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Decision Support for Resource Optimization Using Discrete Event Simulation in Rehabilitation Hospitals

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Abstract

In order to make effective decisions regarding resource allocations in hospitals, managers need to have the ability to evaluate the volume of patients served by the hospitals as well as the based on available resources and examine the efficiency of various processes and procedures in various departments within the hospital. This paper proposes the use of discrete event simulation to provide managers with an evidence-based tool for examining patient flow in the hospital and to help support decisions for optimizing resource allocation in order to improve quality of care and resource utilization. Discrete event simulation can be used to evaluate various operational strategies and examine the execution of various tasks over time. Using simulation models provides a flexible and cost effective method for assessing operational changes prior to the actual implementation of these changes.

Keywords: discrete event simulation; modeling; management; hospital management; evidence based decision making.

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Introduction

Hospital staff planning is an important tool used by managers to address effectively the variability in demand for health services. Staffing levels on the long term affects not only the quality of medical services, but also the hospital key performance indicators. Evidence-based decision making in hospital staffing usually includes the history of medical service demands for each medical specialty, information about regional demographics, and prediction of future medical service demands (Ozcan & Hornby, 1999; Agheorghiesei & Poroch, 2013). Performance evaluation for public hospitals helps determine the efficiency and quality of medical services. The performance evaluation process covers clinical outcomes, personnel, and operational and financial aspects of hospital activities. The literature has documented that many diseases have a socioeconomic component (Dima-Cozma, Mitu, Szalontay, & Cojocaru, 2014).

The key performance indicators are measurable indices that are used to provide an accurate picture of a hospital organization over a certain period of time, usually a year (Barliba, Nestian & Tita, 2012). The modern medical approach involves the use of non-invasive, affordable, cost-effective diagnostic methods (Cozma *et al.*, 2017, Ghiciuc *et al.*, 2016).

Simulation offers hospital managers the evidence for a strategic decision making process in resource allocation planning. For example, determining the impact of the number of patients per physician can leverage the decision making process in the context of the organizational goals. Therefore, this paper proposes the use of discrete event simulation (DES) to develop a model for managing the flow of patients through various departments in a rehabilitation hospital. This model can help managers to investigate the impact of various factors on hospital quality indicators. The proposed DES model in this paper has been used to help managers evaluate bed utilizations, specialist utilizations, nurse utilizations, patients to specialist ratios, patients to nurse ratio, and number of patients waiting for surgery. The proposed model provides a visual mechanism for managers to examine the flow process throughout the hospital and identify opportunities to improve the overall performance. Data used in this paper is based on the publicly available staffing numbers for the Rehabilitation Hospital from Iasi, Romania (Rehabilitation Hospital, 2018). The simulation model was implemented using AnyLogic 8.3.3. PLE (Anylogic Simulation Software, 2018).

Method

Overview of Discrete Event Simulation

DES is a computerized method for simulating the operations of a real world system over time and evaluating operational solutions prior to implementation. Operational tasks in healthcare systems include patient flow, timelines of care and resource utilization. A general DES model includes entities, resources, locations, arrival rate, service times and processing logic. Entities represent what flows through the system, for example patients. Resources process the entities as they move through the system, nurses, doctors, and lab technicians. Processing logic identifies the rules for the flow of entities through the system and the interaction between entireties and resources (Hamrock *et al.,* 2013).

Simulation models can be used to evaluate various scenarios and strategies for efficient resource allocation (Caro, Möller, & Getsios, 2010). DES provides a mathematical method for modelling key parameters of operational tasks to evaluate the execution of these tasks over time (Schnelle, Schroyer, Saraf, & Simmons, 2016). DES can be very beneficial in situations where the proposed changes are expensive to implement or may face unknown risks. In these cases, hospital managers can utilize DES models for assessing quality improvement initiatives while ensuring patient safety and minimizing unintended consequences (Rutberg *et al.,* 2015). DES is used in health care to evaluate resource utilization, impact of changes prior to implementing these changes (Kim *et al.,* 2013). Particular applications of DES include improving patient flow, managing bed capacity, scheduling staff, patient admission and scheduling procedures, and using ancillary resources (Hamrock *et al.* 2013).

Related Work

DES has been applied in many areas in health care. For example, Bleibler *et al.* (2014) developed DES model to estimate the expected lifetime fracture numbers and cost of six osteoporotic fracture types for 50 year old women in Germany. Risk factors included age, of osteoporosis, prevalent fractures, and living in nursing homes. The main outcomes of the model included the occurrence fractures in areas such as hip, pelvis, humerus, and wrist. The model then was used to evaluate direct lifetime cost of different scenarios. Yang *et al.* (2009) used DES to examine the impact of reservation policy for wait-time for non-emergency patients at West China Hospital. The model was used to study the effect of various scenarios on capacity allocation in radiology unit.

Devapriya *et al.* (2015) used DES for bed occupancy analysis to measure admission waiting time and occupancy rates. A what-if analysis was conducted for key parameters such as number of beds at each level of care unit, patient volume, length of stay (LOS), and seasonal trends. The model output results were compared to the actual operational data for fiscal year 2013 from the Geisinger Health System's electronic health records. Pan *et al.* (2015) proposed the use of DES to represent patients and information flow in an ophthalmic specialist outpatient clinic. The model was used to identify strategies to improve patient experience by evaluating the total time between the arrival of a patient and the departure from the clinic (turnaround time).

Schnelle *et al.* (2016) applied discrete event simulation to project nursing aid staffing requirements for activities of daily living in nursing homes. The model was used to determine the number of nursing aid staff that is needed under different work efficiency scenarios. The outcome of the simulation was to percentage of care omission time across all scheduled activities of daily living. DeRienzo *et al.* (2017) developed a DES model for nursing staff needed in a neonatal intensive care unit based on data from the Duke University Hospital NICU from January 2008 to June 2013. The model was used to evaluate changes to the number of nurses scheduled per shift on average daily and yearly census. The model was evaluated using two different staffing levels and comparing the output with historical data. Kim *et al.* (2013) used discrete event simulation to mirror mental clinic operations and evaluate hypothetical changes to staffing in order to understand the impact on the number of patients seen outside clinic scheduled hours and service completion time.

Impact of Patient Volume on Decision Making for Resource Allocation

Understanding the relationship between patient volume (per physician and per hospital) and a hospital`s performance has gained attention from the research community in the health management area. The predominant theory on patient volume is that a hospital gets more procedural practice with a high patient volume, thus causing them to become more proficient, more effective, and to even have better patient outcomes.

The relationship between higher patient volume per physician and better quality of care, combined with better outcomes has been proven for many conditions. Analyzing the association between primary care physician volume and quality of diabetes care, Cheung et al (2017) established that primary care physicians with busier ambulatory patient practices delivered lower-quality diabetes care, but those with greater diabetes-specific experience delivered high-quality care. These results show that the relationship between physician volume and quality can be extended from acute care to outpatient chronic disease care. After examining several studies on the impact of the volume per surgeon on hospital mortality, Caputo *et al.* (2014) found that there are no clear trends between these two indicators. This result was also confirmed by Margulies *et al.* (2001) and highlight that there is no statistically meaningful contribution to the prediction of survival on the basis of per-surgeon patient volume. However, Birkmeyer *et al.* (2003) considered that, at least, for many surgical procedures, patients in hospitals where a high number of such procedures are performed (high-volume hospitals) have lower mortality rates compared to those at hospitals that are less experienced with these procedures.

Consequently, patients can often improve their chances of survival substantially, even at high-volume hospitals, by selecting surgeons who perform the operations frequently. Moreover, higher patient volume at both facility and clinician levels may predispose patients to certain types of infections. Janakiraman *et al.* (2011) found that patients attended by low volume clinicians had higher risks of infection. Analyzing the impact of patient volume (on doctor and hospital level) on various medical conditions, Austvoll-Dahlgren *et al.* (2017) showed that higher volume had a possible impact on quality for both open and endovascular surgeries. Also, higher patient volume can possibly reduce mortality in patients with abdominal aortic aneurysms, thoracic and abdominal aortic aneurysms, carotid artery stenosis, peripheral vascular disease and renal artery disease. They also found that higher patient volume possibly reduces complications in patients with abdominal aortic aneurysms, carotid artery disease and peripheral vascular disease and length of stay in patients with abdominal aortic aneurysms and carotid artery disease.

In addition, Lin *et al.* (2007) indicated that the increased case load of a given diagnosis can provide opportunities for physicians to develop cost-effective as well as technically effective medical treatment skills. Furthermore, increasing caseloads may make them savvier in coordinating the various treatment elements and discharge planning, leading to further reductions in costs related to care content as well as length of stay. The relationship between patient volume and cost efficiency has been studied by Choi *et al.* (2015). The authors remarked that hospitals need a certain point of critical mass of patients to earn an efficiency gain. Their analysis show that the impacts of patient volume on quality of care and cost efficiency indicate opposite directions, an increase in patient volume intended to escalate cost efficiency may decrease hospital quality of care. Large hospitals that can treat a high volume of patients tend to suffer from large- scale management unless there is also an appropriate level of quality of care.

Results and Discussions

Process Flow

The Clinical Rehabilitation Hospital in Iasi, Romania is a 530 bed rehabilitation hospital with ten clinics: Ear, Nose, and Throat (ENT); Neuromotor Rehabilitation; Neurologic Rehabilitation; Rheumatologic I Rehabilitation; Rheumatologic II Rehabilitation; Balneotheraphy Rehabilitation; Orthopedic Traumatology; Cardiac Rehabilitation, Respiratory Rehabilitation, and Labour Medicine Department (Spitalul Clinic de Recuperare, 2018a). The hospital services an average of 26,000 patients annually in a continuous admission, day admissions, and ambulatory regimen (Spitalul Clinic de Recuperare, 2018b). For the purpose of simulation design, and due to the similarities in utilization of hospital resources, demands for diagnosis investigation as well as hospitalization duration, the following clinics are combined together: Rheumatology I and II, and Balneotheraphy; Cardiovascular Rehabilitation, Respiratory Rehabilitation, and Labour Medicine; Neuromotor Rehabilitation and Neurologic Rehabilitation. The grouping results in 5 clinics: Ear, Nose, Throat (ENT); Neuromotor; Rheumatology; Orthopedic; and Internal Medicine respectively.

All patients report first to the hospital triage room where two hospital clerks process patients intake and either direct them to ambulatory consultation or admitting them to the hospital. Patients admitted to hospital can be either continuous admission or day admission. Day admissions receive the same treatment as continuous admission except that they do not occupy a bed in the hospital. A small percentage of previously treated patients are re-admitted for continuous hospitalization within 30 days from discharge date.

The ambulatory consultation is served by five general specialty nurses who assist the specialist physicians during ambulatory service hours. Specialist physicians serve patients in the ambulatory cabinets as well as patients in the 10 clinics within the hospitals. Ambulatory patients come to the hospital being either referred by a family physician or for a follow up consultation requested by a physician with admitting privileges within the hospital. The patients referred by the family physicians are triaged and then seen by an appropriate specialist physician in one of the five ambulatory cabinets: ENT, Neuromotor, Rheumatology, Orthopedic, and Internal Medicine. The specialist physician consultation will have one of the following outcomes: the patient is given a prescription and may be scheduled for a follow up consultation, the patient is scheduled for in-hospital admission to rehabilitation services, or the patient is referred to another hospital. *Figure 1* represents the DES model for the patient triage, ambulatory patient flow, resource utilization, and consultation outcomes.

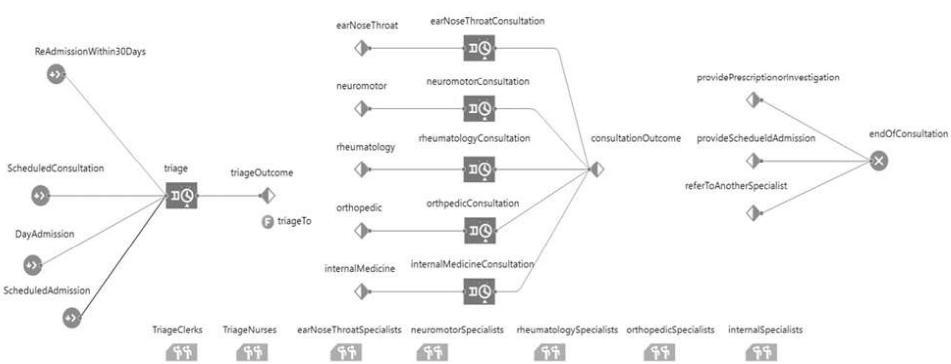

Figure 1. DES model of ambulatory patient flow

The patients who come for rehabilitation procedures are either admitted to the hospital and assigned a bed as per clinical needs determined in a previous ambulatory consultation session or are treated as day admission for the entire duration of the treatment package. Each clinic has specific rehabilitation procedures as outlined in *Figure 2*.

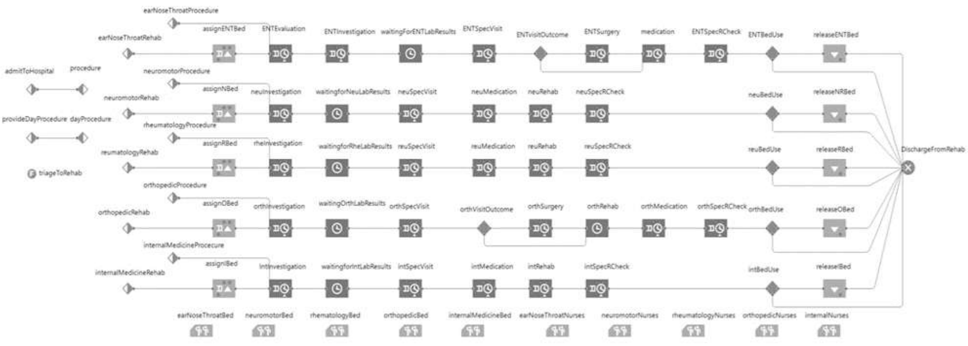

Figure 2. DES model for admission to rehabilitation clinic

Based on the DES model, admitted patients go through the triage process shown in *Figure 1*, then transition to a specific clinic as per the conditions defined in the triage outcome procedure. In order to provide accurate counts of patient flow, day admissions bypass bed assignment in the processing logic of the model.

DES Design Parameters

In designing the simulation model we have used the Rehabilitation Hospital data from 2010 to 2017 to determine the number of patients expected to be served by the hospital as well as the patient distribution for each department. The number of physicians, nurses, and registration clerks was based on the 2017 staffing levels and it is represented in *Table I.*

Table 1. List of resources per department

Department	No. of nurses	No. of specialists	No. of beds
Ear Nose Throat	16	6	30
Neuromotor	20	3	140
Rheumatology	23	11	195
Orthopedic	30	8	80
Internal Medicine	18	9	85

The percentages of patients serviced by each clinic are represented in *Figure 3* for scheduled admissions, *Figure 4* for day admission, and *Figure 5* for ambulatory consultation admission. The rate of distribution is the calculated average for the years 2010 to 2017.

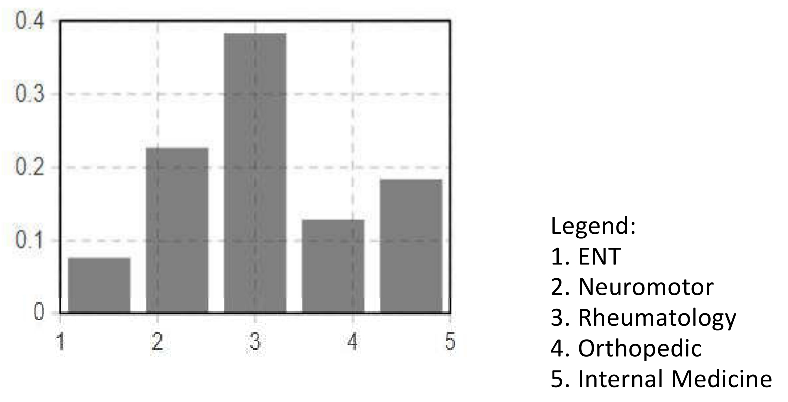

Figure 3. Scheduled admission distribution per clinic

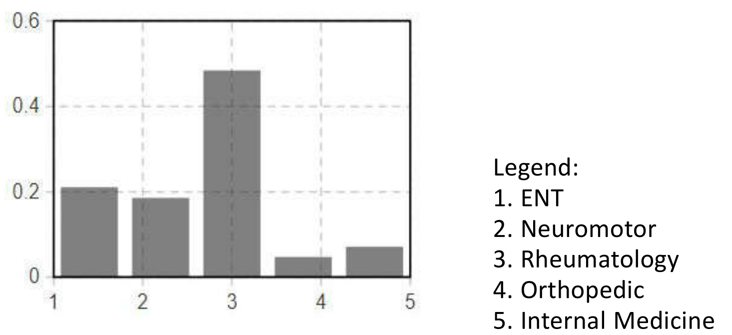

Figure 4. Day admission distribution per clinic

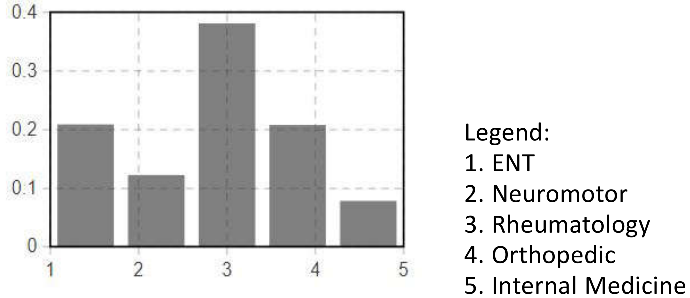

Figure 5: Consultation admission distribution per clinic

The simulation parameters took into consideration the human resources utilized for each type of service provided for each clinic and its correspondent observed duration of the service. The duration of service was modeled as a delay using the Triangular distribution with three parameters, minimum, maximum, and mode. *Table 2* outlines the specific resources, delay time for each process in the model for each clinic.

Table 2. Parameter settings for the DES model

Process Activity		Clinic				
		ENT	Neuromotor	Rheumatology	Orthopedic	Internal Medicine
Evaluation	Resources	1 specialist 1 nurse				
	Delay time	(10,35,15) minutes				
Investigation	Resources	1 nurse	1 nurse	1 nurse	1 nurse	1 nurse
	Delay time	(2,3,2.5) hours	(10,30,20) minutes	(10,30,20) minutes	(30,60,45) hours	(10,30,20) minutes
Waiting for lab results	Delay time	(6,12,8) hours	(12,24,18) hours	(12,24,18) hours	(12,24,16) hours	(12,24,18) hours
Specialist visit	Resources	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse
	Delay time	(5,15,10) minutes	(10,20,15) minutes	(10,20,15) minutes	(15,20,18) minutes	(10,20,15) minutes

Surgery	Resources	1 specialist 2 nurses			3 specialists 4 nurses	
	Delay time	(30,300,180) minutes			(2,7,3) hours	
Medication	Resources	1 nurse	1 nurse	1 nurse	1 nurse	1 nurse
	Delay time	(30,60,45) minutes	(30,50,40) minutes	(30,50,40) minutes	(30,60,45) minutes	(30,50,40) minutes
Rehab	Resources		1 nurse	1 nurse		1 nurse
	Delay time		(18, 32.5, 22.5) hours	(18, 32.5, 22.5) hours	(9,10,10) hours	(18, 32.5, 22.5) hours
Specialist routine check	Resources	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse	1 specialist 1 nurse
	Delay time	(10,30,20) minutes	(90, 180, 135) minutes	(90,180,135) minutes	(60, 100, 80) minutes	(90, 180, 135) minutes

Simulation Design and Implementation Model

The simulation investigated the utilization of several selected resources: nurses, physician specialists, and beds. The bed utilization outcome is between 59% and 96%, the nurses utilization ranges from 14% to 89%, and the specialist physician utilization ranges from 16% to 46%. The nurse and physician utilization takes into consideration only the time spent for direct patient care: consultation, investigation results review, surgery, other rehabilitation procedures, and routine reassessments. *Table 3* shows resource utilizations per clinic.

Table 3. Resource utilization output

Clinic	Nurses	Specialists	Beds
Ear Nose Throat	16%	16%	84%
Neuromotor	75%	46%	87%
Rheumatology	89%	18%	91%
Orthopedic	14%	37%	96%
Internal Medicine	87%	16%	59%

The average number of patients serviced by each specialist, per clinic, per year is represented in *Figure 6*, while the average number of patients serviced by each nurse, per clinic, per year is represented in *Figure 7*.

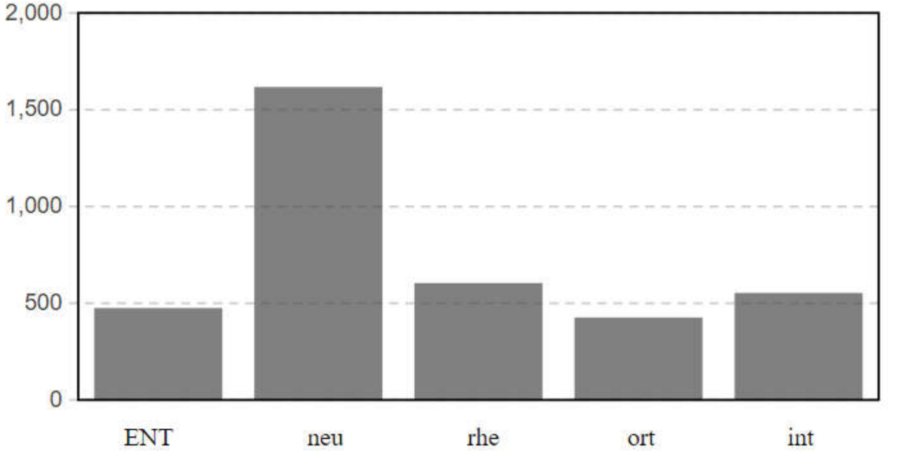

Figure 6. Patients per specialist in each clinic

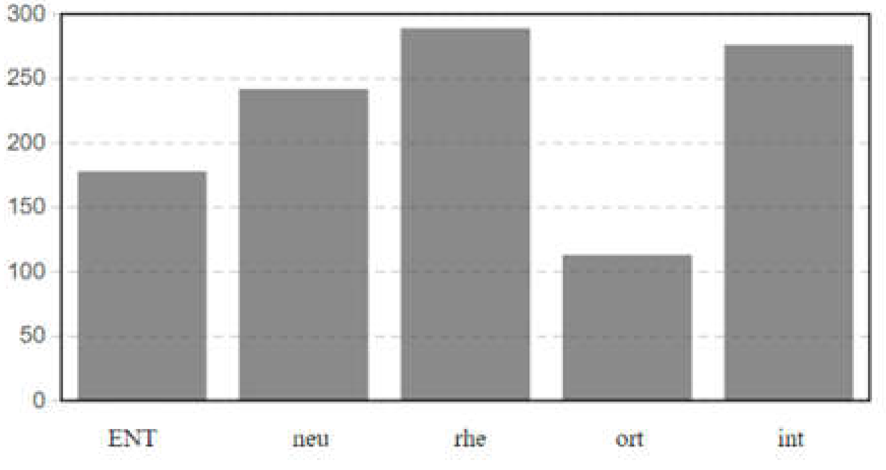

Figure 7. Patients per nurse in each clinic

The variance in the number of patients waiting for ENT surgery is represented in *Figure 8*, while the variance in the number of patients waiting for orthopedic surgery is represented in *Figure 9*. The data is plotted on a weekly basis for a year.

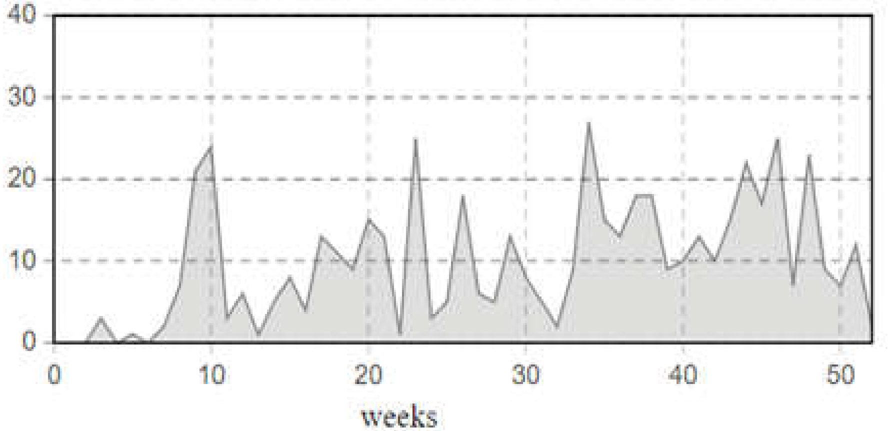

Figure 8. Number of patients waiting for ENT surgery

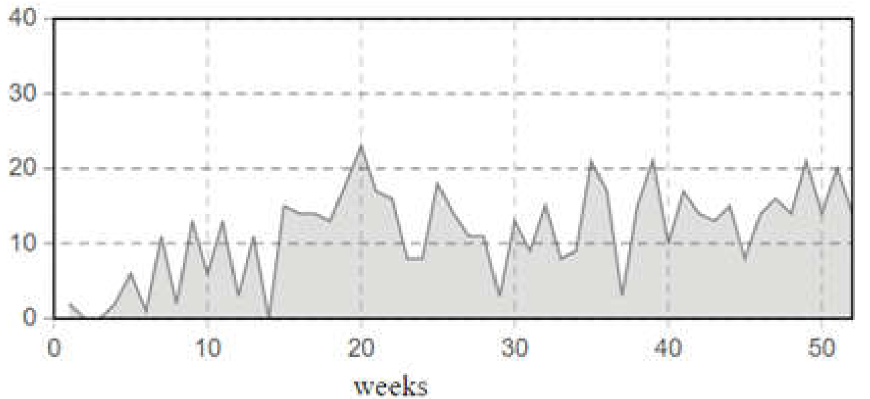

Figure 9. Number of patients waiting for orthopedic surgery

Conclusions

Resource allocation planning can impact the availably and quality of health services provided by hospitals. DES is a computerized method used to mathematically model real world systems and to evaluate the execution of various operations within the system over time. This paper presents a case study for using DES as a decision support tool to examine the impact of variability in patient volume on resource allocation. The simulation model was constructed based on staffing data for the Rehabilitation Hospital from Iasi, Romania. The constructed model simulated the ambulatory consultation and admission processes within the hospital. The input of the simulation is the number of patients consulted or admitted and the model evaluated bed utilization, nurse utilizations, specialist utilizations, number of patients waiting for surgery. Future work includes focus on more detailed simulation of patient influx in the hospital. Also, it would be useful to include other personnel type along physicians, nurses, and clerks to determine their impact on key performance indicators.

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All authors contributed equally to this paper.

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