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Lean healthcare integrated with discrete event simulation and design of experiments: an emergency department eeeexpansion

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Abstract

Background. Discrete Event Simulation (DES) and Lean Healthcare are management tools that are efficient and assist in the quality and efficiency of health services. In this sense, the purpose of the study is to use lean principles jointly with DES to plan the expansion of a Canadian emergency department and to the demand that comes from small closed care centers.

Methods. For this, we used simulation and modeling method. We simulated the emergency department in FlexSim Healthcare® software and, with the Design of Experiments (DoE), we defined the optimal number of locations and resources for each shift.

Results. The results show that the ED cannot meet expected demand in the current state. Only 17.2% of the patients were completed treated, and the Length of Stay (LOS), on average, was 2213.7, with a confidence interval of (2131.8 - 2295.6) minutes. However, after changing decision variables, the number of treated patients increased to 95.7% (approximately 600%). Average LOS decreased to 461.2, with a confidence interval of (453.7 - 468.7) minutes, about 79.0%. In addition, the study shows that emergency department staff are balanced, according to Lean principles.

Keywords: DES; Lean Healthcare; Design of Experiments; forecasting; expansion; demand

1. Introduction

The improvement in the health services quality is extremely important because it directly affects the patient's satisfaction and safety. In fact, the health industry is one of the largest in the world (Bhat, Gijo, and Jnanesh 2014). According to (World Bank 2019), in 2016, health spending in the world was around 10.0% of total GDP. The United States was the country that invested the most per capita, totaling US$ 9,869.74, followed by Switzerland. Canada is among the top 20 countries that invest in health per capita, with a total of US$ 4,458.21, while the world average is 1,025.29 (World Bank 2019).

Given the importance of the health system in the world, decision-makers seek actions to make processes more efficient and agile. Despite this, financial resources and skilled labor are becoming scarce. Consequently, decision-makers use management tools for analysis and process improvements in forecasting, restructuring, and reduce costs. Indeed, (Brailsford et al. 2018) argue that many real problems are complex and, hardly, only one approach and tool helps in their resolutions.

One of the tools used to improve and forecast process behavior is Discrete Event Simulation (DES). DES is the reproduction of a dynamic process, using a computer model to evaluate, measure and improve the performance of any system (Harrell, Ghosh, and Bowden 2012) without any physical risks and additional costs (Banks et al. 2010; Montevechi et al. 2007). Moreover, the literature defines as the model development process, being it hypothetical or real, aiming to perform experiments (Negahban and Yilmaz 2014). Hence, predicting the behaviour of real and complex systems becomes tough, because they are influenced by a set of internal and external factors and the experience are often unfeasible to perform (Budgaga et al. 2016). Therefore, SED is the first step in evaluating a change proposal, gaining insight into potential impacts, and supporting management to take decisions and implement real-world improvements (Bem-Tovim et al. 2016; Dengiz and Belgin 2014).

In addition to DES, the use of Lean Manufacturing is also efficient in improving processes. Lean appeared in the 1950s, where the Japanese automotive industry faced an adverse scenario. The market was limited and demanded a wide variety of vehicles, which was in contrast to the current philosophy of mass production, with few varieties produced on a large scale. Furthermore, the country's economy was weak, with low capital availability and few international trade relations. Thus, the acquisition of modern Western production technologies became difficult (Womack, Jones, and Roos 1990). To meet this challenge, the Japanese automaker Toyota began developing a new production system, the Toyota Production System (TPS). Taiichi Ohno, credited as the main mentor of the STP, aimed to serve customers in the shortest time, at the highest quality and the lowest possible cost. Thereby, it would be necessary to focus the effort on activities that add value to the customer (Graban 2016), eliminating wastes. Over time, Lean has expanded into other sectors, such as healthcare, where it has been renamed Lean Healthcare.

Waste found in manufacturing has been converted to health services where Lean Healthcare applies. Defects correspond to poor administration of medications or incorrect doses. Overproduction characterizes as unnecessary diagnostic procedures. Inefficient transportation is inadequate layouts and laboratories away from collection points. The inappropriate layout may also link to the unnecessary movement of nurses and doctors. Waiting features idle employees with uneven workloads and patients waiting for service. The stock is characterized as expired supplies and super-processing, e.g., data in the patient's registry that will not be used later (Graban 2016).

Finally, the use of experiments jointly with DES is essential for the analysis of the current state process and for proposing improvements to the future state. The experiment is indicated when it is desired to optimize the process under analysis (Banks et al. 2010), determining the configuration of the parameters that cause the responses to approaching the required values and/or have the lowest variability (Montgomery and Runger 2018). The best way to evaluate several factors involved in the process is the use of suitable techniques to plan the experiments, e.g., factorial experiments, Taguchi and Plackett-Burman (Montgomery and Runger 2018). In this case, the factors change simultaneously, allowing observing if there is an iteration between them. In addition, it generally requires fewer tests than the "best guess" strategy, where the expert performs random experiments. According to (Banks et al. 2010), with some adaptations in the factorial arrangements, we may evaluate the individual, interactions, and quadratic effects. Thus, the three techniques presented, when used together, show effective results in health processes. In this sense, the goal of this study is to plan the expansion of a Canadian emergency department (ED) and to meet the demand that comes from small closed care centers. Moreover, it is necessary to size, according to Lean Healthcare the principles, the ideal number of resources, beds for care and beds in the Short Stay Unit (SSU). Additionally, the scope of the project aims to reduce the length of stay (LOS) of the patients in the ED and that they are taken care of as soon as possible after going through the triage. Furthermore, it is necessary to determine the ideal SSU number so that patients do not wait more than 180 minutes for their transfer.

To contribute to the literature, the study uses Design of Experiments (DoE) to determine the influence of staffing on each shift, in addition to identifying the main limiting factors of physical resources for the expansion of the ED. The simulation also allows evaluate the influence of demand variation throughout the day and week in the future state.

The paper is divided as follows: next section presents a review of the literature of DES and Lean in hospital environments, followed by the methodology. Subsequent section presents the results and discussions in order to draw the conclusions.

2. Literature Background

The use of DES in healthcare is not new, dating back to the 1960s (Pitt 2008). However, since then, there has been considerable growth for its interest. According to (Arisha and Rashwan 2017), this growth is strong evidence that the use of simulation provides better decisions in the management of health services, without compromising patient safety. This advantage has increasingly attracted the attention of hospitals and health authorities (Cheng et al. 2017).

However, experts in simulation applied to healthcare claim that its application is more complicated than in other areas (Tako 2015). The main problems are less evident structure; the system is complex; greater effort to collect and accessing the data; barriers due to ethical issues; influence of political issues; less availability of customer time; and more difficulty in ensuring implementation.

Despite the mentioned difficulties, we can find studies with positive results in the health sector. These results link to costs, capacity, wait and stay time, and levels of service and losses. (Zhou and Olsen 2018) applied DES for medical supplies management and decreased the costs involved in the process by reducing expired drugs. Still in stock management, (Baesler et al. 2014) reduced the lack and loss of blood components. (Hussein et al. 2017) presented effective results reducing overcrowding in a hospital. Similar results were shown by (Babashov et al. 2017) and (Shim and Kumar 2010) by decreasing patients' waiting time in an emergency department. (Rau et al. 2013) and (Uriarte et al. 2017) also used DES to reduce patient waiting time in treatment centers and the radiotherapy sector, respectively. Furthermore, (Al-Araidah, Boran, and Wahsheh 2012) applied the tool in an ophthalmology laboratory in order to reduce patients' waiting and appointment time. Regarding planning and capacity analysis, (Pinto et al. 2015) defined the ideal number of beds for a Brazilian hospital. For the balancing of staff work (Reynolds et al. 2011) applied the simulation to reduce the workload of an English pharmacy and (Pongjetanapong et al. 2019) used the tool to evaluate the effect of changes to staff levels in a cytology department.

We also found improvements using only Lean Healthcare. Even when not implemented systematically and comprehensively in the organization, Lean Healthcare can provide several benefits to health services (D'Andreamatteo et al. 2015). Among these benefits, the authors highlight improvements in productivity, costs, financial results, quality of service delivery, and patient and team safety and satisfaction. However, implementing Lean is long-lasting and challenging work in the health sector (Toussaint and Berry 2013). Lean transform the organizational culture from the inside out, requiring managers and leaders to become facilitators, mentors, and teachers and enable employees to take the initiative in making improvements.

Studies that show Lean Healthcare implementation can be found for the elimination of processes that do not add value to the patient (Teichgräber and De Bucourt 2012) and reduction in the instrument collection stage (Kimsey 2010). (Laganga 2011) used lean methodology to increase patient care capacity, while (Papadopoulos, Radnor, and Merali 2011) used Lean Healthcare to reduce delays in receiving samples, prioritize urgent work, standardize processes and anticipate problems identification.

When used jointly, Lean and DES have three goals: to teach, evaluate, and facilitate the process. In order to evaluate, it allows the execution of experiments and the evaluation of their results. It should be employed after holding the team meeting, testing ideas, and creating new solutions (Robinson et al. 2012). The use of DES and Lean Healthcare in hospital settings may bring more quality and efficiency to patients and management (Gaba 2004). In addition, the patient flow may be optimized and served as a motivational factor for employees (Salam and Khan 2016). (Swick et al. 2012) state that hospitals that integrate the tools offer an efficient method of strategic planning and provide employees with a privileged view of how to reduce waste and add value. Moreover, it is possible to reduce patients' waiting time, decreasing employees workload, and promoting resources reallocation (Haddad et al. 2016; Bhat, Gijo, and Jnanesh 2014).

Finally, (Doğan and Unutulmaz 2016) and (Robinson et al. 2014) used the tools to transform static mappings into dynamics.

3. Materials & Methods

Modeling and simulation, used in the study, comprises three main phases: design, implementation, and analysis (Montevechi et al. 2010). In the first phase, i.e., design, we should perform the problem formulation. In this step, we define the process to be modeled, to specify the actions and goals (Balci 2011). The second step is the construction, validation, and documentation of the conceptual model. We may use many languages, but opting for a simulation-oriented is ideal (Montevechi et al. 2010). The last stage is the input data modeling, e.g., time, cost, percentages, capacities, among others, varying according to the purpose of each study (Banks et al. 2010; Montevechi et al. 2010).

The second major phase (implementation) covers the steps of construction, verification, and validation of the computer model. The modeler must use familiar software for computer model construction. Thus, we perform the verification, ensuring that the computer model programming corresponds to the conceptual model (Sargent 2013). Finally, we carry out the validation through hypothesis tests, confidence intervals, and comparison charts (Sargent 2013).

For the analysis, the modeler starts the planning, construction, and analysis of the experiments. In this step, we elaborate possible scenarios, besides the use of experiment planning and statistical tests (Montgomery and Runger 2018). After the experiments, the scenarios are analyzed, obtaining the conclusions and the answers to the problem defined in the first phase.

Based on the three major steps described, we conduct the study as follow:

(1) Conceptual Modeling: we developed the conceptual model using the IDEF-SIM language. We chose because it is considered specific for DES, facilitating computer programming (Montevechi et al. 2010).

(2) Computer Modeling: we used FlexSim Healthcare software.

(3) Model Execution and initial analysis: we decided to perform replicas to confirm the patient and the hospital unit current state. These executions also allowed the choice of the first set of DoE decision variables.

(4) Design and analysis of experiments: we chose a complete factorial arrangement for screening the most significant decision variables. Then, we adopted the Response Surface

Methodology (RSM), using the Composite Face Centered (CFC) design for site optimization. In addition, we carried out a DoE to find out the ideal number of employees at each shift. Some adjustments were made when needed.

(5) Confirmation runs: the optimal values of the decision variables found in the experiments were used in the model to confirm the results.

4 . Results and Discussion

4.1. Case Study

The Emergency Department (ED) studied aims to analyses its expansion to meet the increase of its demand. The DE is located in Canada and its expansion is due to the closure of four small units in nearby locations. Thus, the DE will absorb all this demand.

Patients arrive at the ED alone or by ambulance. Both are triaged and ranked according to severity. This classification is given according to the Canadian Triage Acuity Scale (CTAS). CTAS level I corresponds to the most severe level, resuscitation (blue, to be seen immediately); level II is emergent (red, to be seen <15 minutes); level III is urgent (yellow, to be seen <30 minutes); Level IV is less urgent (green, to be seen <60 minutes) and level V is nonurgent patient (white, to be seen <120 minutes). Patients arriving by ambulance, after triage, go straight to the care. Patients who arrive on their own go to the registry and expect the transfer to their appointment. CTAS level I, II and III patients go to a bed area (45 beds and 3 more for mental health), while those of CTAS IV and V follow to the vertical area (10 seats).

When it arrives at the bed area (BA) or the vertical area (VA), the patient undergoes two evaluations made by the nurse and the physician. Then the ward clerk receives and records the patient's prescription. These prescriptions may include laboratory tests (blood, urine), medical procedures, and diagnostic imagining (DI). Such procedures are assigned according to the patient's category, shown in Table 1. If DI is required, a nurse and a porter must escort CTAS level I patients. For other patients, only the porter is required.

Table 1. Patient's category and specialist

Treatment Category	Specialist	Proportion
General/Minor issues	-	17.7%
Respiratory	Respiratory Therapist	14.6%
Gastroenterology	Gastroenterologist or Internal Medicine	11.9%
Orthopedic	Orthopedist	10.3%
Cardiology	Cardiologist or Internal Medicine	9.7%
Dermatology	Dermatologist	8.3%
Genitourinary	Urologist and Nephrologist or Internal Medicine	6.1%
Ear, nose, and throat	Otolaryngologist	4.9%
Mental Health	Crisis and Psychologist	4.3%
Neurologic	Neurologist	4.2%
Ambulatory Return Visit	-	4.0%
Ophthalmology	Ophthalmologist	1.8%
Gynecology	Gynecologist	1.1%
Substance Misuse	Crisis and Psychologist	0.9%

After waiting for the exam results, the patient may go through an appointment with a specialist or move on to the next stage. If the patient goes through the appointment, he must wait until the specialist arrives, since they are not in the ED. In the next step, the patient may be discharged or go through monitoring. After monitoring, the patient goes to the SSU (10 available beds), where it can remain from one to three days.

The ED Nurses divide into two teams. The first team is responsible for patients CTAS level I and II (EDN1), and the second is responsible for CTAS level III, IV, and V (EDN2). They work in four shifts: 07:00 a.m. to 07:00 p.m.; 09:00 a.m. to 09:00 p.m.; 11:00 a.m. to 11:00 p.m. and 07:00 p.m. to 07:00: a.m. Physicians and Triage Nurse (TN) also start working on the shifts mentioned. In addition, three porters work in the following shifts: 07:00 a.m. to 07:00 p.m.; 10:00 a.m. to 06:00 p.m. and 07:00 p.m. to 07:00 a.m.

Faced with the expected expansion, the study aims to analyses whether ED can absorb the full demand of patients. Other issues to be solved are ideal numbers of resources (TN, EDN, physicians, and porters); ideal number of beds in BA, chairs in VA and beds in SSU; reduction in the time of care after going through the triage, in the time to transfer from BA/VA to SSU and LOS.

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4.2. Conceptual Modeling

We performed the conceptual modeling of the system through the IDEF-SIM language, developed by (Montevechi et al. 2010). The symbols used are directly translated from the conceptual model for the computer model, presenting elements of the simulation, e.g., entities, locations, resources, functions, controls, logical rules and transport (Pereira et al. 2015). Figure 1 shows the patient flow.

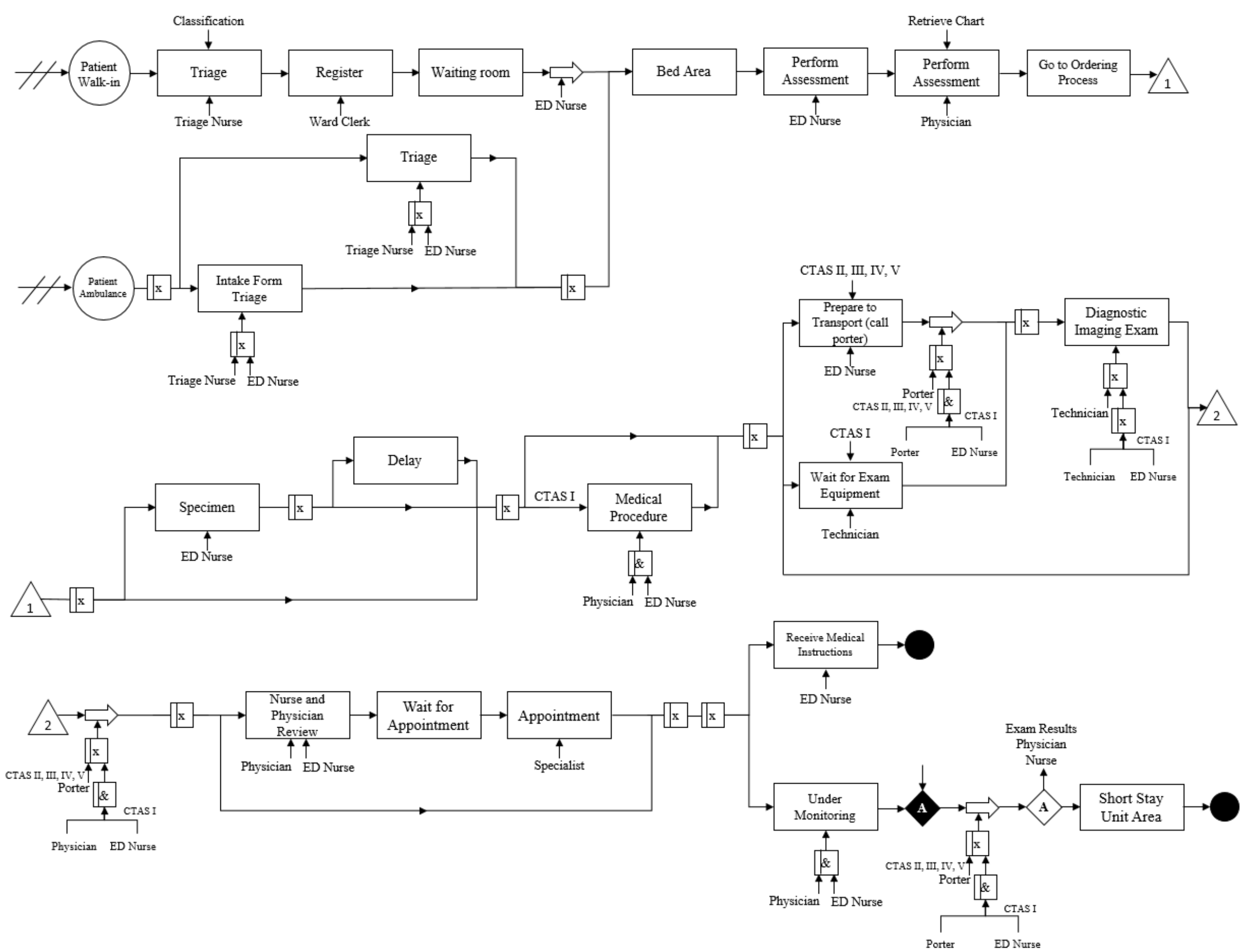

Figure 1. Conceptual Modeling

We have validated conceptual modeling through face-to-face validation, where experts verify if the model matches the real system. Data collection and modeling were based on historical data. Additional information is presented in Appendix A, e.g., the processing time for each activity and resources.

4.3. Computer Modeling

We built the computational model in FlexSim Healthcare® software, programming three different processes. First, we program patient flow according to CTAS levels, because each level may indicate different paths and require different resources. The second process involves the exams procedures, from collection to the result. It implies directly in the patient waiting time, since it can only follow through the flow after the results, characterizing a necessary time, but that does not add value for them. Finally, we construct other processes, such as staff meetings that affect patients' waiting time but do not add value to the flow and must be eliminated or reduced as much as possible. After the model was built, the experts performed the verification. Validation also occurred between the modeling team and the specialists. The model was validated for each flow constructed according to the CTAS level.

4.4. Model Execution and Initial Analysis

After validation, we obtain the metrics for the initial analyses. Thereby, according to the simulation, the ED cannot meet expected demand. Thus, the results obtained were:

- On average, 1504 patients arrived in the model;
- On average, 258 (17.2%) patients were completed treated in the simulated period;
- Around 1157 patients (76.9%) did not even make it triage;
- On average, LOS was 2213.7 minutes;
- Patients wait about 404.3 minutes to be seen after triage;
- Patients who need to go to SSU wait, on average, 367.4 minutes to be transferred.

Regarding the results, the number of patients that do not go through the risk classification is alarming. In addition, after triage, the average waiting time is around 404.6 minutes, which corresponds to approximately 3.5 times what the patient with CTAS level V should wait at most. Moreover, patients expect to be attended after the risk classification on average 25.9, 164.6, 332.2, 649.7 and 419.5 minutes for the CTAS levels I, II, III, IV, and V, respectively, which does not meet the specifications.

For the initial analysis, much of the resources are idle, e.g., triage nurses and physicians. Most nurses and porters are waiting for empty locations. Consequently, the patient's flow is stuck. We

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infer that the number of beds in the BA, mental bed area (MBA), SSU, and VA are occupied most of the time.

In this sense, we proposed improvements by the principles of patient continuous flow. These improvements are intended to reduce patient waiting times, increasing the amount of time to add value. Thus, because sites are the limiting resources, we investigated the interaction between them and their influence on the model behavior.

4.5. Design and Analysis of Experiments

To design the experiments, we used DoE techniques, which studies the influence of factor variation on the events responses. Among DoE techniques, the 2k factorial design establishes the "level +" and "level -" of the experiments. The k value is the number of variables that presented the upper and lower level (Montgomery 2017). We choose the variables related to the number of locations and resources in each area since these were identified as the most model limiting characteristics.

4.5.1. Design and Analysis of Experiments for Locations

For the first set of experiments analyzed, we defined a complete factorial 24, and the variables are the number of locations. We estimated deterministically the required site and staff number due to the demand for each area using Equation (1). The results were rounded to the next integer value and are presented in Table 2.

$$Q_i = \frac{t_i * p_i}{60\ min} \qquad (1)$$

Where:

Qi = Number of locations or staff per patient/hour;

ti = Average time (minutes) that a patient stays in the area or needs a resource;

pi = Daily average number of patients arriving in area i or needing the resource;

To determine the levels of DoE, we used a 20% margin of Qi to define "level -" and "level +". The results were rounded down and up, respectively, and are shown in Table 2.

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Table 2. Variables related to locations and DoE parameters

Variable	Number of location		DoE Parameters		
	Current	Ideal	Low Level	Centre Point	High Level
SSU	10	30	10	20	30
BA	45	49	45	49	53
MBA	3	4	3	4	5
VA	10	13	10	13	15

The performance measures defined in response to DoE were:

(i) Weekly treated patients;

(ii) LOS;

(iii) Time for the patient to be attended after triage;

(iv) Time to transport the patient to SSU.

We chose to use this order in all analyses, since the authors judged more important the number of treated patients, followed by the time spent in the hospital.

The number of SSU beds was the variable that affects all the chosen metrics in a significant way. Based on the charts and the Lenth's method, the number of beds and seats in SSU, BA, MBA, and VA, and some interactions were identified as statistically significant. Figure 2 shows the Pareto's graph for the analyzed metrics. The interaction of some variables hinders the performance of the ED since the locations are used together in some specific points of the model. In this way, we did not remove any variable from the analyses.

In order to obtain more fit metamodels to the system and to identify eventual curvatures in the objective functions, we chose to perform an RSM, through the CFC, defining the minimum, maximum and central numbers for each site (Table 2). Using this design, we got seven central points and four axial points, resulting in another 31 experiments. We analyzed the same performance measures and we obtained an R2 fit of 90.6% for measure (i); 93.1% for (ii); 95.2% for (iii) and 98.6% for (iv) and a predicted R2 of 82.0%; 72.7%; 83.5% and 95.6%, respectively.

The results indicated that the best combination of factors is:

- 30 beds in SSU;
- 45 beds in BA;
- 5 beds in MBA;

- 15 seats in VA;

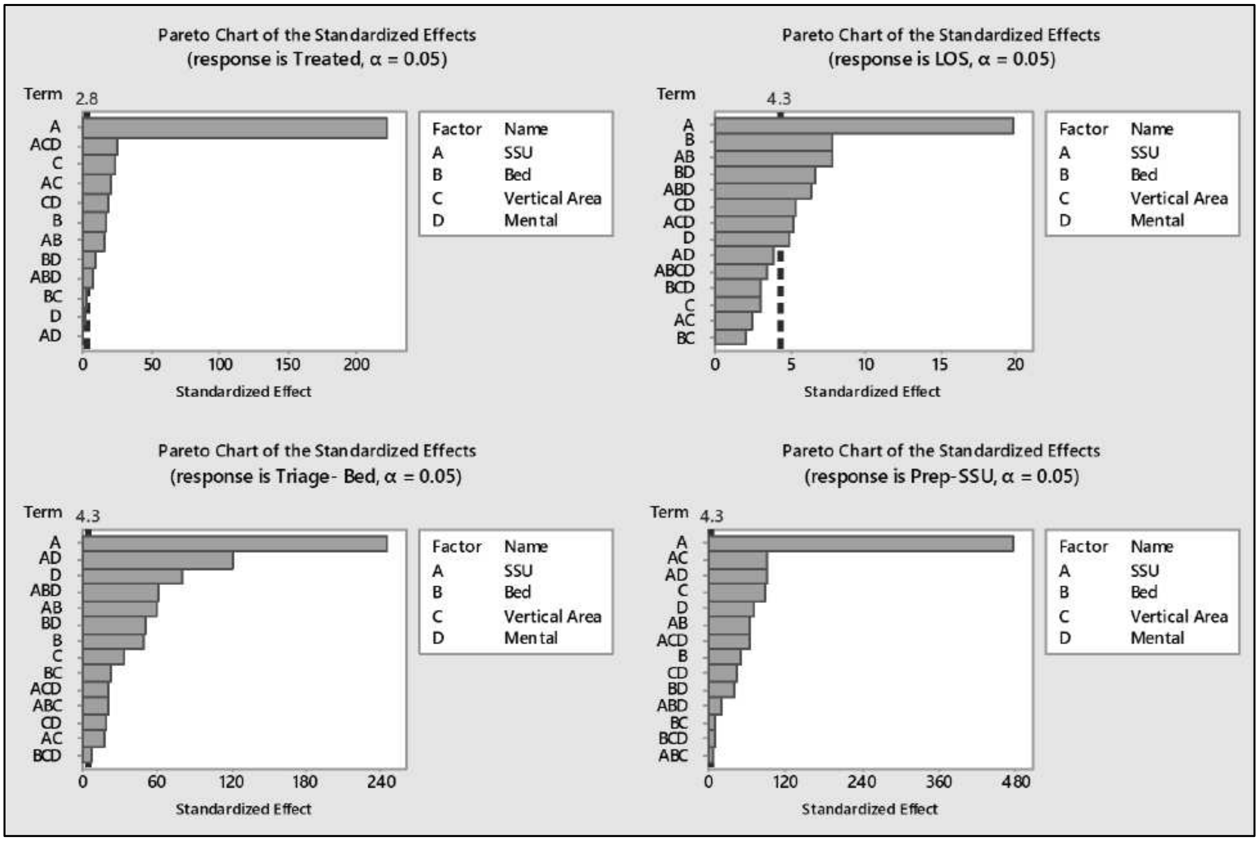

Figure 2. Pareto Chart for metrics (i), (ii), (iii) and (iv)

To verify the result of the scenario, the model was replicated ten times under the same conditions as the current state. In this scenario, the resources do not have a set shift. Thus, analyzing the same parameter studied, we observe:

- On average, 1505 patients arrived in the model;
- On average, 1436 (95.4%) patients were completed treated in the simulated period;
- All patients make it triage;
- On average, LOS was 436.0 minutes;
- Patients wait about 25.7 minutes to be seen after triage;
- Patients who need to go to SSU wait, on average, 128.5 minutes to be transferred.

Compared to the current state, all patients underwent triage, showing that patient flow became more continuous. Still, the number of treated patients increased by around 590%. On the other hand, waiting time to be attended after triage was an average of 25.7 minutes, 5.5 minutes for

CTAS I, 11.0 minutes for CTAS II, 19.6 minutes for CTAS III, 37.5 minutes for CTAS IV and 40.9 CTAS V.

Despite the increasing number of patients and the decreasing in LOS and waiting time to be attended after triage, the resources are not dimensioned. In other words, the staffs are still idle. Thus, the second scenario has as objective the sizing of resources in each group and shift.

4.5.2. Design and Analysis of Experiments for Resources

As mentioned, in the previous scenario, the resources were not defined. Then, we used Equation 1 to define the ideal number of staff per hour. We performed a DoE design 24 to determine the influence of staffing on each shift for TN, EDN1, EDN2, and the physicians. Furthermore, we defined an arrangement 23 for the porters since they have only three start shift options. The maximum number of staff per hour was considered to define the "level +". Table 3 shows the level of each resource group.

Table 3. DoE variables levels for resources

	Shift				**Resource**
	07:00 a.m. 07:00 p.m.	**09:00 a.m. 09:00 p.m.**	**11:00 a.m. 11:00 p.m.**	**07:00 p.m. 07:00 a.m.**	
Level-	1	0	1	1	**TN**
Level+	2	1	2	2	
Level-	4	0	1	4	**EDN1**
Level+	8	2	2	8	
Level-	3	1	1	3	**EDN2**
Level+	6	2	2	6	
Level-	3	0	2	3	**Physician**
Level+	6	2	1	6	
	07:00 a.m. 07:00 p.m.	**10:00 a.m. 06:00 p.m.**	**07:00 a.m. 07:00 p.m.**		
Level-	2	2	2		**Porter**
Level+	3	3	3		

The results presented by DoE show that the amount of staff in each shift is statistically significant for at least one of the chosen metrics. In this way, we did not remove any input variables. After the analysis and some adjustments, we determined the ideal number of resources in each group and shift, presented in Table 4. In addition, we proposed a change in the shift of the porters to the same as the other staffs.

Table 4. Resource number for shift and group

Staff	Shift			
	07:00 a.m. 07:00 p.m.	09:00 a.m. 09:00 p.m.	11:00 a.m. 11:00 p.m.	07:00 p.m. 07:00 a.m.
TN	1	0	1	2
ED1	4	2	0	3
ED2	3	1	2	3
Physician	3	2	2	3
Porter	3	1	0	3

"Level+" was chosen mostly in the shifts from 9:00 a.m. to 9:00 p.m., because the demand is higher at these times. Defining the ideal number of resources and executing the model with ten replicates, we have:

- On average, 1504 patients arrived in the model;
- On average, 1442 (95.8%) patients were completed treated in the simulated period;
- All patients make it triage;
- On average, LOS was 511.6 minutes;
- Patients wait about 45.8 minutes to be seen after triage;
- Patients who need to go to SSU wait, on average, 97.1 minutes to be transferred.

With the resources dimensioning, the number of patients who completed the care continues the same as the first scenario. There was an increase in the LOS average, around 75 minutes. The waiting time to be attended after triage was on average 45.8 minutes, increasing about twice. The waiting time after screening for each CTAS was 6.6 minutes for CTAS I, 13.3 minutes for II, 24.7 minutes for III, 74.0 minutes for IV and 138.0 for V. In addition, we noticed that staff workloads were balanced. For this reason, thinking of improvements that can make a continuous patient flow and avoiding the patient waiting for a long time, the last improvement proposed is related to the number and scales of the specialist.

4.5.3. Specialists in ED

When the patients need a medical appointment, they must wait until the specialist arrives at ED, because they are not available in the unit. Among the specialists mentioned in Table 1, only the urologist, gynecologist, otolaryngologist, and ophthalmologist operate all the time. The other specialists work in shifts from 08:00 a.m. to 05:00 p.m. (on average). At other times, the internal medicine attends the patients who would be attended by the cardiologist, nephrologist, and gastroenterologist. Currently, there is only one specialist available for each specialty at each shift, except the Crisis Response, which has two doctors from 08:30 a.m. to 07:30 p.m.
Moreover, it is necessary to consider the response time after calling the specialists. Psychiatrists take between 1 and 6 hours to reach the unit, while neurologists can take 15 to 90 minutes (according to CTAS level) and Crisis Response specialists take about 5 minutes.
As the specialist's waiting is long, there is the possibility of reducing the patient's LOS through improvements that become the continuous flow proposed by the study. Among the 13 specialists, the most requested are psychiatrist, neurologist, and crisis response. Then, we have decided that these specialists need to be directly allocated to the ED. Thus, the patient could immediately be taken care of. In addition, we made some modifications in the shifts:

- Psychiatrist: a specialist all the time in the unit (avoids the delay that can reach 6 hours);
- Neurologist: a specialist in the same shift of the current state (08:00 a.m. - 05:00 p.m.), but allocated directly to the unit (avoiding a delay that can reach 90 minutes);
- Crisis Response: An expert all the time on the unit rather than two on the predetermined shift (08:30 a.m. - 07:30 p.m.). Although this specialist's response time is relatively short, we chose to allocate it directly to the unit.

After ten runs, we have:

- On average, 1496 patients arrived in the model;
- On average, 1441 (96.3%) patients were completed treated in the simulated period;
- All patients make it triage;
- On average, LOS was 450.7 minutes;
- Patients wait about 19.0 minutes to be seen after triage;
- Patients who need to go to SSU wait, on average, 137.2 minutes to be transferred.

As one of the actions that blocked the continuous patient flow is wait for the specialist, we observed that the LOS decreases by about 11.9%. In addition, the waiting time for patients requiring a transfer to SSU is, on average, 42.8 minutes below that requested.

4.6. Confirmation Runs

To confirm the proposed changes, we simulate the model with 30 replicas and a warm-up from Monday (00:00) to Tuesday (00:00). Data were collected from Tuesday to Tuesday. Table 5 presents the final configuration.

Table 5. Number of locations and resources

Local	Current	Future	Resource	Current	Future
BA	45	45	**TN**	3	4
MBA	3	5	**EDN1**	9	9
SSU	10	30	**EDN2**	8	9
VA	10	15	**Physicians**	12	10
			Porters	3	7

According to simulation results, we recommend that an additional two beds in the MBA and five chairs in the VA are required. Regarding the resources, it is necessary to hire one TN, one EDN2, four porters, and reduce two physicians. Table 4 lists the shift for each group. It was necessary to dimension the employees, avoiding, when possible, hire them. The number of beds in SSU directly affects patients' LOS. Then, the ideal number is 30 beds, which correspond, on average, 146.4 minutes of waiting for transfer to SSU. About the specialist, it is necessary to have a psychiatrist, a neurologist, and a mental health specialist directly assigned to the unit. With the proposed measures, the patient's LOS decreases by 1752.6 minutes. Table 6 presents the results of the current and future scenario.

After the proposed changes, the number of treated patients increased considerably, making their flow continuous during the process. In addition, patients are seen as expected after triage, according to the CTAS classification level.

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Table 6. Outputs for current and future scenario

Metrics (min)		Current Scenario		Future Scenario		Rate (mean)
		Mean	Confidence Interval	Mean	Confidence Interval	
Patients	**Input**	1504	-	1506	-	-
	Output	258	-	1444	-	560%
	Treated (%)	17.2	-	95.7	-	556%
	Triage (%)	23.1	-	100.0	-	433%
LOS	**Average**	2213.7	(2131.8 - 2295.6)	461.2	(453.7 - 468.7)	-79%
	CTAS I	2809.9	(1381.3 - 4750.1)	1072.2	(787.6 - 1356.8)	-62%
	CTAS II	3077.2	(2778.8 - 3375.6)	918.2	(880.9 - 955.5)	70%
	CTAS III	2219.3	(2051.2 - 2387.5)	452.7	(438.8 - 466.6)	-80%
	CTAS IV	1746.2	(1585.5 - 1907.9)	252.8	(246.1 - 259.5)	-86%
	CTAS V	1500.8	(903.5 - 2091.0)	299.9	(275.4 - 324.4)	-80%
Triage to Bed	**Average**	404.3	(369.7 - 439.0)	20.8	(19.8 - 21.8)	-95%
	CTAS I	25.9	(4.2 - 47.5)	11.2	(6.1 - 17.4)	-57%
	CTAS II	164.6	(121.6 - 207.7)	10.4	(6.1 - 16.3)	-94%
	CTAS III	332.2	(275.2 - 389.3)	13.7	(12.9 - 14.5)	-96%
	CTAS IV	649.7	(559.9 - 739.5)	26.9	(25.2 - 28.7)	-96%
	CTAS V	419.5	(131.0 - 707.9)	82.1	(64.6 - 99.7)	-80%
	Bed to SSU	367.4	(253.1 - 481.7)	146.4	(133.8 - 159.0)	-60%

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5. Conclusions

The present study aimed to propose a future state aligned with Lean Manufacturing concepts for a Canadian ED expansion. The purpose was to increase the number of treated patients and reduce LOS, without, however, compromising the quality of services and patient safety. In this way, we dimensioned the optimal number of beds for SSU, BA, MBA, and VA; defined the ideal number of resources; reduced LOS, waiting time after triage phase, and transfer to SSU. Hence, we used the Modeling and Simulation method, proposed by (Montevechi et al. 2010).

We constructed the conceptual model using the IDEF-SIM modeling technique and the input data we obtained through the ED's historical data. We used FlexSim Healthcare® software to build the computer model, and validate it with experts in the field. For the experiments, at first, we used DoE to verify the influence of the expansion of the area (BA, MBA, SSU, and VA) in the chosen metrics. We also use DoE to determine the optimal number of resources at each shift and its optimal scale to meet changing demand throughout the day and week. Finally, experiments were carried out to reduce patients' waiting time by specialists. Among the evaluated metrics, we chose to prioritize them as follow: (i) weekly treated patients; (ii) LOS; (iii) time for the patient to be attended after triage and (iv) time to transport patient to SSU.

After the analysis, we can state that the model in its current state cannot meet the demand. For the future state, we observed that DES and Lean integrated into the DoE allowed increasing the number of patients that went through the triage process from 23.1% to 100.0%. The LOS of the patient reduced from 2231.8 to 461.2 minutes. Moreover, the waiting time after triage is by the CTAS level of Canadian law. In this way, all the questions proposed in the objective were answered and, using the principles of the continuous flow, there was a significant improvement in the process.

Regarding the limitations of this study, we found difficulties in executing replicates due to the computational effort required. For this reason, the simulation warm-up was only one day, and the simulation performed for one week (Tuesday to Tuesday). Finally, for future work, we suggest investigating other resources, e.g., technicians, receptionist, and ward clerk. In addition, the economic viability of different layouts can be assessed for labs and DI, which are relatively distant from the beds where patients are treated.

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Appendix A - Processing Time

Table A. Process time and required staff

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Task	Process Time (min)	Staff Required					
		Triage	Registration	ED Nurse	Physician	Admin	Porter
Triage	T(4,7,10)	x					
Escort to Bed	T(0.5,1,2)			x			
Register Patient	3		x				
Nurse Assessment	CTASIV/V: 5; CTASIII: 10; CTASII: 15			x			
Physician Assessment	T(7,12,15)				x		
Write Patient Orders	T(2,4,5)				x		
Initiate DI/Lab	T(2,2.5,3)					x	
Prepare Patient for DI	3			x			
Receive/Add Tests to Chart	1			x		x	
Review Tests (Nurse)	1			x			
Review Tests (Physician)	2				x		
Take Specimen	T(4,6,15)			x			
Medical Procedure*	T(15,20,60)			x	x		
Initiate Consult	2					x	
Arrange Consultant	2					x	
Discuss with Specialist	3				x		
Make Disposition	20% - 30; 80% - 3				x		
Admission Form	2			x			
Determine Care Plan	T(7,10,12)				x		
Contact Specialist	5				x		
Transport Patient to SSU (I and II)*	T(15,20,25)			x			x
Care Plan and Final Orders	T(2,4,10)				x		
Give Instruction	T(2,5,12)			x			
Prepare Patient	T(1,2,4)			x			
Shift Change Written/Verbal	5				x		
EHS Call	1	x		x			
EHS Triage	T(4,7,10)	x		x			
Prepare Room for Next Patient	1			x			
Huddle*	10	x	x	x	x	x	

*denotes a task which requires all staff indicated (x).

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