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# BUILDING A FLEXIBLE SIMULATION MODEL FOR MODELING MULTIPLE OUTPATIENT ORTHOPEDIC CLINICS

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## ABSTRACT

Often large health care organizations will have multiple satellite clinics in addition to the primary flagship location. The value of having multiple clinics includes the ability to better serve patients by improving accessibility while also increasing efficiencies from common structures and policies. Unlike most simulation models of health care clinics, which are uniquely designed for one specific location and are not easily adapted without significant effort, we develop one flexible discrete-event simulation model to represent two orthopedic centers. In addition to demonstrating the validity of employing the same model for two clinics, a graphical user interface is constructed to enable the clinic managers to modify simulation parameters, minimizing the need for future model adaptations. The value of the simulation model is verified by evaluating the effects of new policies impacting the role of mid-level providers and results show that the best policy for improving timeliness of care varies among clinics.

## 1 INTRODUCTION

The application of simulation models for improving operations in health care settings is well studied. Due to the extensive investments in both the cost and the time involved in the implementation of new policies, mathematical modeling approaches, such as simulation modeling, present cost effective methods for evaluating system costs and benefits. Studies on health care system process improvement through the use of computer simulations emerged at the beginning of 21st century and have examined a variety of different problems such as outpatient clinic layout design, patient flow redesign (Vahdat et al. 2017), and appointment scheduling (Zacharias and Armony 2017). Although the benefits of computer simulation models are clear, health care simulation models are traditionally designed specifically for a particular setting or system and are highly limited by, and dependent on the underlying model assumptions and inputs. As such, works focusing on specific clinics are abundant, but simulation model that represent multiple clinics are still limited (Vanberkel et al. 2010). Ashton et al. (2005) use simulation to identify which best practice from other centers can be transferred to the studied walk-in center. The paper concluded that such an adoption is not trivial as no two centers are equal. Along with technology innovations, there are often systematic changes regarding patient flows and resource usage that may result in previous simulation models no longer being applicable in an updated clinic, even when allowing for parameter changes. With the recent integration of features in simulation packages that allow developers to easily build Graphical User Interfaces (GUIs), there are more opportunities to create simulations that can be reused and updated in response to system changes.

Many studies restrict the developed computer simulation models to represent the features of particular centers such that the results of the model analysis can not easily be applied to other clinics. This difficulty in extending the results to other systems stems from the complexities that define distinct clinics including patient characteristics, provider specialties, physical layouts, and operational policies (Kovalchuk et al. 2018). In order to address these difficulties in this study, we build one holistic simulation model that represents multiple clinics from different locations which provide analogous services. Instead of overly simplifying the assumptions, a fully detailed model is constructed in an object-oriented environment that is parameterized by a database. Therefore, using the flexible simulation model, it is possible to analyze different simulation scenarios for each clinic without construction of distinct simulation models. Additionally, all parameters can be altered during the simulation run by a dashboard enabling convenient changes in the model. Thus, flexibility of the model is defined by the use of one holistic simulation model, in which an identical change in policy can be analyzed for each clinic distinctly, to quantify the unique outcomes for different systems.

This study is designed to demonstrate the benefit of using a single simulation model in order to analyze operations at two distinct, but related, pediatric orthopedic outpatient clinics in Massachusetts. A simulation model with a built-in dashboard is constructed for the clinics using AnyLogic. The constructed simulation model has been proven to be a useful tool in anticipating the effects of changes in system features such as patient volume, provider team mix, and exam room assignment policies. With the development of a flexible simulation model the ultimate goal is to assist clinic managers in their efforts to reduce patient waiting time and lengths of stay in the two distinct orthopedic clinics.

This paper is organized as follows. In the next section we describe the motivation and background of the problem. In Section 3, we describe the similarities and differences of the two orthopedic clinics examined in this study. In Section 4, we provide a detail description of the development of the model and the validation of the model with both observed and historical data. We carry out the analysis of the model and discuss results from a case study focused on changing the role of mid-level providers within the clinics in Section 5. Finally, we conclude our study in Section 6 and provide a summary of the results and areas for future research.

## 2 BACKGROUND

Health care managers are constantly under pressure to control rapid escalating expenses while simultaneously fulfilling the growing demand for health care services. As a result, managers continuously analyze the efficiency of existing systems and seek opportunities for improvements. The evaluation of proposed interventions is crucial prior to implementation. But the evaluation is made more difficult by intrinsic uncertainties in patient demand in health care systems, limited budgets and resources, the underlying complexities of system operations, and the large number of system parameters that must be considered. Through simulation, research and examination of the impact of key resources on waiting times and patient throughput has been advanced significantly (Kaushal et al. 2015; Vahdat et al. 2018). For example, Samaha et al. (2003) develop a simulation model to analyze the effect of physical expansion of emergency departments (ED) on patient service times, La and Jewkes (2013) uses simulation to study optimal fast track strategies in ED. Simwita and Helgheim (2016) explores the implementation of flexible number of orthopedic surgeons and operating room capacity in different stages of the patient treatment process using a simulation model.

Traditionally, simulation models are created to address a specific problem and system setting, commonly with data and logic embedded in the models (Randell and Bolmsjö 2001). Thus, analyzing a second system, even if it shares many features with the first, can require a substantial investment in both resources and time to adapt the simulation to change the underlying code of the model. This is supported by Trybula (1994) and Perera and Liyanage (2000) who found that the most time consuming phase in the development of discrete event simulation models is the input of collected data and the model development. Chwif et al. (2000) and Vanberkel et al. (2010) found that the scope and the level of detail required in a simulation model leads to the model complexity. With the development of one simulation model to represent two distinct clinics coupled with a user-friendly dashboard for changing the system parameters, we aim to minimize the need for substantial changes to the model details, structure, and logic to analyze multiple settings. To the best of the author's knowledge, no studies have examined modeling multiple locations in one simulation model.

One of the key system features addressed by the simulation model is the role of mid-level providers. Mid-level providers (MLPs) refer to non-physician providers,such as Physician Assistants (PAs) and Nurse Practitioners (NPs), who interact with patients and play a critical role in system performance since patient-provider interactions drive patient visit lengths and utilization of resources. For example, Santibáñez et al. (2009) found that when a resident is involved in a consultation, the patient-provider interaction time is as much as twice that of when there is a single consult. The involvement of these health care providers ranges from shadowing physicians, assisting physicians with patient information retrieval, as well as consultation and diagnosis which enables the physician to consult with another patient simultaneously. The Medical Group Management Association (2016) found that the presence of PAs and NPs in surgery clinics help the surgeons to be more available for surgery. They also acknowledged that the usage of PAs and NPs should not be the same across all health care facilities, as other factors such as costs and roles will differ from between organizations and clinics. It is therefore important to individually analyze the role of providers in each clinic accounting for the unique system features.

## 3 PROBLEM DEFINITION

The hospital under study is one of the largest pediatric medical centers in the United States and offers a complete range of health care services for children from birth through 21 years of age. The hospital's pediatric orthopedic department is now known as one of the worlds largest and most experienced centers due to its fast access to care with several locations throughout the region. Every year, they attend to more than 100,000 patient visits and complete more than 6,000 surgeries. Each of the associated health centers throughout the region provides different specialty clinics to treat the full spectrum of orthopedic conditions, ranging from fractures and sports-related injuries to scoliosis, hip conditions, brachial plexus and cerebral palsy. In the following section, a detailed description of similarities and differences between the two clinics under study are provided.

### 3.1 Clinics Characteristics

Two orthopedic centers of the studied hospital are selected for this research to showcase the benefits of using the single computer simulation model in managing the multiple clinics effectively. The first center is located on the hospital's main urban campus providing services to more than 40,000 orthopedic, sports medicine, and cerebral palsy patients each year. The second location is one of their satellite campuses which provides services primarily to orthopedics and sports medicine patients. Although these outpatient centers are located in distinct locations, they are managed by a common department and patients may be seen in either locations based on the visit type and availability of resources. While there are several physicians that visit patients in both locations, the service processes and patient experience in each location differs. The main clinic is a teaching-focused center where residents and mid-level providers (i.e. Nurse Practitioners, and Physician Assistants) are usually part of the physician consultation. In the satellite center, on the other hand, physicians primarily meet directly with patients with limited assistance from the mid-level providers. Having additional help for patient consultations can reduce the time patients spend in exam rooms, but it can also create the need for extra logistics management and communication between the physicians and mid-level providers.

Beyond differences in the structure of patient visits, staffing levels and the number of annual visits differ between the clinics. The main site is more congested with a higher number of patients visited per day, which requires a greater number of providers and staff. Also, the patient no-show rate is slightly higher in the main site. Another key difference between these locations is the clinic layout. According to Vahdatzad and Griffin (2016), the layout of outpatient centers can significantly impact patient flow and a clinic's ability to adopt different policies such as flexible physician room assignments. Together, all these differences have been shown to drive dissimilarities in patient timeliness of care metrics, including average patient waiting time (WT) and length of stay (LOS). While the simulation model is designed to allow for differences pertaining to these features, and others, the underlying similarities in patient and provider flows are incorporated into the model logic and structure.

### 3.2 Patient Flow

Each patient is scheduled for an appointment with a specific physician and, correspondingly, patients arrive to the clinic at different times throughout the day. Although variations occur depending on the unique needs of the patients, Figure 1 depicts the patient's journey in the orthopedic clinic during a typical appointment.

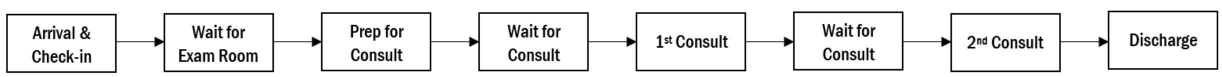


Figure 1: A generic patient flow in the studied orthopedic outpatient center.

The description of the patient flow is as follows. Upon arrival, the patient is required to check-in and is served by one of the multiple check-in staff. Then, the patient waits in the Waiting Area (WA) until an examination room becomes available. Basic vitals and intake questionnaires are performed by the Clinical Assistant (CA) prior to rooming. The patient waits in the exam room until the designated provider becomes available for the visit. For a single consult visit, the provider will enter the room and meet with the patient. For a multiple consult visit, there will be multiple patient-provider interactions, where the provider will enter the room for the consultation and, after the provider leaves the room, the patient will wait for the next provider for a subsequent consultation to take place. After the final consultation is complete the patient will leave the room. For patients who need to book future appointments or other additional services, they will return to the registration desk to check-out before leaving the clinic. Other than the typical patient processes mentioned above, ancillary services, including radiology and cast services, may be required. Such services can occur either before or after the consultation with the provider. While this will not affect the patient flow in the clinic it will lead to an increase in the patient's length of stay, as this time is calculated from the time they arrive at the clinic until they complete all processes.

### 3.3 Provider Workflow

During the orthopedic appointment, patients may be seen by their designated physician or one of the mid-level providers. Mid-level providers (MLPs) in this study refer to Nurse Practitioners (NPs) and Physician Assistants (PAs). The inclusion of collaboration between physicians and the MLPs is a key distinction between this study and others reported in the literature. In both clinic locations, each physician has a dedicated MLP. Accordingly, the patient visit consultation can happen in multiple different ways, but the three most prevalent patterns capture 91% of the appointments. In the first pattern, the patient will only be seen by their designated physician and both the patient and the physician will leave the room after the visit. Second, the patient will only be seen by the MLP and there is no need for further consultation with the physician. In the third visit pattern, multiple patient-provider interactions occur with both the MLP and the physician. Specifically, the MLP will enter the room for the first consult. After leaving the room, the MLP will provide a summary of the visit to the physician and then both the physician and the MLP will enter the room for the second consult. In any of the consultation patterns, providers need to complete patient documentation in their designated work stations prior to meeting with the next patient. Multiple patient-provider interactions are more prevalent in the teaching-focused main campus than in the satellite clinic.

The distinction in patient-provider interactions between these locations presents difficulties in the development of a common simulation model that can be used for both locations. As it is difficult to distinguish between the role of PAs and NPs in each consultation, we model both PAs and NPs as one resource type, namely MLPs. We will use the term MD, to denote physicians, and MLP, for mid-level providers, throughout the paper to address their presence in the consultation. Other than the need to specify various consultation processes, the inclusion of two distinct clinics in one model requires the need for a variations in the number of physicians per day, the number of patients per day, the distribution of visit types, and process times. In order to accomplish this, flexibility to adjust parameters in the model is required to accommodate the differences. The parameters defining each clinic in the common simulation model are described in more detail in the next section.

## 4 METHODOLOGY

In this section, a review of the steps taken to build the discrete-event simulation model are provided. First, inputs and parameters of the simulation model are captured through data analysis and clinic observation, as discussed in Section 4.1. The assumptions and model development process is presented in Section 4.2. The constructed graphical user interface that can be used in defining scenarios for each of the locations is further discussed in Section 4.3. Finally, this section concludes with an overview of the verification and validation of the simulation model in order to demonstrate its accuracy in capturing the current clinic operations and its capabilities in performing scenario analysis for predicting the effects of future changes.

### 4.1 Data Collection

Data used in this study is provided by the hospital and collected through a time study. Data from more than 120,000 appointments between December 2013 and December 2015 were analyzed. The data was analyzed to calculate several model inputs including hourly patient arrival patterns, the average number of patients per physician per day, and patient no-show rates. The hourly patient arrival pattern is modeled as a non-stationary Poisson process for each clinic. Other model inputs pertaining to the differences between the two clinics are shown in Table 1.

Table 1: Resource, staffing, and scheduling parameters in the two clinics.

| **Daily Patient and Staff Levels** | **Main Site (per day)** | **Satellite Site (per day)** |
|---|---|---|
| Average number of patients per physician | 26 | 25 |
| Average number of patients | 160 | 125 |
| Number of physicians | 6 | 5 |
| Staff in cast services | 3 | 2 |
| Clinical assistant staff | 4 | 3 |

In addition to the information provided by historical databases, clinic observations were made to capture the complete patient and provider flow information that was not recorded in these database. Through observation of the system and interviews with the staff, a high-level process map of the appointment visit process was developed. The information was used to design a data collection process and for determining how many data collectors would be required and where they should be located. We sampled and observed both clinics during the course of several weeks, capturing process times for over 600 patient visits. The data provided considerable insight into the patient experience and resource utilization. Collected data was transformed into data-driven probability distribution functions for initial inputs to the simulation model. For ease of interpretation by hospital managers, a triangular distribution was fitted for each process. The results are shown in Table 2. As discussed earlier, while the processes in both clinics are similar, the time required to perform tasks are not necessarily the same.

Table 2: Process time distributions. A non-symmetric triangular distribution, defined by the minimum, maximum, and mode parameters, is fitted for all patient processes.

| **Process** | **Main Site (in minutes)** | % | **Satellite Site (in minutes)** | % |
|---|---|---|---|---|
| Check-in | TRIA(1,8,3) | 100 | TRIA(1,5,3) | 100 |
| Cast | TRIA(3,20,10) | 11 | TRIA(5,30,15) | 30 |
| X-Ray | TRIA(5,20,10) | 40 | TRIA(5,20,10) | 39 |
| Vitals | TRIA(1,3,2) | 100 | TRIA(1,5.5,1) | 100 |
| Check-out | TRIA(1,7,4) | 42 | TRIA(2,10,5) | 42 |

% refers to the percentage of patients requiring the process

One of the major differences between the two clinics is the frequency of different patient-provider interaction types, as discussed in Section 3.3. The three major visit patterns were identified and the time required for the visits were collected for each clinic, as shown in Table 3. The combination of both the percentage of patients in patient-provider interaction processes and the distribution of the durations of these processes, including average and variance are shown to vary between the two clinic locations.

As it is not possible to incorporate all system details in the simulation, several assumptions were made in the model, as follows. The clinic stays open until all patients leave even though patients only arrive to the clinic between 7:00 am and 5:00 pm. Patients arrive to the clinic at the same time as their scheduled appointment time. No early or late arrivals are captured in the model. Each MD will have one dedicated MLP working with them as a team. In both clinics, each MD and their MLP have access to three dedicated exam rooms that are not shared with other MDs.

Table 3: Patient-provider visit type distribution and process times. A patient may be seen only by one provider (Type 1 and 2) or a team of providers (Type 3). A non-symmetric triangular distribution, defined by the minimum, maximum, and mode parameters, is fitted for patient processes.

| **Visit Type** | **Visit Pattern** | **Main Site (in minutes)** | % | **Satellite Site (in minutes)** | % |
|---|---|---|---|---|---|
| Type 1 | MD Only | TRIA(4.5,36,9) | 47 | TRIA(9,33,12) | 52 |
| Type 2 | MLP Only | TRIA(2,24,14) | 9 | TRIA(3,27,9) | 13 |
| Type 3 | $1^{st}$ visit: MLP | TRIA(1,27,6) | 44 | TRIA(2,20,5.5) | 35 |
| | $2^{nd}$ visit: MLP & MD | TRIA(1,24,5) | | TRIA(2,25,7.5) | |

% refers to the percentage of patients requiring the process

### 4.2 Model Development

AnyLogic is used to build a discrete-event simulation (DES) model representing the two orthopedic clinics based on the collected data, identified process flows, and model assumptions. The DES is modeled as a terminating system with no warm-up period. At the beginning of each simulation run, all resources and patients are initialized and each day operates independently. Correspondingly, the model is replicated 250 times for each scenario to generate tight confidence intervals on all metrics of interest, such that the half-width is within 5% of the average.

As shown in Figure 2, data-driven probability distributions for processes are stored in a database connected to the simulation model such that there is the ability to read the parameters and inputs before initiating the simulation runs. During simulation runs, instantaneous information about the state of the system is dynamically updated in a graphical user interface associated with the DES model. This includes information about the number of patients in different areas in the clinic such as Radiology, Cast, and Waiting Area. This information can help the decision maker to visually track the performance of the clinic throughout the operating hours. After running the simulation model, outputs of the model including a summary of the simulation parameters and statistical results based on the performance measures are exported into an embedded spreadsheet. Information pertaining to average patient length of stay and waiting time, percentage of patients visited within a target time frame, and comparison of scenarios are automatically presented graphically.

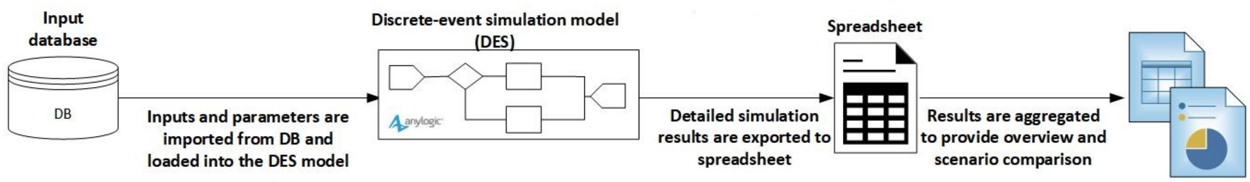


Figure 2: Simulation system overview.

### 4.3 Graphical User Interface

The simulation model is associated with a graphical user interface providing the ability for the user to choose which clinic (or location) to analyze prior to running the simulation (see Figure 3). The user also has the flexibility to make changes to more than 20 parameters in the simulation. These include changes to resource availability, resource assignments, and process times (see Figure 4 and 5). Resource controls (see Figure 4 top-left) refer to staffing levels such as the number of check-in and cast services staff members. Staffing decisions should be made in a way as to increase the efficiency of the clinic while the utilization of resources remains at a satisfactory level. Process time controls enable the decision maker to change the distribution parameters for the durations of each process. For instance, the consequences of a change in capacity or process times in cast services can be estimated by changing the parameters and exploring the outcomes of the simulation model. Additional controls focus on broader systems changes that may occur over the long term, such as changes in patient volumes and the frequency of radiology or cast services.

Apart from adjustments in parameters, four strategic assignments can be performed by the decision maker through the dashboard (see Figure 5): (1) Exam Room to MD assignment, (2) MLP to MD assignment, (3) Visit Pattern Mix, and (4) Visit Pattern Assignment. Currently, each MD team has three dedicated exam rooms. The model is constructed to allow for up to 10 MD teams and 27 exam rooms. The simulation model allows for the flexibility of room assignments to MD teams by introducing a partial room sharing concept between care teams. For example, one option would be for each MD team to have two dedicated rooms and to also have access to two rooms that are shared with another team. Room assignment policies have been shown to have had significant impact on the patient wait times (Vahdat et al. 2017).

MLP assignments to care teams are another feature that can support greater patient volumes in orthopedic outpatient centers. Larger care teams where multiple MLPs work with one physician are becoming more prevalent in outpatient clinics due to both financial and productivity benefits. The simulation model is able to be used to investigate the impact of sharing MLPs between physicians in which two MLPs work with two physicians rather than a one-to-one assignment of MLPs and MDs.

Finally, the way that physicians cooperate with their teams to visit patients may differ. An MD's care team visit pattern mix refers to the frequency of different visit patterns that are used with the team's patients. Two general patterns can be defined by the decision maker, Pattern A and Pattern B. In each of the patterns, the probability that a patient is only visited by the physician (MD only), seen by only the MLP (MLP only), or seen by both the physician and the MLP (MLP, MD&MLP) can be specified. Then

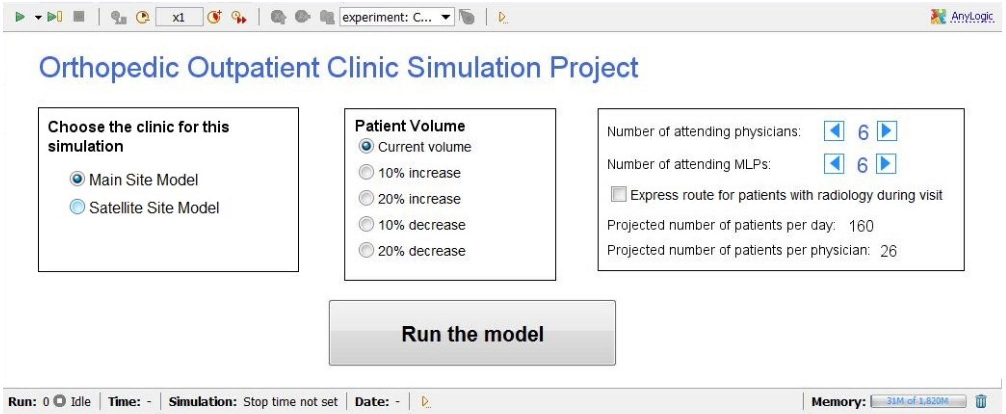


Figure 3: Front page of the simulation model. The user can choose the location, patient volume and number of physicians per day.

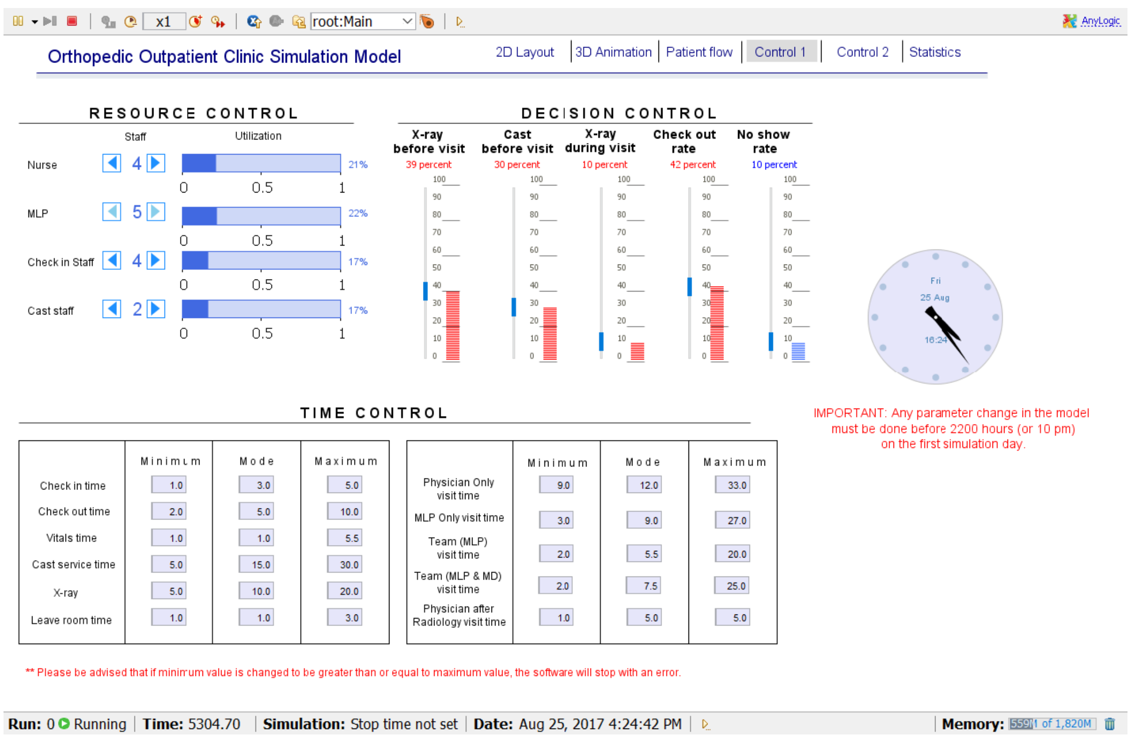


Figure 4: Parameter control 1 in the simulation model.

the decision maker can determine the number of care teams that work under each visit pattern and inspect the performance of the clinic based on different combinations of teams.

## 4.4 Model Validation

The simulation model is verified by experts within the clinic. Also, 2-dimensional and 3-dimensional animations of a simulated clinic day were presented to clinic managers and staff and the behavior of the model in terms of the number of patients in the waiting area during each hour of the day, the utilization of resources, and patient flow were confirmed. Extreme conditions were tested to ensure the model performed as intended. Both clinic managers and physicians were consulted to ratify high-level results. To evaluate

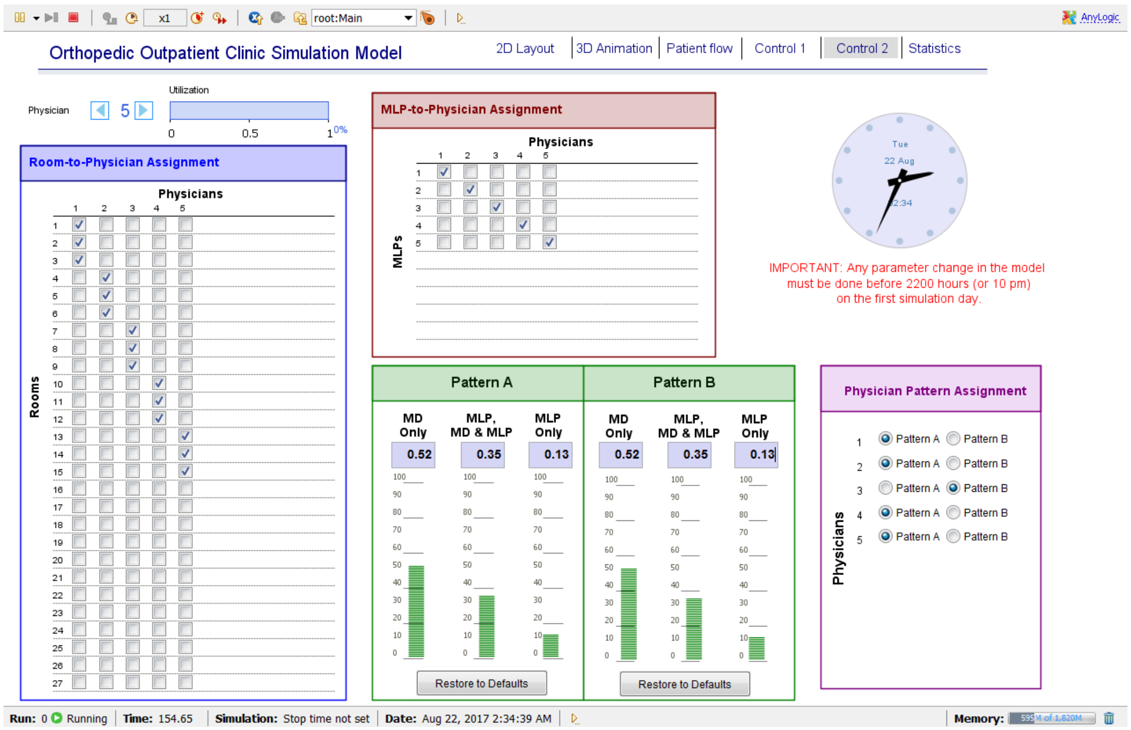


Figure 5: Parameter control 2 in the simulation model.

the performance and validate the model, the following key metrics were examined: (i) patient wait time in waiting area (WTWA), (ii) patient wait times in the exam room (WT), (iii) patient lengths of stay in room (LOSR), and (iv) patient lengths of stay in the clinic (LOS). All these metrics are measured in averages and percentiles (box plot) and are presented in the embedded spreadsheet.

For verification and validation purposes, we only compared outputs with the actual collected data of WTWA, WT, and LOSR due to the complexities in capturing patient process times for additional services (radiology and cast services). Without access to data to effectively model the intricacies of these services the additional service processes were modeled using triangular distributions (shown in Table 2). The process time is derived from data sets provided by the radiology and cast services departments. We exploited the graphical capabilities of AnyLogic by embedding the floor plan of the satellite center in the simulation model and animating the entire system's dynamics. This assisted in the process of validating the model with physicians and management staff as they were able to see what was happening in real time as the simulation took place. Correspondingly, no warm-up period is utilized in the analysis and each scenario is run for a 3-month period of time for both clinics, resulting in more than 10,000 simulated patients to account for the stochastic nature of the procedures. We compared the results between observed and simulated data with 95% Confidence Intervals (CI) as shown in Table 4. The results show no statistically significant differences between the means of the observed and simulated data. Therefore, we concluded that the model is an accurate representation of the system for both clinic sites.

## 5 ANALYSIS OF FINDINGS

With the use of the flexible simulation model defined above, there are many opportunities to analyze the effects of system changes on a variety of performance measures, including wait times, resource utilization, and LOS. Through analysis of the simulation results, it was identified that a significant contributing factor to long patient LOS is both locations is the wait time in the room prior to the first visit with the MLP. The underlying cause of these long waiting times is the need for the MLP to wait until the MD is available

Table 4: Model validation. Results validate the model and show no statistically significant differences between observed and simulated outputs.

| Location | Metric | Simulated | | Actual | |
|---|---|---|---|---|---|
| | | **Mean** | **95% CI** | **Mean** | **95% CI** |
| Main Site | WTWA | 28.09 | [27.42, 28.76] | 26.95 | [24.00, 29.90] |
| | WT | 19.57 | [19.22, 19.92] | 19.37 | [17.00, 21.74] |
| | LOSR | 39.31 | [38.92, 39.70] | 39.00 | [33.00, 45.00] |
| Satellite Site | WTWA | 11.31 | [10.86, 11.76] | 12.90 | [7.04, 18.76] |
| | WT | 16.02 | [15.63, 16.41] | 16.93 | [15.00, 18.86] |
| | LOSR | 36.21 | [35.80, 36.62] | 37.23 | [32.00, 42.46] |

prior to entering the exam room for the second time. This correspondingly prevents the MLP from seeing another patient, resulting in the underutilization of their time. Thus, the average patient wait time in the room increases, even as the MD's time with the patient decreases. To address these long wait times and underutilization of the MLPs, we examine the effects of new flexible policies pertaining to the role and use of the MLPs.

One strategy for updating the use of MLPs is to share the MLPs between physicians. In this case, the sharing of MLPs refers to two MLPs being jointly assigned to two physicians. Despite the sharing, to ensure continuity of care no patient is seen by more than one MLP. As the simulation model includes the flexibility of assigning MLPs to MDs, the joint assignment of an MLP to two physicians can be achieved by checking boxes for two physicians in the column corresponding to the MLP in the graphical user interface (see Figure 5 top-middle). This is also done for the second MLP in order to designate that both the MLPs may be used by either physician. The simulated results from two pairs of physicians sharing their MLPs in both the main and satellite sites are shown in Table 5.

A second strategy proposed by the clinic for expanding the roles of MLPs is to assign MLPs to run the consultation session independently throughout the day and see all of a physician's patients. This is often used for urgent cases where the presence of physician is minimally required. This analysis is performed by adjusting the Visit Pattern Assignments to include 100% MLP-only visits and no MD-only or MLP-MD visits (see Figure 5 bottom-middle). The scenario in which one MLP visits patients independently are shown in Table 5.

Table 5: Effects from implementation of MLP Sharing and Independent MLPs on average (95% CI) timeliness of care (WTWA = Waiting Time in Waiting Area, WT = Waiting Time, LOSR = Length of Stay in Room, LOS = Length of Stay).

| Location | Scenario | WTWA | WT | LOSR | LOS |
|---|---|---|---|---|---|
| Main Site | Base Case | 28 ($\pm$0.67) | 20 ($\pm$0.35) | 39 ($\pm$0.39) | 107 ($\pm$1.19) |
| | MLP Sharing | 26 ($\pm$0.63) | 18 ($\pm$0.33) | 38 ($\pm$0.36) | 102 ($\pm$1.14) |
| | Independent MLPs | 28 ($\pm$0.67) | 19 ($\pm$0.34) | 39 ($\pm$0.38) | 105 ($\pm$1.19) |
| Satellite Site | Base Case | 11 ($\pm$0.45) | 16 ($\pm$0.39) | 36 ($\pm$0.41) | 90 ($\pm$1.09) |
| | MLP Sharing | 9 ($\pm$0.43) | 15 ($\pm$0.37) | 35 ($\pm$0.39) | 86 ($\pm$0.99) |
| | Independent MLPs | 9 ($\pm$0.44) | 15 ($\pm$0.37) | 35 ($\pm$0.39) | 86 ($\pm$1.05) |

As shown in Table 5, either change in MLP usage policies will result in decreased average patient waiting and lengths of stay at both locations. At the main site, the greatest improvement is achieved with

MLP Sharing resulting in a 6% improvement in the Waiting Time in Room (WT) and 4% in the Length of Stay (LOS), but only a 2% improvement with the use of Independent MLPs. At the satellite site, on the other hand, the same level of improvement is achieved for both policies with a 6% improvement in WT and a 5% decrease in LOS. Thus while either policy change can be implemented in the satellite site to improve timeliness in patient care, at the main site, MLP Sharing performs better.

## 6 CONCLUSIONS

As shown in the results here, even in clinics that have many similar features and clinical structures, similar policy changes can have different results. To assist a pediatric orthopedic department in examining the effects of changes to clinic operations at their multiple clinics in different locations, one simulation model, which was validated for both locations, was developed. Due to the need to represent the effects of a variety of policy changes in the clinics a graphical user interface was developed that allowed for changes in the assignment of rooms and staff to allow for more flexibility in the clinic. Additionally, the interface allows for changes to the model parameters to account for future changes in the make-up of the clinic or introduction of technological changes that can decrease process times.

In the analysis of the effects of new MLP usage policies, it was shown that while Independent MLPs and MLP Sharing had a similar 5% decrease in the average patient length of stay in one clinic, in the other clinic the improvement in LOS was only 2% with Independent MLPs and 4% with MLP Sharing. As the best policy for the different clinics varies, it is clear that each clinic needs to be analyzed independently. Through the development of one simulation model that can represent both, with the appropriate parameter changes, we can achieve personalized recommendations for each clinic without the need to invest in the development of two different models. Further with the integration of a database and graphical user interface this simulation model has the potential for continued use by decision makers as the system evolves and for use in modeling additional pediatric orthopedic outpatient clinics in the future.

## REFERENCES


Ashton, R., L. Hague, M. Brandreth, D. Worthington, and S. Cropper. 2005. "A Simulation-Based Study of a NHS Walk-in Centre". *Journal of the Operational Research Society* 56(2):153–161.

Chwif, L., M. Ribeiro, P. Barretto, and R. J. Paul. 2000. "On Simulation Model Complexity". In *Proceedings of the 2000 Winter Simulation Conference*, edited by J. A. Joines et al., 450–455. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Kaushal, A., Y. Zhao, Q. Peng, T. Strome, E. Weldon, M. Zhang, and A. Chochinov. 2015. "Evaluation of Fast Track Strategies using Agent-Based Simulation Modeling to Reduce Waiting Time in a Hospital Emergency Department". *Socio-Economic Planning Sciences* 50(June):18–31.

Kovalchuk, S. V., A. A. Funkner, O. G. Metsker, and A. N. Yakovlev. 2018. "Simulation of Patient Flow in Multiple Healthcare Units using Process and Data Mining Techniques for Model Identification". *Journal of Biomedical Informatics* 82(June):128–142.

La, J., and E. M. Jewkes. 2013. "Defining an Optimal ED Fast Track Strategy using Simulation". *Journal of Enterprise Information Management* 26(1):109–118.

Medical Group Management Association 2016. "The Rising Trend of Nonphysician Provider Utilization in Healthcare". Technical report, MGMA. https://www.acponline.org/system/files/documents/about_acp/chapters/ga/rising_trend_of_nonphysicianprovider_utilization_in_healthcare_2017.pdf. Accessed March 22nd, 2018.

Perera, T., and K. Liyanage. 2000. "Methodology for Rapid Identification and Collection of Input Data in the Simulation of Manufacturing Systems". *Simulation Practice and Theory* 7(7):645–656.

Randell, L., and G. Bolmsjö. 2001. "Database Driven Factory Simulation: a Proof-of-Concept Demonstrator". In *Proceedings of the 2001 Winter Simulation Conference*, edited by B. A. Peters et al., 977–983. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Samaha, S., W. S. Armel, and D. W. Starks. 2003. "Emergency Departments I: The Use of Simulation to Reduce the Length of Stay in an Emergency Department". In *Proceedings of the 2003 Winter Simulation Conference*, edited by S. Chick et al., 1907–1911. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Santibáñez, P., V. S. Chow, J. French, M. L. Puterman, and S. Tyldesley. 2009. "Reducing Patient Wait Times and Improving Resource Utilization at British Columbia Cancer Agency's Ambulatory Care Unit through Simulation". *Health Care Management Science* 12(4):392–407.

Simwita, Y. W., and B. I. Helgheim. 2016. "Simulation Analysis of Resource Flexibility on Healthcare Processes". *Journal of Multidisciplinary Healthcare* 9(2016):519–528.

Trybula, W. 1994. "Building Simulation Models without Data". In *Proceedings of IEEE International Conference of Systems, Man and Cybernetics*, Volume 1, 209–214. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Vahdat, V., J. Griffin, S. Burns, and R. Azghandi. 2017. "Proactive Patient Flow Redesign for Integration of Multiple Outpatient Clinics". In *Proceedings of the 2017 Winter Simulation Conference*, edited by W. K. V. Chan et al., 2893–2904. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Vahdat, V., J. Griffin, and J. E. Stahl. 2017. "Decreasing Patient Length of Stay via New Flexible Exam Room Allocation Policies in Ambulatory Care Clinics". *Health Care Management Science*:1–25. https://doi.org/10.1007/s10729-017-9407-5.

Vahdat, V., J. A. Griffin, J. E. Stahl, and F. C. Yang. 2018. "Analysis of the Effects of EHR Implementation on Timeliness of Care in a Dermatology Clinic: a Simulation Study". *Journal of the American Medical Informatics Association* 25(7):827–832.

Vahdatzad, V., and J. Griffin. 2016. "Outpatient Clinic Layout Design Accounting for Flexible Policies". In *Proceedings of the 2016 Winter Simulation Conference*, edited by T. M. K. Roeder et al., 3668–3669. Piscataway, New Jersey: Institute of Electrical and Electronics Engineer.

Vanberkel, P. T., R. J. Boucherie, E. W. Hans, J. L. Hurink, and N. Litvak. 2010. "A Survey of Health Care Models that Encompass Multiple Departments". *International Journal of Health Management and Information* 1(1):37–69.

Zacharias, C., and M. Armony. 2017. "Joint Panel Sizing and Appointment Scheduling in Outpatient Care". *Management Science* 63(11):3978–3997.

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