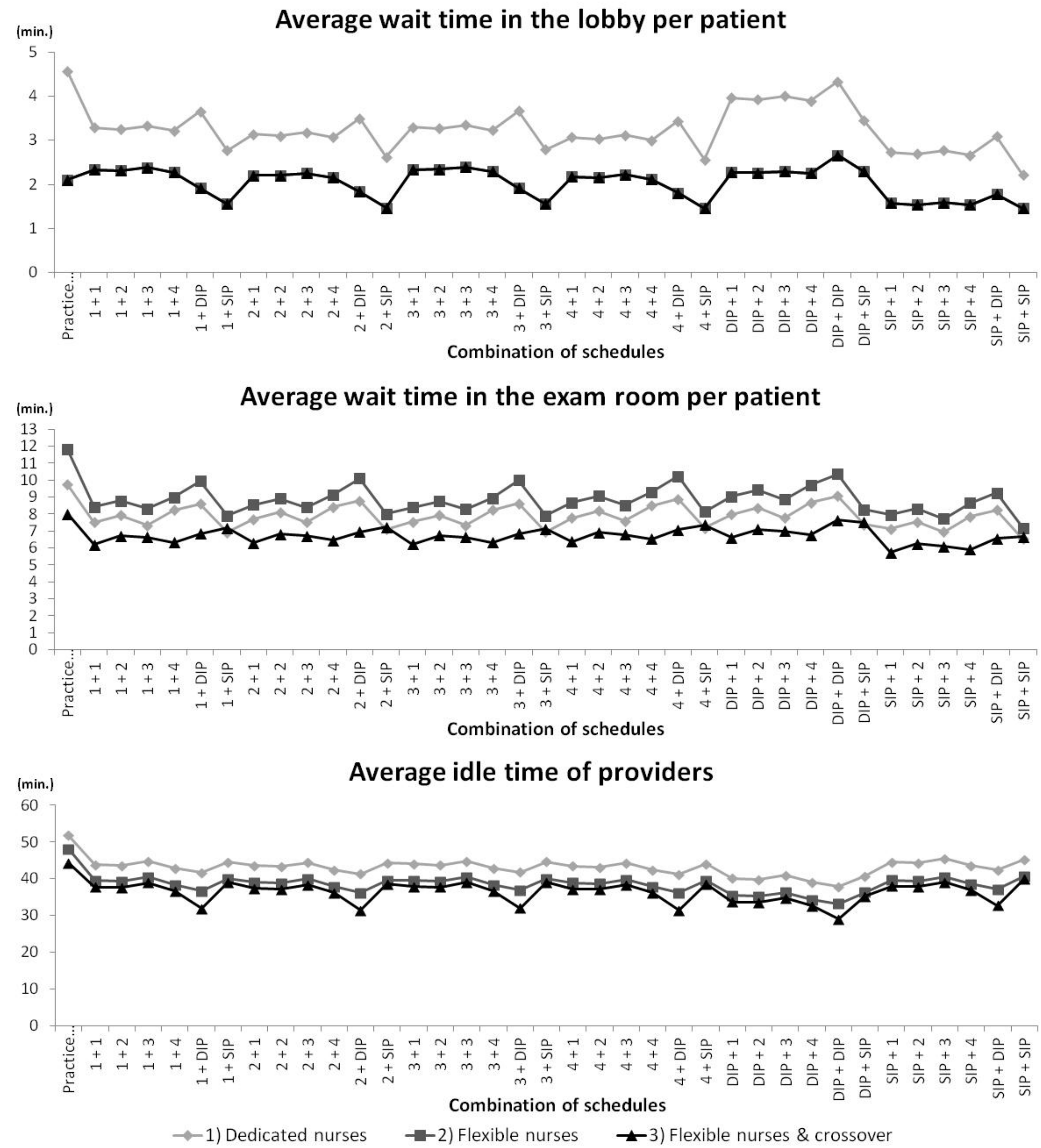

Figure 4: Average performance of wait time in the lobby and exam room per patient, and average idle time of providers among schedules between 1) dedicated nurses, 2) flexible nurses, and 3) flexible nurses & crossover.

As expected (shown in Figure 4), having flexible nurses significantly improves the wait time in the lobby, by 37%, except when the practice schedules are used. With 2) flexible nurses, unfortunately, these time savings are partially washed away by an increase exam room wait by 12% on average of the schedules. As a result, the total patient wait time of flexible nurse practices is 2% better than that of dedicated nurse practices. In addition to the flexible nurses, however, when the provider decides to see patients whoever finishes earlier, patient wait time in the exam room even 14% improve than the dedicated nurse practices, on average. In this case, the total wait time has 21% improvement than that of the dedicated nurse practices.

In addition, provider idle time is significantly reduced by 11% by adding flexibility in the nursing step. Along with flexible nurses, the crossover also grants 16% improvements in the idle time. The reduction in provider idle time is particularly relevant because the provider is the most expensive resource and the bottleneck in the operation of primary care practices. Any improvements in the utilization of this resource should be easily translated into higher system capacity and revenues.

Note that the optimal schedule identified by SIP has significant impact on the objective performance; in particular, it plays a critical role in wait times in the cases of 1) dedicated nurses and 2) flexible nurses. In the case of 3) flexible nurses and crossover, on the other hand, the DIP optimal schedule provides the best performance. This highlights the need for coordinating the schedules of the two providers in the case of flexible nurses, which is the focus of our on-going study.

Next, we study the worst case, 90th percentile of idle time versus wait time in Figure 5. For brevity, we show only some combinations of schedules.

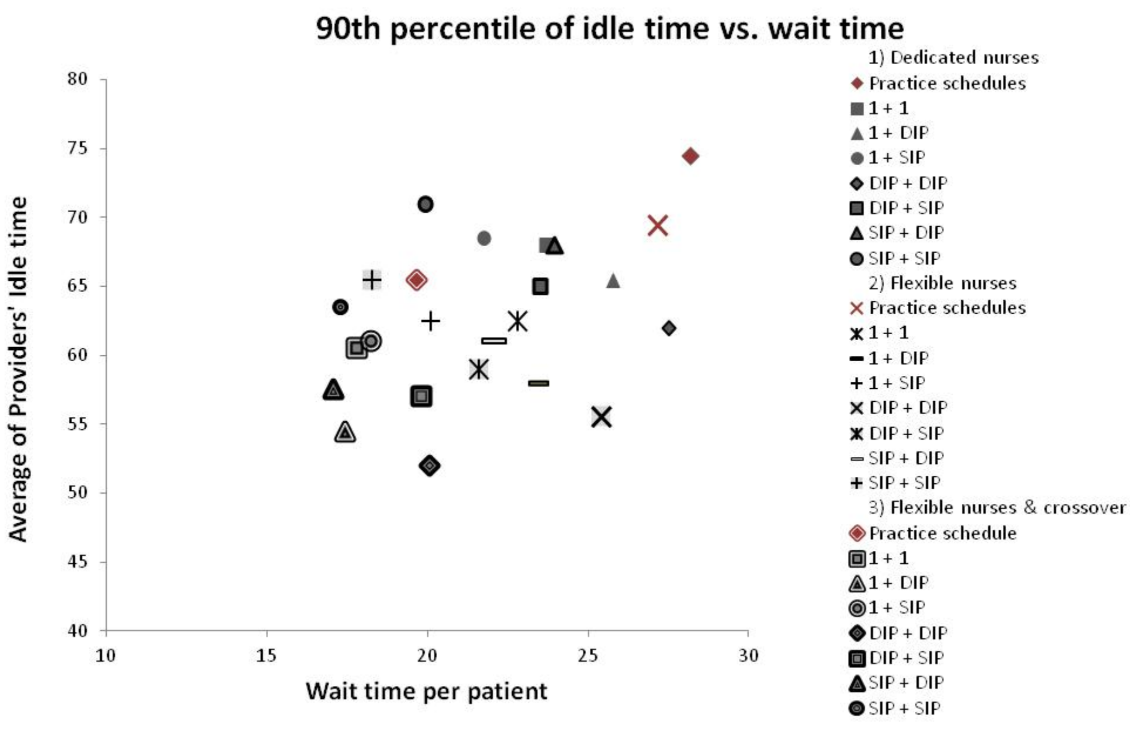

Figure 5: 90th percentile of idle time versus wait time among practice schedules and combinations of optimal and heuristic schedules between 1) dedicated nurses, 2) flexible nurses, and 3) flexible nurses & crossover.

When we look at the 90th percentile of idle time versus wait time (Figure 5), we see that combinations of optimal and heuristic schedules have consistently better performance in both idle and wait time compared to practice schedules. Also, optimal and heuristic schedules of 3) flexible nurses & crossover dominate those of 1) dedicated nurses and 2) flexible nurses. Most of the schedules in the efficient frontier are optimal schedules by DIP or SIP. We also study 90th percentile of session completion time; combinations of optimal and heuristic schedules improve approximately 5% when compared to the practice schedule.

Therefore, allowing for flexible nurses and crossover has significant impact on the schedule performance.

5 DISCUSSION

Primary care practices include high variability in service times with both nurse and provider, different patient conditions and various appointment types. In our previous study, Oh et al. (2013), we found that an effective scheduling system is the key to improving utilization of the practice. However, it is not easy for small family practices to access advanced optimization or simulation software. Thus, we develop an easy-to-use Excel simulation tool. We use the tool in this paper to compare dedicated and flexible nurse settings, based on empirical data and schedules from the previous study. In the cases tested, we find evidence that flexible nurses and crossover do provide significant benefits.

The Excel simulation tool has the following features. First, by including a color-coded Gantt chart based on average service times, the tool provides a visual aid to the scheduler. Second, it allows the scheduler to dynamically test out different patient mix, sequence and start time combinations in a format that resembles provider calendars. Finally, the Excel tool allows the scheduler to input random scenarios and calculate not just averages, but key percentiles of wait time, idle time, and session completion time. The tool can be used dynamically, as schedules develop over time. One drawback to real time use is that precise estimates of the stochastic simulation depend on the number of scenarios, which in turn increases computation time. For example, the simulation time takes approximately 20 min with 1000 scenarios. It was run on window 8.1 pro and 64 bit with Intel(R) Core™ i7-4770 CPU @ 3.40 GHz, 3401 Mhz, 4 Core(s), 8 Logical processor(s) and 32GB RAM. For quick answers, therefore, the scheduler could reduce the number of scenarios accordingly. Another way to overcome this is to test various scheduling possibilities before the day begins or during lunch time.

The Excel tool can be readily adjusted by practices to suit their data and needs. Practices can use their own patient classifications by changing the VBA code to link with data in *nurse* and *provider* spreadsheets. They can also use different service time input data in *nurse* and *provider* spreadsheets.

ACKNOWLEDGMENTS

This work was funded in part by from the National Science Foundation (NSF CMMI 1254519). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

ADDENDUM

In the case of flexible nurses and crossover, the performance metrics reported here are slightly off because of a small error in calculation. The corrected results display very similar trends but the gains associated with crossover are lower, with an average of 12% as opposed to the reported 18%.

REFERENCES

Anderson, R. T., F. T. Camacho, and R. Balkrishnan. 2007. "Willing to wait?: The influence of patient wait time on satisfaction with primary care." *BMC Health Services Research* 7, no. 1: 31.

Bagust, A., M. Place, and J. W. Posnett. 1999. "Dynamics of bed use in accommodating emergency admissions: stochastic simulation model." *BMJ: British Medical Journal* 319, no. 7203: 155.

Camacho, F., R. T. Anderson, A. Safrit, A. S. Jones, and P. Hoffmann. 2006. "The relationship between patient's perceived waiting time and office-based practice satisfaction." *NC Med J* 67, no. 6: 409-413.

Cayirli, T., and E. Veral. 2003. "Outpatient scheduling in health care: a review of literature." *Production and Operations Management* 12, no. 4: 519-549.

Gul, S., B. T. Denton, J. W. Fowler, and T. Huschka. 2011. "Bi-Criteria Scheduling of Surgical Services for an Outpatient Procedure Center." *Production and Operations management* 20, no. 3: 406-417.

Harper, P. R., and H. M. Gamlin. 2003. "Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach." *Or Spectrum* 25, no. 2: 207-222.

Oh, H. J., A. Muriel, H. Balasubramanian, K. Atkinson, and T. Ptaszkiewicz. 2013. "Guidelines for scheduling in primary care under different patient types and stochastic nurse and provider service times." *IIE Transactions on Healthcare Systems Engineering* 3, no. 4: 263-279.

Rojas, S., F. A. Castaño, N. Velasco, and C. A. Amaya. 2011. "A decision support tool to generate the monthly schedule for consulting rooms in a public hospital." http://dspace.uniandes.edu.co/xmlui/handle/1992/1133

AUTHOR BIOGRAPHIES

HYUN JUNG ALVAREZ OH is a Ph.D. candidate in the department of Mechanical and Industrial Engineering at University of Massachusetts, Amherst. She received her M.S. in Industrial Engineering from Lehigh University. Her email address is hjoh0814@gmail.com.

ANA MURIEL is an Associate Professor in the department of Mechanical and Industrial Engineering at University of Massachusetts, Amherst. She received her M.S. and Ph.D. in Industrial Engineering and Management Sciences from Northwestern University. Her research focuses on different aspects of logistics and supply chain management. Her email address is muriel@ecs.umass.edu.

HARI BALASUBRAMANIAN is an Assistant Professor in the department of Mechanical and Industrial Engineering at University of Massachusetts, Amherst. He received his M.S. and Ph.D. in Industrial Engineering from Arizona State University. His research deals with operations research applied to healthcare delivery. His email address is hbalasub@admin.umass.edu.