REVIEW OF PREDICTING NUMBER OF PATIENTS IN THE QUEUE IN THE HOSPITAL USING MONTE CARLO SIMULATION

Gateri Judy Muthoni[1], Stephen Kimani[2], Joseph Wafula[3]

[1]Computer Information Technology, Kenyatta University
P.O Box 43844 - 0100, Nairobi, Kenya

[2]Institute of Computer Science & Information Technology, Jomo Kenyatta University of Agriculture and Technology
P.O Box 62000 - 00200, Nairobi, Kenya

[3]Institute of Computer Science & Information Technology, Jomo Kenyatta University of Agriculture and Technology
P.O Box 62000 - 00200, Nairobi, Kenya

Abstract

Healthcare is essential to the general welfare of society. It provides for the prevention, treatment, and management of illness through the services offered by medical and allied health professions. Emergency Department crowding causes a series of negative effects, e.g. medical errors, poor patient treatment and general patient dissatisfaction. In light of these challenges, a need for review and reform of our healthcare practices has become apparent. One road to improve the typical clinical system is to describe the patient flow in a model of the system and how the system is constrained by available equipment. Various predictive control models have been developed to try and ease overcrowding in hospitals. Such models are the Model Predictive Control to control the queuing systems. In this study the research will compare the existing prediction models and come up with Monte Carlo Simulation model to predict the number of patients in the queue.

Keyword: *Emergency Department, Prediction Model, Queuing System, Monte Carlo Simulation*

1. Introduction

Healthcare is essential to the general welfare of society. It provides for the prevention, treatment, and management of illness and the preservation of mental and physical well-being through the services offered by medical and allied health professions [1]. Today, the issue of healthcare is receiving much attention through the media and politics.

The national budget for the health sector is always criticized for falling short of demand. Hospital cost consumes a significant amount in the national budgets. Patients especially in the public health facilities suffer from the effects of overcrowding. These include lack of vacant beds and caretakers. Congestion is a major headache both to the patients, administrators and health workers who are always overwhelmed by the number of patients [2]. Healthcare is faced with unprecedented challenges, such as staffing shortages [3] an aging population [4], rising costs [5] and inefficient hospital processes [6]. [7] Observes that Emergency Department (ED) and Inpatients units (IU) crowding causes a series of negative effects such as medical errors, poor patient outcomes and patient dissatisfaction. Patient satisfaction, staff satisfaction, and hospital revenue are all negatively impacted when patients, information, and materials do not move through hospitals in a timely and efficient way. In light of these challenges, a need for review and reform of our healthcare practices has become apparent. [2] States that patient flow can be considered as the movement of patients through a set of locations in a healthcare facility. The burden on the provision of services can be reduced by model predictive control which will be predicting the number of patients queue.

2. A REVIEW OF HOSPITAL PREDICTION MODELS

2.1 Early Empirical Approaches

To understand how these factors affect emergency department operations, [8] developed a conceptual model figure 1 that consists of three components: emergency department input, throughput, and output. Patient input is described as any condition, event, or system characteristic that contributes to the demand for emergency services [9]. Input includes demand for emergency care, urgent care, and safety net care. Hospital emergency departments across the nation have seen an increase in the demand for all three types of care in recent years [10]. Patient throughput is described as the time it takes to provide emergency care and the length of stay of a visit in the emergency department [11]. The throughput component identifies patient length of stay in the emergency department as a contributing factor to emergency department crowding. There are two primary throughput phases. The first phase includes registration, triage, room placement, and the initial provider evaluation. The second phase involves diagnostic testing and treatment.

Patient output describes the factors that prevent timely disposition of patients. The patients' emergency department care is completed, but patients are prevented from progressing to the next stage of care, being discharged out of the emergency department, admitted to an inpatient bed, or returned to a skilled nursing facility [12].

One of the most commonly cited output bottlenecks facing the emergency department is the lack of available inpatient beds, especially intensive care unit and telemetry beds [11]. Ongoing care for hospital inpatients that remain in the emergency department consumes nursing and physician resources and may delay evaluation of new patients causing "backflow" [13]. A "backflow" of patients occurs when the patient cannot be placed from the emergency department to an inpatient unit because of a lack of available beds or other bottlenecks that is room cleaning [14]. This problem forces the emergency department to board (keeping a patient in a bed after he/she has already been medically treated) admitted patients until inpatient beds are available. Time spent by emergency department providers arranging appropriate follow-up visits can undermine the efficiency of care and prolong emergency department length of stay [11].

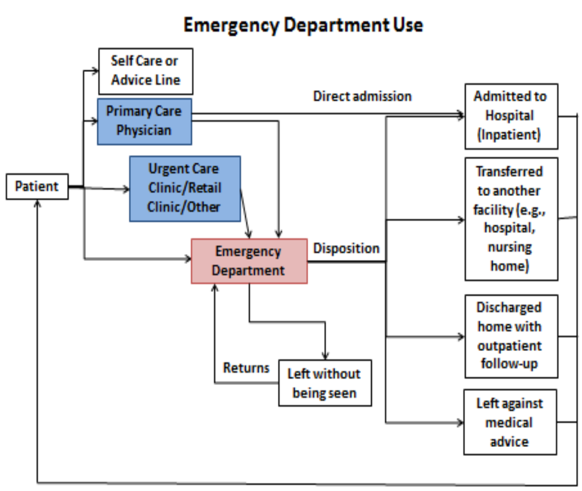

Figure 1 Conceptual Model for ED Use

Figure 1 highlights a patient's possible decision pathways regarding ED use. In the discussion below, we describe clinical decision points on the pathway. They include: (1) patient chooses to seek medical care from various options, including the ED; (2) primary care physician chooses to either directly admit a patient or refer to the ED; and (3) emergency physician determines the patient's disposition from an array of options. At the end of the process, a patient may start the cycle over again by returning to his/her primary care provider or by making a repeat visit to the Emergency Department.

2.2 Prediction model Approaches

2.2.1 Existing prediction model

Hidden Markov models (HMMs) have been used in various fields, ranging from Bioinformatics to Storage Workloads [15]. HMMs were first used in the late 1960s in statistical papers by Leonard E. Baum for statistical inference of Markov chains [16] and also for statistical estimation of Markov process probability functions [17]. Speech recognition became a field for training HMMs in the 1970s and 1980s [18], with many such speech models still used today [19]. A hidden Markov model (HMM) is a probabilistic model (a bivariate Markov chain) which encodes information about the evolution of a time series. The HMM consists of a hidden Markov chain $\{C_t\}$ (where t is an integer) with states not directly observable and a discrete time stochastic process $\{O_t\}t\geq0$,which is observable. Combining the two, we get the bivariate Markov chain $\{(C_t, O_t)\}$ $t\geq0$. The Hospital arrivals model was found to train successfully on patient arrivals, collected over months of analysis. The means and standard deviations matched well for raw and HMM-generated traces and both traces exhibited little autocorrelation. HMM parameters, fully converged after training, were used to predict the model's own synthetic traces of patient arrivals, therefore behaving as a fluid input model (with it's own rates). An enhancement could be to assume instead that the arrival process is Poisson, with corresponding rates, and produce a cumulative distribution function for the patient arrivals workload. The Hospital arrivals model was found to train successfully on patient arrivals, collected over months of analysis. The means and standard deviations matched well for raw and HMM-generated traces and both traces exhibited little autocorrelation. HMM parameters, fully converged after training, were used to predict the model's own synthetic traces of patient arrivals, therefore behaving as a fluid input model (with it's own rates). An enhancement could be to assume instead that the arrival process is Poisson, with corresponding rates, and produce a cumulative distribution function for the patient arrivals workload.

Queuing Theory with Markov Chain (QTMC) and Discrete Event Simulation (DES) - The first model Queuing Theory with Markov Chain is only able to consider limited scenarios that can occur [2]. One published QTMC model of the orthopedic department of the Middelheim hospital focuses on the impact of outages of the personnel (preemptive and non-preemptive outages), on the effective utilization of resources, and on the flow time of patients [20] Discrete Event Simulation (DES) has been well recognized in healthcare and is broadly used for the validation of other models. The DES models offer a valuable tool to study the trade-off between the capacity structure, sources of variability and patient flow times [21]. In the model they used residence time variable, is the time when the patients arrival at the hospital until they come out of the hospital. The residence time in the hospital includes the residence time at each department and the transfer time. For a department, the residence time includes the waiting time, and the processing time (service time). The residence time in a process following is considered as an Exponential distribution. In actual processes, the distribution can be studied from the history data. The mean value of arrival rate is influenced by many factors. There is a big difference between weekdays and weekends, working time and resting time, and so on. Big events may also increase the number of patients, e.g. anniversary, sports event, traffic accidents etc. In a day more patients arrive at the hospital during the day and evening than the morning. The planned patients make an appointment with the hospital. The patients will come to the hospital based on a schedule, which also means this variable can be controlled. To analyse stochastic variables, the corresponding distributions of interarrival rate and residence time should be found. Herein, Exponontial distribution, Weibull distribution, and Poission distribution are inverstageted. The Weibull distribution has a flexible shape. This distribution has been used successfully in many applications as a purely empirical model [22]. The Exponential distribution has only one unknown parameter, this distribution has a memory less property, which means previous states don't influence the future states [23]. If the variable in the Exponential distribution is integer, the variable can be expressed by Poisson distribution. Poisson distribution has the same properties with Exponential distribution.

In DES, the operation of a system is represented as a chronological sequence of events. Each event occurs at an instance in time and marks a change of state in the system [24]. The modeled system is dynamic and stochastic. DES includes Clock, Events List, Random Number Generators, Statistics and Ending Condition [25].

The simulation based on Queuing Theory and Markov Chain can be a good approach for implementation in the real hospital. This model provides a quite good method to handle the randomness and uncertainty in the patient flow, but it is not easy to find a proper mathematical model when the process is complex. The DES models are commonly used in checking the other models. The approach of using this model in patient flow also gives a quite realizable result.

Decision-tree model for predicting outcomes after out-of-hospital cardiac arrest in the emergency department [26]. The research developed a simple and generally applicable bedside model for predicting outcomes after cardiac arrest. The model analyzed data for 390,226 adult patients who had undergone OHCA, from a prospectively recorded nationwide Utstein-style Japanese database for 2005 through 2009. The primary end point was survival with favorable neurologic outcome (cerebral performance category (CPC) scale, categories 1 to 2 [CPC 1 to 2]) at 1 month. The secondary end point was survival at 1 month. They developed a decision-tree prediction model by using data from a 4-year period (2005 through 2008, n = 307,896), with validation by using external data from 2009 (n = 82,330). Recursive partitioning analysis of the development cohort for 10 predictors indicated that the best single predictor for survival and CPC 1 to 2 was shockable initial rhythm. The next predictors for patients with shockable initial rhythm were age (<70 years) followed by witnessed arrest and age (>70 years) followed by arrest witnessed by emergency medical services (EMS) personnel. For patients with unshockable initial rhythm, the next best predictor was witnessed arrest. A simple decision-tree prediction mode permitted stratification into four prediction groups: good, moderately good, poor, and absolutely poor. This model identified patient groups with a range from 1.2% to 30.2% for survival and from 0.3% to 23.2% for CPC 1 to 2 probabilities. Similar results were observed when this model was applied to the validation cohort.

On the basis of a decision-tree prediction model using four prehospital variables (shockable initial rhythm, age, witnessed arrest, and witnessed by EMS personnel), OHCA patients can be readily stratified into the four groups (good, moderately good, poor, and absolutely poor) that help predict both survival at 1 month and survival with favorable neurologic outcome at 1 month. This simple prediction model may provide clinicians with a practical bedside tool for the OHCA patient's stratification in the emergency department. The more-fascinating but controversial aspect of outcome prediction is the possibility of helping guide decision making and risk assessment for individual patients [27]. By predicting which treatment strategies will be futile for an individual, human suffering and costs could be reduced while increasing the capacity for treating other critically ill patients [27].

Table 1 summarizes the definition of prediction groups for OHCA by using four prehospital factors

These results indicate that our decision-tree model might be applicable for other countries with different EMS systems.

Prediction groups		Prehospital factors			
		Shockable initial rhythm	Age (years)	Witnessed arrest	Witnessed by EMS personnel
Good	1	Yes	<70	Yes	
	2	Yes	≥71		Yes
Moderately good	1	Yes	<70	No	
	2	Yes	≥ 70		No
Poor		No		Yes	
Absolutely poor	No			No	

Table 1 summarizes the definition of prediction groups for OHCA by using four prehospital factors

Support Vector Machine (SVM) and a Cox Regression based approach [28] for Predicting Readmission Risk with Institution Specific Prediction Models. The model is able to predict for a new patient, a risk score indicating the likelihood of him/her being readmitted. In the last ten years, there have been numerous studies that attempted to model the risk of readmissions, with accuracies (measured by the area under the curve [AUC] or c-statistics in validation sets) ranging approximately from 0.6 to 0.78. Some of the models aimed to predict readmissions in general population settings. One popular model called LACE is presented in [29] where an index to predict early death or unplanned readmissions after discharge from hospitals from the community was created using data from 4,000 patients from 11 hospitals in Ontario. See Fig. 2 for the final model.

Attribute	Value	Points
Length of Stay, d (L)	<1	0
	1	1
	2	2
	3	3
	4-6	4
	7-13	5
	≥ 14	7
Acute admission (A)	Yes	3
Comorbidity (Charlson index) (C)	0	0
	1	1
	2	2
	3	3
	≥ 4	5
Visits to ER in past 6 months (E)	0	0
	1	1
	2	2
	3	3
	≥ 4	4

Fig. 2. The LACE scoring function for readmission risk prediction [29]

The framework has three components. First, it extracts past patient data from the hospital, including demographics, labs, medications, ICD and CPT codes, etc. For the current work it focus on structured data only, but it can be naturally extended to include data extracted from unstructured data. It also identifies which patients were readmitted to the same hospital within 30 days of discharge. Second, it combines all the available information for each patient and builds a statistical model to predict readmission (to the same hospital). If a condition-specific risk prediction model is desired, the framework can adjust the model fitting only to the patients that have that condition. Third, the model can be applied to new patients and output a risk score.

In the predictive modeling component, it was experimented two approaches, one treating the readmission risk prediction as a binary classification problem (i.e., 1 if the patient was readmitted within 30 days, and 0 otherwise), and the other viewing this as a prognosis analysis problem, which leverages the exact elapsed date between discharge and readmission. They used SVM to tackle the classification view of the problem, and used Cox Regression to solve the prognosis view.

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. In the readmission prediction problem, this is to predict whether or not the patient will be readmitted within 30 days. In survival or prognosis analysis, they were interested in the survival time of each individual from a certain population

Variable	Availability	Hospital
Age	Admission	2, 3
Gender	Admission	2, 3
Race	Admission	2, 3
Number of prior hospital visits	Admission	2, 3
Number of prior emergency room visits	Admission	2, 3
Patient type	Admission	2, 3
Primary ICD9 code	Discharge	2, 3
Length of stay	Discharge	2, 3
Discharge status	Discharge	2, 3
Comorbidities	Discharge	2, 3
Hospital ward	Admission	2
Admission source	Admission	3
Admission type	Admission	3

Table 2 Availability of variability of variables at hospital 2 & 3

The proposed approach was implemented as follows. For each institution, four models were trained, one for patients admitted for each of the conditions in consideration: Acute

Myocardial Infarction (AMI), Heart Failure (HF), Pneumonia (PN), and All Cause. To examine the effects of different choices of predictive model, they tried three methods: linear SVM, polynomial kernel SVM, and a Cox regression model. In contrast to the two SVM methods, the Cox model does not dichotomize time until readmission into durations of 30 days or less and greater than 30 days, but rather uses the actual duration between an admission and the subsequent admission in the model. Performance was evaluated using several metrics. AUC was used as a general measure of the predictive power of each model. We additionally considered the precision and recall in the highest risk decile of patients as estimated by each model. These metrics more closely reflect the potential impacts on clinical practice, by indicating the percentage of patients designated high risk who were actually readmitted (precision) and the percentage of overall readmissions captured in the high risk group (recall).

The predictive performance of the proposed approach and LACE are shown in Tables III. Using all features available at discharge, the hospital and condition-specific models outperformed LACE on all metrics in almost all cases across both institutions. In almost all cases, the improvement in AUC was statistically significant under a paired t-test with a confidence level of 0.05. This shows that tailoring models to each condition and institution achieves better readmission prediction than applying a single general purpose model across conditions and institutions.

The framework has the advantage that it can take all variables the hospital has collected for its patient population (possibly with missing values). The model building does not need human involvement (e.g., manual tune-up, heuristics) and is very efficient so one can effectively re-build the model regularly with new patient data (e.g., every night). The use of polynomial kernels or Cox regression did not appear to improve on the performance of the standard linear SVM. The use of Cox regression has the unique advantage that of handling the 30-day readmissions cut-off more robustly, as it does not create arbitrary distinctions between readmissions occurring near the cut-off (e.g. a readmission on the 30th versus the 31st day after a discharge). However, this did not appear to substantially affect performance due to the fact that the great majority of readmissions in our dataset occurred in the first 2-3 weeks of the prior admission.

Forecasting model, Poisson Autoregressive (PAR) model and logistic regression models for Ensemble-based methods for forecasting census in hospital units [30]

The ensemble-based method for short-term census forecasts under a framework that simultaneously incorporates hospital unit arrival trends over time and patient specific baseline and time-varying information. Such approaches represent the future of census forecasting as hospital departments around the country move toward more efficient methods for collecting and processing patient-level information upon admission and through the duration of stay. The method differentiates between arrival, departure, and census counts for the NICU. The arrival count was defined on a particular day as the number of patients admitted to the NICU during a 24 hour period. Similarly, the departure count for a particular day is defined as the number of patients who depart the NICU as a result of a healthy discharge during a 24 hour period. By healthy discharge they refer to cases where a patient was discharged from the NICU as a result of adequate physiological health, as determined by clinical criteria. Lastly, they define the daily census count as the number of patients residing in the NICU at the end of the day (11:59pm). Predicting the number of arrivals – they modeled daily arrival using the Poisson Autoregressive (PAR) model. Predicting the number of departures - To predict the number of departures from a group of patients residing in the NICU, they incorporated both patient-specific baseline covariate information and any covariate information collected throughout their stay in the NICU. The model is efficient because it integrates arrival trends over time as well as patient level information. The former is crucial to the development of accurate and reliable models for predicting the probability departure, while the latter is integral to attainment of a model that can predict the number of census arrivals with a high degree of accuracy. Our justification for using a conditional logistic regression framework for predicting the number of departures was motivated by two principle issues. As a result of our general forecasting framework, our interest was primarily focused on the expected number of departures for a cohort of patients currently residing in the census. Thus, treating each patient within a cohort as independent, the expected number of departures for a given cohort can be efficiently estimated by summing the individual predictions for departure for each patient. The idea of predicting the probabilities of departure as opposed to length of stay predictions lends itself nicely to a logistic regression framework. An alternative approach involves using length-of-stay distributions within a queuing theory analysis. However, unlike the framework described here, such an approach would not facilitate the attainment of the subject-specific probabilities of departure, which is of interest to clinicians.

Autoregressive Inductive Moving Average (ARIMA) [31] - Used Autoregressive Inductive Moving Average (ARIMA) modeling to predict the number of surgical beds required at a UK hospital [32]. Further, McManus describes the use of Queuing Theory to predict monthly responsiveness to changing bed demand [33]. ARMA processes are useful in describing or approximating a wide variety of stationary processes whose auto covariance functions approach zero as the lag approaches infinity.

2.2.1 Weakness of existing prediction model

Queuing Theory with Markov Chain (QTMC), and Discrete Event Simulation (DES) - The DES plots have more fluctuation between each simulation plots. These unstable properties can be improved by increasing ensemble size, but a large ensemble size of simulations will lead to a higher computation cost. In turn, if multiple patients were admitted simultaneously, queuing analysis would only account for one patient in the model [2]. It is not easy to find a proper mathematical model when the process is complex and limitation of the control variable e.g. more efficiently handling the integral variables and the constraints. The model lacked Model Predictive Control theory of practice and should reduce and optimize the matrices computing which is time consuming and take up lots of resources.
Decision tree model - First, they did not consider the time-related factors to be potentially correlated with outcomes such as collapse time, time interval from collapse to ROSC, time interval from collapse to CPR initiation, and time interval from collapse to AED use. It could be difficult to recall the exact time-of-collapse events in emergency situations. Second, they also did not analyze the model by using the variables of prehospital administration of adrenalin or advanced airway managements techniques performed by ELSTs because previous Japanese studies have reported that the prehospital use of adrenalin and advanced airway management do not increase the chance of survival and good functional outcomes after cardiac arrest among OHCA patients [34]. Third, the detailed in-hospital interventions were not evaluated. They assumed that OHCA patients received standard advanced life support according to the Japanese CPR guidelines [35], which are based on the 2000 and 2005 American Heart Association guidelines [36,37]. Fourth, it is not known whether our decision-tree model is valid for communities with other emergency care characteristics. It may be necessary for other countries to validate the present prediction model. Fifth, unmeasured confounding factors might have influenced outcomes.
Support Vector Machine (SVM) and a Cox Regression based approach - A patient's final LACE score is calculated by summing the points for each attribute. The index was externally validated using administrative data in a random selection of 1,000,000 Ontarians with a reported accuracy of 0.68 in AUC. Since the base readmission rate of the population used for LACE development is around 8%, it is arguably not well suited for the Medicare population in the US, for which the base readmission rate is around 20%. Other models based on general population data include [38].
Weakness Forecasting model, Poisson Autoregressive (PAR) model and logistic regression models - The arrival data used in this analysis consisted of only approximately a year and a half of admission information, thus we are limited in our ability to ascertain long-term seasonality trends.
Weakness of Autoregressive Inductive Moving Average (ARIMA) - Using ARIMA modeling, [39] found that the daily number of occupied beds due to emergency admissions is related to both air temperature and influenza illness rate. It was found that a period of high volatility, indicated by GARCH errors, would result in an increase in waiting time in the A&E department. The model has limitations and especially of the inherent variability of emergency inpatient flow. There have been several methodologies developed for forecasting arrival and census counts in various hospital departments [40] evaluated the use of seasonal autoregressive integrated moving average (ARIMA), time series regression, exponential smoothing, and artificial neural network models to forecast daily patient volumes in emergency departments at three diverse hospital emergency departments. The time series methods considered in that analysis provided improved absolute prediction error (MAPE) relative to a multiple linear regression approach, considered the benchmark model for forecasting emergency department patient volumes.

3.Conclusion

In this study the research will compare the existing models and come up with appropriate model and use Monte Carlo Simulation methods to predict the number of patients in the queue. State Monte Carlo Simulation is a technique that computes or iterates the project cost or schedule many times using input values selected at random from probability distributions of possible costs or durations, to calculate a distribution of possible total project cost or completion dates. Monte Carlo simulation samples probability distribution for each system variable to produce hundreds or thousands of possible outcomes. The research will come up with model design to estimate patients demand in the Emergency department which will use arrival time, waiting time and service time. It will also use Poisson rule and exponential distribution to facilitate how Monte Carlo Simulation will work. In order to facilitate Monte Carlo Simulation, the research will consider the simple multi-server queuing model as $M/M/c/\infty$.
Suppose arrival time fit Poisson distribution with rate λ and service time to obey exponential distribution with mean μ, the number of service windows in the Emergency Department is c.
Let

$$\gamma = \frac{\lambda}{\mu}, \rho = \frac{\lambda}{c\mu} < 1$$

With the knowledge of queue theory we know the queuing length is

$$L = \gamma + \frac{\gamma^c \rho}{c!\,(1-\rho)2} P_0$$

When $c_\omega \leq \frac{\lambda c \mu}{2}$ the optimal service rate =

$$\mu = \mu_3' = \frac{1}{2c\mu}\sqrt{c_\mu \lambda (c_\mu \lambda + c_\omega - \sqrt{4c_\mu \lambda c_\omega + c_\omega^2})}$$

When $c_\omega \geq \frac{\lambda c \mu}{2}$ the optimal service rate =

$$\mu = \mu_1' = \frac{1}{2c\mu}\sqrt{c_\mu \lambda (c_\mu \lambda + c_\omega + \sqrt{4c_\mu \lambda c_\omega + c_\omega^2})}$$

c is the number of the service windows, c_μ as the cost of the service in an hour, c_ω is the cost that customers waiting in the queue system, *L* is the queuing length of the queue model in the Emergency Department. *O* as other costs include the costs of facilities and other personnel costs. The research might implement the Monte Carlo Simulation using C++ or Java programming.

References

[1] Houghton. The American Heritage® Medical Dictionary (2007).

[2] Lei Zhao, a. B. Modeling and Simulation of Patient Flow in Hospitals for Resoure Utilization. 1-10 (2008).

[3] American Nurses Association, I. Nurse Staffing. Retrieved 2010, 2-November from American Nurses Association. (2010).

[4] Hellmich, N. Aging population making more visits to the doctor's (2008).

[5] Bodenheimer, T. High and Rising Health Care Costs. Part 1: Seeking an Explanation (2010).

[6] New England Healthcare, I. Waste and Inefficiency in Health Care (2010).

[7] E. M. W. Kolb, T. Lee, J. Peck, eds. proceeding Effect of Coupling between emergency department and inpatient unit on the overcrowding in emergency department (2007)

[8] Asplin, B. R. A Conceptual Model of Emergency Department Crowding. Annals of Emergency Medicine , 173-179 (2003).

[9] Joint commission resource Managing Patient Flow: Strategies and Solutions for Addressing Hospital Overcrowding. 1-88 (2004).

[10] McCaig L, a. N. National Hospital Ambulatory Medical Care Survey 2004 Emergency Department Summary. Washington, DC: U.S. Department of Health & Human Services, Center for Disease Control & Prevention. National Center for Health Statistics,No. 372 (2006).

[11] Bazzoli, G. Does U.S. Hospital Capacity Need to be Expanded? Health Affairs 22(6) , (2003) 40-54

[12] Asplin, B. R. Measuring emergency department crowding and hospital capacity. Academic Emergency Medicine. (9): , (2002).366-367

[13] Vissers, J. A.. Health Operations Management. Patient Flow Logistics in Healthcare 1st Ed. New York, NY: Routledge Publishing (2005).

[14] Trzeciak, S. a. Emergency Department Overcrowding in the United States: An Emerging Threat to Patient Safety and Public Health. Emergency Medicine20 (5): , (2003). 402-405

[15] Harrison, P. G., Harrison, S. K., Patel N. M., Zertal, S.: Storage Workload Modelling by Hidden Markov Models: Application to Flash Memory, In: Performance Evaluation, 69, (2012) pp. 17-40

[16] Baum, L. E., Petrie, T.: Stastical Inference for Probabilistic Functions of Finite Markov Chains, In The Annals of Mathematical Statistics, 37, (1966) pp. 1554-63

[17] Baum, L. E., Eagon, J. A.: An Inequality with Applications to Statistical Estimation for Probabilistic Functions of a Markov Process and to a Model for Ecology, In Bulletin of the American Mathematical Society, 73, (1967) pp. 360-3,

[18] Rabiner, L. R.: A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, In IEEE, 77, (1989) pp. 257-286

[19] Ashraf, J., Iqbal, N., Khattak, N. S., Zaidi, A. M.: Speaker Independent Urdu Speech Recognition Using HMM (2010)

[20] S. Creemers, and M. Lambrecht Modeling a Healthcare System as a Queueing Network: The Case of a Belgian Hospital. Catholic University of Leuven (KUL), Belgium. (2007)

[21] Arnoud M, a. G. Bottleneck analysis of emergency in-patient flow (2007).

[22] http://www.itl.nist.gov/div898/handbook/apr/section1/apr163.htm

[23] http://www.itl.nist.gov/div898/handbook/apr/section1/apr161.htm

[24] K.S. Trivedi Probability and Statistics with Reliability, Queuing and Computer Science Applications, Second edition, Wiley & Sons (2001).

[25] http://en.wikipedia.org/wiki/Queueing_model

[26] Yoshikazu Goto, T. M. Decision-tree model for predicting outcomes after out-of-hospital cardiac arrest in the emergency department (2013).

[27] Nielsen N. Predictive scores, friend or foe for the cardiac patient. Resuscitation, 83: (2012) 669-670.

[28] Shipeng Yu, Alexander van Esbroeck, Faisal Farooq, Glenn Fung, Vikram Anand and Balaji Krishnapuram Predicting Readmission Risk with Institution Specific Prediction Models (2013)

[29] Carl vanWalraven, Irfan A. Dhalla, Chaim Bell, Edward Etchells, Ian G. Stiell, Kelly Zarnke, Peter C. Austin, and Alan J. Forster. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. CMAJ, 182(6) (2010).

[30] Devin C Koestler, Hernando Ombao and Jesse Bender Ensemble-based methods for forecasting census in hospital units (2013)
[31] Mark P. Joy and Simon Jones Predicting Bed Demand in a Hospital using Neural Networks and ARIMA models: a Hybrid Approach (2005)
[32] Farmer, R. a. Models for forecasting hospital bed requirements in the acute sector. Epidemiological community Health (1990).
[33] McManus, M. L. Queuing theory accurately models the need for critical care. Anaesthesiology, vol. 100, (2004) 1271-1276 .
[34] Nagao T, Kinoshita K, Sakurai A, Yamaguchi J, Furukawa M, Utagawa A, Moriya T, Azuhata T, Tanjoh KEffects of bag-mask versus advanced airway ventilation for patients undergoing prolonged cardiopulmonary resuscitation in pre-hospital setting. J Emerg Med, 42: (2012). 162-170.
[35] Japanese Guideline for Emergency Care and Cardiopulmonary Resuscitation 3 edition. Tokyo: Health shupansha; (2007)
[36] American Heart Association: Guideline for cardiopulmonary resuscitation emergency cardiovascular care. Circulation, 102: (2000) I1-384.
[37] American Heart Association: Guideline for cardiopulmonary resuscitation and emergency cardiovascular care. Circulation 112: (2005) V1-203.
[38] Omar Hasan, David O. Meltzer, Shimon A. Shaykevich, Chaim M. Bell, Peter J. Kaboli, Andrew D. Auerbach, Tosha B. Wetterneck, Vineet M. Arora, James Zhang, and Jeffrey L. Schnipper. Hospital readmission in general medicine patients: A prediction model. Jornal of General Internal Medicine, 25(3): (2010) 211–219.
[39] Jones, S. a. Forecasting demand of emergency care. Healthcare Management Science, (2002). vol.5,297.
[40] Jones SS, Thomas A, Evans RS, Welch SJ, Haug PJ, Snow GL: Forecasting daily patient volumes in the emergency department. Acad EmergMed, 15(2): (2008) 159–170.

First Author Judy Gateri is a holder of BSc. Computer Information System (2012), Ongoing MSc. Software Engineering Jomo Kenyatta University of Agriculture and Technology. Worked at Jomo Kenyatta University of Agriculture and Technology and currently working at Kenyatta University. has the following academic qualifications is an ICT officer at Kenyatta University department of Computing and Information Technology. She was awarded certificate of Instructor Excellence Award by Cisco Networking Academy® program (2013).

Second Author Dr. Stephen Kimani is the current director of the School of Computing and Information Technology of the Jomo Kenyatta University of Agriculture and Technology (JKUAT) in Kenya. He has previously been a researcher at CSIRO (Australia) and Sapienza University of Rome (Italy). He has the following academic qualifications: BSc in Mathematics and Computer Science (JKUAT); MSc in Advanced Computing (University of Bristol, UK); PhD in Computer Engineering (Sapienza University of Rome, Italy)

Third Author Dr. Joseph Wafula is the current director of the Information Communication Technology of the Jomo Kenyatta University of Agriculture and Technology (JKUAT) in Kenya. He has the following academic qualifications: BSc in Science - Physics and Computer Science (Kenyatta University - Kenya); MSc in Physics (University of Nairobi, Kenya); PhD in Information Technology (JKUAT, Kenya)