Lean Thinking by integrating with Discrete Event Simulation and Design of Experiments: an emergency department expansion

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Background. Many management tools, such as Discrete Event Simulation (DES) and Lean Healthcare, are efficient to support and assist health care quality. In this sense, the study aims at using Lean Thinking (LT) principles combined with DES to plan a Canadian emergency department (ED) expansion and at meeting the demand that comes from small care centers closed. The project`s purpose is reducing the patients' Length of Stay (LOS) in the ED. Additionally, they must be assisted as soon as possible after the triage process. Furthermore, the study aims at determining the ideal number of beds in the Short Stay Unit (SSU). The patients must not wait more than 180 minutes to be transferred.

Methods. For this purpose, the hospital decision-makers have suggested planning the expansion, and it was carried out by the simulation and modeling method. The emergency department was simulated by the software FlexSim Healthcare®, and, with the Design of Experiments (DoE), the optimal number of beds, seats, and resources for each shift was determined. Data collection and modeling were executed based on historical data (patients' arrival) and from some databases that are in use by the hospital, from April 1st, 2017 to March 31st, 2018. The experiments were carried out by running 30 replicates for each scenario.

Results. The results show that the emergency department cannot meet expected demand in the current state. Only 17.2% of the patients were completed treated, and LOS was 2213.7 (average), with a confidence interval of (2131.8-2295.6) minutes. However, after changing decision variables and applying LT techniques, the treated patients' number 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%. The time to be attended after the triage decrease from 404.3 minutes to 20.8 (19.8-21.8) minutes, around 95.0%, while the time to be transferred from bed to the SSU decreased by 60.0%. Moreover, the ED reduced human resources downtime, according to Lean Thinking principles.

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2   **experiments: an emergency department expansion**

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12   **Abstract**

13   Many management tools, such as Discrete Event Simulation (DES) and Lean Healthcare, are
14   efficient to support and assist health care quality. In this sense, the study aims at using Lean
15   Thinking (LT) principles combined with DES to plan a Canadian emergency department (ED)
16   expansion and at meeting the demand that comes from small care centers closed. The project`s
17   purpose is reducing the patients' Length of Stay (LOS) in the ED. Additionally, they must be
18   assisted as soon as possible after the triage process. Furthermore, the study aims at determining
19   the ideal number of beds in the Short Stay Unit (SSU). The patients must not wait more than 180
20   minutes to be transferred. For this purpose, the hospital decision-makers have suggested planning
21   the expansion, and it was carried out by the simulation and modeling method. The emergency
22   department was simulated by the software FlexSim Healthcare®, and, with the Design of
23   Experiments (DoE), the optimal number of beds, seats, and resources for each shift was
24   determined. Data collection and modeling were executed based on historical data (patients'
25   arrival) and from some databases that are in use by the hospital, from April 1st, 2017 to March
26   31st, 2018. The experiments were carried out by running 30 replicates for each scenario. The
27   results demonstrate that the emergency department could not meet the expected demand in its
28   first approach. Only 17.2% of the patients were fully treated, and the LOS was 2213.7 minutes
29   (on average), with a confidence interval of (2131.8-2295.6) minutes. However, after changing
30   decision variables and applying LT techniques, the number of treated patients increased to
31   95.7% (approximately 600%). The average LOS decreased to 461.2, with a confidence interval
32   of (453.7-468.7) minutes, about 79.0%. The time to be assisted attended after triaged decreased
33   from 404.3 minutes to 20.8 (19.8-21.8) minutes, around 95.0%, while the time to be transferred

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35   downtime, according to Lean Thinking principles.

36   **1. Introduction**

37   Improvements in the health services quality sector are significant because it directly affects the

38   patient's satisfaction and safety. In fact, the health industry is one of the largest in the world

39   (Bhat, Gijo, and Jnanesh, 2014). According to (World Bank, 2019), in 2016, the world spending

40   on health was around 10.0% of total GDP. The United States was the country who invested the

41   most per capita, totaling US$ 9,869.74, followed by Switzerland. Canada is among the top 20

42   countries who invest in health per capita, US$ 4,458.21 in total, against the world average of

43   1,025.29 (World Bank, 2019).

44   Given the importance of the world health system, decision-makers seek out solutions to make

45   more efficient and agile processes. Besides that, financial resources and skilled labor are

46   becoming scarce. Consequently, decision-makers apply management tools for analysis and

47   process improvements in forecasting, restructuring, and reducing costs. Indeed, many real

48   problems are really complex. Rarely one single approach or tool is enough to reach solutions

49   (Brailsford et al., 2018).

50   Discrete Event Simulation (DES) is one of the tools used to improve it and forecast process

51   behavior. DES is the imitation of a dynamic process, using a computer model for evaluating,

52   measuring and improving the performance of any system (Harrell, Ghosh & Bowden, 2012)

53   without any physical risks and additional costs (Banks et al., 2010; Montevechi et al., 2007).

54   Moreover, the literature defines DES as the model development process (hypothetical or real)

55   aiming at performing experiments (Negahban & Yilmaz, 2014). Hence, predicting the behavior

56   of real and complex systems becomes a really tough challenge, because they are influenced by a

57   set of internal and external factors, and the experience is often unfeasible to perform (Budgaga et

58   al., 2016). Therefore, DES is the first step in evaluating a change proposal, obtaining insight into

59   a set of potential impact, and supporting management to make decisions and implement real-

60   world improvements (Bem-Tovim et al., 2016; Dengiz & Belgin, 2014).

61   In addition to DES, Lean Manufacturing is also efficient in improving processes. Lean emerged

62   in the 1950s when the Japanese automotive industry faced a challenging scenario. The market

63   was limited and a wide variety of vehicles were demanded. It was in contrast to the current

64   philosophy of mass production until then (few varieties produced on a large scale). Furthermore,

65   Japan`s economy was weakened, with low capital availability and few international trade

66   relations. Also, the acquisition of modern western production technologies became harder

67   (Womack, Jones & Roos, 1990). To meet this challenge, the Japanese automaker company

68   Toyota began developing a new system of production, the Toyota Production System (TPS).

69   Taiichi Ohno, credited as the facilitator of the TPS, aimed to serve customers in the shortest

70   time, at the highest quality and the lowest possible costs. Thereby, it would be necessary to focus

71   all effort on activities that add value to the customer and eliminating wastes (Graban, 2016).

72   Over time, Lean has expanded throughout other sectors, such as healthcare, which has been

73   renamed to Lean Healthcare (LH).

74   Finding wastes in manufacturing has been adapted to health services. Defects correspond to poor

75   medication administration or incorrect doses, while overproduction characterizes as unnecessary

76   diagnostic procedures. Inefficient transportation is inadequate layouts and laboratories away

77   from collection points. The inappropriate layout may also link to the unnecessary movement of

78   nurses and doctors. Waiting features idle employees with uneven workloads and patients waiting

79   for service. The stock is characterized as expired supplies and super-processing, e.g., data in the

80   patient registry that will not be used later (Graban, 2016).

81   Finally, performing experiments with DES is essential for the analysis of the current scenario

82   and for proposing improvements. The experiment is indicated when the modeler desired to

83   optimize the process (Banks et al., 2010). A good experiment demand to set the parameters so

84   the responses may approach the required values with the lowest variability (Montgomery &

85   Runger, 2018). The best way to evaluate several factors in a process is by using suitable

86   techniques to plan the experiments, e.g., factorial experiments, Taguchi, and Plackett-Burman

87   (Montgomery & Runger, 2018). In this case, the factors change simultaneously, observing if

88   there is an interaction between them. Moreover, it generally requires fewer tests than the "best

89   guess" strategy, where the expert performs random experiments. According to (Banks et al.,

90   2010), with some adaptations in the factorial arrangements, we may evaluate the individual,

91   interactions, and quadratic effects.

92   Thereby, the three presented techniques, when used together, show effective results in health

93   processes. In this sense, this study aims to plan the expansion of a Canadian emergency

94   department (ED). The expansion is necessary because four nearer small centers were closed and

95   all the patients needed to be attended to in the new ED. According to LH principles, the study

96   aims to define the ideal number of resources, beds for care, and beds in the Short Stay Unit

97   (SSU). The project purposes of reducing the patients' Length of Stay (LOS) in the ED.

98   Additionally, they must be taken care of as soon as possible after going through the triage.

99   Furthermore, it is necessary to determine the ideal number of SSU beds because the patients

100 should not wait for more than 180 minutes for their transfer.

101 In order to contribute to the literature, the study uses the Design of Experiments (DoE) to

102 determine the resource numbers influence on each shift, in addition to identifying the main

103 limiting factors of physical resources for the ED expansion. The simulation also allows

104 evaluating the influence of demand variation throughout the day and week in the future scenario.

105 The paper is divided as follows: the next section presents a literature review of DES and Lean in

106 hospital environments, followed by the methodology. The subsequent sections present the results

107 and discussions to conclude the study.

108 **2. Literature Background**

109 This section describes the studies that used Discrete Event Simulation and Lean Healthcare

110 to improve the healthcare sector. Moreover, this section presents the two main tools used in

111 our paper, the IDEF-SIM technique and the Design of Experiments.

112

113 *2.1. Discrete Event Simulation and Lean in healthcare systems*

114 Performing DES in healthcare is not new, dating back to the 1960s (Pitt, 2008). However, since

115 then, there has been considerable growth for its interest. According to (Arisha & Rashwan,

116 2017), this progress is strong evidence that the simulation provides better decisions in health

117 services management without compromising patient safety. This advantage has increasingly

118 attracted the attention of hospitals and health authorities (Cheng et al., 2017). However, experts

119 in healthcare simulation claim that its use is more complicated than in other areas (Tako &

120 Robinson, 2015). The main problems found in the healthcare simulation are less evident

121 structure; the system is complex; more significant effort to collect and access data; barriers due

122 to ethical issues; client's shortage of time; and more difficulty in ensuring implementation.

123 Despite the difficulties, it is possible to find studies with positive results linked to costs, capacity,

124 wait and stay time, and levels of service and losses. (Zhou & Olsen, 2018) applied DES for

125   medical supplies management and decreased the costs involved in the process by reducing

126   expired drugs. (Hussein et al., 2017) presented effective results reducing overcrowding in a

127   hospital. Similar results were shown by (Babashov et al., 2017) and (Shim & Kumar, 2010) by

128   decreasing patients' waiting time in an emergency department. (Rau et al., 2013) and (Uriarte et

129   al., 2017) also used DES to reduce patient waiting time in treatment centers and the radiotherapy

130   sector, respectively. Furthermore, (Al-Araidah, Boran & Wahsheh, 2012) applied the tool in an

131   ophthalmology laboratory to decrease patients' waiting and appointment time. Regarding

132   planning and capacity analysis, (Pinto et al., 2015) defined the ideal number of beds for a

133   Brazilian hospital. In the balancing of staff work, (Reynolds et al., 2011) applied the simulation

134   to reduce the workload of an English pharmacy and (Pongjetanapong et al., 2019) used the tool

135   to evaluate the change effect to staff levels in a cytology department.

136   Although these studies present positive results, we found some limitations in them. Some papers

137   did not consider variables and statistical distributions for different workgroups (Reynolds et al.,

138   2011) and processes (Rau et al., 2013). (Pinto et al., 2015) state that the simulation results have a

139   slight underestimation, although it seems reliable and more effective for decision making than

140   empirical calculations. Although articles use powerful tools jointly with DES, some studies do

141   not test the interaction of resources, locations, and factors using the "best guess" approach (Al-

142   Araidah, Boran & Wahsheh, 2012; Uriarte et al., 2017). In contrast, (Hussein et al. 2017) use

143   DoE to observe the interaction of two factors in their scenarios. Nevertheless, they did not

144   observe the interaction in the resource number in each shift (present in this study). (Shim &

145   Kumar, 2010) state that the simulation did not take into account the varying resource capacities

146   (doctors and nurses) and locations (workstations from the sorting station to the payment station)

147   involved in the emergency care process. Finally, (Babashov et al., 2017) use simulation to

148   determine the average waiting time for all patients overall, not for each patient type.

149   It was also possible to verify improvements using only LH. Even when not implemented

150   systematically and comprehensively in the organization, LH can provide several benefits to

151   health services (D'Andreamatteo et al., 2015). Among these benefits, the authors highlight

152   improvements in productivity, costs, financial results, quality of service delivery, and patient and

153   team safety and satisfaction. However, implementing Lean is long-lasting and challenging work

154   in the health sector (Toussaint & Berry, 2013). Lean transform the organizational culture from

155   the inside out, requiring managers and leaders to become facilitators, mentors, teachers, and

156   enable employees to take the initiative in making improvements.

157   Studies that show LH implementation can be found for the elimination of processes that do not

158   add value to the patient (Teichgräber & De Bucourt, 2012) and reduction in the instrument

159   collection stage (Kimsey, 2010). (Laganga, 2011) used lean methodology to increase patient care

160   capacity, while (Papadopoulos, Radnor & Merali, 2011) used LH to reduce delays in receiving

161   samples, prioritize urgent work, standardize processes and anticipate problem identification.

162   Although LH application is useful and essential in waste elimination and increasing patient

163   value-added time, it can be time-consuming, and the staff involved may resist the methodology.

164   When used jointly, Lean and DES have three goals: to teach, evaluate, and facilitate the process.

165   In order to evaluate, it allows the execution of experiments and the evaluation of their results. It

166   should be employed after holding a team meeting, testing ideas, and creating new solutions

167   (Robinson et al., 2012). The use of DES and LH in hospital settings may bring more quality and

168   efficiency to patients and management (Gaba, 2004). Also, the patient flow may be optimized

169   and served as a motivational factor for employees (Salam & Khan, 2016). (Swick et al., 2012)

170   state that hospitals that integrate these tools offer an efficient method of strategic planning and

171   provide employees with a privileged view of how to reduce waste and add value. Moreover, it is

172   possible to reduce patients' waiting time, decreasing employee workload, and promoting resource

173   reallocation (Haddad et al., 2016; Bhat, Gijo & Jnanesh, 2014). Finally, (Doğan & Unutulmaz,

174   2016) and (Robinson et al., 2014) used the tools to transform static mappings into dynamic.

175   Some limitations were found in these studies. (Salam & Khan, 2016) did not use arrival and staff

176   modeling. (Swick et al., 2012) limited the work to the daytime hours (more considerable

177   resources demand), and there was no adjustment for the night shift. (Bhat, Gijo & Jnanesh, 2014)

178   conducted the study in an environment where patient arrival cannot be adequately controlled.

179   (Haddad et al., 2016) conducted the study limited to a process that ignores interdependencies

180   with internal and external parts and laboratory tests. (Doğan & Unutulmaz, 2016) used only

181   Value Stream Mapping and did not carry out planned experiments.

182   *2.2. IDEF-SIM Technique*

183   The IDEF-SIM (Integrated Definition Methods - Simulation) process mapping technique was

184   developed by (Montevechi et al., 2010). It aims to support modeling work in the implementation

185 and analysis phase, reducing project time. The IDEF-SIM was created based on existing logical

186 elements in other mapping techniques, such as IDEF0, IDEF3 and flowchart (Peixoto et al.,

187 2017; Montevechi et al., 2010). To our best knowledge, there is no history of this technique used

188 in healthcare systems, although we have found in manufacturing (Pereira et al., 2015;

189 Montevechi et al., 2010) and transports (Lopes et al., 2017). Nevertheless, we chose to use this

190 technique because the symbols are directly translated from the conceptual model for the

191 computer model, presenting elements of the simulation, e.g., entities, locations, resources,

192 functions, controls, logical rules, and transport (Pereira et al., 2015). The symbols used in the

193 IDEF-SIM are (Peixoto et al., 2017; Montevechi et al., 2010):

194   a) Entity (circle): items processed in the system, e.g., raw materials, products, people.

195   b) Functions (rectangle): places where entities change or have delays, e.g. workstations,
196   conveyors, queues, stocks, beds, waiting lines.

197   c) Entity flow (arrow): direction that the entities follow in the model.

198   d) Resources (arrow under the rectangle): elements that move the entities or perform the
199   functions, e.g. people, such as operators, nurses, doctors.

200   e) Controls (arrow above the rectangle): rules used in the functions, e.g. rules of scheduling,
201   queuing, sequencing.

202   f) Movement (large arrow): it is used when there is a significant entity displacement.

203   g) Explanatory information (dashed arrow): it is used to include some explanation.

204   h) Rules for parallel and/or alternate flows: entities must follow in parallel (AND – "&");
205   alternatively (OR – "X"); or in parallel and/or alternate paths (AND/OR – "O").

206   i) Input flow (initial arrow): determines the input or entities' creation.

207   j) End of the system (painted circle): determines the end of a path.

208   k) Connection with another figure (triangle): divide the model into different figures.

209 *2.3. Design and Analysis of Experiments*

210 Design of Experiment (DoE), is considered one of the most relevant methodologies for

211 researchers performing applicable experiments. Moreover, according to Montgomery (2017),

212 DoE is a collection of statistical techniques capable of generating and analyzing experimental

213 projects in which several factors are varied at the same time. In DoE, the modeler chooses

214 different levels for the independent variable and can vary the factors simultaneously to study the

215   effects in the responses (dependent variables). These effects can be separate from each

216   independent variable or the interaction between them (Baril, Gascon & Vadeboncoeur, 2020).

217   When experimental designs are appropriately designed, trial and error analysis are avoided. Also,

218   it is possible to detect unimportant factors and simplify the simulation model. Among DoE

219   techniques, the 2^k factorial design is used as it requires few executions per factor, and data

220   interpretation can proceed mainly through arithmetic and graphs. In DoE, k value is the number

221   of factors that presented the upper (+) level and lower (-) level. In the literature, many studies use

222   DoE to plan and dimension resources around healthcare systems and EDs. (Baril, Gascon &

223   Vadebonceur, 2019) used the DoE to vary the number of doctors, nurses and beds to decrease

224   LOS in Canada. (Bhattacharjee & Ray, 2018) used DoE and DES to gain insights into

225   appointment scheduling. Moreover, (Gul, Guneri, & Gunal 2019) dimensioned an emergency

226   department to support natural disasters analyzing the number of nurses and doctors. Although

227   these articles use DoE, our study is different because we use DoE to dimension beds and the

228   number of resources in each shift.

229   **3. Materials & Methods**

230   Modeling and simulation, used in the study, comprises three phases: design, implementation, and

231   analysis (Montevechi et al., 2010). In the first phase, i.e., design, we should formulate the

232   problem. In this step, we define the process to be modeled, actions and goals. The second step is

233   the conceptual model building, validation, and documentation. It is possible to use many

234   languages, but opting for a simulation-oriented is desirable (Montevechi et al., 2010). The last

235   stage is the input data modeling, e.g., time, cost, percentages, capacities, varying according to the

236   study (Banks et al., 2010; Montevechi et al., 2010).

237   The second major phase, implementation, covers the steps of computer model building,

238   verification, and validation. The modeler must use familiar software for computer model

239   building. Thus, it is performed the verification, ensuring that the computer model programming

240   corresponds to the conceptual model (Sargent, 2013). Finally, it is carried out the validation

241   through hypothesis tests, confidence intervals, or sensitivity analysis (Sargent, 2013).

242   For the analysis, the modeler starts the planning, construction, and analysis of the experiments.

243   In this step, the modeler defines possible scenarios, besides the use of experiment planning and

244   statistical tests (Montgomery & Runger, 2018). After the experiments, the scenarios are

245   analyzed, and the team obtains the conclusions and answers to the problem.

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

247   **(1)**   Conceptual Modeling: we developed the conceptual model using the IDEF-SIM

248   technique. We choose this language because it is considered specific for DES, facilitating

249   computer programming (Montevechi et al., 2010).

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

251   **(3)**   Model Execution and initial analysis: we performed replicas to confirm the patient and

252   the hospital unit's performance measure in the current scenario. These executions

253   allowed us to choose the first set of DoE decision factors.

254   **(4)**   Design and analysis of experiments: we chose a complete factorial design because it

255   requires few runs per factor and a better fit model. It was carried out a DoE to find out

256   the ideal number of employees at each shift.

257   **(5)**   Confirmation runs: the optimal values of the decision variables found in the experiments

258   were used in the model to confirm the results.

259   **4. Results and Discussion**

260   *4.1. Case Study*

261   Cape Breton Regional Hospital (CBRH) is one of four facilities that make up the Cape Breton

262   Health Care Complex, a Canadian public health network of four hospitals, serving approximately

263   100,000 inhabitants. This paper aims to plan the expansion of a Canadian ED to meet the

264   demand that comes from the small closed care centers. The exponential increase in demand is

265   due to the closure of these small service units in locations near the CBRH.

266   Regarding the patients` flow, they arrive at the ED by themselves or by ambulance. Both are

267   triaged and ranked according to severity. This classification is given according to the Canadian

268   Triage Acuity Scale (CTAS). CTAS level I corresponds to the most severe level, resuscitation

269   (blue, to be seen immediately); level II is emergent (red, to be seen < 15 minutes); level III is

270   urgent (yellow, to be seen < 30 minutes); Level IV is less urgent (green, to be seen < 60 minutes)

271   and level V is non-urgent patient (white, to be seen < 120 minutes). Patients arriving by

272   ambulance, after triage, go straight to care. Patients who arrive on their own go to the registry

273   and expect the transfer to their appointment. CTAS level I, II, and III patients go to a bed area

274   (45 beds and 3 for mental health), while CTAS IV and V follow to the vertical area (10 seats).

275   When the patient arrives at the bed area (BA) or the vertical area (VA), he undergoes two

276   evaluations made by the nurse and the physician. Then the ward clerk receives and records the

277   patient's prescription. These prescriptions may include laboratory tests (blood, urine), medical

278   procedures, and diagnostic imagining (DI). Such procedures are assigned according to the

279   patient's category, shown in Table 1. If DI is required, a nurse and a porter must escort CTAS

280   level I patients. For other patients, only the porter is required.

281   **Table 1. Patient's category and specialist**

282   After waiting for the exam results, the patient may go through an appointment with a specialist

283   or move on to the next stage. If the patient goes through the appointment, he must wait until the

284   specialist arrives, since they are not in the ED. In the next step, the patient may be discharged or

285   go through monitoring. After monitoring, the patient goes to the SSU (10 available beds), where

286   it can remain from one to three days.

287   The ED Nurses are divided into two teams. The first team is responsible for patients CTAS level

288   I and II (EDN1), and the second is responsible for CTAS level III, IV, and V (EDN2). They

289   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.

290   and 07:00 p.m. to 07:00: a.m. Physicians and Triage Nurse (TN) start working at the same shifts.

291   In addition, three porters work in the following shifts: 07:00 a.m. to 07:00 p.m.; 10:00 a.m. to

292   06:00 p.m. and 07:00 p.m. to 07:00 a.m.

293   The study aims to analyze whether the ED can absorb the full demand from the closures. Other

294   issues to be solved are ideal numbers of resources (TN, EDN, physicians, and porters); the ideal

295   number of beds in BA, chairs in VA and beds in SSU; reduction in the time of care after going

296   through the triage, in the time to transfer from BA/VA to SSU and LOS. In this sense, the decision-

297   makers from the hospital proposed an approach to be tested by the simulation, called Initial

298   Planning (IP). We used DES because patients are individual entities with particular characteristics,

299   and the procedural flow depends on the CTAS of each one. Moreover, we chose DES over System

300   Dynamics because it has the most relevant characteristics of the work responses. We can say that

301   DES is better in decision-making, prediction, optimization, and comparison; it behaves well for

302   high rates of change and presents the high importance of tracking individuals. In addition, it is

303   suitable for systems with few entities and relatively small-time scales (Brailsford & Hilton, 2001).

4.2. Conceptual Modeling

304

305 We performed the conceptual modeling of the system through the IDEF-SIM language. Figure 1

306 shows the patient flow. We do not present percentages for each process because there are many

307 combinations based on the disease category and CTAS level.

308 **Figure 1. Conceptual Modeling**

309 As mentioned in section 2.2, the first circle represents the entities in the model, i.e., patients.

310 Rectangles mean delays in patient flow or procedure waiting (queue, exam results). Large arrows

311 represent transport for the patient, e.g., an exam performed in another room. Processes that need

312 a nurse or doctor are indicated with an arrow at the bottom of the rectangle, while the upper

313 arrows are controls. Symbols with an "x" inside them indicate an option (OR connection), while

314 symbols with an "&" represent an obligation (AND condition). The diamonds represent a

315 stopping point. The entity only follows the flow if the given conditions have been met. In the

316 model, the patient only continues the flow if the test results are ready, and there is an evaluation

317 by a doctor and a nurse. We ensure that the conceptual model presents high reliability since it

318 was validated by face-to-face validation, where experts verify if the model matches the real

319 system (Kleijnen, 1995; Sargent, 2013).

4.2.1. Data set

320

321 Data collection and modeling were based on historical data (patients' arrival) and from some

322 databases that are used in the hospital from April 1st, 2017 to March 31st, 2018. Through the

323 historical data, we observed that patients arrive at different rates hourly and daily. These rates are

324 repeated weekly. As soon as a patient is screened in the emergency room their information is

325 entered into the system. After that, Medietch® is used for registration, diagnostic codes, CTAS

326 level, treatment time, diagnostic test ordering, and blood exams. Figure 2 shows the patient's

327 arrival rate based on weekday and the two-hour scale.

328 **Figure 2. Arrival rate for each patient CTAS level**

329 We notice that the curves show similarity in the shape where the number of patients starts to

330 increase from 08:00 a.m. Moreover, the curves present a peak between 10:00 a.m and 12:00 p.m.

331 The days with the highest arrival rates are Tuesday, Wednesday and Thursday. Regarding the

332 type of patient, the curves do not differ significantly, showing the same behavior throughout the

333 day and week. Patients of CTAS level III and IV are predominant in the ED. As shown in Figure

334 1, the patient may be admitted for SSU placement or be discharged. Each of these stages

335 involves different resources, such as doctors, nurses, porters, and the patient suffers a delay

336 (process time). These times were estimates from the ED manager and nurses through Delphi

337 method (Table 2).

338   **Table 2. Processing Time and required staff**

339 As previously stated, ED patients may require a sample, consultation and/or lab work. The

340 patients may carry out a sample, e.g., blood work (BW) and specimen (SP). In addition, patients

341 may have DI exams, such as X-Ray (XR), electrocardiogram (EKG), echocardiogram (ECHO),

342 computerized tomography (CT), and ultrasonography (US) according to the CTAS level and

343 patient's category (Table 1). Table 3 summarizes the probability if the patient needs an exam.

344   **Table 3. Exam probability for each CTAS level**

345 There is a probability of the patient having an appointment with one or two specialists.

346 Moreover, when the patient needs an appointment with an expert, some response delay can

347 happen according to the specialist and the CTAS patient level. This delay occurs because the

348 specialist is not staffed in the ED unit all the time. They release the patient to the attending

349 physician while consulting the patient unless they are CTAS level I. After a specialist arrives in

350 the ED to consult with a patient, he attends all patients that need him, from lowest to highest

351 CTAS level. The specialist will start a new consult any time before the end of their shift. Any

352 patients still in need of a consult at the end of the day will be seen by Internal Medicine or wait

353 until the beginning of a specialist's shift the following day to receive an appointment. Internal

354 Medicine covers cardiology, nephrology and gastroenterology. Table 4 describes these data.

355   **Table 4. Specialist probability appointment for each CTAS level and data set**

356 *4.3. Computer Modeling*

357 We designed the computer model in FlexSim Healthcare® software, programming three

358 different processes. First, we programmed patient flow according to CTAS levels, because each

359 level may indicate different paths and require different resources. The second process involves

360 the procedures exam, from sample collection to the end result. It directly impacts the patient

361 waiting time, since it can only follow through the flow after the results, characterizing a

362 necessary time, but that does not add value for them. Finally, we construct global processes, such

363 as staff meetings that affect patients' waiting time and must be reduced to a sufficient level.

364 Figure 3 shows the computer model designed for the current scenario.

365   **Figure 3. Computer model screen in the FP scenario**

366   After the model was built, we performed a verification process. The process was conducted

367   through a face-to-face technique for each CTAS level. The specialists and the modeling team

368   analyzed the simulated model and agreed that it was as close to the real patient flow as possible.

369   We also performed the validation. If the modeled system is a non-observable system, it is

370   recommended using a subjective approach (Sargent 2013; Sargent, Goldsman & Yaacoub, 2016).

371   In this sense, we carried out a sensitivity analysis to see the model variability. We have tested

372   patient arrival rates at five levels: 100%, 75%, 50%, 25% and 10%. We got the mean LOS and

373   the percentage of treated patients to perform the validation. For LOS, in minutes, the simulations

374   show: 2213.7 (100%), 428.2 (75%), 352.9 (50%), 270.9 (25%), 243.4 (10%). We expected to

375   increase the number of patients, LOS would increase in the same way. This situation occurs

376   because the patients have to wait more time for available resources. Although, if we are

377   decreasing the arriving rate, the percentage of treated patients starts to increase because there are

378   more staff available for each one. Figure 4 shows the sensitivity analysis for the validation.

379   **Figure 4. Sensitivity analysis for validation (LOS and % Treated Patient)**

380   *4.4. Model Execution and Initial Analysis*

381   After the computer validation, the model was simulated for one week, and data were collected

382   from Tuesday to Tuesday. A warm-up of one day (Monday) was necessary to get a stable

383   process. Consequently, according to the computer simulation, the ED cannot meet the expected

384   demand for IP. Moreover, the obtained results were:

385   • On average, 1504 patients arrived in the model;

386   • On average, 258 (17.2%) patients were completed treated in the simulated period;

387   • Around 1157 patients (76.9%) did not even make it triage;

388   • On average, LOS was 2213.7 minutes;

389   • Patients wait about 404.3 minutes to be seen after triage;

390   • Patients who need to go to SSU wait, on average, 367.4 minutes to be transferred.

391   Regarding the results, the number of patients that do not go through the risk classification is

392   alarming. In addition, after triage, the average waiting time is around 404.3 minutes, which

393   corresponds to approximately 3.5 times what the patient with CTAS level V should wait at most.

394   Moreover, patients expect to be attended after the risk classification, on average 25.9, 164.6,

395   332.2, 649.7 and 419.5 minutes for the CTAS levels I, II, III, IV, and V, respectively, which does

396   not meet the specifications.

397   The result is unsatisfactory and below the current quality standard offered by the hospital. We

398   conclude the initial ED planning for the possible scenario after closing the surrounding care

399   centers still has deficiencies. This reinforces the importance of using simulation to ensure that

400   ED, in this scenario, continues to offer a high quality of care. Especially in disruptive situations

401   where planning becomes more difficult.

402   Moreover, for the initial analysis, most of the resources are idle, e.g., triage nurses and

403   physicians. Most nurses and porters are waiting for empty locations (beds and seats).

404   Consequently, the patient's flow is stuck. It other words, beds in the BA, MBA, SSU, and VA are

405   occupied most of the time.

406   In this sense, based on LT, some improvements have been proposed. These improvements aim to

407   reduce patient waiting time, thereby increasing the safety of their care. Therefore, we

408   investigated the interaction between places in the ED and the resources in the patient flow.

409   ***4.5. Design and Analysis of Experiments***

410   *4.5.1. Design and Analysis of Experiments for Locations*

411   For the first set of experiments, we defined a complete factorial 2^4, where the factors are the

412   number of beds in the SSU, Mental Bed Area (MBA), Bed Area (BA), and the number of seats in

413   the Vertical Waiting Area (VA). We estimated these numbers using Equation (1):

$$Q_i = \frac{t_i * p_i}{60 \ min} \tag{1}$$

414   Where:

415   Q_i = Required number of location or staff per patient/hour;

416   t_i = Time in minutes that a patient stays in the area or needs a resource (average);

417   p_i = number of patients that arrives in area i or needs a resource (average);

418   Thus, considering these variables, a full factorial design was planned. We choose a full factorial

419   design (2^4 = 16 runs) since the number of runs is lower, and design reliability is higher than half

420   factorial ($1/2*2^4$ = 8 runs). To determine the levels of DoE, we used a 20% margin of factor

421   target to define "level -" and "level +". The results were rounded down and up, respectively, and

422   are shown in Table 5.

423 **Table 5. Variables related to locations and DoE parameters**

424 The performance measures defined in response to DoE were: (i) Weekly treated patients; (ii)

425 LOS; (iii) Time for the patient to be attended after triage and (iv) Time to transport the patient to

426 SSU. We chose to use this order in all analyses, since the number of treated patients is more

427 important, followed by the time spent in the hospital.

428 The number of SSU beds was the factor that affects all the chosen metrics in a significant way.

429 Based on Lenth's method, the number of beds and seats in SSU, BA, MBA, VA, and some

430 interactions were identified as statistically significant. The factors interaction hinders the ED

431 performance since the locations are used together in some specific points of the model. In this

432 way, we did not remove any variable from the analyses.

433 In order to obtain fit meta-models to the system and to identify eventual curvatures in the

434 objective functions, we chose to perform a Response Surface Methodology (RSM). Using this

435 design, we got seven central points and four axial points, resulting in another 31 experiments. A

436 central point test the model in the upper level, lower level, and the middle of these points. We

437 analyzed the same performance measures and it was obtained an R^2-adjusted fit of 90.6% for

438 measure (i); 93.1% for (ii); 95.2% for (iii) and 98.6% for (iv) and a predicted R^2 of 82.0%;

439 72.7%; 83.5% and 95.6%, respectively. R^2 refers to the degree of model reliability, and higher

440 values indicate that the model better fits its data. The value of R^2 is always between 0 and 100%.

441 Therefore, the results indicated the best factors combination is:

442   • 30 beds in SSU;

443   • 45 beds in BA;

444   • 5 beds in MBA;

445   • 15 seats in VA;

446 The model was replicated ten times under the same conditions as the IP scenario in order to

447 verify the optimized response. In this case, the resources do not have a set shift. Thus, analyzing

448 the same parameters, we observed:

449   • On average, 1505 patients arrived in the model;

450   • On average, 1436 (95.4%) patients were completed treated in the simulated period;

451   • All patients make it triage;

452   • On average, LOS was 436.0 minutes;

453   • Patients wait about 25.7 minutes to be seen after triage;

454   • Patients who need to go to SSU wait, on average, 128.5 minutes to be transferred.

455   Compared to the IP scenario, all patients underwent triage, showing that patient flow became more

456   continuous than in the first approach. Still, the number of treated patients increased by around

457   590%. On the other hand, the waiting time to be attended after triage was an average of 25.7

458   minutes, 5.5 minutes for CTAS I, 11.0 minutes for CTAS II, 19.6 minutes for CTAS III, 37.5

459   minutes for CTAS IV and 40.9 for CTAS V.

460   Despite the increasing number of patients and the decreasing in LOS and waiting time to be

461   attended after triage, the resources were not dimensioned. In other words, the staffs are still idle.

462   Thus, the second scenario goals to dimension the resources in each group and shift.

463   *4.5.2. Design and Analysis of Experiments for Resources*

464   As mentioned, in the previous scenario, the resources were not defined. We performed a DoE

465   design 2^4 to determine the influence of staffing on each shift for TN, EDN1, EDN2, and physicians.

466   Furthermore, it was defined as an arrangement 2^3 for the porters since they have only three start

467   shift options. The maximum number of staff per hour was considered to define the "level +". Table

468   6 shows the level of each resource group.

469   **Table 6. DoE variables levels for resources**

470   The results presented by DoE show that the amount of staff in each shift is statistically

471   significant for at least one of the performance metrics. In this way, we did not remove any input

472   variables. After the analysis and some adjustments, it was determined the ideal number of

473   resources in each group and shift, presented in Table 7. In addition, we proposed a change in the

474   shift of the porters to the same as the other staff.

475   **Table 7. Resource number for shift and group**

476   "Level+" was chosen mostly in the shifts from 9:00 a.m. to 9:00 p.m., because the demand is

477   higher at these times. We decided to maintain the workload of 85% (average) for nurses and

478   doctors because emergencies may happen. Thereby, these features can meet emergencies without

479   compromising patients already in the ED. Defining the ideal number of resources and executing

480   the model with ten replicates, the results show:

481   • On average, 1504 patients arrived in the model;

482   • On average, 1442 (95.8%) patients were completed treated in the simulated period;

483   • All patients make it triage;

484   • On average, LOS was 511.6 minutes;

485   • Patients wait about 45.8 minutes to be seen after triage;

486   • Patients who need to go to SSU wait, on average, 97.1 minutes to be transferred.

487   The workload was balanced, and the number of treated patients continues the same. However,

488   the LOS average increased around 75 minutes. The waiting time to be attended after triage was,

489   on average, 45.8 minutes, increasing about twice. The waiting time after screening for each

490   CTAS was 6.6 minutes for CTAS I, 13.3 minutes for II, 24.7 minutes for III, 74.0 minutes for

491   IV, and 138.0 for V. Finally, the last improvement proposed is related to the number and scales

492   of the specialist in the unit care.

493   *4.5.3. Specialists in ED*

494   When the patients need a medical appointment, they must wait until the specialist arrives at ED,

495   because they are not available in the unit. All the specialists, except the urologist, gynecologist,

496   otolaryngologist, and ophthalmologist, operate all the time. The other specialists work in shifts

497   from 08:00 a.m. to 05:00 p.m. (on average). At other times, the internal medicine covers the

498   cardiologist, nephrologist, and gastroenterologist. Currently, there is only one specialist available

499   for each specialty at each shift, except the Crisis Response, which has two doctors from 08:30

500   a.m. to 07:30 p.m.

501   Moreover, it is necessary to consider the response time after calling the specialists. Psychiatrists

502   take between 1 and 6 hours to reach the unit, while neurologists can take 15 to 90 minutes

503   (according to CTAS level), and Crisis Response specialists take about 5 minutes.

504   Among the 13 specialists, the most requested are psychiatrists, neurologists, and crisis response.

505   Then, these specialists need to stay most of the time in the ED. Therefore, we made some changes

506   in the shifts:

507   • Psychiatrist: a specialist all the time in the unit (avoids the delay that can reach 6 hours);

508   • Neurologist: a specialist in the same shift of the current state (08:00 a.m. - 05:00 p.m.),

509   but allocated directly to the unit (avoiding a delay that can reach 90 minutes);

510   •   Crisis Response: One expert all the time on the unit rather than two on the predetermined
511   shift (08:30 a.m. - 07:30 p.m.). Although this specialist's response time is relatively short,
512   we chose to allocate it directly to the unit.

513   After ten runs, the results are:

514   •   On average, 1496 patients arrived in the model;

515   •   On average, 1441 (96.3%) patients were completed treated in the simulated period;

516   •   All patients make it triage;

517   •   On average, LOS was 450.7 minutes;

518   •   Patients wait about 19.0 minutes to be seen after triage;

519   •   Patients who need to go to SSU wait, on average, 137.2 minutes to be transferred.

520   One of the actions that blocked continuous patient flow is to wait for the specialist. In this sense,
521   the simulations show that the LOS decreases by about 11.9%. In addition, the waiting time for
522   patients requiring a transfer to SSU is, on average, 42.8 minutes below that requested.

523   *4.6. Confirmation Runs*

524   In order to confirm the proposed changes, the model was simulated 30 times and a warm-up from
525   Monday (00:00) to Tuesday (00:00). Data were collected from Tuesday to Tuesday. Table 8
526   presents the Final Planning (FP) configuration for locations and resources.

527   **Table 8. Number of locations and resources**

528   According to simulation results, the study recommends two additional beds in the MBA and five
529   additional chairs in the VA. Regarding the resources, it is necessary to hire one TN, one EDN2,
530   four porters, and reduce two physicians. Table 7 lists the shift for each group. It was necessary to
531   dimension the staff, avoiding, when possible, hire them. The number of beds in SSU directly
532   affects patients' LOS. Then, the ideal number is 30 beds, corresponding, on average, 146.4 minutes
533   of waiting for transfer to SSU. About the specialist, a psychiatrist, a neurologist, and a crisis
534   response must stay directly in the unit. With the proposed measures, the patient's LOS decreases
535   by 1752.6 minutes. Table 9 presents the results of the IP and FP scenario.

536   **Table 9. Outputs for IP and FP scenarios**

537   (Sargent, Goldsman & Yaacoub 2016) suggest that, for a non-observable system, an objective
538   approach is to compare the results from the developed model with another similar system to

539   perform the validation. In this sense, we decide to compare the model with another ED that works

540   in the same way to verify the results from the future state. In our model, the mean LOS is 461.2

541   minutes and a standard deviation of 20.7 minutes. In the other ED, the LOS is 472.1 minutes. Then,

542   we carried out a 1-Sample Equivalence test that evaluates if the mean of a population is close

543   enough to a target value, specifying a range to be equivalent. In the test, we can say that the

544   difference between the model's results and benchmarking is not significant, less than 5% (p-value

545   <0.001). In other words, the models are equivalents, and we can affirm that the future state and the

546   results are validated.

547   After the proposed changes, the number of treated patients increased considerably, making their

548   flow continuous during the process (LT principles). In addition, patients are seen as expected after

549   triage, according to the CTAS classification level.

550

551   **5. Conclusions**

552   The presented study aimed to propose an ideal state aligned with LT for a Canadian ED

553   expansion. The purpose was to increase the number of treated patients and reduce LOS, without

554   compromising the quality of services and patient safety. In this way, it determined the optimal

555   number of beds for SSU, BA, MBA, and VA; defined the ideal number of resources; reduced

556   LOS, waiting time after triage phase, and transfer to SSU. Hence, the study used the Modeling

557   and Simulation method proposed by (Montevechi et al. 2010).

558   We built the conceptual model using the IDEF-SIM modeling technique and the input data was

559   obtained through the ED's historical data, registrations from a system, and experts from the

560   hospital. The computer model was built in FlexSim Healthcare® software, and validated it with

561   experts and sensitivity analysis technique. For the experiments, at first, we carried out the DoE to

562   verify the influence of the area expansion (BA, MBA, SSU, and VA) in the chosen metrics. We

563   also used DoE to determine the optimal resource number at each shift and its optimal scale to

564   meet changing demand throughout the day and week. Finally, experiments were performed to

565   reduce patients' waiting time by specialists. Among the evaluated metrics, we chose to prioritize

566   them as follows: (i) weekly treated patients; (ii) LOS; (iii) time for the patient to be attended

567   after triage and (iv) time to transport the patient to SSU.

568   After the analysis, the simulation indicates that the model in its IP scenario cannot meet the

569   demand. For the FP scenario, we observed that DES and LT integrated into the DoE allowed

570   increasing the number of patients that went through the triage process from 23.1% to 100.0%.

571   The patient LOS reduced from 2231.8 to 461.2 minutes. The resource workload was balanced

572   according to LT principles. In this way, we got a significant improvement in the process.

573   Regarding the limitations of this study, we found difficulties in executing replicates in the

574   current scenario due to the computational effort required. For this reason, the simulation warm-

575   up was only one day, and the simulation performed for one week (Tuesday to Tuesday). Another

576   significant difficulty was to obtain some data from hospital processes. Even with the use of

577   systems like Meditech®, some data are still obtained through expert estimation. According to the

578   literature, this limitation is common in healthcare simulation projects. Finally, for future work,

579   we suggest investigating other resources, e.g., technicians, receptionists, and ward clerk. In

580   addition, the economic viability of different layouts can be assessed for labs and DI.

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Table 1. Patient's category and specialist

Treatment Category	Specialist	Proportion
General/Minor issues (GMI)	-	17.7%
Respiratory (RE)	Respiratory Therapist	14.6%
Gastroenterology (GA)	Gastroenterologist	11.9%
Orthopedic (OR)	Orthopedist	10.3%
Cardiology (CA)	Cardiologist	9.7%
Dermatology (DE)	Dermatologist	8.3%
Genitourinary (GE)	Urologist and Nephrologist	6.1%
Ear, nose, and throat (ENT)	Otolaryngologist	4.9%
Mental Health (MH)	Crisis and Psychologist	4.3%
Neurologic (NE)	Neurologist	4.2%
Ambulatory Return Visit (ARV)	-	4.0%
Ophthalmology (OP)	Ophthalmologist	1.8%
Gynecology (GY)	Gynecologist	1.1%
Substance Misuse (SM)	Crisis and Psychologist	0.9%

Table 2. Processing time and required staff

Task	Process Time (min)	Staff Required					
		Triage Nurse	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	

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

Table 3. Exam probability for each CTAS level

Exam	CTAS	Treatment Category												
		GMI	RE	GA	OR	CA	DE	GE	ENT	MH	NE	OP	GY	SM
CT	I and II	1%	x	✓	50%	x	x	✓	✓	x	✓	50%	x	x
	III	1%	x	50%	10%	x	x	50%	x	x	x	x	x	x
	IV and V	1%	x	x	x	x	x	x	x	x	x	x	x	x
ECHO	I and II	x	x	x	x	10%	x	x	x	x	x	x	x	x
	III	x	x	x	x	x	x	x	x	x	x	x	x	x
	IV and V	x	x	x	x	x	x	x	x	x	x	x	x	x
EKG	I and II	x	✓	x	75%	✓	25%	x	x	x	x	x	x	x
	III	x	x	x	75%	✓	x	x	x	x	x	x	x	x
	IV and V	x	x	x	x	✓	x	x	x	x	x	x	x	x
US	I and II	1%	x	✓	x	x	x	✓	x	x	x	x	✓	x
	III	1%	x	50%	x	x	x	50%	x	x	x	x	✓	x
	IV and V	1%	x	x	x	x	x	x	x	x	x	x	x	x
XR	I and II	50%	✓	✓	✓	✓	25%	✓	✓	x	✓	25%	x	x
	III	50%	✓	50%	✓	75%	x	50%	25%	x	x	x	x	x
	IV and V	50%	25%	x	50%	75%	x	x	x	x	25%	x	x	x
BW	I and II	50%	✓	✓	✓	✓	75%	✓	✓	✓	✓	✓	✓	✓
	III	50%	✓	✓	✓	✓	25%	✓	25%	✓	✓	x	✓	✓
	IV and V	50%	x	x	x	25%	x	x	x	50%	10%	x	50%	75%
SP	I and II	x	✓	50%	25%	x	25%	✓	25%	✓	✓	x	✓	✓
	III	x	75%	50%	10%	x	25%	✓	50%	✓	50%	x	✓	✓
	IV and V	x	25%	x	x	x	x	✓	x	50%	x	x	50%	75%

Table 4. Specialist probability appointment for each CTAS level and data set

Treatment Category	Consult 1	CTAS I and II		CTAS III		CTAS IV and V	
		C1	Time (min)	C1	Time (min)	C1	Time (min)
RE	Respiratory Therapist	75%	60	10%	15	x	x
GA	Gastroenterologist	✓	T(15,22,30)	25%	T(15,22,30)	x	T(15,22,30)
OR	Orthopedist	✓	10	✓	5	50%	3
CA	Cardiologist	✓	T(30,45,60)	50%	T(30,45,60)	10%	T(30,45,60)
DE	Dermatologist	25%	T(30,45,60)	10%	T(30,45,60)	x	x
GE	Urologist	✓	T(15,22,30)	✓	T(15,22,30)	x	x
ENT	Otolaryngologist	✓	60	50%	20	x	x
MH	Crisis Response	✓	T(60,75,90)	✓	T(60,75,90)	✓	T(60,75,90)
NE	Neurologist	✓	60	✓	60	x	x
OP	Ophthalmologist	10%	T(30,45,60)	5%	T(30,45,60)	x	x
GY	Gynecologist	✓	T(15,22,30)	✓	T(15,22,30)	x	x
SM	Crisis	✓	T(60,75,90)	✓	T(60,75,90)	✓	T(60,75,90)

Treatment Category	Consult 2	CTAS I and II		CTAS III		CTAS IV and V	
		C2	Time (m)	C2	Time (m)	C2	Time (m)
GE	Nephrologist	50%	T(10,15,20)	25%	T(30,45,60)	x	x
MH	Psychologist	✓	T(60,75,90)	75%	T(60,75,90)	25%	T(60,75,90)
SM	Psychologist	✓	T(60,75,90)	50%	T(60,75,90)	25%	T(60,75,90)

Table 5. Variables related to locations and DoE parameters

Variable	Number of location		DoE Parameters		
	IP	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

Table 6. 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		

Table 7. 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

Table 8. Number of locations and resources

Local	IP	FP	Resource	IP	FP
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

Table 9. Outputs for IP and FP scenario

Metrics (min)		Initial Planning		Final Planning		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%

Figure 1

Figure 1. Conceptual Modeling
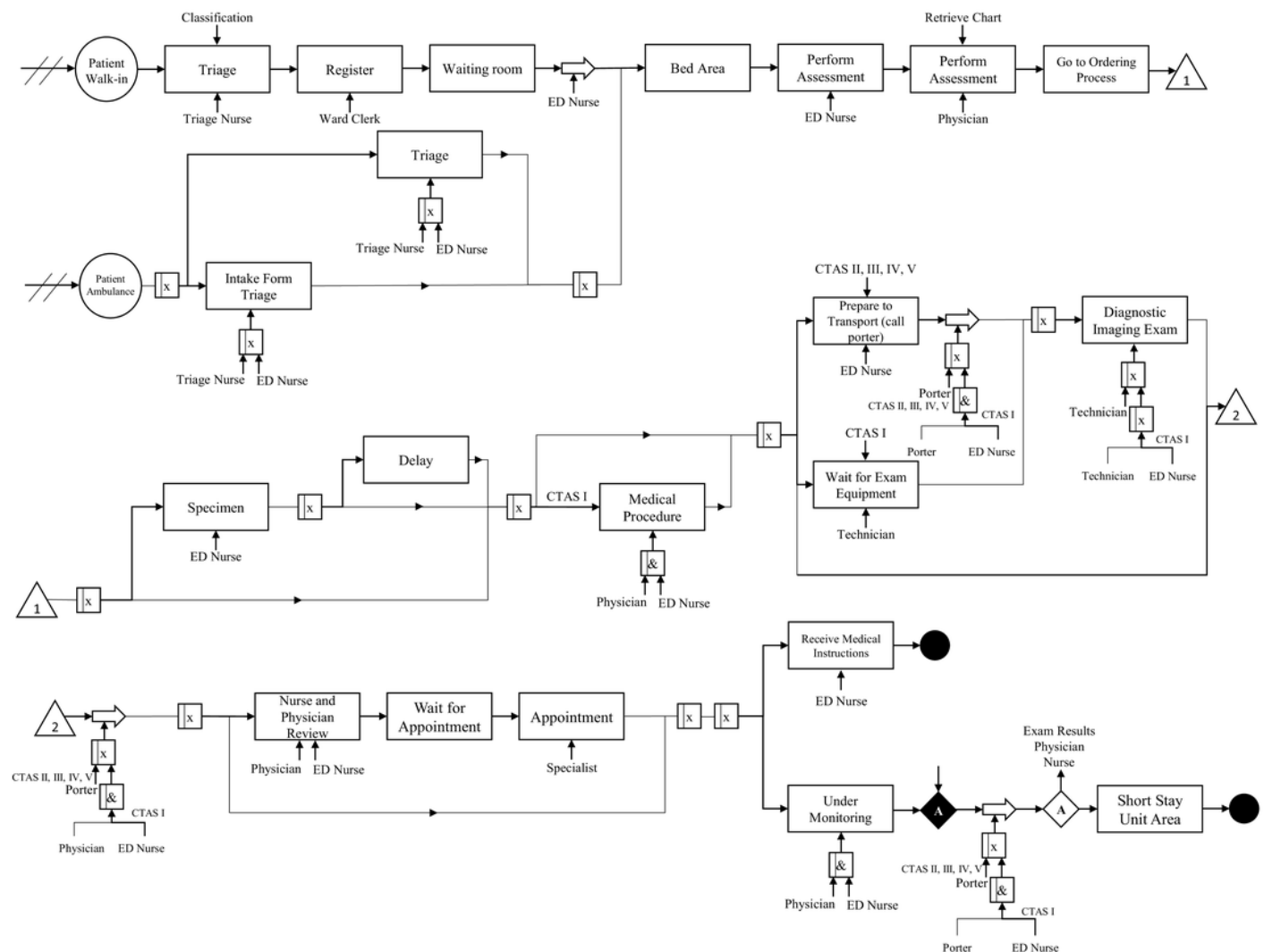
Figure 2

Figure 2. Arrival rate for each patient CTAS level

(A) CTAS level I patient arrivals during the week. (B) CTAS level II patient arrivals during the week. (C) CTAS level III patient arrivals during the week. (D) CTAS level IV patient arrivals during the week. (E) CTAS level V patient arrivals during the week.
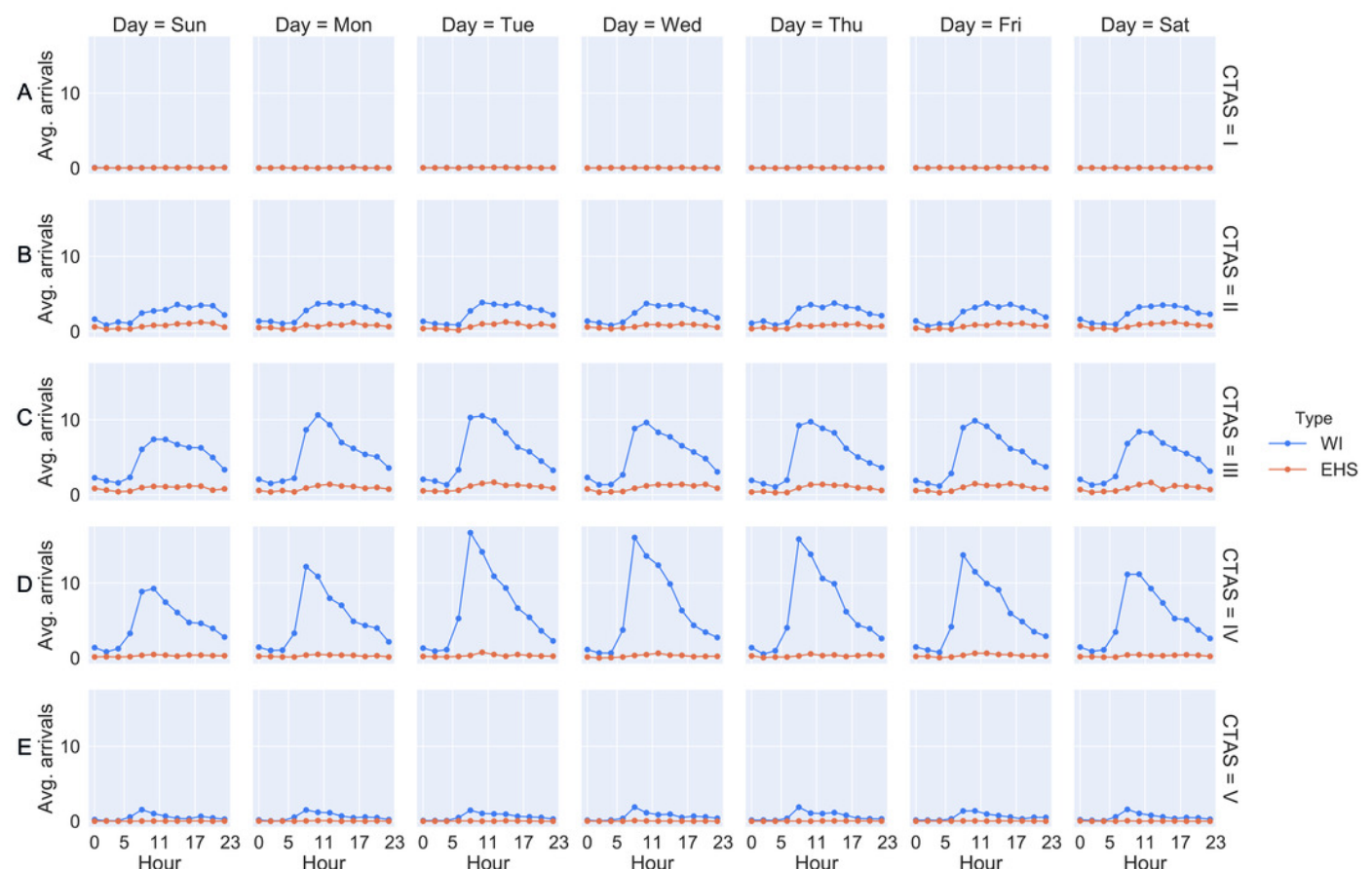
Figure 3

Figure 3. Computer model screen in the FP scenario
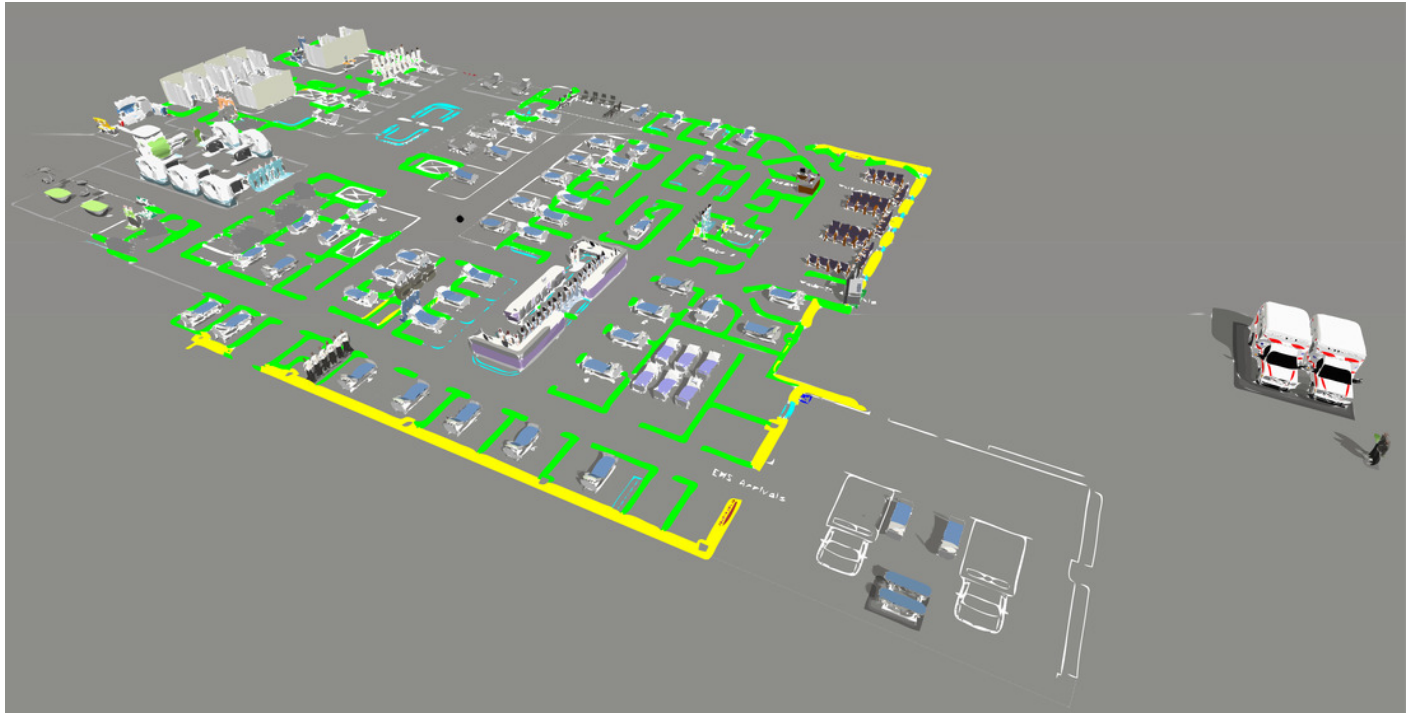
Figure 4

Figure 4. Sensitivity analysis for validation (LOS and % Treated Patient)