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SIMULATION AND OPTIMIZATION IN A HEALTH CENTER IN MEDELLIN, COLOMBIA

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ABSTRACT

Simulation has been widely applied to health care cases in numerous countries. In Colombia, these applications are scarce. We use a systemic approach, discrete event simulation, simulation-optimization and linear programming to reduce waiting times in a health center in Medellín, Colombia. With this reduction we ensure a high level of satisfaction of patients with a relatively low additional cost.

1 INTRODUCTION

Health services at a national level have been recognized as adaptative complex systems (Kanagarajah *et al*. 2006) and useful studies from a dynamic point of view have been modest. Health services, especially those that covers an entire country, have problems ranged from the large waiting times for users (van Ackere and Smith 1999), until the lack of full coverage, as happens in Colombia.

This article presents an approximation to the waiting time problem in a health center in Medellín, Colombia, combining a systemic view and tools from discrete event simulation (DES) and Optimization.

The health center offers health services, including general practitioner, dentistry, specialists and also promotion and prevention (P&P) programs that disseminate health promotion and disease prevention. The structure of the health center allows patients to arrive to their service, but before an appointment the patient must go through the admission center (AC). It has 11 booths that are open according to the staffing of the personnel of the AC (that is set by the perception of peak hours). Each member of the AC staff has a 9-hour shift daily.

There are three different types of booths at the AC that are currently assigned as follows: two booths for patients in P&P programs (booth type 1), two for medical appointments, dentistry and priority appointments (booth type 2) and the rest for medical orders, x-rays, lab, vaccines and other specialties (booth type 3). The complete scheme of patient arrival and departure is shown in Figure 1.

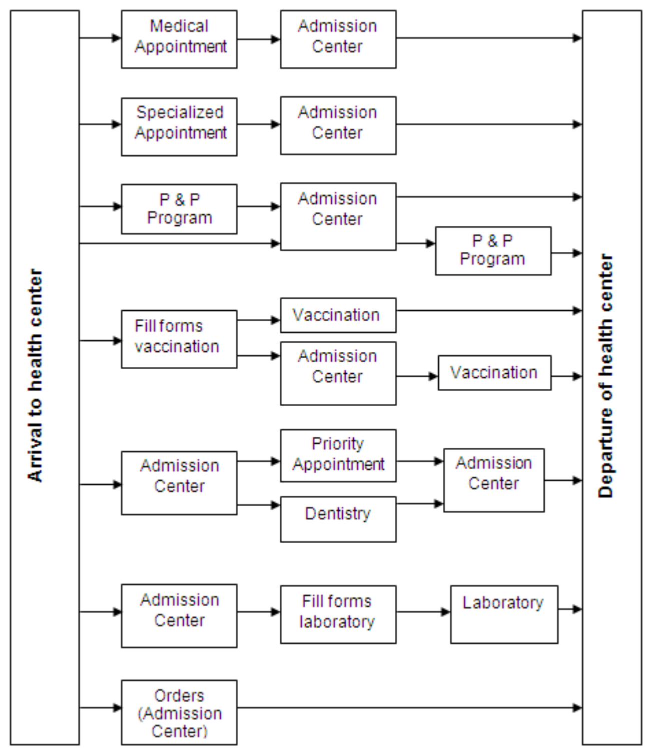

Figure 1: Scheme for the patient transit in the health center

The following subsection gives a brief description of how health services have been modeled when it comes to waiting times and with a systemic approach. Section 2 describes variables, construction and results of the DES model with the criteria that will be used in section 3 for the optimization. Section 3 describes the optimization of the DES model and the posterior linear programming model. Finally, some conclusions are given.

1.1 Systemic Approach

One of the major problems in health care is the waiting time of patients. This time tends to be longer for public services than for private ones. If one focuses on patient´s waiting times, the causal relationships in the system will be determined by the available resources and the total demand.

Resources and demand are seen as a black box because their components are not disaggregated and relationships with other variables are not shown. According to Ann van Ackere (1999), to a greater demand there is a greater waiting time and to a higher waiting time there is a lower demand (with a delay), closing a cycle of balance. On the other hand, higher resources cause lower waiting times and to higher waiting times there are higher resources, losing another cycle of balance, as shown in Figure 2.

The relation between the waiting time and the resources is affected by the investments health centers make because the waiting times are a signal of the occupation of the system and when the capacity limit close to be reached, there is a need for investments to enhance the system´s capacity.

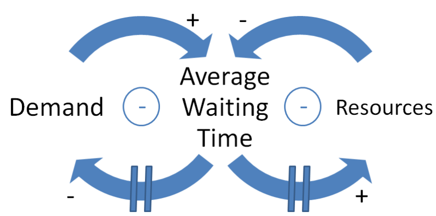

Figure 2: Causal diagram of the average waiting time

For the managers in the health center is of paramount importance to keep track of the satisfaction of patients. To include the satisfaction in the causal diagram a satisfaction survey was used and helped to determine that the most important fact in satisfaction is the waiting time in the health center. When the waiting time grows, the satisfaction decreases (with a delay) and when satisfaction grows the demand tends to grow. The delay in the relation between waiting time and satisfaction is due to the distrust in the system that patients have, in other words, the patient's satisfaction grows after perceiving a low waiting time more than once.

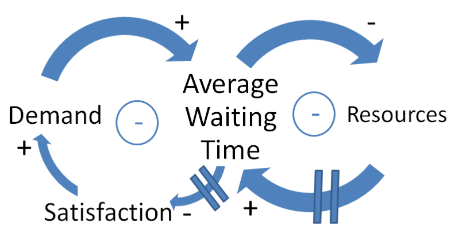

Figure 3: Causal diagram with satisfaction

With the information that the causal diagram provides is clear that in order to accomplish a satisfaction growth, the average waiting time must decrease. Because the managers of the health center do not want to decrease the demand, the resources must grow. In this case the amount of resources are not as problematic as the scheme and processes that this resources used to keep the capacity, in patients per hour, to its maximum.

In the next sections a complete model and its optimization is develop in order to improve the scheme used for the resources.

2 DISCRETE EVENT SIMULATION MODEL

In this section a brief description of the construction of the model will be presented, along with the most important results and the identification of the area that could reduce the waiting time.

2.1 Variables

There are two different ways for collecting the data. One of them is the classical approach by experiment design. The other one is taking information from an existing database. The first one is better as for the control and the second one as for the cost (Leemis 2004). In this case a combination of both methods was used. Information in database was used and data that did not exist was collected using experiment design.

To collect data through experiment design a critical day of the week was selected (when, according to managers, waiting times in all queues was the highest).

To build the model many variables were taken into account. The most important were time between arrivals, service time in AC and probability of selecting certain routes. After collecting the two first ones, some statistical analysis was made.

For the time between arrivals, data was collected in different moments of the day (early morning, morning, noon and afternoon), in order to be able to test changes in the parameters and distribution of the variable. The first step was to prove independence of data (no autocorrelation).

After proving that no autocorrelation existed in the variables it was necessary to fit a distribution, as well as the corresponding parameters, to data in each time interval (Kolmogorov-Smirnov test was used in this part).

Regarding service time, no pattern in a day was considered, but dependence of the type of service the patient requires is expected. That is why an Analysis of Variance (ANOVA) was used to determine which services would have the same mean, and therefore could be modeled with the same statistical distribution. According to the Duncan test time of service in AC were grouped as follows: medical appointment, priority appointment, dentistry and vaccination were the first group, laboratory and orders was the second group and P&P and other specialties were the third group. After proving no autocorrelation in the variables distributions were adjusted to each group.

Table 1: Type of service and its boot type

Type of service	Boot type
P&P Program	1
Dentistry and priority appointments	2
Medical orders, x-rays, lab, vaccines and other specialties	3

2.2 Model Translation

After all data was analyzed the next step is to build the discrete simulation model. We used DES because of its power to simulate complex and detailed systems, like the health center, also because it is a tool very easy to work with and finally, because of its friendly interface which allows a better understanding and use of people who will make decisions based on the model (Simul8 Corp. 2003).

Validation of the model was made using data provided by health center managers of total number of patients in a day, patients of medical appointments, specialized appointments, dentistry and priority appointments. As shown in Table 2 the percentage error (respect to the average) is not over 10% in any case.

Table 2: Simulation Objects and its simulation error

Simulation Object	Performance Measure	Avg.	Real Data	Percentage Error
Entrance	People Entered	1067	1100	3.02%
Queue other specialties	People Entered	44	41	7.97%
Queue medical appointments	People Entered	272	300	9.38%
Queue dentistry	People Entered	78.8	86	8.37%
Queue priority appointments	People Entered	141.8	157	9.68%

2.3 Results

The main results addressed by this modeled are shown in Table 3. Before explaining these results it is important to take into account that the waiting time in queues where people had appointments is the time since the person gets to the queue until he/she is attended by the doctor, and does not stand for the time since the time of the appointment until it really starts.

Table 3: Main results of the Discrete Simulation Model

Simulation Object	Simulation Results (Minutes)		
	-95%	Average	95%
Maximum Queuing Time for Booth Type 3	24.70	33.55	42.38
Average Queuing Time for Booth Type 3	9.32	14.12	18.90
Maximum Queuing Time for Booth Type 2	40.80	49.10	57.38
Average Queuing Time for Booth Type 2	12.70	15.97	19.23
Maximum Queuing Time for Booth Type 1	8.05	9.15	10.27

Results are the ones expected, but yet disappointing: maximum time in system is very high, around 2 hours for a patient whose appointment lasted at most 25 minutes. Regarding average waiting time, 30 minutes in the whole system is too much time: this means that almost half of the time of a patient is spent in queues. This let us think that people's waiting time is really high in most of the cases.

The queue where people spend most of the time is he one of AC. If waiting time in AC queues is compared with the ones of queues of specific services it can be stated that most of the time spent in the health center, by every patient except those of P&P, is in the AC. Therefore, it can be identified as a critical area and it is necessary to make some changes in such area in order to reduce waiting time in the health center.

3 OPTIMIZATION MODEL

As noticed in section 2, one of the main problems in patient´s waiting times in the system is the AC. It could be because almost every patient in the health center has to go to the AC at least once, regardless of the type of service needed.

The AC is where the administrative processes take place. It has 11 booths that are open according to the staffing of the personnel of the AC (that is set by the perception of peak hours). Each member of the AC staff has a 9-hour shift daily.

There are three different types of booths at the AC that are currently assigned as follows: two booths for patients in P&P programs (booth type 1), two for medical appointments, dentistry and priority appointments (booth type 2) and the rest for medical orders, x-rays, lab, vaccines and other specialties (booth type 3).

One of the targets of the simulation of the health center is to evaluate and to reduce, if possible, the total time in the system of the patients. It was clear in the simulation of the system that the AC plays an important role when it comes to waiting times. A better performance in the AC could reduce the waiting times of patients and therefore their total time in the system.

A way to improve the performance in the AC is having a better staffing of the AC personnel; it should be related to the affluence of patients and should look for a reduction of the waiting time in the AC queues. This staffing was made in two steps. First the simulation-optimization of the DES model and then a personnel scheduling model with linear programming (LP).

3.1 Simulation-optimization

As it has been shown, the affluence of patients has a stochastic behavior that has been represented by the DES model presented earlier. Simulation-optimization was selected as an optimization tool because it allows the optimization of a DES model, incorporating the stochastic behavior in the optimization. The goal of the optimization of the simulation model is to reduce the queuing times of the patients at the AC by appropriately assigning the available personnel.

A simulation-optimization problem can be formulated as follows (Azadivar 1999):

$$\begin{aligned}&\max(\min)\, f(x) = E[z(x)]\\ &\text{subject to}: g(x) = E[r(x)] < 0\\ &\text{and} \qquad h(x) < 0\end{aligned}$$

Where x represents the vector of decision variables of the problem; z and r are random vectors that represent different responses of the simulation model for a given x. The variable h represents a vector of parametric constraints of the decision variables.

Optimization problems can be divided into monobjective and multiobjective. For the health center, there was a need to minimize the average time in the AC queues but with minimal cost of personnel. This could be translated into a multiobjective optimization problem and be solved through Pareto-optimal solutions or could be translated into a monobjective problem with a weighted objective function (Régnier, Sareni and Roboam 2005). The last was selected for a more convenient use of the available optimizing tools. The selected problem formulation is:

$$\begin{aligned}&g(x) = \sum\nolimits_{i=1}^{k} w_i f_i(x)\\ &\text{subject to } \ h(x) < 0\end{aligned}$$

Where w_i are the weight functions that determine the importance of each objective, with the summation of w_i equals to 1; f_1 is a function of the average waiting time in the PS queues and f_2 is a function of the personnel cost. The variable x are the minimum requirements of personnel throughout the day. There are only parametric constraints of the decision variables and capacity constraints.

Taking into account the previous staffing we established a matrix of available personnel per hour throughout the day as a combination of the existing shifts (Table 4). The simulation-optimization model was created to find the minimum amount of personnel requirements per hour with an average queuing time under 5 minutes in each one of the lines.

Table 4: Distribution of shifts per hour is used to find minimum resource requirements per hour

TIME PERIOD	SHIFT							MIN. RESOURCE REQ.
	S1	S2	S3	S4	S5	S6	S7	
6:00-7:00			x		x		x	a_1
7:00-8:00		x	x		x	x	x	a_2
8:00-9:00		x	x		x	x	x	a_3
9:00-10:00		x	x		x	x	x	a_4
10:00-11:00	x	x	x		x	x	x	a_5
11:00-12:00	x	x	x	x	x	x	x	a_6
12:00-13:00	x	x	x	x	x	x	x	a_7
13:00-14:00	x	x		x	x	x	x	a_8
14:00-15:00	x	x		x	x	x	x	a_9
15:00-16:00	x	x		x	x	x		a_{10}
16:00-17:00	x	x		x		x		a_{11}
17:00-18:00	x			x		x		a_{12}
18:00-19:00	x			x		x		a_{13}
19:00-20:00	x			x				a_{14}
20:00-21:00				x				a_{15}

The simulation-optimization was made using the inbuild optimization routine in Simul8, Opt Quest. Opt Quest uses metaheuristic elements such as scatter search, Tabu search and neural networks (Fu 2002). The results of the simulation-optimization were the minimum number of personnel that should be available in the AC in each hour of the day and also the number of lines of each type that should be open at peak hours to give the best performance for the available personnel (the number of lines of each type open at non-rush hours is up to the managers of the health center).

3.2 Staffing

After having the minimum requirements in each hour of the day, a LP model was formulated with the minimum amount of personnel per hour in order to change these minimum requirements into actual staffing. The objective function, shown in (1), is used to minimize the total number of staff at the AC subject to availability of the shifts per hour in the previous staffing with the minimum requirements found in the simulation-optimization and restrictions of capacity (the total number of existing lines).

$$\min \sum_{i=1}^{7} x_i . \tag{1}$$
$$g_j \le a_j ,\ \ j = 1,2,\ldots,16$$

where a_j is the minimum resource requirement per hour (as shown in Table 3) and g_j is a function of the available shifts at that hour.

This model was solved using a LP tool and had multiple solutions because some of the restrictions are parallel to the objective function. The solution established the optimum number of staff that should be scheduled in each one of the previously set shifts, in order to achieve the reduction of waiting times as mentioned in section 3.1.

The results of the LP model were implemented in the simulation model to evaluate the optimal staff level. Comparing the results of the original model with the results of the optimal staff level, the average and the maximum queuing time in each type of booth was reduced in every line with the new staffing. This reduction translates into a statistically significant reduction of 35% of the total time in system of the patients (see Table 5).

Table 5: Original and optimum staffing with the respective average time in system.

SHIFT	#PERSONS (original)	#PERSONS (optimum)
1	1	1
2	2	0
3	1	3
4	1	2
5	1	1
6	1	2
7	1	2
TOTAL STAFF	8	11
Average time in system (sec)	1868	1208

This new staffing implies the hiring of three more people at certain times of the day. This will increase the personnel costs. However, the cost-benefit analysis between the personnel costs and the reduction of the waiting times turns out positive because the first is not too high and the last can make an impact in the satisfaction level of the costumers, which is the main interest of the heath center managers.

Although the new staffing improves significantly the queuing times in the AC, this reduction has an impact in other parts of the system. Using the simulation model, it was found that the average waiting times in the dentistry section increased significantly. This can be explained by the reduction in the waiting times in the AC queues. The patients that attend to dentistry services have to go first to the AC and then to the waiting room in the dentistry office. Because the waiting times in the AC diminished, patients go faster to the waiting room and will have to wait longer for the service. Nevertheless, this is not relevant compared to the great improvement of the system in all other areas. Further work can be done to ensure a better performance in every part of the system.

With the simulation-optimization of the DES model and the LP model we could find a staff level for the AC that significantly reduces the queuing times and therefore the total time in the system of the patients. This translates into patient satisfaction and has a relatively low cost.

The solutions found in the LP model were implemented in the real system after the end of the project. The experts in the AC area noticed relevant improvements in the waiting times at the AC queues. This reduction was not measured.

4 CONCLUSIONS

Combining different tools for solving the same problem can improve the effectiveness of each tool. In this case a combination between the systemic approach and the discrete event simulation model helps the researchers to know which variables are important in the optimization, which improves the optimization effectiveness.

The discrete simulation model has been very important in the research. After validation and the certainty it represented the Health Center, it made possible to analyze the Health Center as a whole, and to determine that the main problem was the AC. Therefore a solution to this key area had to be proposed.

With the simulation-optimization of the DES model and the LP model we could find a staff level for the AC that significantly reduces the queuing times and therefore the total time in the system of the patients. This translates into patient satisfaction and has a relatively low cost.

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