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DEMAND FORECASTING AND CAPACITY PLANNING FOR HOSPITALS

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Abstract:

Forecasting demand and planning capacity for certain health services are complicated tasks due to the inherent uncertainty, complex relationships involved, and typically high public exposure. We present a study of the behavior of health service demand in three Chilean hospitals and show that it can be forecasted with good accuracy using Neural Networks and support vector regression. This has allowed us to design a process to manage capacity by transforming the respective forecasts into the necessary resources. Comparing required with available resources and simulating various scenarios allow taking corrective actions when capacity is not aligned with demand.

The proposed forecasting method and the capacity management process have been accepted by hospital management and staff and are currently in use in one of the hospitals. To support the efficient use of the developed forecasting and management modules, advanced IT systems have been implemented that allow the routine use of the processes. We are currently implementing processes and systems in one of the other hospitals. The results have been so encouraging that National Health Authorities are considering the extension of the proposed demand forecasting and management practices to the more than hundred public hospitals in Chile.

Keywords: Health care management, forecasting, process management, capacity planning.

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1. INTRODUCTION

Public hospitals in Chile have, in general, more demand for health services than available capacity. Hence it is important to forecast demand with good precision, in order to adjust capacity or take alternative courses of action, e.g. transfer demand to other facilities. For example, it is possible to discharge demand from a hospital to a local health service center for non-complex pathologies; also private services can be hired in case of an emergency that cannot be treated at a public hospital. Since demand forecasts are not sufficient by its own, but serve as input for hospital management, it is required that service demand be predicted not only on an aggregated level but for different pathology types, which makes it technically more demanding.

The forecasted demand for each pathology type allows determining the required resources, such as doctors of different specialties, attention box capacity, and operating room capacity. Comparing the resources needed to satisfy demand with available capacity permits to take decisions to adjust capacity or prevent or transfer demand.

Public hospitals in Chile, which process 70% of the country's demand for health services (Ruiz-Esquide M., 2009), are not using any formal way to forecast demand and manage capacity. Current procedures are informal and defined based on the experience of the process participants; they are mainly oriented to solve the problem of excess demand when it occurs. To be fair, there are some informal attempts to foresee how bad is going to be the winter period, when most excess demand is produced, and take some decisions regarding the number of doctors and hospital beds that will be made available during the winter season at a given hospital.

Given the situation outlined, we agreed with the Chilean Health Authority to perform an applied research program that will use state-of-the-art analytical tools, process design methodologies and IT to develop a general solution for demand forecasting and capacity management that could eventually be used at all Chilean hospitals.

Benefits expected from this work are:

- A significantly better service to hospital patients, satisfying better occurring demand.
- A better use of resources at the health system level as a whole, due to a better distribution of demand to the level that could best service it.
- A better use of resources at each hospital, since their planning can be made with an advanced knowledge regarding demand that allows capacity optimization.

We started the research in March 2009 and selected three hospitals to be studied to develop the methods, processes, and systems that will eventually be used in all Chilean hospitals.

Demand forecasting and management is part of a larger design that intents to provide a systemic solution to global hospital management. Such solution is based on the design of a general process structure we developed for hospitals and which defines the management processes that are needed to ensure a predefined service level for patients and to optimize the use of resources in doing so. The general process structure allowed us to determine the key processes where implementation of new practices would generate most value (Barros and Julio, 2010a, 2010b). In agreement with Health Authorities we selected the process described here and one related to operating room scheduling. In each of the selected hospitals we evaluated the current situation of demand forecasting and capacity management to determine the feasibility of introducing analytical and formal practices to improve the respective processes.

The results we present in this paper have been developed in collaboration with hospital staff, which reviewed all the steps described below, to end up with a working process to forecast and manage capacity. Emphasis is also given to the experiences we obtained during this work and that could be beneficial in future similar projects.

Section 2 of this paper reviews the literature on the use of analytical methods in forecasting and the experience in hospital demand forecasting. Section 3 presents how hospital demand has been modeled using several methods and the results obtained. The management processes that convert forecasts into the resources needed to satisfy demand and manage capacity is described in Section 4. Section 5 concludes this paper and provides hints for future work.

2. REVIEW OF RELEVANT EXPERIENCE

Demand forecasting is a useful and well-studied subject (Armstrong, 2001) that has generated important results in different areas, like the retail industry and inventory control of several enterprises such as Dell (Kapuscinki et al, 2004). Forecasts provide relevant information to make decisions on the stock needed to give adequate service to the potential demand and to avoid stock breakdowns or an overstock.

There is another line of demand forecasts focused on services. Here the variable to predict is the number of clients that will demand the service, in order to manage capacity needed to provide a given service level. In a recent work joint demand and capacity management has been proposed for services in a restaurant (Hwang et al, 2010) where the main focus lies on optimizing revenue for given dynamic demand without considering, however, explicitly demand forecasting. A similar study has been proposed for scheduling elective surgery under uncertainty (Min, Yih 2010) but again without considering uncertain demand which is the main focus of our paper. In the case of hospital services the capacity is determined by available physical facilities, such as medical boxes, operating rooms and beads, and human resources, such as doctors, which perform diagnoses and treatments on patients. This capacity should be planned to guarantee a given service level and optimize use of resources; for this a good forecast of patients that will arrive in the future is needed.

Many different methods have been proposed for forecasting (Armstrong, 2001; Box et al, 1994) and there a few studies that compare such methods in terms of accuracy of results. One of these studies relevant to us is the one performed by (Adya and Collopy, 1998) that compares Neural Networks with other methods, which concludes that the former gives, in general, better results. This is in agreement with the experience that we will detail below.

Few studies of formal demand forecast in the health area have been published. Some of these have focused mostly on predicting the number of beds required to meet the emergency demand (Jones et al, 2002; Schweigler et al, 2009, Farmer and Emani, 1990). These studies have focused on forecasting demand in the emergency room where all patients must be attended, even with a considerable delay. This is relevant because there is no waiting list to be transferred to another date or patients who leave without attention, which is relevant to the input data, because historical demand is equal to patients attended, without loss of information. This fact will be important for this work, since we were only able to find good data for emergency services.

Another work that uses an approach similar to ours is reported in (Shirxia et al, 2009) but we will show that our approach provides better results.

For capacity planning the usual approach has been to simulate the flow of patients through emergency facilities. None of the papers we have reviewed considers an explicit state of the art demand forecasting technique to model patients arrival; only one by (Marmor et al, 2009) uses an estimated demand based on a moving average over the data. Other papers that use the common approach of static arrival probability distribution justified with empirical data are the following: (Garcia et al 1995), (Samaha et al 2003), (Rojas and Herrera 2008), and (Khurma et al 2008).

3. FORECASTING METHODS: APPLICATIONS AND RESULTS

In this section we review data available for forecasting, determine how it should be processed, establish the model that fitted to such data produces best results, and present actual forecasts .

3.1. Analysis and preprocessing of available data for forecasting

To be able to forecast effectively, one of the key ingredients is the quality of historical information. In addition the hospital operating conditions and environment should remain relatively stable.

This work focuses on two public pediatric hospitals: Luis Calvo Mackenna (from now on HLCM) and Exequiel González Cortes (HEGC), and a general purpose hospital, San Borja Arriarán (HSBA). These hospitals have quality data in the emergency area.

However, to turn this quality data into useful information for the forecasting models further analyses and a series of transformations were necessary. By analyzing the demand that arrives to the emergency department outliers were detected; we found that two months had substantially higher demand than the average of the respective months and decided therefore to replace them by the respective average. Complete demand data is presented in Table 1, where outliers are shown in bold. This treatment of outliers leads to better defined pattern in the available data resulting finally in more stable models.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
1	6876	6895	6633	6430	5972	6321	5927	5288	5521	6207
2	5520	5965	5397	5018	4664	4534	3984	4118	4223	4825
3	7475	7840	7701	7327	6765	7181	6089	6409	6806	7066
4	7764	8265	9304	8274	8287	8063	6942	8614	7809	8147
5	8282	8040	8836	10921	8181	8154	7867	6661	7288	8248
6	10668	6862	8652	8755	8365	7198	7137	5939	N.A.	7947
7	8558	9363	9424	6611	7260	7556	5395	6548	N.A.	7589
8	8375	9261	8262	6758	6857	7493	5684	6956	N.A.	7456
9	7080	9290	7736	7093	7313	6881	6159	6116	N.A.	7209
10	7592	8964	9404	7578	8374	7674	7548	7646	N.A.	8098
11	7960	8762	8875	7638	9704	8571	7160	6512	N.A.	8148
12	7722	7446	7332	6716	7999	7513	6475	6120	N.A.	7165

Table 1: Finding Outliers in HLCM

Visual inspection of aggregated demand reveals a strong seasonal pattern, as shown in Figure 1. We observe a low demand during the summer months (January-February) and a high affluence of patients during the months of the winter season (May – June - July) in the southern hemisphere. This is due to the fact that high air pollution, smog, and low temperatures lead to respiratory diseases increasing the number of emergencies. In general a downward trend can be observed over the years.

Outliers

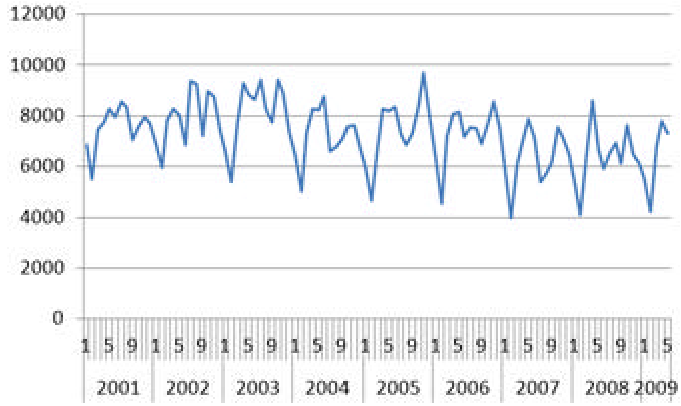


Figure 1: Aggregated demand for HLCM

When data is disaggregated by pathology type, e.g. medical and surgery, we notice huge differences: the first is much more volatile since it depends on factors such as temperature and in?uenza like illness rate as suggested in (Jones et al, 2002), while the second is more stable, as shown in Figures 2 and 3.

From the data it is also possible to conclude that medical demand is 70 % of the emergency cases and surgery 30%.

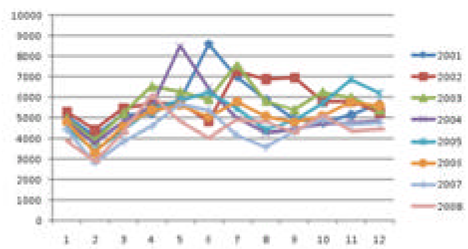


Figure 2: Medical demand for HLCM

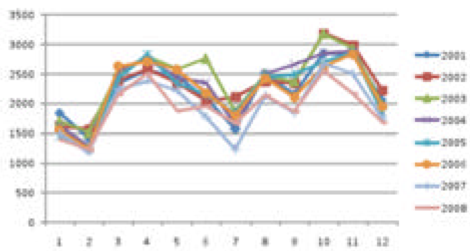


Figure 3: Surgical demand for HLCM

Demand at HEGC shows a behavior which is very similar to the demand at HLCM, since both are children hospitals with similar size and target population. HSBA data also follow a similar pattern.

On arrival to the emergency facilities each patient is registered, including personal data, incoming time, diagnosis and classification according to severity of illness. For the purposes of this work we got all this historical data for the three hospitals as follows:

- HLCM: from January 2001 to December 2009
- HEGC: from January 2001 to July 2009
- HSBA: from January 2000 to December 2009.

For the purpose of capacity planning it would also be interesting to have the exact time when medical attention starts. This could differ significantly from arrival time but it has not been registered.

Unusual demand for pathologies that appear occasionally, like allergies and A H1N1, was also discarded, because there is not enough data to detect a pattern; and, in general, outliers were discarded replacing them with an average as mentioned already. Daily individual data for patients was aggregated for each month to conform the time series that we modeled.

The same data cleaning was applied to data from the HEGC and the HSBA.

3.2. Forecasting methods and their testing

Four forecasting methods were tested: Linear Regression, Weighted Moving Averages, Neural Networks as suggested in (McLaughlin et al 2008) and Support Vector Regression (SVR). The first two are well known techniques used for forecasting and described in the respective literature; e.g., see (Armstrong, 2001). Neural Networks and SVR are recently used techniques for forecasting and they will be described briefly.

The particular type of network we used is the Multilayer Perceptron (MLP). Its basic units are neurons that are grouped in layers and which are connected by means of weighted links between two layers. Each neuron receives inputs from other neurons and generates a result that only depends on the information locally available and which serves as input to other neurons. The architecture of the network is shown in Figure 4.

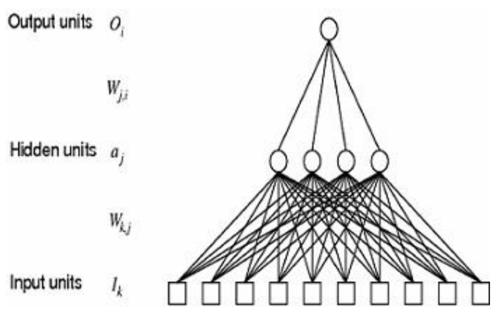


Figure 4: Architecture of a Neural Network

Each neuron operates according to the structure in Figure 5 where the output y is determined as function of the weighted inputs.

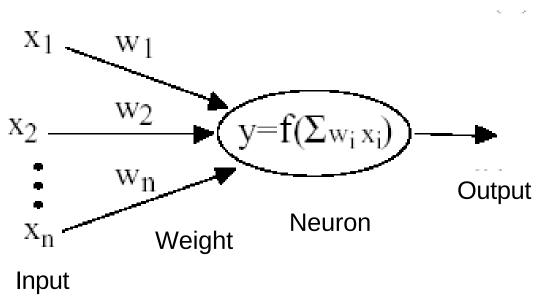


Figure 5: Neuron details

In Figure 5 the function f is the activation function and may take the following form:

$$f(x) = \frac{1}{1+e^{-x}}$$

The network was trained with the above mentioned historical data. The basic idea is that previous data predict a given future month, for which we have the objective value. In particular we assumed that the pattern was seasonal and that previous values of the same month we want to predict were some of the inputs to the model. The structure of the network consists of an output layer with one neuron that generates the desired forecast. The input layer contains the variables we will use to explain the demand. As hidden layer we used a number between input and output neurons, since a high number will tend to copy the data (over fitting) and a small number will not produce good forecasts.

As it was said, previous months were used as input data; however there are months that are more relevant than others that we tried to determine using a genetic algorithm to select dominant attributes, as suggested in (Shirxia et al, 2009), but results were not encouraging. In (Shirxia et al, 2009) a common pitfall in network design was made, which is to separate the data set into two groups: one for training and one for testing (Zhang, 2007). This results in trying to minimize the error over the testing data and indicates a small over adjustment of the resulting model. In our case, we divided the data into three sets: 70% for training; 20% for testing, where the network is trained minimizing the test error; while the third set with 10% of the data is independently used to validate results. This use of an independent set provides a better evaluation of future results.

We tested several parameters to configure the network training, such as the number of epochs to use, the learning rate, and the number of intermediate neurons. Best results were obtained for 10000 training epochs, but maintaining the model with the minimum error in the training set; a learning rate of 0.2 with a momentum of 0.3. Also decaying was introduced, but this only helps to get faster to the solution with no significant changes in results.

Based on results shown later, we selected a Neural Network with 18 input neurons. If N is the index of the month to be forecasted, three neurons corresponding to the values of the same month in previous years N-12, N-24 y N-36 were included; 3 neurons to represent the tendency between months given by the differences of N-12 and N-13, N-24 and N-25, N-36 and N-37 and a set of 12 binary variables to represent the months of the year are also part of the network. This provided a solution that can forecast up to a year in advance and takes account of tendencies. Thus it has 18 input neurons plus an additional bias neuron that helps to separate cases and allows having smaller neural nets than without bias.

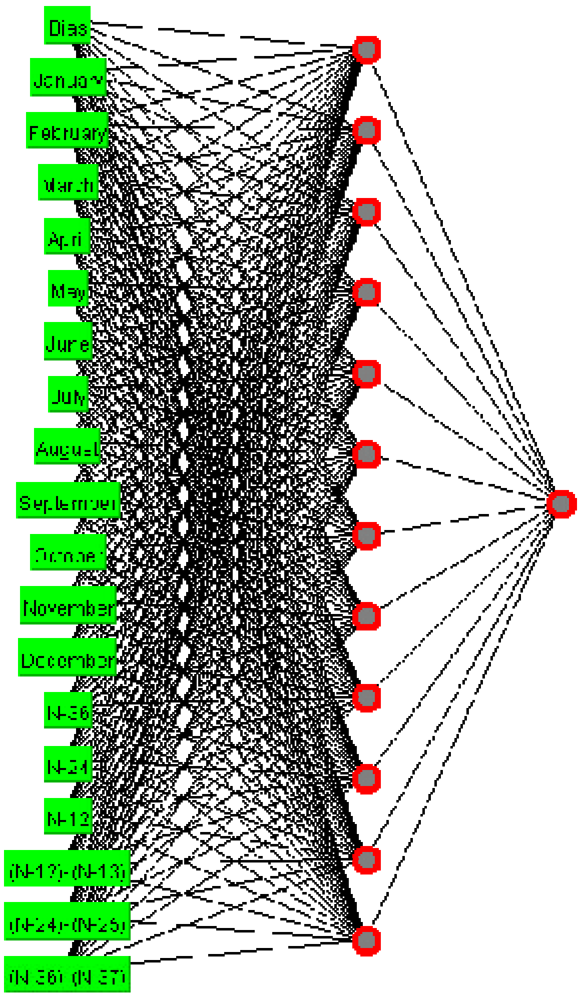


Figure 6: Resulting Neural Network Architecture

The output layer contains simply one neuron that generates the forecasted demand in month N. The hidden layer contains 10 neurons to provide the model an adequate degree of freedom usually calculated by (Number of input neurons + Number of output neurons)/2.

We also tested Support Vector Regression (Chen P. et al 2005, Hofmann et al 2008, Smola et al 2004), which is a variation of Support Vector Machines with the following idea.

The Support Vector Machines regression (SVR) performs linear regression in the high-dimension feature space which uses the so called e -insensitive loss function proposed by (Vapnik 1995).This function allows a tolerance degree to errors not greater than e as the Figure 8 shows. The description is based on the structure and terminology used in (Smola et al. 2004):

Considering a set of training data $\{(x_1, y_1),...., (x_\ell, y_\ell)\}$, where each $x_i \subset R^n$ denotes the input space of the sample and has a corresponding target value $y_i \subset R$ for i=1,..., l ,where l be the training data points available to build a regression model. The SVR algorithm applies a transformation function Φ to the original data points from the initial Input Space (R^n) to a generally higher dimensional Feature Space (F). In this new space, a linear model f is constructed, which represents a non-linear model in the original space:

$$\Phi: R^n \to \mathrm{F}; \mathrm{w} \in \mathrm{F}$$
$$f(\mathbf{x}, w) = (w \cdot \Phi(\mathbf{x})) + b$$

When the identity function is used, i.e. $\Phi(x) \to x$, no transformation is carried out and linear SVR models are obtained.

The goal when using the e -insensitive loss function is to find a function f that fits given training data with a deviation less or equal to e, and at the same time is as flat as possible in order to reduce model complexity. This means that one seeks a small weight vector w. One way to ensure this is by minimizing the norm $\|w\|^2$ (Smola et al. 2004) leading to the following optimization:

$$\min \quad \frac{1}{2}\|w\|^2$$

$$\text{s.t.} \quad \begin{cases} f(\mathbf{x}_i, w) - y_i \le e \\ y_i - f(\mathbf{x}_i, w) \le e \end{cases}$$

This problem could be unfeasible. Therefore, slack variables x_i, x_i^* $i = 1,...n$, are introduced to allow error levels greater than e (see Figure 7), arriving at the following formulation:

$$\min \quad \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} (x_i + x_i^*)$$

$$\text{s.t.} \quad \begin{cases} y_i - f(\mathbf{x}_i, w) \le e + x_i^* & \forall i = 1,..., n \\ f(\mathbf{x}_i, w) - y_i \le e + x_i & \forall i = 1,..., n \\ x_i, x_i^* \ge 0, & \forall i = 1,..., n \end{cases}$$

This optimization problem can transformed into the dual problem (Vapnik 1995) and its solution is given by:

$$f(\mathbf{x}) = \sum_{i=1}^{n_{SV}} (a_i - a_i^*) K(\mathbf{x}_i, \mathbf{x}) \quad \text{s.t. } 0 \le a_i^* \le C, 0 \le a_i \le C,$$

where n_{SV} is the number of Support Vectors (SVs) and the kernel function, Here, the expression $K(\mathbf{x}_i, \mathbf{x})$ is equal to $(\Phi_i(x), \Phi(x))$ which is known as the Kernel Function (Vapnik 1995) The existence of such a function allows us to obtain a solution for the original regression problem, without concerning about the transformation $\Phi(x)$ applied to the data.

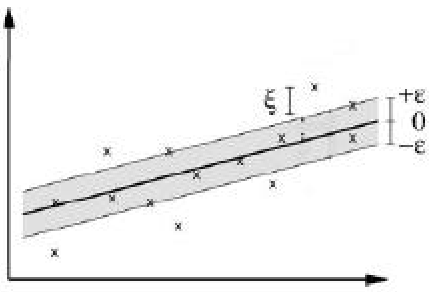


Figure 7: Support Vector Regression to Fit a Tube with Radius e to the Data

Some common kernels are shown in Table 2.

Kernels	Functions
Linear	$x \cdot y$

Polynomial	$[(x * x_i) + 1]^d$
RBF	$\exp\{-g\lvert x - x_i\rvert^2\}$

Table 2: Common kernel functions

It is well known that SVM generalization performance (estimation accuracy) depends on a good setting of meta-parameters parameters C, e and the kernel parameters. The problem of optimal parameter selection is further complicated by the fact that SVM model complexity (and hence its generalization performance) depends on all three parameters (Vladimir C et al 2004).

We use a Grid-Search to find good parameters for SVR with Radial Basis Function as kernel (gamma parameter). Firstly, the ranges of parameter C, e and gamma must be specified (for example in our case we use, $C=10^{-1},10^{0}...10^{10}$; $e=2^{-10}, 2^{-9}..2^{-1}$; gamma=$2^{-8}\,2^{-7}...\,2^{0}$).

We used the same data as in the Neural Network for model training, testing and validation.

3.3. Forecasting Results

The performance measure for model accuracy was Mean Absolute Percentage Error (MAPE), calculated as:

$$E = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|X_i - X_i^{real}\right|}{X_i^{real}}$$

X : Forecasted Demand

X^{real} : Real Demand

For the Linear Regression, Weighted Moving Average and SVR the same inputs as the ones described for the neural network are used (except for the BIAS). Results obtained using these four methods for the validation sets of all hospitals are shown in Table 3.

As can be seen in Table 3 best results are obtained in all cases using SVR.

These results were achieved using Rapid Miner 4.6.000, the Neural Network library from WEKA and SVR from LIBSVM (Chang C. et al. 2001) Library but using Rapid Miner as graphic user interface (GUI).

Results are presented graphically in Figures 8-9, where forecast and real demand are shown, with a 90% confidence interval for the forecast. This interval has been calculated by assuming (and testing) that the forecast error has a normal distribution.

	Linear Regression	Weighted Moving Average	Neural Net	SVR
HLCM **Medical Demand**	12,67%	7,53%	7,45%	**5.61%**
HLCM **Surgery Demand**	6,54%	7,36%	8,99%	**5,09%**
HEGC **Medical Demand**	15,91%	16,5%	7,7%	**6,86%**
HEGC **Surgery Demand**	8,55%	8,96%	8,3%	**5.88%**
HEGC **Trauma Demand**	8,41%	8,60%	5,12%	**4.44%**
HSBA **Medical Demand**	8,27%	11,83 %	7,9%	**6.97%**
HSBA **Maternity Demand**	10,54%	4,41%	10,6%	**3,24%**

Table 3: Forecast Results (best results underlined)

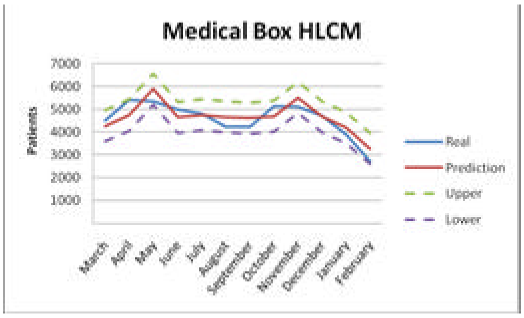


Figure 8: Medical box forecast

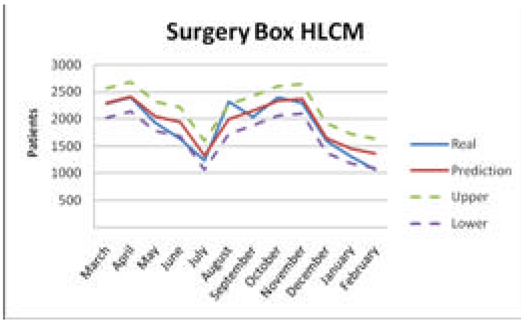


Figure 9: Surgery Box forecast

In the same way results for the HEGC are shown in Figures 10, 11 and 12.

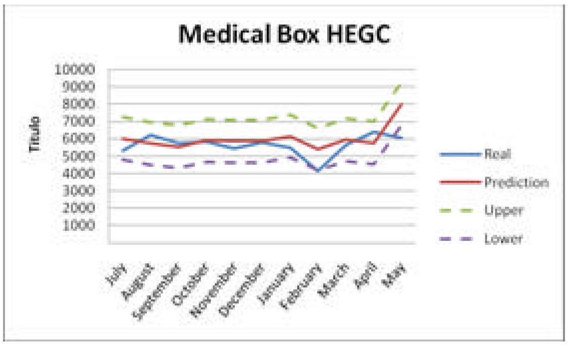


Figure 10: Medical Box forecast

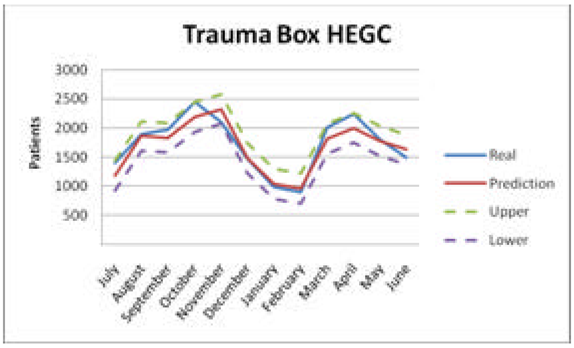


Figure 11: Trauma Box forecast

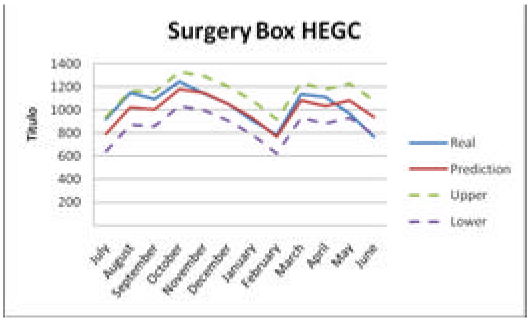


Figure 12: Surgery Box forecast

Similarly, results for the HSBA are shown in Figures 13 and 14.

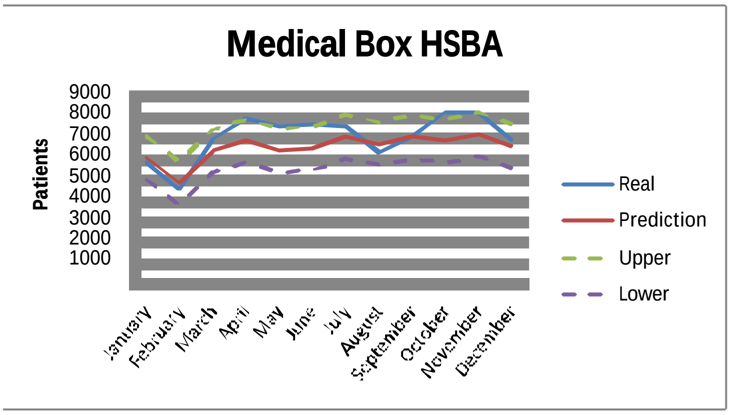


Figure 13: Medical Demand

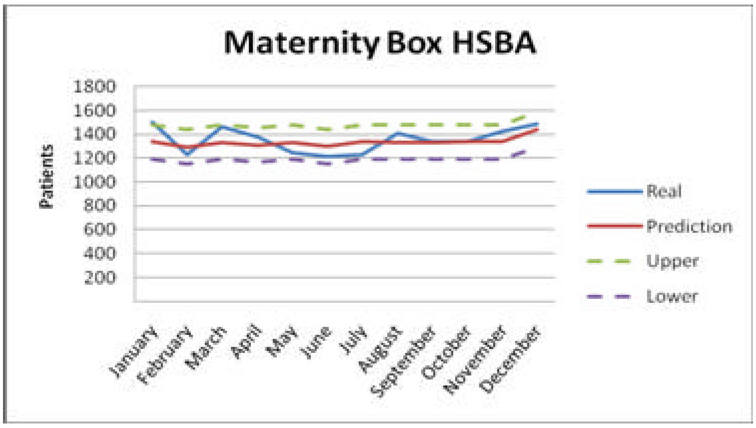


Figure 14: Maternity Demand

Based on the results described above, we conclude that Support Vector Regression is a very good method for predicting demand in hospitals in our case. However, other methods, which are simpler, also produce acceptable results and may be considered when use of complex methods is not feasible.

We decided on the use of the more complex methods because the confidence interval assures us with a high probability to forecast the real amount of patients that will arrive in the next months. This is critical because managing capacity, which is our final purpose, would be very difficult without quality results.

4. CAPACITY MANAGEMENT BASED ON THE FORECAST

As already stated in (Jones et al, 2002) having a forecast is by itself still not a useful contribution to hospital management. In order to support such management we need to convert the forecasted number of patients into relevant information, such a resources needed, through time distributions and categorization of severity among others, which is necessary for capacity planning of such resources.

As mentioned earlier, in Chile's public hospitals medical hours is one of the most scarce and expensive resource. In estimating this resource the following distributions are considered:

- Categorization of demand by severity per month.
- Referral to hospitalization rate
- Time distribution of demand per day.

4.1. Severity Segmentation

Following hospital practices, patients are divided into 4 categories according to severity, as shown in Table 4.

Categorization	Gravity
C1	Dying Patient
C2	High Risk Patient
C3	Low Risk Patient
C4	No risk Patient

Table 4: Category types

The results shown in Figure 15 indicate that the severity distribution depends on the particular month, but those percentages are relatively stable over time.

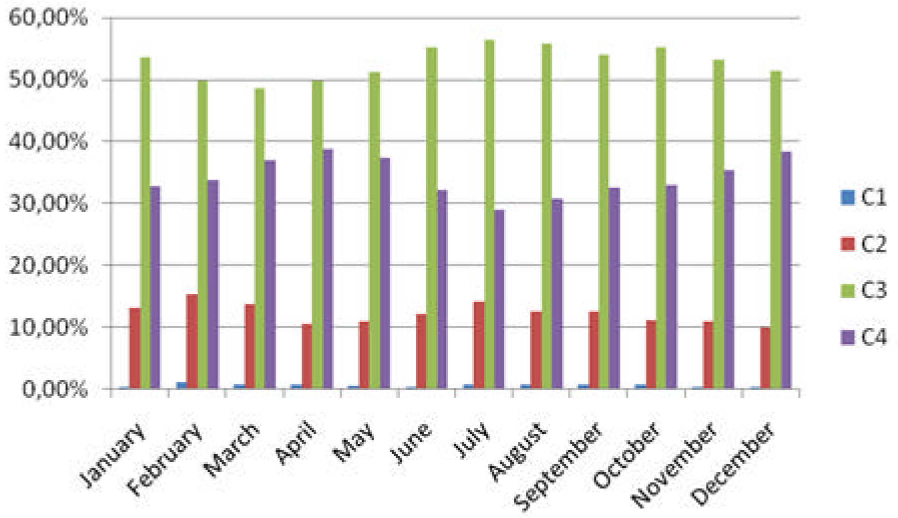


Figure 15: Monthly categorization distribution

Once we obtain the number of patients per category, the next step is to know the amount of time spent by the doctors with each one of the patients per category. For this purpose, we used a representative sample of individuals to estimate the behavior of the medical examinations.

For C1 patients, the reanimation room logbook registers the patients who come to the ward for resuscitation. This way we obtained a log normal distribution, with the behavior as shown in Figure 16. Then we estimated the number of doctors needed to care for each patient, which resulted to be an average of two doctors.

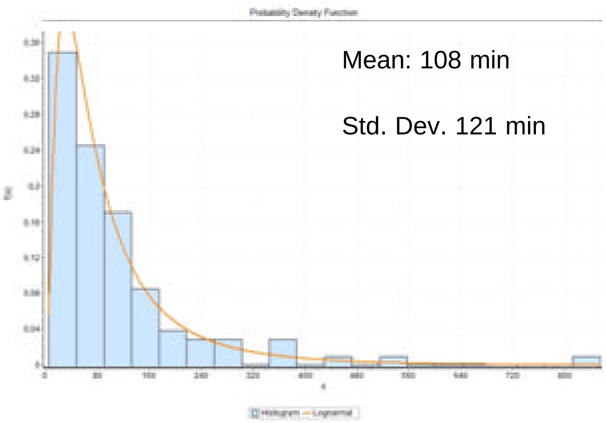


Figure 16: C1 Patients Probability Density Function

Secondly we tried to categorize C2 patients, for which we did not obtain a good representation. However, after discussion with doctors, medical consensus was reached in that 60 minutes was the average time for attention, with a deviation of 20 minutes. Therefore, a normal distribution was chosen.

Finally, for C3 and C4 patients it was possible to obtain meaningful distributions with the results as shown in Figures 17 and 18.

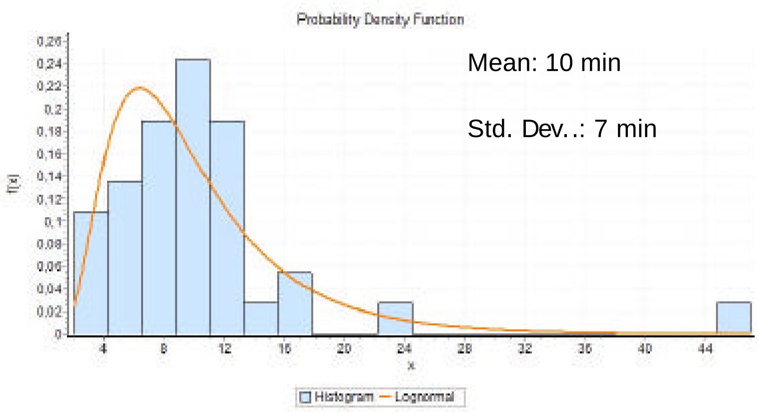
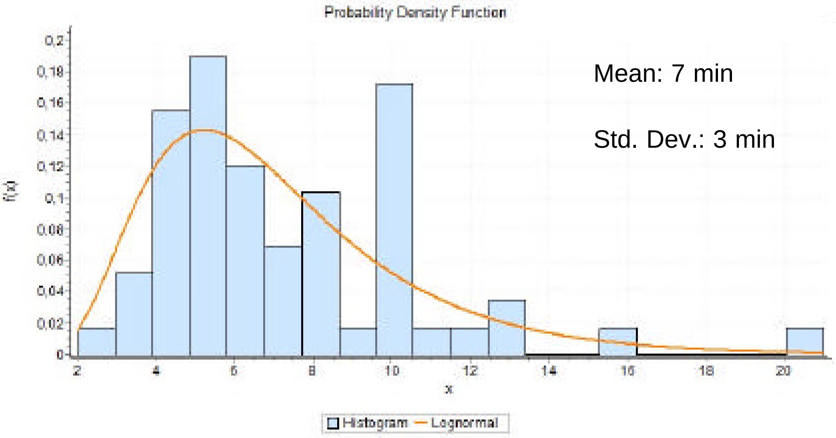


Figure 17: C3 Patients Probability Density Function



Figure

With these probability distributions we obtained a realistic representation that allowed us to estimate the time doctors spend with patients in the attention room.

4.2. Referral to Hospitalization or Observation

As a second parameter of patient distribution we have the patients that were assigned to the observation or to the hospitalization units of care. The monthly distribution that was obtained is shown in Figures 19 and 20.

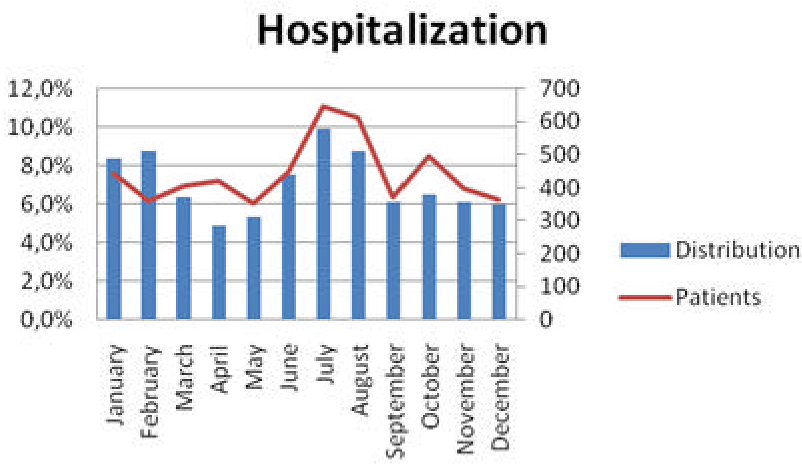


Figure 19: Hospitalization Distribution

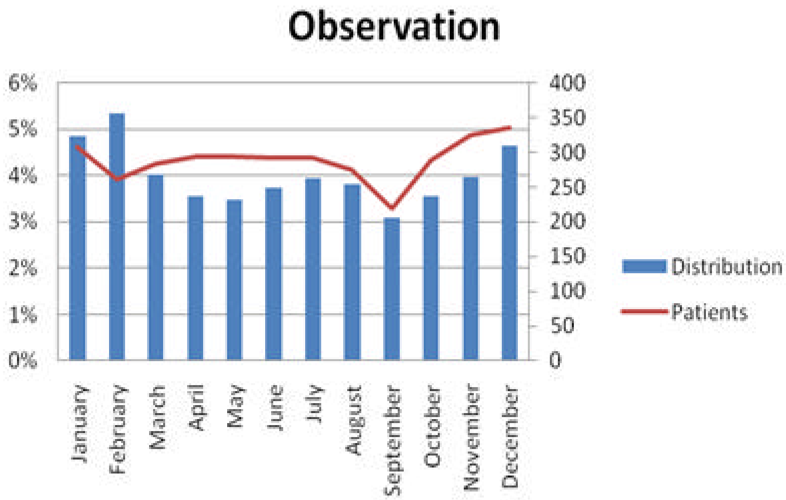


Figure 20: Observation Distribution

Finally, we proceeded to establish the time distribution of patients during the day, shown in Figure 21. The distribution in the day showed the greatest influx of patients from hours close to noon to 20:00.

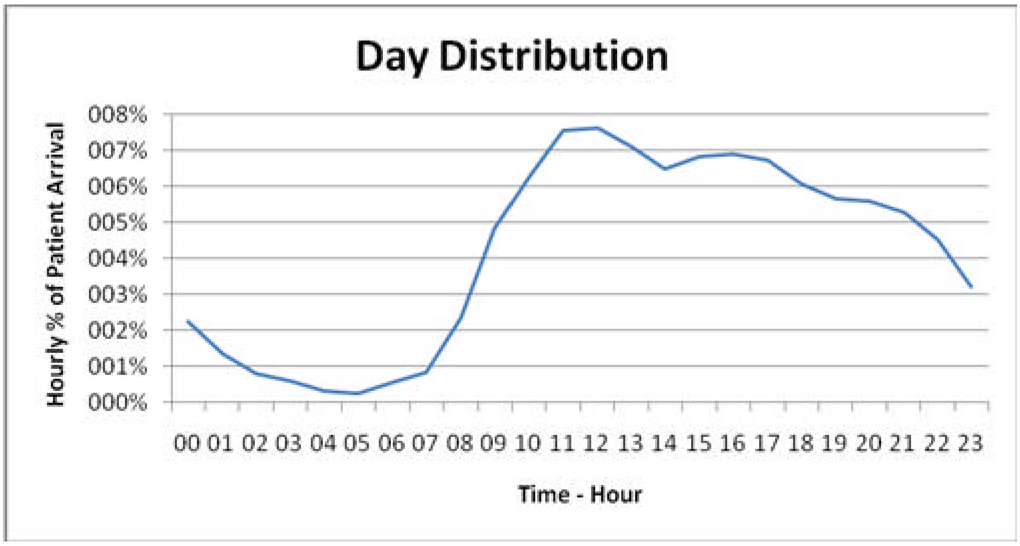


Figure 21: Patients Time Distribution

4.3.Resource Balance

Having defined all the distributions for the variables, the next step was to define the comparison unit of the existing resources and those needed by the forecasted demand. The unit selected was medical hours per month (MHM). To transform existing resources it was necessary

to know the team working in emergency care, which consists of 5 doctors in each of the 12 hours shift, where 3 are pediatricians and 2 surgeons. To obtain medical hours per month the following formulas were used:

$$\begin{aligned}&MHM = x \cdot H \cdot D\\&MHM : \text{Medical Hours per Month}\\&x : \text{Number of Doctors (3)}\\&H : \text{Hours per Day (24)}\\&D : \text{Number of days}\end{aligned}$$

$$\begin{aligned}&MHM = x \cdot H \cdot D\\&MHM : \text{Medical Hours per Month}\\&x : \text{Number of Doctors (3)}\\&H : \text{Hours per Day (24)}\\&D : \text{Number of days}\end{aligned}$$

Then we defined the methodology to convert the number of patients per month in hours per month. The first step taken was to categorize patients by severity as follows:

$$\begin{aligned}&C_x = P \cdot D_x\\&C_x : \ Categorization\ (C_1, C_2, C_3, C_4)\\&P : Forecasted\ Patients\\&D_x : \ Distribution\end{aligned}$$

The second step was to convert the categorized patients in hours of medical examinations. For that, the statistical distributions showed in figures 16, 17 and 18, supported by the above mentioned analyses and summarized in Table 5 were used.

Categorization	Distribution
C1	Log Normal
C2	Normal
C3	Log Normal
C4	Log Normal

Table 5: Categorization vs. Distribution

In parallel, we identified patients which are referred for hospitalization or observation, using the same method as for obtaining the number of patients based on their categorization. After obtaining this number, we converted it into hours for the necessary medical supervision.

Finally, these times are added and distributed in a table according with the arrival hours so we can observe the behavior of demand during the day and the state of occupation of the emergency resources, as shown in Table 6.

With all this data, structural changes can be suggested in the medical care. For example, HLCM requires a greater number of physicians between 12:00 and 24:00, as shown in Table 6,

and fewer in the night shift, but always preventing a potential emergency with one doctor on duty at home during the night.

While there is a theoretical best use of resources, this should be contrasted with the feasibility of changing established customs. But this is a problem of change management rather than resource management.

Arrival Time	Available Resources [Hours Medical Month]	Resources Needed [Hours Medical Month]	Medical Hours Available [Available Res. – Res. Needed	Occupation Rate
0	90	41	49	46%
1	90	24	66	27%
2	90	15	75	17%
3	90	11	79	12%
4	90	6	84	7%
5	90	5	85	6%
6	90	10	80	11%
7	90	15	75	17%
8	90	42	48	47%
9	90	87	3	97%
10	90	114	-24	127%
11	90	136	-46	151%
12	90	138	-48	153%
13	90	129	-39	143%
14	90	117	-27	130%
15	90	123	-33	137%
16	90	125	-35	139%
17	90	122	-32	136%
18	90	110	-20	122%
19	90	102	-12	113%
20	90	101	-11	112%
21	90	95	-5	106%
22	90	81	9	90%
23	90	58	32	64%

Table 6: Use of Emergency Attention Physician Box.

4.4. Simulation of Demand Processing on Hospital Facilities

In order to have a more dynamic and detailed view of how demand is processed on hospital facilities, we developed a simulation model. Such model allows us to see how the flow of patients will demand services of the different hospital facilities and how capacity is able to respond to such demand. As a consequence capacity can be modified to try to eliminate bottlenecks and avoid unused resources. This provides a powerful tool to adjust capacity to the level needed to guarantee a given service level at the minimum cost. The model represents facilities and flows as shown in Figure 22.

It is important to mention that all the flows in the emergency department are dynamic; this means that depending on the patient's characterization (showed in Table 4) he/she can take different flows. The different flows are represented by probabilistic decisions based on the data collected in the HLCM and from interviews with the hospital personnel.

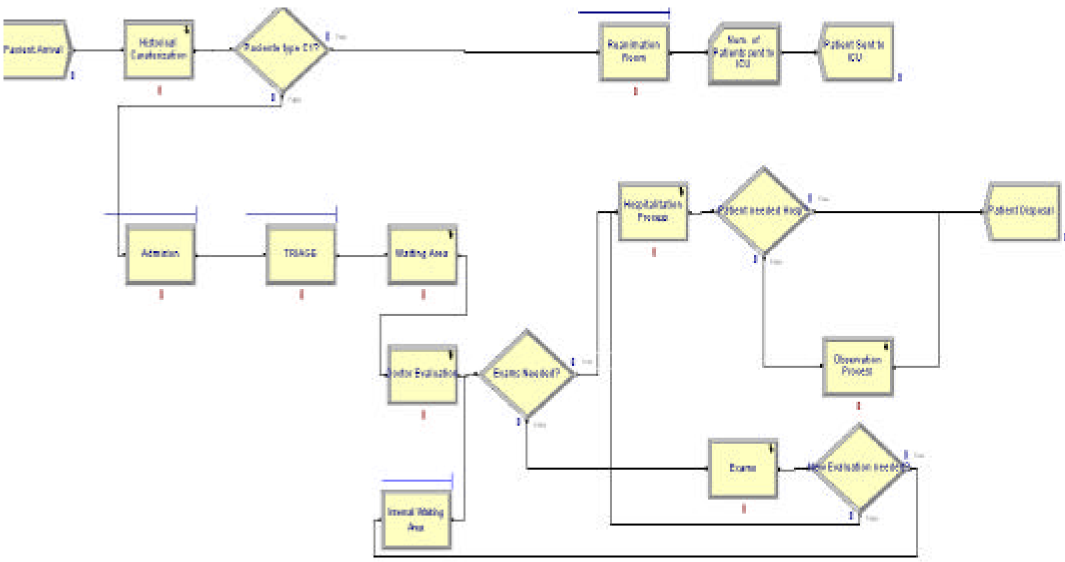


Figure 22: Emergency Department Simulation Model

As shown in Figure 23 the simulation process has a patient arrival module which takes the forecasted month demand and transforms it into a day distribution using the pattern showed in Figure 21.

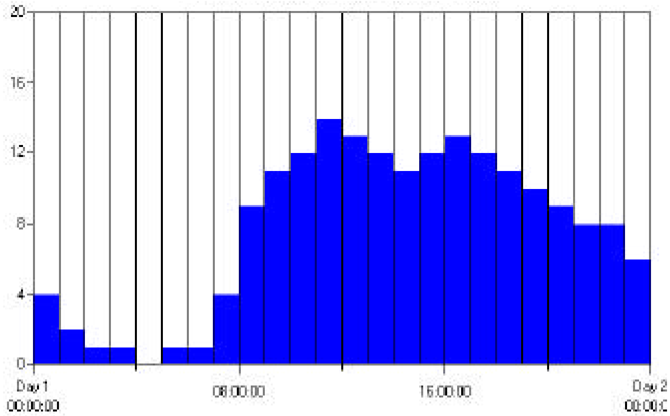


Figure 23. Forecasted Demand during a Day

Now the different flows that represent the hospital´s services needed to attend the patients that arrive are:

- Patient sent to ICU or ITU
- Patient sent to Hospitalization
- Patient Discharge.

Then we can define the activities in the emergency department and the resources that address these flows, as shown in the simulation model in Figure 22. These are shown in Table 7.

Process	Resource	Time Distribution
Admission	2 Secretaries per Shift	Uniform (5,15) (min)
Triage	1 Nurse	Uniform (2,5) (min)
Doctor Evaluation	3 Doctors per Shift	C2 Normal(20,3) (min) C3 Weibull(10.44,2.29) (min) C4 Weibull(7.68,2.61) (min)
Patient Exams (Laboratory)	3 Paramedic per Shift	Triangular (5,10,15) (min)
Patient Observation	20 Observation Beds	Triangular (2.5,3,3.5) [hours]

Table 7. Process, Resources and Time Distributions of the Simulation Model

We did simulation runs to validate if the model represents the current situation of the hospital and also to get some indicators to measure performance. The indicators selected where: doctors occupation rate, time until first medical consult and length of stay in emergency department.

The results obtained with the current situation of the emergency will be shown next but it is important understand that the Triage acts only as a first evaluation exam and has no effect in the prioritization of the patients.

Two more scenarios where evaluated to see the impact they have in the emergency department. Those scenarios are:

- Incorporation of a Prioritization Triage
- Incorporation of a Prioritization Triage plus a Fast-Track Box to attend C4 patients in the day shift.

The results obtained are presented in Table 8.

		Average		
Resource	Shift	Current Situation	Triage Prioritization	With Fast-Track
Doctor 1	Day	133%	130%	121%
Doctor 2				
Doctor 3				
Doctor 4	Night	38%	37%	35%
Doctor 5				
Doctor 6				

Table 8. Resource Average Schedule Utilization

The following figures show the average length of stay until first medical evaluation. In Figure 24, which corresponds to the current situation, all the type of patients are attended with almost the same average time, which is consistent with the existing condition.

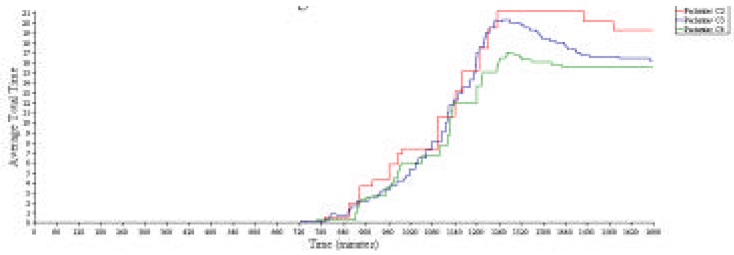


Figure 24. Time until first medical evaluation. Current Situation

Results of the second scenary, shown in Figure 25, shows that the more acute patients (C2 and C3) have an important decrease in the time until first evaluation; in contrast the least acute patients (C4) that have an important increase in length of stay until first evaluation.

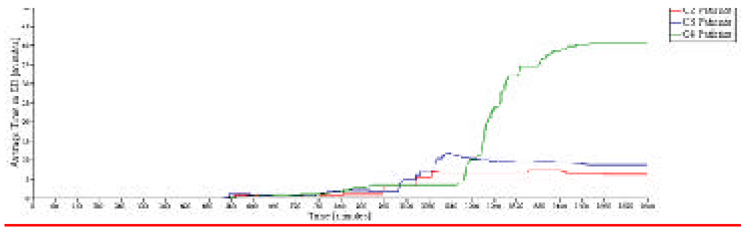


Figure 25. Time until first medical evaluation. Prioritization Triage

Finally analyzing the third scenary, Figure 26, the more acute patients have a small decrease in the time until first evaluation and the C4 patients also have a decrease in the average time until first evaluation. It is important to note that the increase of average time until first evaluation occurs after the fast-track box is closed.

Results are summarized in Table 9.

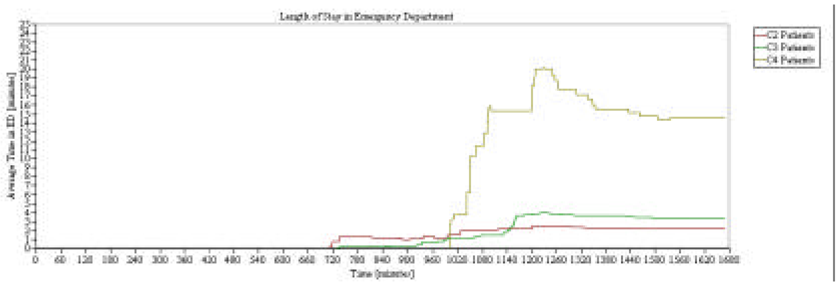


Figure 26. Time until first medical evaluation. With Fast-Track

	Average		
	Actual Situation	Triage Prioritization	With Fast-Track
Length of Stay (LOS)	114	116	106

Table 9. Length of Stay in Emergency Department (minutes)

After analyzing the simulations' results we can conclude:

- The principal bottleneck are the doctors and the evaluation process
- The day-shift is pretty much saturated.
- Using a Triage without prioritization is useless and does not results in that more acute patients have a sooner medical attention.
- Unless the Prioritization Triage augment the length of stay in the emergency department, C2 patients and C3 patients will have a time until first medical attention much better than without it.
- The Fast-Track medical attention box helps to improve the Prioritization Triage by giving C4 patients a quicker attention and improving length of stay in emergency department in almost 10% (approximately 10 minutes).

5. IMPACT OF THE WORK AND CONCLUSIONS

We have shown that hospital demand can be forecasted with good accuracy using VSR, which give better results than simpler methods. This has allowed us to design a process to manage capacity that is based on transforming the forecast into resources needed for its satisfaction, which can be compared to available resources, in order to take corrective actions when capacity is not aligned with demand.

The forecasting method proposed and the demand management process have been accepted by hospitals management and staff and are currently in use in one of the hospitals. For this we developed support computing systems that allow the routine use of the processes we designed directly by hospital staff. We are currently implementing processes and systems in one of the other hospitals. The results have been so encouraging that National Health Authorities are considering the extension of the demand forecasting and management practices we have developed to the more than hundred public hospitals in Chile.

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