Enhancing Service Quality of New Draftees' Physical Examination Using the Hybrid Simulation

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Abstract. Simulation application is widely perceived for problem solving in healthcare industry. This research presents a hybrid simulation which combines discrete event simulation (DES) and agent-based simulation (ABS) together to improve draftees' physical examination service by reducing the waiting time of the processes. The simulation models were developed by using Anylogic7. To our knowledge this is the first time such a hybrid model has been used in a healthcare setting. Our results show that after applying the proposed approach, the average waiting time of the physical examination center dropped from 94 minutes to 54.38 minutes. By applying the proposed approach to the healthcare industry, its practicability and utility are verified.

Keywords: Agent based modeling; simulation; physical examination; healthcare

1. INTRODUCTION

The pressure on hospitals recently increased due t o remarkable growth in demand (for different reasons such as low productivity and limited budget and resour ces). The physical examination center may well be one of the most complex healthcare systems and the coop eration of many departments in the hospital is necessar y.

In Taiwan, every new draftee is required to undergo a physical examination. A general public hospital in our case study is assigned by the Taiwanese government to provide physical examination services for new draftees. We interviewed the new draftees after finishing the physical examination processes. They all said that they spent most of the time waiting in line without getting served by healthcare staff. Patient waiting time is the time that is spent by a patient in queue until the start of the consultation. Throughput time is defined as the amount of time a patient spends in a hospital process from beginning to end. The amount of time a patient waits to be seen is one factor which affects hospital service quality. The long waiting time can be a cause of stress for both patient and doctor. To increase patient satisfaction, healthcare providers need to reduce the waiting time. There are many approaches available that attempt to reduce the waiting time, namely, regression modeling, time series analysis, queuing theory and simulation modeling. From among these methods, simulation seems to be well-suited to tackle the problems of physical examination process, which is very complex. Nowadays, there are many stochastic optimization problems that are very difficult to solve mathematically that an alternative approach known as computer simulation must be used for their solutions. A simulation model can depict the patient flow, emulate the process under certain random distribution, and provide prediction for performance measurement. The trend of using computer simulation to improve healthcare operations has been recently increasing. Simulation modeling approach started to be used for solving healthcare problems more than three decades ago. Nikakhtar and Hsiang (2014) proposed a simulation model for a local community health clinic. They assumed epidemic diseases that could affect the patient flow in a healthcare system. Baril et al. (2016) reduced patient delays in an oncology clinic by using computer simulation. The scenarios defined by team members during a Kaizen event were tested. Their results showed that patient delays before receiving their treatment were reduced by 74 percent after 19 weeks. Robinson et al. (2012) applied simulation in the implementation of lean in healthcare. The objective is to increase the impact of both approaches in the improvement of healthcare systems. The paradigms of DES and ABS are both well established with much openly published literature available that spans decade of research. DES is a computer-based methodology capable of modeling complex healthcare system. It also allows modelers to estimate the impact of operational changes before expending resources to implement those changes [4]. Over the last decade there have been significant efforts in applying DES for solving healthcare management problems. Ahmed and Amagoh (2008) conducted a DES model to investigate patients' flow in a hospital, and how the resources are utilized to respond to the health care system. Monks et al. (2012) revolutionized a discrete-event simulation from prospective data for patients with stroke arriving at our large district hospital. They assessed the impact on stroke outcomes of measures to reduce in-hospital delays. Gul and Guneri (2012) presented a DES model to determine the optimal staff level to reduce the patient average length of stay (LOS) in an emergency department, as well as to improve patient throughput and utilization of resources. Wong et al. (2011) improved operation efficiency of emergency department by applying DES. The simulation model is able to facilitate emergency department workflow decision making and examine possible process improvement initiatives. Ta-Ping et al. (2013) used DES to enhance service quality in an orthopedic outpatient clinic.

Entities built into a DES model are typically simple, reactive, and limited in decision-making (Chung, 2003). ABS is a new approach to model systems of autonomous, interacting agents (North and Macal, 2009). It is very different from DES because most DES models employ a top-down modeling approach and use passive entities. On the other hand, ABS is a bottom-up modeling approach and has active entities (Lin and Long, 2011; Siebers et al., 2010). ABS is more general and powerful because it enables to capture more complex structures and dynamics. It also provides for construction of models in the absence of the knowledge about the global interdependencies. Charfeddine and Montreuil (2010) applied ABS to simulate population with a specific chronic disease. Cabrara et al. (2012) improved performance of emergency department by using ABS to design a decision support system. The objective of this study is to find the optimal ED staff configuration, which includes doctors, triage nurses, and admission staff. Kim and Yoon (2014) conducted ABS to understand the future status of a service system and used a case study on a healthcare industry to verify the utility of the proposed approach. Silverman et al. (2015) used ABS to help healthcare managers discover interventions that increases population wellness and quality of care while, simultaneously, decreasing costs. This study developed a hybrid DES and ABS to reduce new draftees' waiting time in a physical examination center. This prototype conceptual model incorporates a DES model of the physical examination process with an ABS model of new draftees requiring examinations at the hospital. It allows the relative strengths of DES and ABS to be brought together in order to aid the hospital management in their decision making.

The rest of this paper is divided into five sections. In Section 2, we provide a detailed description of the physical examination center, basic elements of the simulation model. The results after applying the proposed approach are showed in section 3. Section 4 discusses the results before and after applying the proposed approach. Finally, Section 5 contains conclusions and suggestions for future research studies.

2. METHODS

The general public hospital in this research is a 689-patient-bed medical center with more than 20 clinical departments. The physical examination has around 8,000 draftees visit per year.

2.1 Description of Physical Examination Process

The visiting hours of the physical examination center in the case study are 8:00 am to 12:00 pm and 1:00 pm to 4:00 pm. New draftees begin their visit by registering at the registration counter (station 1). Then they have to pass through a series of 14 stations (from registration to completion of all services). Except for station 7 to station 11, there is no process sequence. Figure 1 shows the flow paths for new draftees in the physical examination center.

2.2 System Analysis

To understand the processes, we observed and measured times for the operational steps in patient flow for five months (October to February) at the physical examination center and collected data from the hospital database. We collected the total process time, waiting time, arrival time, service time, queue size, and traveling time between stations. The October data were used to build an initial simulation model while the November data were used to validate the initial simulation model. Figure 2 shows the floor plan of the physical examination center.

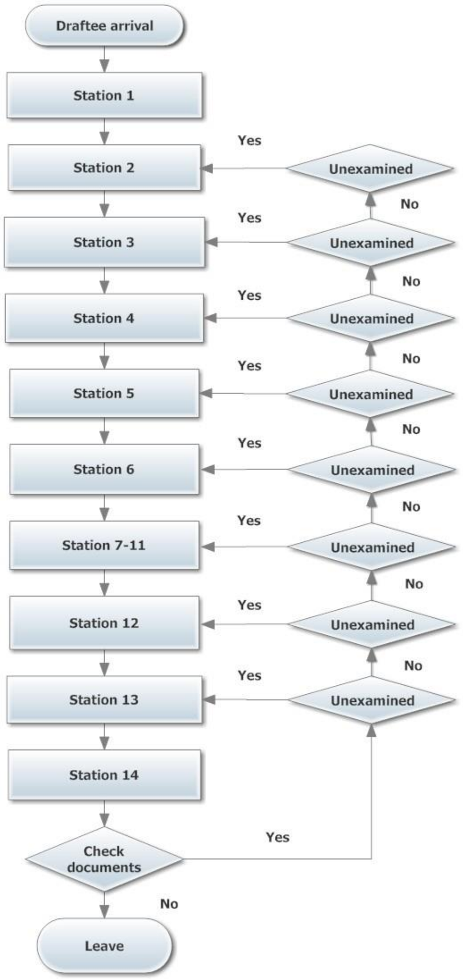

Figure 1: The common flow of operations at the physical examination center

2.3 Model Design

The simulation process involves specific steps in order for the simulation study to be successful. Regardless of the type of problem and the objective of the study, the process by which the simulation is performed remains constant. The steps in a simulation study are: formulate problem and plan study, collect data and define model, construct a computer program and define model, make a pilot run, design experiments, make production runs, analyze output data, and document, present, and implement results (Baldwin, 2004). In this study, we proposed a hybrid DES and ABS to represent the physical examination center model. The DES was used to simulate the physical examination processes while the ABS was used to model the new draftee population

Figure 2: Physical examination center floor plan

2.4 Simulation and Implementation

The simulation model was developed in Anylogic7 which supports the seamless integration of DES and ABS. We used the simulation of the current system without any changes as the case-based model. The results of the simulation provide a baseline for comparing operational changes.

In the simulation implemented, new draftees must pass though the station 1 and 2 first. After that they could go to any of the stations. When they completed all the examinations, they must return to the station 14, and then they left the hospital.

3. INITITAL RESULTS

3.1 Model Validation

One of the most difficult problems facing the simulation analyst is determining whether a simulation model is an accurate representation of the real world or not. Model validation is the process of determining the degree to which a computer model is an accurate representation of the real world from the perspective of the intended model applications. In this research, we used historical data validation technique to validate the simulation models (Sargent, 2007). The simulation model was validated by comparing the waiting time, throughput time, and doctors' utilization between the model and data collected from the physical examination center.

3.2 Initial Results

The goal of the simulation study was to reduce the new draftees' waiting time in the physical examination center by using the hybrid simulation. The output measure was the average waiting time after applying the proposed approach. The results are presented in Table 1.

Table 1: Waiting time improvement at the physical examination center.

Month	Average real world waiting time (hh:mm:ss)	Average waiting time after applying the proposed approach (hh:mm:ss)	Waiting time improvement (%)
October	01:06:09	00:49:38	28.49
November	02:01:51	01:07:17	44.78

4. DISSCUSSION

The study demonstrated the usefulness of the hybrid simulation for enhancing service quality at the physical examination center. From the results, it can be seen that the average waiting time was reduced significantly: in October, from 66.15 minutes to 47.3 minutes for a waiting time improvement of 28.49%; in November, from 121.85 minutes to 67.28 minutes for a waiting time improvement of 44.78%. This research shows that the hybrid simulation can help improve healthcare providers' operations and management at the physical examination center and can also be applied to any departments in hospitals.

5. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

Healthcare providers always work on dealing with human lives, which are often at risk. Hospital services have to be effective since patients wish to leave a hospital as early as possible since nobody is happy to stay on treatment beyond what is necessary. Many studies found that the waiting time obviously affected patient satisfaction. Computer simulation has revolutionized research tools of engineers and now is essential to many scientists. This paper performed on the novel application of a complex systems simulation architecture which is capable of modeling the interaction between a healthcare provider system, and the population served by that system. The research results show that the proposed approach can reduce the new draftees' waiting time at the physical examination center. So, it should be applicable to any physical examination centers, and be able to explain the complex processes of healthcare systems.

In spite of the meaningful contributions, our approach does have some limitations, and future research is needed. Firstly, the proposed approach greatly depends on existing data. To build a hybrid simulation model, service providers should make a plan and collect related data in advance. Secondly, simulation is not precise. It does not yield an answer, but merely provides a set of the system's responses to different operating conditions. Finally, this research uses only two months, more months are needed for the sake of external validity. Future work will focus on using the rest of the data (December to February) to prove the effectiveness of the proposed approach. We will also try to integrate the optimization with the simulation to find the optimum healthcare staff for each station at the physical examination center.

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