Chapter 4
A Simulation Model for Resource Balancing in Healthcare Systems

Arzu Eren Şenaras
Uludag University, Turkey

Hayrettin Kemal Sezen
Uludag University, Turkey

ABSTRACT

This study aims to analyze resource effectiveness through developed model. Changing different number of resources and testing their response, appropriate number of resources can be identified as a basis of resource balancing through what-if analysis. The simulation model for emergency department is developed by Arena package program. The patient waiting times are reduced by the tested scenarios. Health care system is very expensive sector and related costs are very high. To raise service quality, number of doctor and nurse are increased but system target is provided by increased number of register clerk. Testing different scenarios, effective policy can be designed using developed simulation model. This chapter provides the readers to evaluate healthcare system using discrete event simulation. The developed model could be evaluated as a base for new implementations in other hospitals and clinics.

INTRODUCTION

The growing costs of healthcare are a major concern for healthcare providers. As healthcare organizations move towards the goals of reducing costs, optimizing patient experience, and improving health of populations; operations research tools are becoming more important. These tools provide the ability to assess trade-offs between resource utilization, quality of service, and operating costs (Lal and Roh, 2013).

The Emergency Department (ED) is the service within hospitals responsible for providing care to life threatening and other emergency cases over 24 hours daily, 7 days a week. Therefore, such departments are highly frequented by patients and this frequency is continuously increasing (Weng et al. 2011, Saghafian et al. 2012, Ghanes et al. 2014).

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Emergency Departments (ED) are one of the most complex parts of hospitals to manage, and yet a major entry point for patients. It deals with patients without an appointment and with a wide range of illnesses. Even if most patients arriving to an ED leave the hospital after having seen a physician at the ED, a significant part of them need to be hospitalized. In many hospitals, finding available beds for unscheduled patients is extremely complicated. Even if all patients arriving at the ED do not require the same level of care, many hospitals proceed with the following policy: accept any patient until no bed is available. However, more sophisticated policies, including bed booking strategies and dynamic decisions, can lead to significant improvement of overall hospital performance (Prodel et al., 2014).

Discrete event simulation (DES) is one of the most commonly used operations research tool in healthcare. Its unique ability to account for high levels of complexity and variability that exist in the real world, along with animation capability makes it easier to illustrate and gain buy-in from physicians and other clinical providers compared to other black-box mathematical models offered by operations research. However, DES also has some limitations. In scenarios where there is a large number of stochastic input decision variables and there is little information about the structure of output function using simulation modeling by itself can be tedious and complicated. In such cases, optimization via simulation can help to maximize or minimize measures of the performance by evaluating the system using discrete event simulation (Banks et al, 2004).

DES models for healthcare facilities commonly focus on improving wait time, patient flow and management of capacity (Hamrock et al. 2014; Jacobsen et al. 2006). Although DES is adept at modeling the complex queuing structure for patients in healthcare environments, transition process variation driven by organizational and human factors is more difficult to capture mathematically. For example, analyses of patient location data used to construct DES models may find that patients are consistently waiting for servers (e.g., beds, imaging suites, clinicians) at time-points despite their availability. In the DES, queued patients would efficiently shift to open servers. However in clinical practice, transition process factors such as inefficient communication, lack of awareness of server availability, complex administrative guidelines, interruptions, and cumbersome documentation create further delays (Shi et al. 2015; Armony et al. 2010). These delays are not inherent to queuing nor well understood from time-stamped patient flow data alone. To fully capture the dynamics of healthcare facilities or any flow-based socio-technical system, transition process variability should be understood.

Not accounting for these processes can lead to results that severely under-estimate waiting. Moreover, DES wait time distributions may be difficult to validate against the observed healthcare system. To achieve sufficient validation, the model developer may be motivated to input additive time intervals to patients at transition points that are drawn from a distribution representing the difference between the current model and observed waits (Shi et al. 2015). A more in-depth approach, borrowed from lean methods, may motivate the model developer to map out the transition process and measure or elicit expert estimates of time distributions for each component; independent value of this investigation exists (Kang et al. 2014; Simon and Canacari 2012).

The aim of this paper is to develop methods to identify efficient hospitalization admission control policies for the emergency department patients.