Cyclicality, Public Policy, Assignment, And Care. Simón Bolívar Hospital Colombia.

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Abstract
The following article studies the use of the number of beds for different services at the Simon Bolivar Hospital in Bogota, Colombia, using records of admissions, average stays, and patient discharges for different services. The quality of health care is simulated from available information and using queue theory, identifying patient waiting time. Method; First, information on the hospital's 20-month operation for the years 2014 and 2015 is obtained, organized and refined using public information. Then the spectral coherence between the behavior of patients, and beds used in the Hospital is estimated identifying the consistency between the behavior of variables to use it as input in M/M/S queue models, where S is the number of beds available in parallel for each clinical specialty of the service provided; this, using software assuming infinite population. These results are used to analyze the sensitivity of the servers to change and thus estimate the optimal number of servers to reduce the system's queue.
Results; Different modeled services lead to different types of waiting lines; the variables present coherent behavior; it is observed that the system queue can be reduced by changing the number of servers installed in each service, by improving efficiency in sensitivity analysis.

Keywords
Humanitarian Logistics, Simulation, Signal Analysis, Queue Theories, Wavelet

1. Introduction
Here we estimate the use of the hospitalization capacity at the Simon Bolivar Hospital based on the information from 2015 to 2016. For this purpose, we use queue theory with flow techniques based on Little's Law and statistical techniques to compare the data with the probability distribution function.
The congestion of the emergency departments of a hospital is of interest to clinical management, patients and the community in general in different areas for each one. Thus, hospital managers use approximations based on average waiting times, daily average of patients attended, among others, which greatly facilitates planning calculations, simplifying a phenomenon of a complex nature.
This study is proposed to analyze the state of congestion of patients waiting for a bed, in order to determine whether to increase the number of beds in the service to decrease the waiting time of patients to be attended.

1.1 Objetives
Study the capacity of beds installed in the Simon Bolivar Hospital to propose changes to reduce the waiting time in the hospitalization of patients.
We first propose to identify the discrete probability distribution function that fits the collected data. And second, to simulate from the data the number of hospital admissions and days of stay by discharge in a certain medical specialty

and/or service to review the behavior of the system and to conclude from the results in waiting times using the Queue Theory, with Little

2. Literature Review

The engineering and data analysis techniques used in hospital management are multiple.

As an example, Edet and Gidado identify the effect of the partnership scheme and participation in financial capital between public and private agents on the level of satisfaction for medical staff as the main actor in the provision of hospital services in the United Kingdom. They use medical staff job satisfaction data and weigh it on a fixed scale; from the data, they suggest that private equity participation and its management methods improve medical staff satisfaction (Edet & Gidado, 2008).

Another example, Eskandari and his colleagues use the simulation technique to represent and estimate changes in patient flow in Hospitals in Tehran, Iran; the flow simulation results for different scenarios are weighted with hierarchical analysis techniques and estimate the probability of occurrence of environments (Eskandari et al., 2011).

Also, the allocation of resources for operational activities of the hospital service uses techniques and empirical knowledge based on the administrative record of service delivery, associated with the availability and structure of information systems(Freitas et al., 2011).

Engineering techniques have been used for decades to support the delivery of health services such as: inventory management (Messer III & Word, 1977); monitoring productivity (Mazzolla & Kauffman, 1978); the forecast of the productive capacity (Hancock & Chan, 1984) the simulation of the estimation of the number of assigned beds (Dumas, 1984); measuring operational efficiency and productivity with index numbers (Gerst, 1995); measuring financial efficiency with index number measurement techniques such as data envelopment analysis (Ozcan & McCue, 1996)(O'Neill, 1998) and workload allocation methods for medical specialties (Barbera et al., 2003).

Other studies from engineering not only focus on administrative areas, but also include operational and strategic activity such as: the effect of improving operations on strategic planning and its effect on the community (L. X. Li et al., 2002),(L. Li & Benton, 2003); the effect of the merger of health service centers and hospitals on the health service (Ferrier & Valdmanis, 2004) and performance measurement (Neumann et al., 2004)-(Gholami et al., 2015).

These techniques used for the study of health services inherently deal with the uncertainty inherent in human activity in the provision and application of the service such as: the planning of programming in the operating room (Steins et al., 2010); forecasting resources for emergency care, emergencies and disasters (Valdmanis et al., 2010); experimentation for optimal calculation of airflow conditions in operating rooms (Khalil & Kameel, 2010).

It should be noted that hospital administration has been a field for the use of techniques such as data wrap-around analysis in: multiple indicator systems (Yang et al., 2005); index numbers (Armstrong et al., 2007)-(Kao et al., 2011); comparison of hospital services (Zhong, 2009)-(Arya & Yadav, 2018),(Zheng et al., 2018).

Other techniques are also used such as : system dynamics models (Gonul Kochan et al., 2018), the time series (Zhu et al., 2017); the simulation of discrete systems (Kemeny et al., 2016), (Pujowidianto et al., 2017); the theory of systems (Lee et al., 2017); the queuing theory (Chan et al., 2017); flow measurement (Stock et al., 2016)-(Godinho Filho et al., 2015); value and service chain analysis; Fuzzy Logic (Kahraman, 2015).

In Colombia, the study of the efficiency of hospitals in the conditions of the armed conflict has been identified [36]; the design of maintenance plans for facilities and equipment (Guarin & Usaquen-Perilla, 2013) and the inflow of patients (Salazar et al., 2016),(Caicedo-Torres & Payares, 2016).

Multiple techniques are required and their results are affected by the availability and quality of information, so the effect of the availability of this information on the service has been studied (Freitas et al., 2011) and in the estimates obtained, (Baird et al., 2011), (Ioan et al., 2011) as well as the effect of the method of processing this information on the prediction of service delivery (Kao et al., 2011), (Barrento et al., 2013).

Operational aspect simulation of hospitals uses scenario or quasi-experimental designs to propose modifications and improvements in different activities from the operational to the strategic (Evans et al., 1996), (Steins et al., 2010), (Dekhici et al., 2011), (Gunal & Pidd, 2011),(Taheri et al., 2012), (Weerawat et al., 2013).

Survival analyses are a set of statistical methods to understand the duration of a process, directly linked to the estimation of performance measures in hospital centers. The analysis examines time to death of study populations or time to mechanical systems failure, or time to patient care (also called reliability analysis) are typical applications. Given the hazard, function to determine the event rate, λ, in the time t conditional to survive until moment *t* the Cox proportional risk model, a model that can be directly related to a linear regression.

A study where a regression model of the waiting times is inserted to represent the variation in the transition processes as within the Discrete Event Simulation Model, DES, for an urban academic hospital of 1000 beds, model used to characterize the strategies of management of the flow of patients, the model allowed to observe that the patients according to their attributes attended different services that the studied hospital system provided. That is to say, the parameters or characteristics of the service and of the patient affect the times between arrivals and the times in service and permanence of the patients.

As a conclusion of that study, the occupation of the clinical department was the proportion of beds occupied for the specific department (service). The Cox regression model was implemented in the DES to estimate an approach time for each patient. The incorporation of estimates of the approach time based on Cox regression in the DES of the hospital coincided with the observed distribution of our data set and the transfer times to the hospital room

The simulation logic specific to each patient was based on the patient's waiting lines until admission to a bed, by means of the risk distribution and the probability density function for each of the admissions in the hospital. The DES was used to test multiple scenarios for improving patient flow. One scenario was to move 13 unused drug beds from the previous section of the hospital to the new area where they can be actively used. This would add 13 adult medicine beds to the 187 already in operation, representing a 7% increase in capacity.

A second study used an empirically calibrated simulation model to quantify the impact of the proposed discharge profiles on timely access to inpatient beds under a hospital-wide early discharge policy. For that study, there are M sources of inpatient bed requests according to the major diagnostic medicine modalities, MDC. The number of requests from source *i* in time t is denoted by the random variable. λ it and is randomly sampled without replacement to reflect the effect of time of day and day of week.

These requests fall into some category of MDC and are therefore assigned to the demand of N hospitalization units. The total number of beds requested for unit j in hour t is denoted by the random variable λ jt. As an example, for Monday 8 a.m., random samples were taken, without replacement, from the arrival source, MDC and the desired unit requests observed on 52 Mondays at that exact time. Each unit has *Bj* beds, and each unit is a variable time in a G/G/*Bj* queue model.

The simulation results show that prioritizing discharges has the greatest impact on queue size when compared to the empirical baseline (40% reduction). If most discharges occur before noon, as in the hospital discharge policy, ECD, there are 6 fewer people waiting in the queue compared to the baseline, clinical importance, but no statistical difference identified.

A third study estimated the number of patients waiting and waiting time in emergency department services at an Iranian emergency hospital and proposed scenarios for reducing their queue and waiting time. Arena software was used to simulate patient queues in the emergency department. It is worth mentioning that any destination other than admission in the five sections of the ED bed area was considered as "exit".

The parameters required for the construction of the models include the time of service, the hourly capacity of the server and the route for the transfer between the rooms. The time of service was defined as the time interval between entry and exit of a section.

In this study, the response variables were: Number of exits, waiting time, Number of waiting, Instantaneous utilization, Total number in the system, and Number occupied. The arrival distribution function was set to ED data arrival of one year, from March 2012 to February 2013. Three scenarios were contrasted:

First, increase the capacity of the servers until the number of waiting in the queue tends to zero.

Second, limit the time served by excluding the fourth quartile in our sample serving time distribution in each emergency room and unit separately.

Third, increasing server capacity until variable utilization reaches approximately 80%, when servers can overcome the variability of patient arrival patterns

The first result scenario in the number of beds had to be increased from 81 to 179 in order for the number of waiting "bed zone" server to be almost zero. The second scenario that attempted to limit the time of hospitalization in the ED bed area for the third quartile of the time distribution serving could decrease the number of waiting to 586 patients.

A final study, Analyzes the flow of patient stays in a university hospital, with the help of discrete event simulation, EDS, to estimate the impact of operational changes on hospital bed capacity in heart attack patients, in eight scenarios. The arrival module evaluates data from a total of 687 patients arriving at the hospital's emergency department over a period of 549 days. This represents an average patient admission of 5 patients every 4 days (i.e., a time between arrivals of 19.2 hours). The test sequence operations module keeps track of the number of patients waiting in the queue (i.e. work in progress (WIP)) and their respective queue waiting times. There are different modules that allow the modeling of test services as resources in Arena that have variable capacities depending on the number of devices available in the tracing unit.

In the validation of the model, a comparison was made between the output statistics derived from the simulation model against the statistics deduced from the data recorded in the hospital database. The results show that the implementation of three additional time intervals per test service per week results in significantly lower average queue times among other changes in service times that can dramatically improve queue time. Finally, the implementation of a balanced distribution of time slots over the days of the week reduces queue times. This study demonstrates the added value of using the simulation approach to highlight important areas of improvement and also as a powerful tool for process improvement.

2.1 Theory of tails

Little's Law links process flow to system performance measures, which are described by several theoretical frameworks that include accounting and financial aspects , Little's Law is a proven mathematical formulation since 1961(Little & Graves, 2008), depends on the arrival rate, residence time and the average inventory remaining in the system, from here the theoretical model has defined the theory or performance measurement of queuing systems based on :

The source of the population, in this case, it is infinite since it is a hospital service.

Arrivals to the system (patients/day), amount of elements, objects, or entities that enter the system for a period, in this case the daily average for each month.

The service rate (patients/day), this measure is the patients who complete adequate care in the service per unit of time.

Server, in this case represented by each of the examination beds that exist in the corresponding area studied.

These are presumed to be a specific distribution depending on the service being evaluated, so it should be considered whether they present a controllable or uncontrollable mode or are affected by the behavior and access to other services

For this reason, spectral coherence and Wavelet analysis are used to identify the variation of the hospital's historical operating parameters and to identify the global variation of the base parameters to be used in the simulation models to define these changing parameters. These parameters are distributed according to functions of discrete probability distributions theorized for each hospital service evaluated

As performance measures the average number of patients that are within the system's limit are represented by the letter L; the concept of the arrival rate, λ corresponds to the number of patients that enter the system in a time interval. The system average time corresponds to the approximate average time of patients in the W system, so the formulation of Little's law would remain:

$$L = \lambda W$$

However, the subsequent revision of the same law makes it possible to be in terms of the number of units leaving the system, μ,

$$L = \mu W$$

From here the performance measures that characterize the behavior of the system can be defined how:

L: expected number of patients in the system at a given time, i.e. waiting and being attended
Lq: Expected queue length, i.e. number of patients waiting to be seen
Lb: Expected length of patients in the queue, i.e., number of patients waiting for a server to be cleared
W: Time spent in the system for each patient
Wq: Waiting time in the queue for each patient
Wb: Waiting time in the queue for each patient, which waits for a server to be cleared

2.2 Correlation and Determination in Time and Frequency.

For a pair of random variables or a pair of not necessarily random vectors, but of the same dimensional, two coefficients have been identified based on the sequence of data: the correlation coefficient or degree of similarity between a pair of data and the determination coefficient or degree of effect of one set on the other; the determination coefficient is the correlation coefficient squared.

The correlation coefficient or cosine is described as the point product of two vectors centered concerning for to their mean divided by the standard of centered vectors, as follows:

$$-1 \leq C_{xy} = X_c{}'Y_c/(((X_c{}'X_c)*(Y_c{}'Y_c))^{\wedge(1/2)}) \leq 1$$

Where to go:

Cxy: correlation coefficient for the pair of vectors x, y
Xc': transposed vector X centered on the average of X
Yc': transposed X vector centered on the average of Y

The coefficient of determination is:

$D_{xy} = C_{xy} * C_{xy}$

Analogous to the determination coefficient, the spectral coherence coefficient is established, which compares the two sets of signals according to the similarity in their two frequency components. In other words, while the correlation compares two sets of data in one or several instants of time, the spectral coherence compares the data in the frequency variable. Wavelet coherence can be identified as a possible extension of the spectral coherence in multiple instants or periods, i.e. the wavelet coherence discriminates the frequency correspondence of two signals for each of the instants where data for the two compared signals are available. Thus, the components present in a pair of sequential data sets are compared, identifying the consistency or simultaneous presence of the same component in wave frequency. To obtain the spectral coherence coefficient:

$$E(f)_{xy}= ((P(f)_x{}' \, P(f)_y))^{\wedge 2})/((P(f)_x{}' \, P(f)_x)*(P(f)_y{}' P(f)_y)^{\wedge(1/2)})$$

Where to go:

E(f)xy: spectral correlation coefficient for the pair of vectors x,y at frequency (f)
P(f)x: spectral power vector of signal X the frequency f
P(f)y: spectral power vector of signal Y the frequency f

Similarly, the wavelet determination coefficient is

$$0 \leq W_{xy} (E(f)_{xy}, t) \leq 1$$

Where t is the instant of time considered, for simplicity monthly data will be taken with annual frequency and its results will be presented graphically.

3. Methods

This text uses publicly available historical information on the use of the Simon Bolivar Hospital in Bogotá Colombia, based on the accepted performance measurement reporting scheme. From this information and using the techniques of information analysis, the evolution of performance, typical of simulation techniques, is estimated.

When requiring data for each type of hospital service, Little's Law is taken as a base, which is invariant before the functional form of the distributions of arrivals and waiting times according to different distributions of probability of each hospital service

Signal analysis, Wavelet and spectral decomposition techniques are used to contrast the assumption of homogeneity, i.e. non-cyclicality of the data, and statistics to simulate changes in the configuration and allocation of beds within the hospital.

Based on the literature review and the available information, the average waiting time of the patient to obtain a bed at his service is chosen as a response variable, since it is the indicator of quality of medical care in the hospital. For each one of the specialties and/or services present in the hospital system, the proposed procedure will be performed, since the model used will provide different results for capacity in number of beds, in order to integrate and verify the existence of queues with several servers or beds.

The information used is that publicly reported by the Simon Bolivar Hospital before the reform of the structure of the health service in Bogota in 2016, the data corresponds to 2014 and 2015. The causal variables are the number of beds for 7 of the 23 subspecialties and the performance variable is the average time spent or waiting to obtain a bed. However, both the number of beds, discharges, and average time in hospital are reported.

Information is available for 18 months, since both the number of beds changes every month, as well as the average time of stay. Several analyses are performed on the input data: correlation between variables, spectral coherence and wavelet coherence. The selected specialties are: Internal Medicine, HIV Special Program, Surgery, Gynecology and Obstetrics, Pediatrics, Adult ICU, Burn ICU.

4. Data Collection

The correlation between the number of beds for the 7 specialties is available, in table 1 correlations between the number of beds and the number of days is observed.

Table 1 Correlation between the number of beds for 7 specialties

	mes	*Dias en M.I*	*Dias en H.I.V*	*Dias en CIRUGÍA*	*Dias en GINECO-OBS*	*Dias en PEDIATRÍA*	*Dias en U.C.I ADULTO*	*Dias en UCI QUEMADOS*
camas M.I	(0,04)	(0,07)	(0,42)	(0,24)	0,25	0,04	0,02	(0,05)
camas H.I.V	(0,52)	0,17	0,21	0,33	(0,04)	(0,23)	0,17	0,29
camas CIRUGÍA	0,08	(0,35)	0,07	0,49	0,11	0,33	(0,25)	(0,20)
camas GINECO-OBS	0,39	0,14	0,45	0,32	(0,41)	(0,09)	(0,43)	(0,31)
camas PEDIATRÍA	(0,14)	0,27	(0,30)	(0,60)	(0,07)	(0,03)	0,01	0,25
camas U.C.I ADULTO	(0,51)	(0,18)	0,23	0,30	(0,28)	(0,16)	0,25	0,28
camas UCI QUEMADOS	0,27	(0,01)	0,23	0,19	(0,55)	0,17	(0,24)	(0,20)

Table 2 of determination indicates the effect of the number of the month with the beds HIV ,27%; and Adult ICU ,26%; on the other hand the number of pediatric beds in 36% and the beds in surgery, 24% affect the number of days in surgery; the number of ICU beds burned affects the number of days in gynecobstetrics.

Table 2 Determination between the number of beds for 7 specialties

	mes	Dias en M.I	Dias en H.I.V	Dias en CIRUGÍA	Dias en GINECO-OBS	Dias en PEDIATRÍA	Dias en U.C.I ADULTO	Dias en UCI QUEMADOS
camas M.I	0	1	18	6	6	0	0	0
camas H.I.V	27	3	4	11	0	5	3	8
camas CIRUGÍA	1	12	0	24	1	11	6	4
camas GINECO-OBS	15	2	20	10	16	1	19	10
camas PEDIATRÍA	2	7	9	36	0	0	0	6
camas U.C.I ADULTO	26	3	5	9	8	2	6	8
camas UCI QUEMADOS	7	0	5	4	31	3	6	4

Therefore, with the information available, with which the correlation and determination coefficients were calculated, the spectral coherence between each pair of signals in each specialty is estimated: the number of beds and the average time spent in each of them over a year. The coherence graphs are made on two axes: the frequency, horizontal axis; and the determination or coherence on the vertical axis. The frequency axis presents the number of periods to be compared; the determination axis represents the simultaneity or agreement or coherence between the pair of variables, number of beds available and average time spent in the service.

As an example, in frequency 4 a coherence number of 0.7 indicates that, at the frequency of every 4 months, the number of beds determines the average time a patient stays in the hospital by 70%, for all average time of stay. Each of the lines is a clinical specialty. The horizontal axis contains the frequencies that can be interpreted as the number of months of the year divided by the frequency 12/f; from 0, or fixed constant value, going through the frequency 1, 12/1= 12 months, the simultaneous annual variation; the frequency 2 or half-yearly causal variation, 12/2= 6 every six months; up to the bimonthly frequency 12/6=2, every two months.

It can be seen that for all the specialties up to frequency 4, every 3 months or 12/4, the effect of the available beds on the average time of stay is greater than 0.60 or 60%, which identifies that the number of fixed beds in the specialties affects the time of stay in hospital by at least 60%. Together with this analysis and the correlation table, some slight relationships of complementarity and competence and increase in time between the availability of beds in the different specialties are identified.

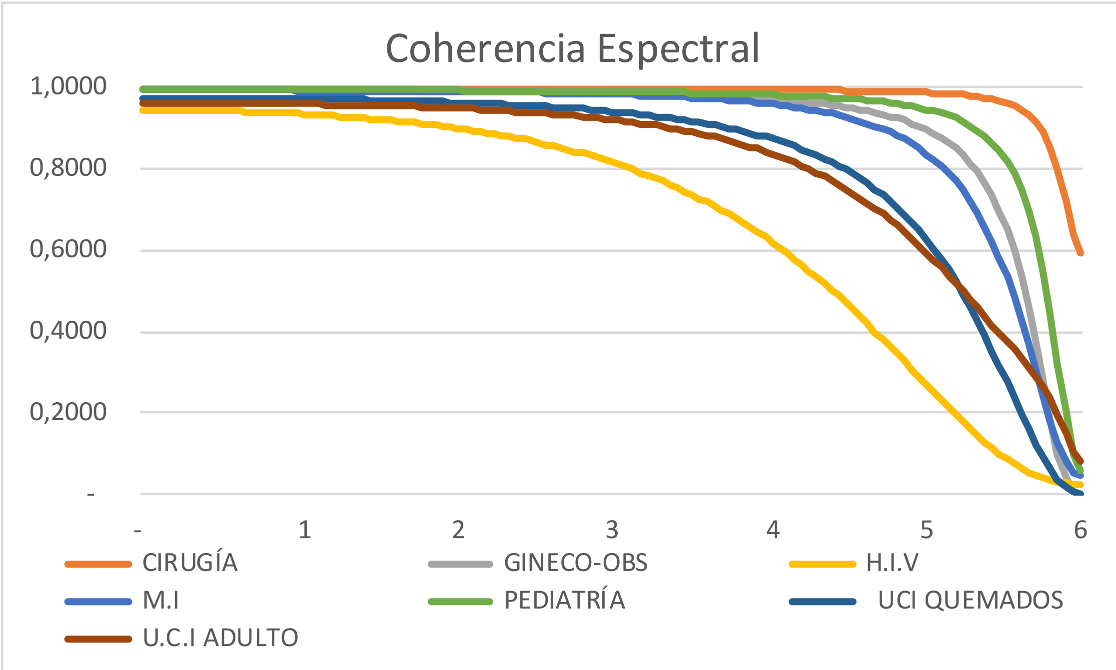

Figure 1 Spectral Coherence

5. Results and Discussion

In the Time Spectral Coherence Wavelet, given the variable nature of bed availability and demand, wavelet coherence is used to identify causality across time and frequencies of bed availability and length of stay. The coherence graphs are for each of the six specialties: surgery; obstetrics and gynecology, HIV, pediatrics, burns and adult ICU; in alphabetical order. Surgery beds and surgery time present continuity of causality in all time, from the instant 0 to 1.5 years with cyclicity 2, that is repeating its behavior in cycles of 5 months, most probably associated with the working vacation cycles of the population and the medical assistance personnel, from the instant 0 to 1.5 years with cyclicity 1.5, that is repeating its behavior in cycles of 9 months, most probably associated with perinatal and fertilization cycles; The same can be said of the internal medicine and pediatric services, which present causalities that are not continuously represented in the yellowest bands. On the other hand, the ICU for burn care and the ICU for adult care have a cyclical behavior; for burn care cycles of 9 to 11 months; for adults with repetitions of six to three months. With this it can be seen that as a whole from the aggregated data, cross-correlations of effects between services can be identified; the existence of a correlation in the availability of beds and the time spent in the different frequencies of both variables and also the different wave or frequency components in time that affect the demand for health services have been identified, with which the programming and allocation of beds could be made more "adaptive or flexible" in correspondence to cycle sizes.

5.1 Simulation

The technique selected to represent the behavior at the Simon Bolivar Hospital was modeled as a queue system since it has a single queue with multiple servers in parallel, but in addition to this a finite capacity of service (number of beds), each server is specified as a bed placed in the service, and human resources are the doctors, nurses and other workers in the area. For this purpose, first the structure of the "arrival rate" to the system was determined, λ, patient arrivals per unit of time; as well as the "service rate", μ, patients to whom the service is completed per unit of time.
The rate calculations used the data in the database; for the arrival rate, the monthly admissions to the service were taken and divided into the days of the respective month. In this scenario, it was taken into account that the study was for 18 months; therefore, to find out how the response variable behaves in the following month, it was simulated with the historical data mentioned above, generating unit measures such as admissions/day.
Also, besides the service rate was estimated by means of the admissions between the total days of stays in the service, generating measures of patient units in bed/day or in some of these beds/hours.
Second, the probability distribution following each of the seven service data sets was evaluated selected to model. In this case the Internal Medicine service in the distribution for arrival rate. Easy Fit software was used to fit the data to different types of probability distribution functions and select the best model to simulate.

Third, the same procedure was used to find the probability distribution for service rate by calculating the average waiting times in the queue, and in the system, for each patient, as well as the queue size, i.e., patients that will be waiting for service, and the number of patients that are in the system, both in the queue and receiving care. Finally, from the calculation of both rates, the fundamental parameters of the system were determined. The source of the data was the monthly list of patients attended by days; said rate follows a Poisson distribution. Once this data is available by month, the averages of all months were considered for said number of arrivals per day.

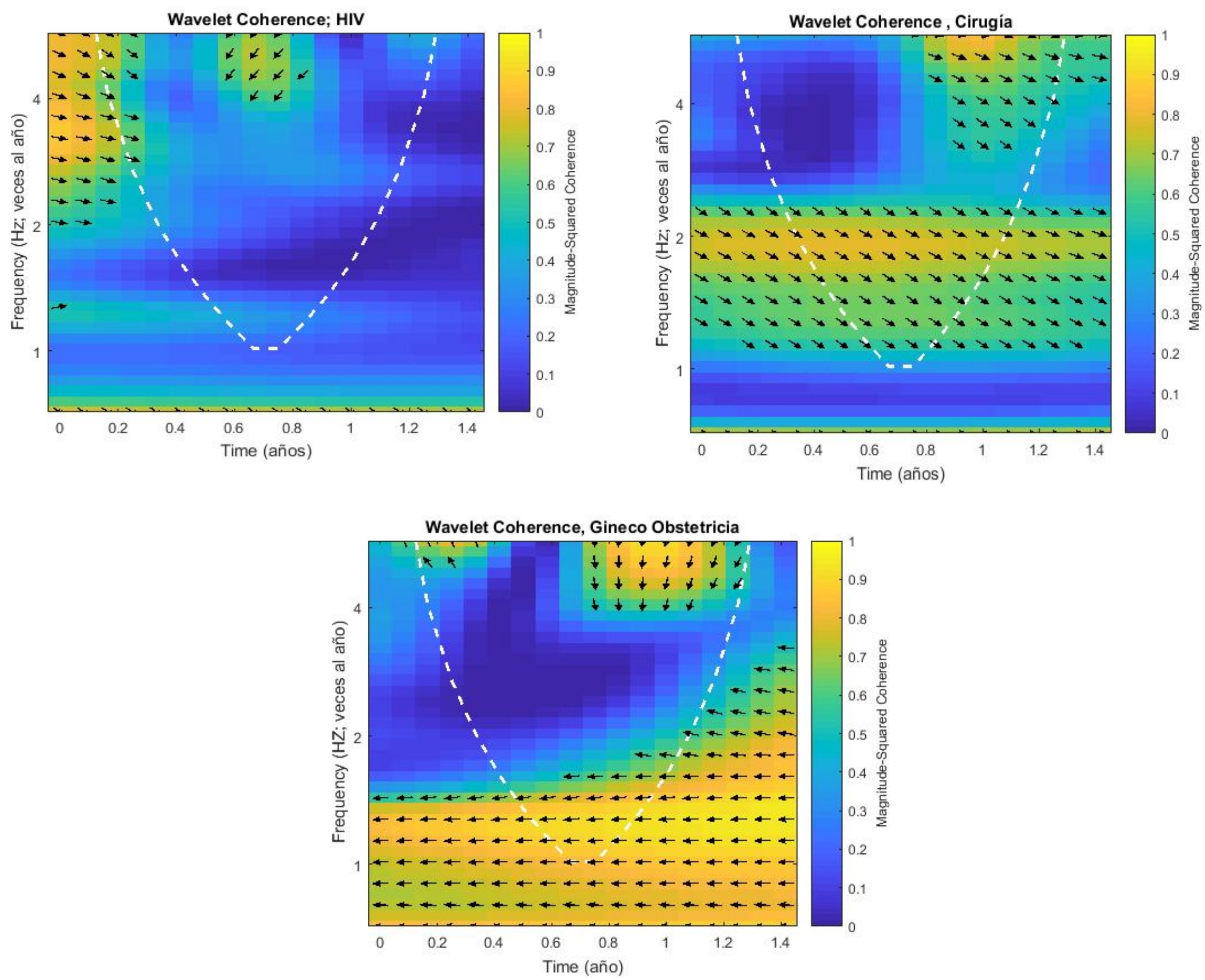

Illustration 2 Wavelet coherence; HVI, Obstetrics & Gynecology, Surgery.

We included the form or type of distribution of probability of arrival and service rates according to the period and based on the comparison wavelet generate for different number of servers considered, beds presented in each of the services, once determined both rates are simulated queues for several some many servers, hospital beds, until the key parameters of the system are stabilized, ie, seek the optimal times of stay in the queue and in the service as well as the optimal number of patients in the queue and the service.
Similarly, through the data on patient care times, this time corresponds to the difference between the moment the patient is placed in his or her bed, and the time he or she leaves the bed after being discharged from the different services, i.e., the time a bed was occupied by a given patient, resulting in an adjustment of the service rate for a Poisson distribution.

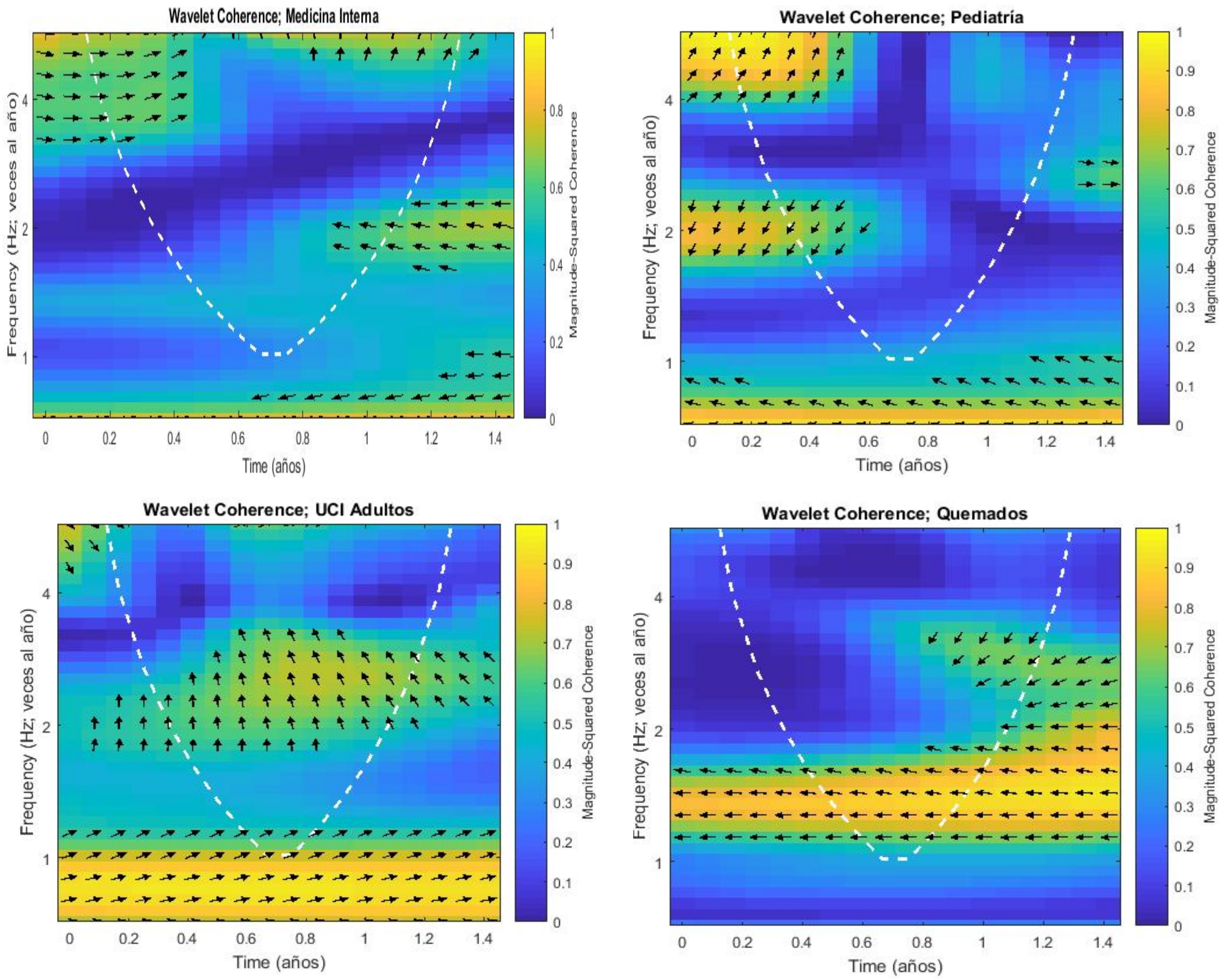

Illustration 3 Wavelet coherence; Internal Medicine, Pediatrics, Adult ICU, Burns.

As the study was carried out to determine the behavior of the system in the different services, the basis was taken with all those attended in 18 months 20,493 patients, who were evaluated in the different services over the years 2015-2016, 22.8% of this population is from the Internal Medicine area, the service follows the distribution for both arrival and service rates, it is simulated to have the data for a corresponding month (behavior of the following month), once this is simulated, the same procedure begins to be performed for each of the services as a queuing system, it was analyzed using Simulation techniques.

5.1 Analysis of results

The public data of the Simon Bolivar Hospital during the 18 months evaluated allowed to review the behavior of the different services, some of them comply with the amount of adequate servers where there is no queue, but in some of them more of these should be introduced, for example, in the study service Internal Medicine, in order to minimize the time and amount of patients that congest the system, it can be determined that with a total of 92 beds there would be no queue. Waiting lines were simulated; Table 3 summarizes the system's performance in each of the seven (7) medical services. Where the current beds are located and how the system normally operates in each of the units. On the other hand, we have the stable system, and finally we have the number of beds per unit that should be held so that there is no queue.

Table 3. Results for each of the services performed, the procedure described above.

Service	Beds	General use of the system	L (Patients)	Lq (Patients)	Lb (Patients)	W (Days)	Wq (Days)	Wb (Days)
Internal Medicine	55 current	84%	638.763	176.641	29.9	75.584	1.025	17.321
	92 stable system		916.075	0	0	106.383	0	0
	No line	-	-	-	-	-	-	-
HIV	10 current	97%	427.038	330.484	35.703	26.168	19.669	21.249
	12 stable system		811.256	692.873	732.118	46.953	40.101	42.373
	28 no queue		118.383	0	0.7325	0.6852	0	0.0424
Surgery	54 current	4%	18.732	0	0	0.1815	0	0
	Stable system	-	-	-	-	-	-	-
	No line		2.077	0	0	0.1968	0	0
Gynecobstetrics	24 Current	2.00%	0.5105	0	0	0.0814	0	0
	Stable system	-	-	-	-	-	-	-
	33 No line		0.5967	0	0	0.0926	0	0
Pediatrics	39 Current	68%	265.675	0	0	37.071	0	0
	36 Stable system		7.619.155	7.259.645	7.331.363	1.071.445	1.020.889	1.030.974
	57 No line		359.523	0.0013	1.708	50.558	0.0002	0.2402
Adult ICU	7 Current	51%	3.604	0.0106	0.0771	31.782	0.0075	0.0547
	8 Stable system		118.124	47.704	7.351	111.902	45.191	69.638
	No line	-	-	-	-	-	-	-
Burned	10 Current	49%	49.286	0.031	0.4741	42.749	0.0192	0.2945
	12 Stable system		1.166.253	1.047.347	1.086.952	1.166.253	1.047.347	1.086.952
	28 No queue		118.906	0	0.7381	118.906	0	0.7381

5.2 Discussion

The performance measures found with the simulation system used in conjunction with the Queue Theory systems as evidenced in the state of the art, there have been numerous studies of the health world to estimate changes and propose improvements in hospital services through the modification in the number of servers, affecting the waiting time of patients in line, so the proposed model condescends to study the behavior that produces internal and external changes in a hospital service, so, strategies that can be used knowing changes, it is observed that any decrease in the number of beds would bring queues in certain services mostly demanded. Therefore, the provision and reorganization of more beds in each service, it is thought that this would only modify to a certain extent the time of patients in line (Wq) and the number of patients in line (Lq), but this change would increase the average number of patients in the system (L) causing it to modify the utilization rate in each designated service.

Conclusion

The increase of beds in a given hospital service helps to have a more efficient functional structure, since this change will decrease the number of patients in waiting lines.
The hospital service arrival rate is uncontrollable, so increasing the number of beds would not completely solve the problem in the system, it may improve a little the quality of service by decreasing patients in the queue, but the service rate could improve if we take into account that it uses hospital networks to face these cases of congestion, therefore patients in the queue can be transferred to a hospital that has the necessary service and the capacity to receive them.
Based on the spectral decomposition it can be identified that both arrival and stay rates share common frequencies among different medical specialties.
Therefore, the simulation process requires identifying changes in these specialties simultaneously, since they could cause cross effects in the congestion of other types of resources such as general services personnel, other assistance services, and congestion in activities such as collection, invoicing and authorizations, since these services are shared.
Therefore, it is recommended for future studies to use varying arrival and service rates for each instant of time based, as well as performance standards of hospital resources based on the interrelationships identified between service delivery. However, since no other level of access to this information is available, so it is not possible to identify

methods or to arrange detailed descriptions and to attribute difference and interaction effects in the use of services, then for this study it is preferred to use the global service rate based on the data and information.

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