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# Incorporating the dynamics of epidemics in simulation models of healthcare systems

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ABSTRACT

A growing concern among healthcare planners is the ability to determine the capacity of medical resources in various potential situations and prepare accordingly. In this study, we consider uncertain situations such as epidemic diseases that could affect the patient flow in a healthcare system by developing a discrete-event simulation model for a local community health clinic in Lubbock, Texas. Conventionally, in these healthcare system models, patients are assumed to arrive at the system based on a schedule, along with some random entries to represent walk-in patients; we propose an additional level of uncertainty based on the dynamics of an epidemic. After developing the simulation model for the baseline probability of the clinic, we simulate the susceptible-infected-recovery (SIR) process to generate epidemic patients for the model developed for the clinic. Ideally, this shows how epidemic diseases could affect the flow of patients which in turn affects the performance of the clinic. We examine eleven epidemic scenarios with different levels of disease outbreak. Our performance measures include the conditional expected value of the length of stay (LoS) of patients and the system throughput. The incorporated model reveals how the various epidemic scenarios affect the performance measures of the clinic. Moreover, based on the statistics of LoS and system throughput, we examine different alternative clinic designs for each epidemic scenario. We consider two views of analyzing the alternative designs, scenario-oriented and design-oriented views, to obtain the six best alternatives and evaluate the costs and benefits of each to find the best design.



## 1. Introduction

In today's fast-changing, unpredictable world, any healthcare provider must prepare for many uncertain situations, such as epidemics and natural disasters [1]. These situations increase pressure on healthcare systems' capacity to care for patients. In order to assess the impact of epidemics and propose robust designs for addressing them, the specific aim of this paper is to simulate the effect of epidemics on patient flow. Performance here is measured, as in other service industries, through customer satisfaction, which is affected by factors such as waiting time [2].

Due to the lack of epidemic data available, the only means to evaluate the robustness of any proposed solution is through event-based simulation. In order to sufficiently simulate, we need to represent the limited number of resources available in medical systems and their associated costs to healthcare providers and managers [3,4]. There are a number of tools that can assist managers and planners in coping with these challenges. For example, discrete event simulations can help decision

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makers ask what-if questions, better understand the system under study, and predict the effect of potential changes in the system on its performance [3–5]. Such a performance prediction can be considered a difficult task especially in complex systems that are subject to uncertainty [6]. In situations where implementing any changes in the real-world system is costly and risky, decision makers could be benefited from using computer simulation to evaluate and address design shortcomings through synthetic situations [3]. Computer simulation could also analyze the situations dynamically (rather than statically) which leads to more practical assessment of the situation. Resource allocation, scheduling, screening, strategy evaluation, etc. are examples of areas in which computer simulation has been used widely [6,7]. It has been suggested that there is a great need for simulations in the future as tool for system of systems modeling [6].

Successful applications of computer simulations in the healthcare business have been reported in several studies. Dehlendorff et al. [2] developed a discrete event simulation model for an orthopedic unit where patients from orthopedic wards and emergency care units were considered as the inputs with triangular and exponential distributions, respectively. The aim was to minimize the total waiting time, specifically focusing on long delays. By using simulation-based scenarios with different levels of resource allocation, they examined the sensitivity of the performance measure to changes in allocation.

Ramwadhdoebe et al. [3] did a feasibility study on the implementation of ultrasound screening at an infant health care center, comparing the current, centralized to the proposed, localized screening, through developing a discrete event simulation model and comparing each strategy. The inter-arrival time newborns were the model inputs and the performance measure was the rate of attendance at the screening session.

Berg et al. [8] simulated a colonoscopy suite to evaluate its patient throughput and resource utilization. In their model, the patient arrival is assumed deterministically on time, according to the predetermined appointment time. A baseline simulation model was constructed for the suite using current resource allocation levels, wherein different scenarios were defined by changing the resource allocation level and the influence of turnaround time was examined.

Both Venkatadri et al. [5] and Gupta et al. [9] focused on the performance of Cardiac Catheterization labs (CCL). Venkatadri et al. [5] included inpatients, outpatients, and emergency patients with non-stationary Poisson arrivals. They considered alternative scenarios which reduced or eliminated the sources of delays such as inpatient transfer delays, and procedure room turnaround time in the system to show how each scenario affected the performance measures. Similarly, to study the effect on the patient waiting time and to achieve their targeted waiting time, Gupta et al. [9] studied different capacity and patient arrival scenarios for the simulated lab.

Chetouane et al. [1] used computer simulation as a decision making tool in designing a hospital emergency service, where the performance measure was the conditional expected value of time-in-system. They assumed that patients' arrivals are exponentially distributed depending on the days of the week and proposed a trade-off between sensitivity of the design alternative to the changes in patient arrival rate and the conditional expected value of the time-in-system.

In addition to the average time-in-system, Villamizar et al. [10] also used the system throughput as a performance measure in their simulation study for a physiotherapy clinic. They characterized the patient arrival as log-normally distributed and have run their simulation model under different scenarios based on number of patients and human resources.

Ahmed and Alkhamis [11] conducted another study for an emergency department unit, with a Poisson arrival of patients. Their goal was to find the best resource configuration for the unit that maximized the unit throughput under resource constraints. Accomplishing that goal was also done in another simulation study by Coelli et al. [12] for a mammography clinic. The simulation model for the clinic was run with different resource configurations and patient arrival rates to determine the best configuration with minimum value given the length of stay. In the study, the authors considered the arrival of patients to be distributed exponentially.

Reyes-Santías et al. [13] and Oddoye et al. [14] have conducted simulation studies for different healthcare units to evaluate the effect of number of beds in a hospital on the patients waiting time. Reyes-Santías et al. [13] simulated the patient flow in three hospitals in which the arrival of patients was considered to be normally distributed. By changing the number of hospital beds, they determined how affected the length of stays of patients. Oddoye et al. [14] developed a simulation model of a medical assessment unit in which patients were generated based on an exponential distribution. They also considered the number of beds as a key factor and increased and decreased it to evaluate its effect on the length of stay of patients and the length of patient queue.

Having reviewed all the literature references, we found that the patient arrival in most healthcare systems is either assumed based on a predetermined schedule or based on a probability distribution (e.g. Poisson, Johnson, etc.). In this study, to enhance the assumed distribution of patient arrivals, we propose a situation dependent assumption based on the dynamics of an epidemic development, as a source of patient arrivals. In other words, besides different probability distributions considered for the arrival of patients, we also consider a conjoint model based on the dynamics of the epidemic disease and generates additional patients who get infected with the disease. Our motive is to show how epidemic diseases could affect the flow of patients. We aim at finding the most cost-effective alternative designs for a specific system of a local community health clinic in Lubbock, TX, given different epidemic scenarios. We make our decisions for the clinic design based on two performance measures: length of stay (LOS) and system throughput.

The rest of the paper is divided into five sections. In the next section, we develop a discrete-event computer simulation model of a local clinic. Following that, Section 3 is dedicated to description of epidemic diseases as dynamic systems. In this section, we also conduct computer simulation of an epidemic disease. In Section 4, the simulation model of the epidemic disease is incorporated to the model developed for the clinic. The incorporated model is then run for different epidemic