Modeling a Public Hospital Outpatient Clinic in Peru using Discrete Simulation

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Abstract: Having insurance or not makes a difference in terms of the procedure patients need to follow to be attended in public hospitals in Peru. Studies show a high dissatisfaction towards the service offered by public hospitals, mainly due to long waiting times, specially for patients with insurance. The initiatives implemented by the government to solve these problems were not supplemented with a rigorous analysis to help quantify their impact. The main objective of this study is to assess the quality of care at one of the most visited public hospitals in Peru. Discrete simulation was used to build a model which was validated through historical data and hospital personnel. The model is capable of measuring the service level and it facilitates the identification of bottlenecks. It identified the most critical medical specialties most utilized and that have the longest queues. The results also serve to identify the services with a low utilization rate. High idle time during the insurance verification process was identified as a problem. It seems insurance verification could be integrated with admission tasks or during other services. The model can be applied to any public hospital in Peru given the fact that their outpatients processes are similar.

1 INTRODUCTION

The health system in Peru has two sectors: public and private. The public sector is divided in two programs: the government subsidized program and the social insurance program. The social insurance program is supported by employee and employer direct contributions. In Peru there are hospitals, EsSalud hospitals, exclusively for people having social insurance.

People without social insurance go to MINSA hospitals. Here, the government offers health services to those without social insurance. If these people are poor, they have access to a subsidized insurance program called SIS "Seguro Integral de Salud" (Integral health insurance). To maintain this subsidized insurance, they need to make a monthly minimum payment to cover the hospital's variable costs. If they are not eligible for the SIS insurance or do not make this payment, and do not have social insurance, they can go to the MINSA establishments as well but they need to pay for the service (Dirección General Parlamentaria, 2010).

About 30% of the Peruvian population has either social insurance or private insurance. About 31% has the subsidized insurance (SIS), and about 38% of the population lack any type of medical insurance (Instituto Nacional de Estadística e Informática, 2012), Table 1. The percentage of people without insurance has diminished since 2008, from 58% to 38.1%. (Jacqueline Elizabeth Alcalde-Rabanal, Oswaldo Lazo-González, & Gustavo Nigenda, 2011).

Table 1: Percentage of population with and without insurance*, 2012.

Indicator	Piura 2012	Peru 2012
Population with social insurance	20.3	24.4
Population with private insurance	3.65	6.06
Population with subsidized insurance (SIS)	31.2	31.4
Population with some insurance (subsidized or not)	55.1	61.9
Population without insurance	44.9	38.1

*Data retrieved from INEI (Instituto Nacional de Estadística e Informática), 2012.

Another critical factor in the health system is the number of physicians per 1000 units of population.

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Peru has a physician's density of 1.42 (Instituto Nacional de Estadística e Informática, 2012), while other countries in South America have larger densities, such as 1.76 for Brazil, and 3.16 for Argentina (Central Intelligence Agency).

The hospital used in this study is located in Piura which is the second largest province in Peru. Piura has approximately 1.8 million habitants, 6% of the total population in Peru. For the province of Piura 32.1% of the population is considered poor. In 2012, there were 27 hospitals in Piura or if evenly distributed each hospital serves on average 66,666 habitants; compared to 44,059 habitants per hospital in Lima. Piura has a physician density about 0.75, compared to the national average of 1.42. In Piura, the percentage of people with some insurance is 55.1% (Instituto Nacional de Estadística e Informática, 2012).

The hospital examined in this study is a MINSA hospital where people with SIS insurance or without insurance can gain admittance. This hospital is one of the most visited in the region.
Satisfaction surveys administered by the Peruvian Health Ministry show a very high dissatisfaction rate towards the service offered by the hospitals, mainly due to the long waiting times (MINSA, www.minsa.gob.pe). This hospital is not exempt from that situation. While many initiatives that have been implemented to solve the problems all of these initiatives have used quality tools such as satisfaction survey and brainstorming without using quantitative tools to quantify the impact of different possible solutions by carrying out "what-if" scenario analysis.

Discrete event simulation has been used for a variety of health care applications (Jahn et.al. 2010). For example, it has been used to improve patient care in emergency departments (Abo-hamad, and Arisha, 2013; Brenner et.al., 2010; Cabrera et. al., 2012; Hoot et.al., 2008; Jamon and Lin, 2012; and Zeng et. al., 2012), to improve bed utilization in hospitals (Holm et.al., 2012), to model outpatient's clinic (Al-Araidah et. al., 2012; Villamizar et.al., 2011), to analyze the capacity of the Intensive Care Unit at hospitals (Troy and Rosenberg, 2009), and to improve radiation therapy planning process (Werker et.al. 2009).

For all the above, discrete simulation with ARENA was used for modelling the outpatient's clinic of the MINSA hospital under study. The simulation tool can help hospital management assess the service level through measuring queue length, waiting times, and utilization rates for the different health services. Additionally, it allows trying many operational changes to determine an optimal system configuration.

2 SYSTEM DESCRIPTION

The outpatient clinic at the hospital studied offers 25 medical specialties. In 2010, 60,351 outpatients were serviced. As it can be seen in Figure 1, the demand does not fluctuate much across time. The drop in October and November for 2010 was due to a strike at the hospital during which only critical cases were admitted.

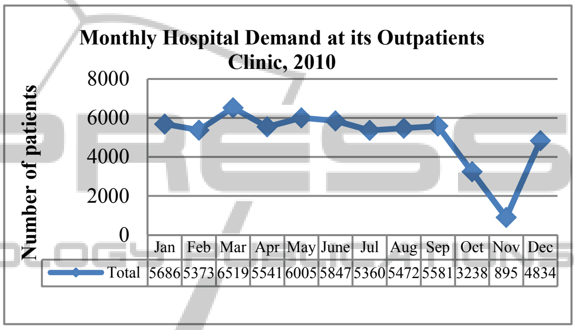

Figure 1: Monthly demand for the outpatient clinic at the hospital, 2010.

According to the hospital records, 30% of patients had SIS insurance, 60% did not, and the rest were exonerated of the payment due to their economic situation. These percentages are also steady over time.

The outpatient clinic has a four stage service process. First is admission. Second is the insurance documentation (SIS module) just for the patients with subsidized insurance, where they will receive the payment waiver. The third stage is the medical assessment itself. Finally, the last stage includes medical support services such as pharmacy, x-ray, and laboratory tests. From Monday to Friday, all areas work from 7:00 am to 1:00 pm, except x-ray which works until 4:00 pm.

The process at the outpatient clinic is:

(1) Patients arrive at the clinic's admission area, where they can schedule a medical appointment for that day. If the patients have insurance, they must complete the insurance process; here, the insurance staff verifies if the insurance will cover the medical expenses, otherwise the patient need must pay for service.

(2) Patients go to the waiting room to be called by the specialist for their assessment. The hospital

offers 25 specialties. Most visits are for obstetrics, gynaecology, paediatrics, ophthalmology, gastroenterology, cardiology, echography, internal medicine, neurology, odontology, otorhinolaryngology, rheumatology, orthopedics, and urology.

(3) After the assessment, patients go to pharmacy, x-ray diagnostics, and laboratory, according to the doctor's instructions. Laboratory is the only one that has two subsystems: reception and lab test. Before these services can be utilized the patients with insurance must go through an insurance process to receive a payment waiver for services.

Throughout the process, patients' experience long waiting times and queues.

3 SIMULATION MODEL

An extended survey was carried out in order to collect data on the arrival process, and the service times at the different stages. To represent the real process, process observation; database retrieval; interviews of doctors, nurses, and hospital employees; and time studies were conducted.

The service process was modeled by a discrete event simulation system, using Arena software (Kelton et. al., 2009, and Law & Kelton, 2007)

3.1 Input Analysis

Input Analyzer from Arena was used to model the probability distributions for describing the time between arrivals and service time, Table 2.

Table 2: Probability distributions.

Variables	Probability distribution
Time between patients' arrivals	Exponential
Receptionist's service time for patients with insurance	Erlang
Receptionist's service for patients without insurance	Lognormal
Service time of the 15 specialties	Triangular
Service time of pharmacy, x-ray, and laboratory	Triangular
Service time of the receptionist at the laboratory	Normal

External arrivals to these services—those coming from hospitalization or the emergency room were also considered in the model. The time between external arrivals in the pharmacy was described as a weibull distribution, while x-ray and laboratory external arrivals were described as uniform distributions.

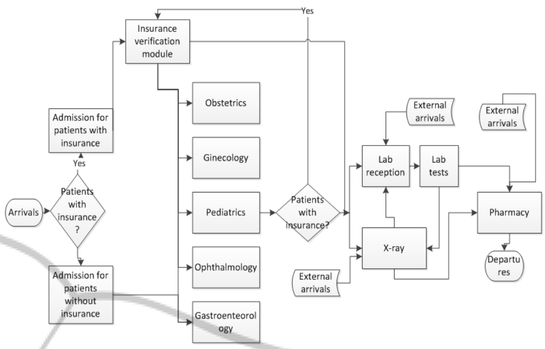

Figure 2: Process flow of the outpatients' clinic.

3.2 Model

The conceptual model is represented in Figure 2. Based on those processes, resource availability, and the results from the input analysis, a simulation model was developed using ARENA 10.

First, a small portion of the model was built, and after its functionality was established, more areas and complexity were added. Once the model was complete, its functionality was verified. After checking the model to insure it provided the intended information, the model was validated. At this stage, the amount of daily average patients treated was compared to the historical data. Meanwhile, other service indicators such as average time spent at the different queues and total average waiting time in the hospital were validated by the hospital personnel working in those services. Subsequently, it was concluded that the model is a credible representation of the system.

4 RESULTS

One of the objectives of this study was to measure the service level of the different medical services offered to the outpatients. To do that, some indicators, approved by the hospital management, needed to be defined. One of these was the total average patient wait time, which was 83.27 minutes for patients with insurance and 77.84 minutes for the patients without insurance. Even though this seems like a short waiting period, it is only an average. The maximum total waiting time for a patient reached 326.67 minutes or 5.4 hours. Other indicators were:

average waiting time, queue length, and utilization rate at every stage of the process.

For admission, the average waiting time was not as high as expected, and there is almost no difference between the waiting time for patients with insurance and patients without insurance, 28.80 and 28.75 minutes respectively; nonetheless, there is a slight difference for the average maximum waiting time 135 and 148 minutes respectively. However, was a large difference between the number of patients with insurance in queue (3.85) and the ones without insurance (9.03), getting an average maximum queue length of 27 and 55 patients respectively. Even though the average is not that high, the admission area gets very congested during the first two hours of the day, reaching 40 patients in queue on average (for patients without insurance). This is because the receptionist starts attending patients at point 120 in time (7 am), and then it dramatically dropped to less than five (in less than an hour), Figure 3. The admission's utilization rate was also analyzed. On average, the receptionist is busy 57.11% of the time.

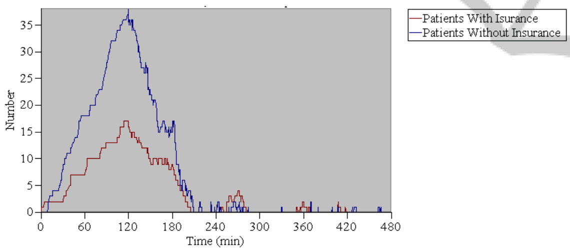

Figure 3: Number of Patients in queue at the admission for patients without insurance and with insurance.

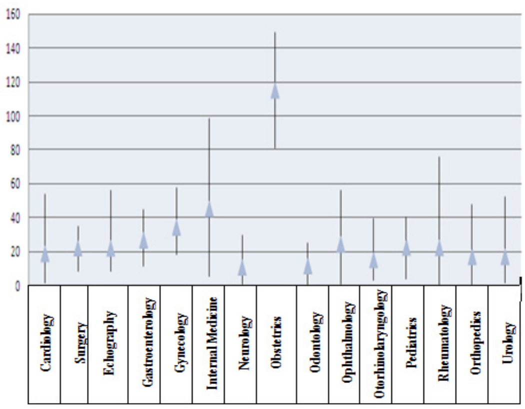

Figure 4: Queue waiting time for each specialty.

Each of the 15 specialties was analysed. As Figure 4 shows, Obstetrics was the specialty with the highest average waiting time, more than 2 hours, reaching a minimum average time of 1 hour 20 minutes, and a maximum of 2 hours 28 minutes.

The average patient waiting time for the Internal Medicine specialty is not so great, about 40 minutes, but it has the highest range (maximum value – minimum value) which is approximately 100 minutes. For the rest of the specialties, the average waiting time is between 20 and 40 minutes.

Another indicator analyzed was the average number of patients in a queue. The results show that on average, a normal day, Gynecology has up to 10 patients in its queue and after approximately three hours this number plummets to 0. Obstetrics quickly reaches up to 13 patients in its queue, then it drops to 6 patients, then this number stays steady, Figure 5.

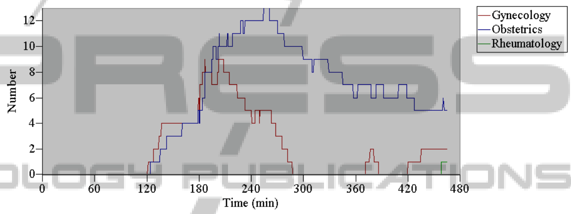

Figure 5: Number of patients in queue for Obstetrics, and Gynecology.

Analysis of the utilization percentage indicates that Obstetrics has a high utilization rate (on average it is 100%). Gynecology and Internal medicine have the second highest utilization rate, 72.90 and 73.68 on average respectively. Results show that the insurance module is fully occupied for just 30 minutes during the day, when the average queue is 10 patients.

When it comes to the pharmacy, the average utilization rate is 65.05, with an average queue length of maximum 6 patients during the first 60 minutes, and an average length of between 1 and 2 patients after that.

In the laboratory, the average utilization rate at reception is 47.60, while for the lab test is 32.82. The length of the queue at reception is very high during the first two hours, and then peaks at six patients for short times. Apparently, there is no problem with the patients waiting for lab test procedures, given that the queue reaches a maximum of only one patient.

Finally, x-ray service shows an average utilization rate of 54.85, receiving up to five patients during the first two hours of service, and then it dropped to zero or between one and three.

5 WHAT-IF SCENARIOS

Given the results, one obstetrician was added as a resource in the model. The average patient length is then reduced to six, instead to 13, and after an hour it drops to three patients, and continues to decrease. The rest of the indicators are shown in Table 3.

Table 3: Comparison between current and proposed scenario.

Number of obstetricians	Average waiting time in queue (min.)	Average length queue	Utilization rate
1	148.93	6.48	100%
2	41.66	1.09	69.35%

Another possible scenario analyzed was adding a receptionist for patients without insurance. The results are show in Table 4.

Table 4: Comparison between current and proposed scenario at admission.

Receptionists for patients w/o insurance (admission)	Average queue waiting time (min.)	Average queue length	Utilization rate
1	28.75	9.03	57.11%
2	20.17	3.14	29.03%

Results of the current situation show that the lab reception is a bottleneck; long queues are formed when the hospital opens for service. By adding another lab receptionist, the bottleneck is move downstream to the subsequent process, lab test. By adding a second receptionist, the average waiting time is not reduced much.

6 CONCLUSIONS AND DISCUSSION

Discrete simulation is a tool for analyzing complex systems where there is a number of random variables involved. It can provide understanding of the system, and hence allows improved decision making. This tool is perfectly applicable to the health sector and as the study demonstrates the use of this tool at a public hospital in Peru, can be used to improve patient services.

In this study, a simulation model of a public hospital´s outpatient clinic was presented. The simulation results were compared with the observed results at the outpatient clinic with minimal differences, which validates the model used for the study. The results give a better understanding of the current process at the clinic. The first stage of the study can be used by hospital management to identify objectives for the service level indicators (utilization rate, queue length, waiting time). Results show that the most critical medical specialties are Obstetrics, Internal medicine, and Gynecology, which are the most utilized and have the longest patient queues. There is a need for increasing resources in these areas, especially at Obstetrics due to a high utilization rate, 100.

The model also helped identify high idle time at the insurance module and a low utilization rate in pharmacy, lab, x-ray and admission areas. Therefore, it seems adequate to integrate the insurance module tasks with the admission and the other services.

Some what-if scenario analyses were performed. Such analyses permit a quantification of the impact from implementing possible solutions. By adding a second obstetrician, the service level improves drastically: the average waiting time for a patient can be reduced by 72% (from an average of 148.93 to 41.66 minutes in the que). It also shows that adding more staff at admission or reception lab does not improve the service level at the clinic. More analysis to try different resource allocation and system configuration will be done in subsequently studies. It is also proposed to study hospital management.

Finally, it can be said that the model used in this study can be used for continuous improvement at the hospital and given the fact that the outpatient process is similar to any public hospital in Peru, the model with slight modifications can be used at other medical facilities.

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