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USING DISCRETE EVENT SIMULATION TO IMPROVE PERFORMANCE AT TWO CANADIAN EMERGENCY DEPARTMENTS

Evgueniia Doudareva

Department of Mechanical and Industrial Engineering
University of Toronto
5 King's College Road
Toronto, ON M5S 3G8, CANADA

Michael Carter

Department of Mechanical and Industrial Engineering
University of Toronto
5 King's College Road
Toronto, ON M5S 3G8, CANADA

ABSTRACT

Emergency Departments' (EDs) critical role in patient care and their complex process flow contribute to them being one of the most frequently modelled systems in healthcare Operations Research (OR). The goal of this research was to develop models of two EDs that could diagnose bottlenecks and evaluate performance improvement approaches using a generalized approach. We used Discrete Event Simulation (DES) to model two EDs in Toronto, Canada, based on existing processes and empirical data. Model outputs include wait times, treatment times, and selected process durations. Management of both EDs used the models to evaluate performance and preview the effects of staffing and flow changes before committing to the improvement measures. The examples of successful performance improvement opportunities include a new triage flow for patients arriving by ambulance, merging of the treatment zones, and increases in staffing levels.

1 INTRODUCTION

Emergency Departments (EDs) play a critical role in patient care. Improving the flow within ED is a priority across the globe (Ackroyd-Stolarz et al. 2011; Bernstein et al. 2009). Problems in the ED, such as prolonged length of stay (LOS) and resources' allocation, are associated with increased patient morbidity and mortality, especially among the elderly population (Cheng et al. 2018; Derlet and Richards 2000; Finamore 2009; Forero 2011).

Long wait times in triage, testing, physician assessments, shortage of nursing staff, and delays in admitted patients' transfer to inpatient beds are other key issues identified in literature (Cheng et al. 2018; Bernstein et al. 2009; Finamore and Turris 2009). Numerous strategies have been proposed to overcome these problems, such as improving the layout and flow of the work environment or applying Lean principles (Kulkarni 2007; Miro´ et al. 2003; Tanabe et al. 2008).

Despite multiple strategies being implemented by the EDs worldwide, the problems continue to persist. There is a gap in a more generalized modelling approach that would be useful for all EDs regardless of hospital size and operational setup differences. We aimed to gain a detailed understanding of how various EDs operate in order to build a more generic model that could accurately capture the ED patient flow and identify improvement strategies, as well as provide a quantification to the improvement measures before their implementation. Our model is meant to be input-driven and flexible. The current study presents the generic model implementation through the lens of a detailed view of operations of two specific EDs, and their results will be discussed in the following sections.

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2 BACKGROUND AND PROBLEM

The City of Toronto, Canada is home to over forty hospitals, out of which there are a total of thirteen with Emergency Departments. All Toronto EDs provide 24-hour emergency care and diagnostic testing, in an unscheduled manner, with differing levels of urgency ranging from immediate intervention to the treatment of minor problems. A substantial proportion of visits are made by patients who prefer ED attendance to accessing primary care, for reasons such as convenience or community culture, which is consistent with other EDs across the globe (Salmon et al. 2018).

Toronto EDs differ in their size and communities they serve. Common issues include overcrowding and prolonged length of stay (LOS), funding constraints and performance metrics targets mandated by the regional (provincial) jurisdiction. Toronto (and other Ontario) EDs have been using pay-for-performance, or, 'Pay for Results' (P4R), which allocates annual base funding to designated Ontario hospitals to meet ED wait time reduction targets and variable funding if they exceed targets, since 2008. Unmet targets can lead to the funding to be retracted. As a result, strategies to improve wait times, reduce the ED LOS are consistently of interest to ED management in Toronto (Cheng et al. 2018).

Two Toronto EDs – Sunnybrook Health Science Centre (Sunnybrook ED), and St. Joseph's Health Centre (St. Joseph's ED) are featured in this study. Both focus their efforts on their individual P4R goals and were interested in understanding whether simulation modelling could provide them with insights on planned (and hypothetical) improvements. We aimed to understand the similarities and differences of these EDs and develop a generic model that could be further applied to other EDs in need of similar analysis.

3 METHODOLOGY

3.1 Generalized Emergency Department Process Flow

ED patients arrive as a walk-in or in an ambulance. The first stop is the triage station, where the triage nurse evaluates the patient and assigns them a severity level (e.g. 1-5) based on their initial diagnosis. Patients are then routed to a treatment zone based on this severity and other factors such as age or other specializations (such as mental health, trauma, or pediatric unit). Registration for the highest severity patients is done at the bedside. All other patients complete their registration and wait to be called to their stretcher or examination area. Once the patient is in the ED stretcher, they are examined by a physician and appropriate diagnostic tests are ordered. The ED physician then reviews the test results and either requests a consult with a specialist, or recommends either that the patient be discharged or admitted to the hospital. For admitted patients, if a bed is available, the patient is sent to the unit, otherwise they are held in the ED.

3.2 Generic Features of an ED

The design of our ED model and discussion of its applicability, was guided by the definitions of generic modeling provided by Fletcher and Worthington (2009). This research focuses on the development of a practical and transportable simulation model which could be re-modeled using any software. Using Fletcher's definitions, our design falls into a setting specific generic model category.

Two categories of ED features were considered in the design: activities and resources. The modelled activities included arrival (ambulance, walk-in), triage and registration (multiple design options to fit a hospital), placement/routing to zone (includes allocation of a stretcher or a chair), initial assessment by a physician and/or nurse, treatment/tests (e.g. bloodwork, diagnostic Imaging), physician re-assessment, consultation, disposition, discharge/admission. The modelled resources include physicians, nurses (including different nurse types, where necessary), physician assistants, consulting physicians, stretchers, chairs, assessment rooms, resuscitation rooms, laboratory and diagnostic imaging staff, clerks.

These ED features were validated through the reviewed literature. A useful systematic review that guided our design was found in Furian et al. (2018). Additional generic models are outlined by Mes and Bruens (2012) and Paul and Lin (2012). We believe that the past generic models have showcased limited combination of flexibility and sufficient granularity. Our model aims to provide a flexible, input-driven modelling options that can be applied to any ED. While the current paper focuses on the application of the model to two sites in Canada, detailed implementation and multi-site, multi-county validation of this model can be found in Doudareva et al. (2021).

3.3 Comparison of EDs in Scope for This Study

The two EDs in this study have different annual patient throughput levels, from 70,000+ at Sunnybrook ED to almost 100,000 at St. Joseph's. The EDs also differ in the numbers of zones or units to handle patient severity.

The two EDs had different motivations for building the simulation models. While Sunnybrook ED's focus was on improving their P4R metrics, i.e., meeting the provincial targets for patient LOS, St. Joseph's ED was planning an expansion and was interested in maintaining (and improving) the overall service levels, i.e., maintaining LOS and time to PIA. Both EDs had a limitation for inpatient bed availability modelling as a resource due to lack of data availability.

Table 1 compares the hospitals demographics and characteristics. St. Joseph's ED has higher volume of patients of the two. To accommodate this volume, St. Joseph's ED also has more stretchers, and has a Pediatric unit and Mental health ED unit. Sunnybrook ED has a significantly lower consultation rate (26.5% vs 41.5%), and a higher proportion of patients that are discharged (73.8% vs 61.0%) than St. Joseph's ED. St. Joseph's ED has a much higher volume of pediatric visits comparing to Sunnybrook ED, whereas the latter has almost twice as high volumes of geriatric visits. Consultation rate refers to the rate at which patients require additional evaluation by a specialist physician.

Table 1: Characteristics of Sunnybrook ED and St. Joseph's ED

ED Characteristic	Sunnybrook ED	St. Joseph's ED
Annual ED Visits	70,000-80,000	94,000-96,000
ED Stretchers	36	50
Number of Zones/Units	4	6
Pediatric Visits (0-18 yr.)	6.2%	16.5%
Geriatric Visits (80+ yr.)	15.0%	8.7%
Pediatric ED unit	No	Yes
Mental Health ED unit	No	Yes
Consultation rate	26.5%	41.5%
Discharges	73.8%	61.0%
Admission rate	22.3%	34.9%
Death	0.2%	0.2%
Left without being seen	3.6%	3.9%

Figure 1 shows the average daily arrival patterns for Sunnybrook ED and St. Joseph's ED (walk-in patients). It is notable that while arrival rates are higher at St. Joseph's ED, the overall hourly arrival patterns are very similar.

Figure 1: Patient arrival pattern for walk-in patients at Sunnybrook ED (left), and St. Joseph's (right).

3.4 Performance Metrics

The performance metrics of the two hospitals included Time to Physician Initial Assessment (Time to PIA) and LOS for Sunnybrook ED; and LOS, Time to PIA, and Ambulance Offload time for St. Joseph's ED. While Sunnybrook ED's goal was to reduce Time to PIA and LOS to better meet provincial targets, St. Joseph's ED goal was maintaining performance during an expansion and an increase in patient volumes.

3.5 Simulation Modelling Approach

We developed a generalized ED process flow based on the individual ED processes. Key flow components included modelling multiple (and specialized) treatment zones/units, along with the rules for allocating patients to the correct zones, additional nurse activities (where relevant), as well as ensuring that the correct resources are available to perform the right actions. An important resource to model was ED beds/stretchers, which are utilized throughout the flow, at first assessment, nurse visit, reassessment, consult, and decision to admit/discharge. Detailed description of the design and implementation of our generic model can be found in Doudareva et al. (2021).

We used Discrete Event Simulation (DES) to model the EDs. DES is used widely in health-care services (Salmon et al. 2018) and allows complex decision logic to be incorporated that is not as readily possible in other types of modelling. Figure 2 showcases the design of our generic ED DES model. The model was built using Simul8 Professional, and includes key activities modelled as a part of the overall patient flow.

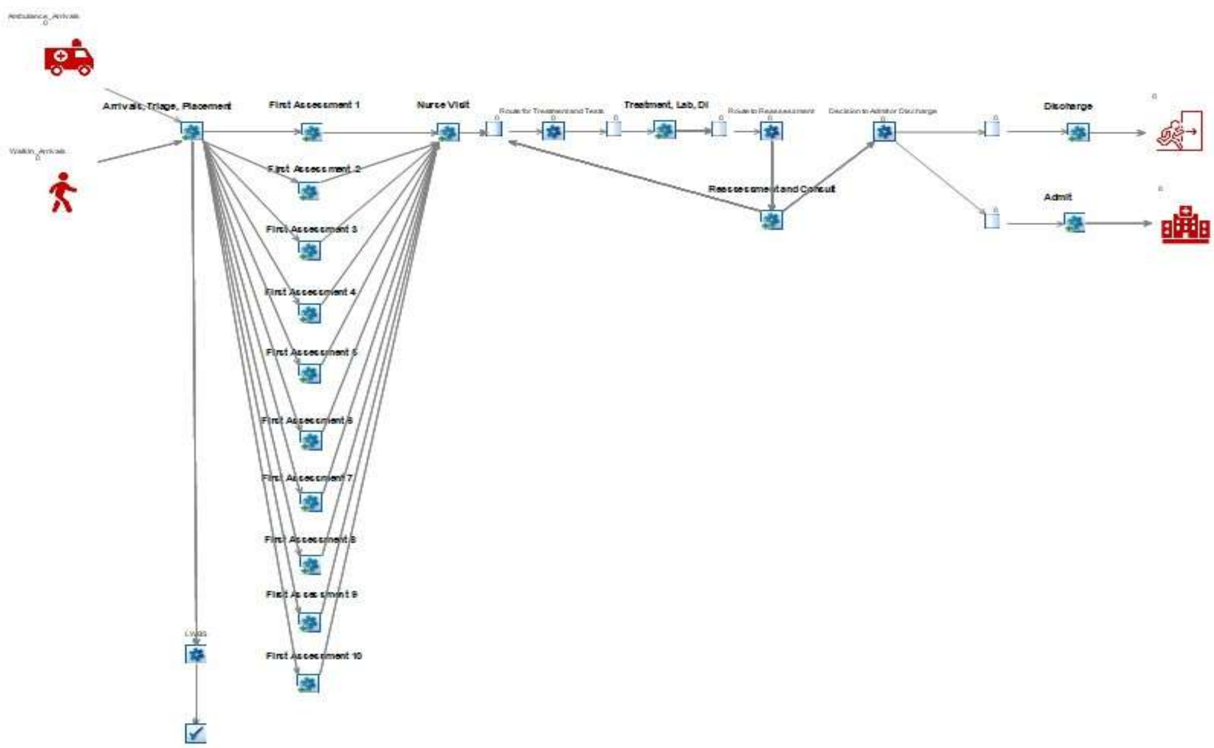

Figure 2: Generic ED DES model design

3.6 Model Inputs

Both sites used a combination of available data extracts, scheduling details, and expert interviews to generate the list of necessary inputs. A data request spreadsheet has been designed for sharing the target sites to obtain the required information in an efficient manner.

Figure 3 summarizes the input types that are required to model the key features of an ED. These are consistent with a generic simulation framework presented in (Furian et al. 2018). We requested this information from the participating sites in order to run the respective models via the data request spreadsheet Full sample of the created data request can be found in Figure 10 (in Appendix A).

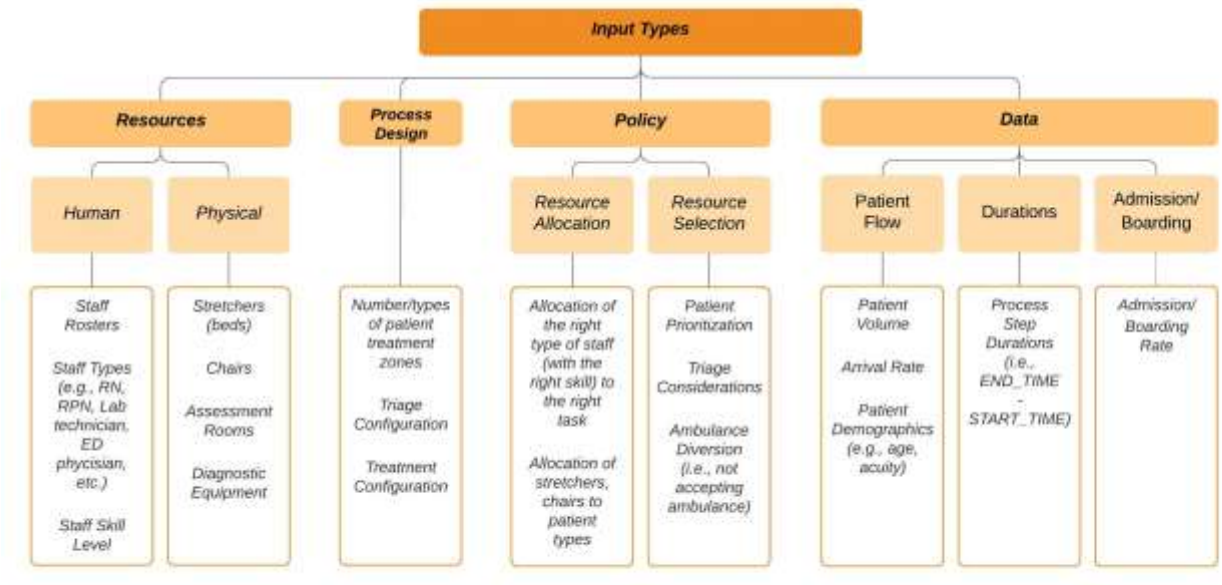

Figure 3: Types of data inputs requested from the EDs to enable modelling

Some of the data provided by the sites required further exploration and distribution fitting in order to be used by the model. For example, for St. Joseph's ED, the data analysis team explored multiple ways of grouping arrivals into "timeslots": every 1 hour (e.g., 12-1am, 1am-2am, etc.), every 2 hours, every 4 hours, every 6 hours, and every 8 hours. 2-hour windows, and fitting a Poisson distribution to each time window, provided the best result. To fit distributions, the number of arrivals in each timeslot in each day over the 10 years of data was counted. For each timeslot, all observations over the 10 years were pooled and the Poisson distribution was fitted. Figure 4 presents a sample plot that shows that the distributions are a good fit to the data.

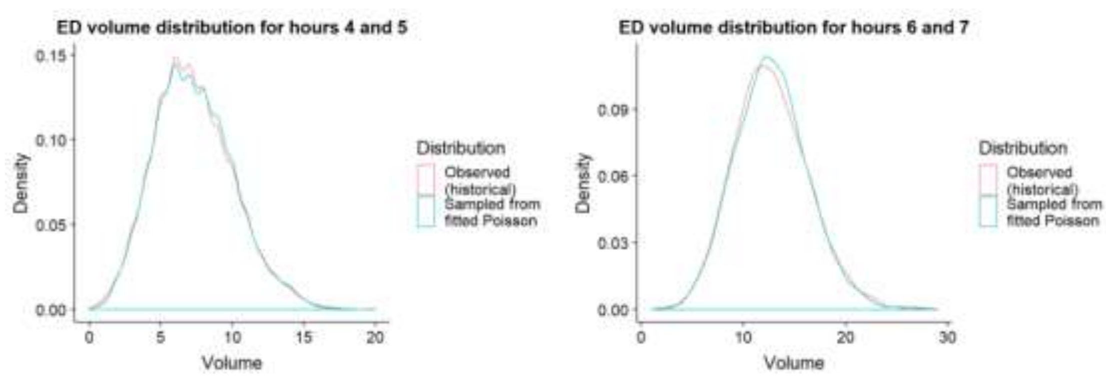

Figure 4: Example of distribution fitting for St. Joseph's ED

4 RESULTS

4.1 Model Runs and Outputs

For both sites, trials consisting of 20 runs were conducted. Each run duration was 1 year (365 days), with a warm-up period of 10080 minutes. All results presented in the sections below are averages.

4.2 Model Verification and Validation

The validity of the models was established by comparing the simulation results with expert opinions (hospital staff) and the available ED data, as per approach presented in (Sargent 2010). Validation results for both sites are presented in Tables 2 and 3 in Appendix B.

4.3 Sunnybrook ED – Evaluated Scenarios

4.3.1 Scenario Group 1 – Stretcher Number Changes

For this group of scenarios, we were interested in evaluating the effect of changing the number of available ED stretchers to demonstrate the effect of physical resource level changes on current key performance indicators (KPIs), such as Length of Stay (LOS) and Time to Physician Initial Assessment (Time to PIA). The following scenarios were considered:

- We increased the number of stretchers in the model by 10%, 20%, 50%, 100% in each zone (rounded up to the nearest whole number).
- Decreased the number of stretchers by 10%, 20%, 50% in each zone.

Figures 5 and 6 represent the results obtained from the Scenario Group 1. It appeared that the number of stretchers available per zone affected the time it takes from Patient Arrival to PIA. The number of stretchers per zone did not affect the time it takes from PIA to Consult arrival. For “Arrival to PIA”, effects are seen up to 20% increase in stretcher numbers. However, due to nursing/physician availability, higher number of available stretchers has no additional benefits. Increasing stretchers by 20%, would reduce PIA by 1 hour but not overall LOS. Biggest LOS effects are seen for CTAS 1 patients at all levels of increases. Overall, effects taper off for 50 and 100 percent increases likely due to staffing constraints. 10 and 20 % increases in the numbers of stretcher in each zone correspond to 15 – 30 % decrease in LOS for non-admitted patients. Total LOS decreases from 8.0 to 6.8 and 5.68 hours for 10% and 20% increase scenarios, respectively.

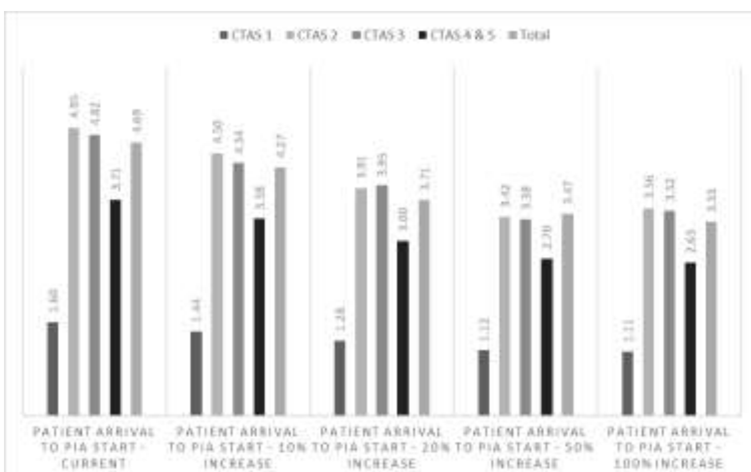

Figure 5: Scenario 1 – Stretcher number changes – Time to PIA

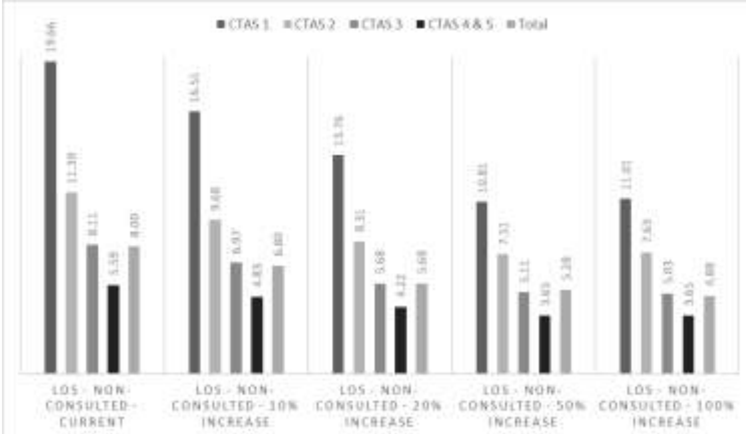

Figure 6: Scenario 1 – Stretcher number changes – LOS (Non-consulted)

4.3.2 Scenario Group 2 – Targeted 1-hour Reductions

The purpose of these scenarios was to demonstrate the effect of targeted duration restrictions on current key performance indicators (KPIs), such as LOS. This scenario is hypothetical in nature and was meant for the purpose of the ED's decision support – i.e., understand whether the reduction in a single interval duration would have positive effects on the overall LOS. As such, we enforced 1-hour reductions in the following intervals through parameter tuning: patient arrival to PIA start, patient entry to PIA – Ambulance only, PIA end to CT First Report, PIA end to Consult Arrival.

Figures 7 and 8 represent the results obtained from the Scenario Group 2. Enforced reductions affect the intended areas in the simulation directly, i.e., 1-Hr Reduction in Arrival to PIA Start is reflected in the output, 1-Hr Reduction in PIA End to CT First Report is reflected in the simulation output, 1-Hour reduction to Start to PIA results in direct 1-hour reductions to all CTAS patients, e.g., 1.6 hours to 0.6 hours to PIA, etc. 1-Hour reduction to PIA End to CT First Report results in a proportional 1-hour reductions for PIA End to CT First Report duration. Enforced reductions' effects were not sustained throughout the entire patient flow. 1-Hour reduction in one area did not translate to 1-Hour reduction overall. The biggest reduction seen for CTAS 3-5 patients (10-16% reductions in LOS across scenarios) vs. a reduction of 2-6% for CTAS 1-2 patients. 1-Hr reduction to "Arrival to PIA" results in the most noticeable reduction – the total reduction was from 8.0 hours to 7.06 hours.

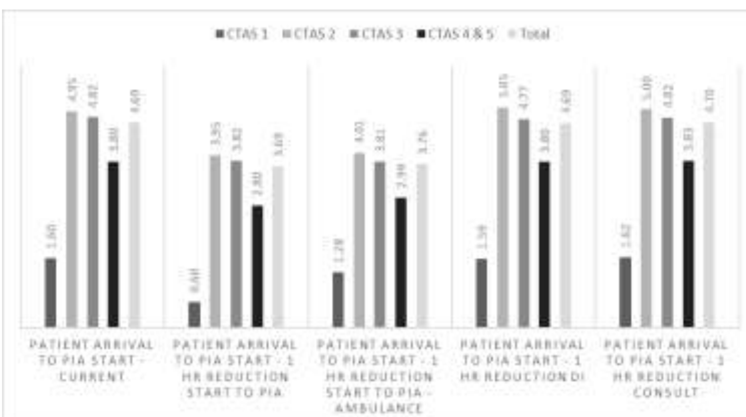

Figure 7: Scenario 2 – Enforced 1-Hour reductions effects on Time to PIA

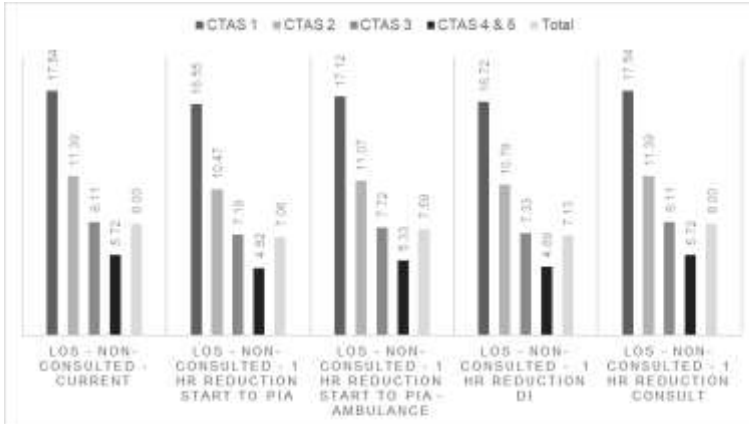

Figure 8: Scenario 2 – Stretcher number changes – LOS (Non-consulted)

4.4 St. Joseph's ED – Evaluated Scenarios

The purpose of the model was to understand the key bottlenecks in the existing ED department and to evaluate the impact of planned and desired changes to the ED on the patient flow and ED gridlock. Specifically, impact on such ED metrics as LOS and time to PIA were of interest. ED gridlock for St. Joseph's Healthcare Centre is defined as follows:

- 10 – 15 ANB (admit-no-bed) patients
- 0 acute ED beds + 1 resus bed available

The simulation model was evaluated both against the LOS metrics and ED gridlock metrics.

4.4.1 Evaluated Scenarios

A total of 20 scenarios were evaluated for this model. The purpose of scenario development was to understand how St. Joseph's Healthcare Centre's ED would behave under variable conditions. The scenarios are grouped as follows:

1. **Group 1 – 10-year projections**. This group of scenarios focuses on understanding how ED performance metrics will change within 10 years.
2. **Group 2 – Physical resource changes**. This group of scenarios focuses on understanding whether changing the number of physical resources (chairs and stretchers) can positively affect the ED performance metrics and gridlock metrics.
3. **Group 3 – Planned physical resource changes.** This group of scenarios focuses on planned physical resource changes, such as addition of Health Records space.
4. **Group 4 – Flow changes.** This group of scenarios focuses on understanding the impact of changing the current ED flow.
5. **Group 5 – Combination on flow and planned physical space changes.** This group of scenarios is a combination of Group 3 and 4 work.
6. **Group 6 – Human resource changes.** This group of scenarios focuses on changes to human resources, i.e., addition of physicians and nurses.
7. **Group 7 – Combination of human resource changes, physical resource changes, flow changes.**

Select detailed results for the groups are available in Appendix C. The most impactful group of scenarios was Group 7. This group of scenarios focused on changing the numbers of human resources (i.e., physician and nurse shifts) as well as process flow changes.

4.4.2 Group 7 – Combination of Human Resource Changes, Physical Resource Changes, Flow Changes

Group 7 scenarios were the most successful at improving the ED KPIs. For example, a scenario that incorporated an addition of a single physician shift with ED expansion (Health Records Space + additional unused space) lead to LOS decreases projected between 15 and 20%, with non-admitted patients having the biggest positive impact on LOS. Time to PIA and ambulance offload time were also projected to decrease, by 7% and 16%, respectively.

The scenario that yielded the most improvements included an ED Expansion (Health Records and additional unused Space) combined with Merging of the Zones, Increase in Staffing Levels (+1 Physician Shift – Morning shift), assuming Aging Population Increase. This scenario incorporates merging of ambulatory and SuperTrack (low acuity) zones, an addition of a single Physician shift (morning). It assumes a projected increase in 65+ population over a period of 10 years to align with provincial projections (% increase). The results of this scenario are compared against a 10 year "as-is" projection.

The results of the scenario are shown in Figure 9 and indicate that LOS decreases projected between 30 and 65%, with non-admitted patients having the biggest positive impact. Time to PIA and ambulance offload times are not significantly impacted. LOS for admitted patients appears to be slightly longer than originally, which can be attributed to an increase in aging population patients in the model.

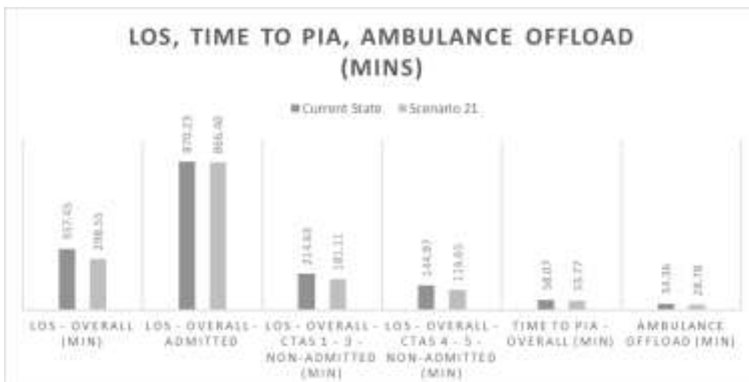

Figure 9: Scenario 1 – Stretcher number changes – LOS (Non-consulted)

5 DISCUSSION

This study demonstrated that computer simulation is useful in modeling all operational details in a complex system such as an ED, with a great deal of modeling flexibility. The DES models can efficiently enact actual events using historical data that represent patients, staff, laboratory and imaging studies, and associated resources. The logic of patient moves and waiting for resources is captured by the simulation model so that patient LOS data are obtained.

The generalized approach proposed in this article would be valuable to hospitals in achieving improvement of throughput or decreasing waiting time because each hospital is different and only a detailed analysis such as that made possible by our methodology could reveal the true bottlenecks.

6 STUDY LIMITATIONS

Data availability and quality may affect model accuracy. In both models, lack of availability of precise consulting physician schedules, as well as of rate of admission to inpatient units reduced model accuracy for admitted patients' metrics. Activity durations data was often lacking, which lead to a need to conduct manual time-studies, and rely on expert opinions for those inputs.

7 CONCLUSIONS

This work focused on the development of a DES model that was implemented at Sunnybrook ED and St. Joseph's Healthcare Centre's ED using a generalized approach. The models aimed at representing the patient flow throughout the ED. The result of the current state model design was models that were deemed valid for the overall flow and non-admitted patients. Due to lack of data for inpatient bed availability, admitted LOS was consistently shorter in the model than in the "real system" for both hospitals.

For St. Joseph's ED, the evaluated 20 scenarios highlighted the importance of considering space, flow, and staffing together as strategies to improve ED performance metrics that are driven provincially. The positive effects hold for the current state, as well as when projecting patient (and elderly patient) volumes increases ten years into the future. Some of the client's questions could not be answered due to the model limitation for admitted patients.

For Sunnybrook ED, the model was used successfully and further adapted by the team to evaluate proposed and piloted process flow changes, including additions of a nurse and a specialized process flow for Ambulance Offload, and additional staffing changes. The model was used to validate these real-life changes successfully.

A SAMPLE DATA REQUEST

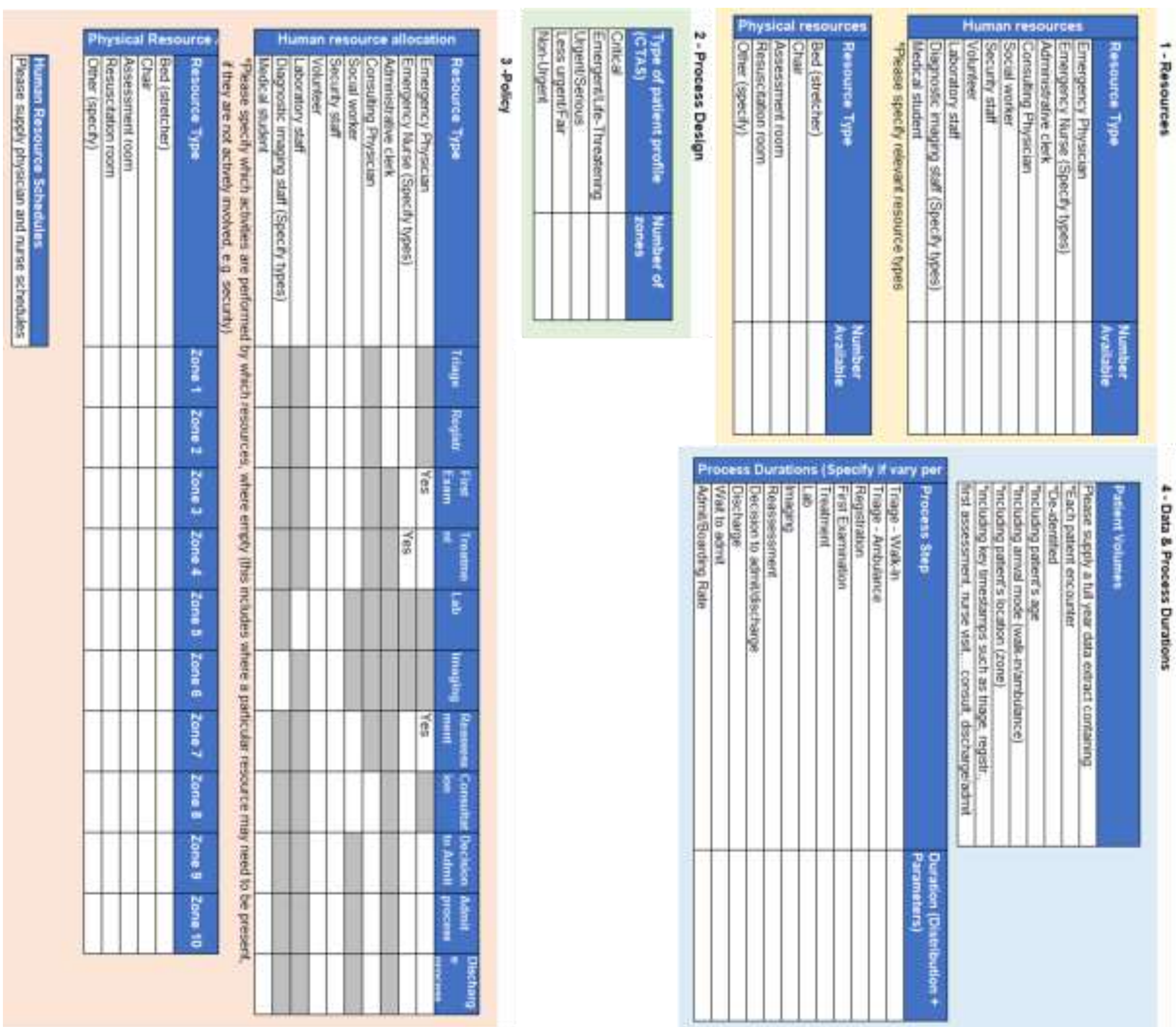

Figure 10: Sample Data Request

B MODEL VALIDATION

Most of the model outputs are within 3% range difference from the real data. LOS for admitted patients varies between 13 and 38%. This is due to the lack of data on inpatient bed availability. Admitted patient flow has also appeared to be the least sensitive to parameter changes as a part of scenario development. This is a reasonable result considering the fact that admitted "flow" is outside of the ED control, and no additions in staff or space can alleviate the bottleneck from the side of the ED. Overall, LOS, time to PIA, ambulance offload and other metrics do appear valid when comparing to the real system, and thus results obtained from the developed scenarios can provide meaningful insights into future system performance.

Table 2: ED Performance Metrics Validation for St. Joseph's ED

Verification/Validation Metric	Mean Model (Mins)	Mean ED Data (Mins)	% Difference
Annual Volume	95175	95767	0.62
LOS – Overall	357.45	368.67	3.04
LOS – Resus – Non-Admitted	215.32	225.7	4.60
LOS – Ambulatory – Non-Admitted	210.22	214.4	1.95
LOS – SuperTrack – Non-Admitted	114.11	113.6	0.45
LOS – Main – Non-Admitted	251.25	291.1	13.69
LOS – Overall – CTAS 1-3 – Non-Admitted	214.63	213.36	0.60
LOS – Overall – CTAS 4-5 - Non-Admitted	144.97	147.96	2.02
Time to PIA – Overall	58.07	67.56	14.05
Ambulance Offload	34.36	35.7	3.75

Table 3: ED Performance Metrics Validation for both sites

Site Name	Sunnybrook Health Sc. C.	St. Joseph's Health Centre
Location	Toronto, Canada	Toronto, Canada
Type	Teaching	Community, Teaching
Verification	Yes - volume, qualitative	Yes - volume, qualitative
Time to PIA (mins) - Model Average	142.9	58.1
Time to PIA (mins) - Data Average	147.1	67.6
Time to PIA (mins) - Low 95% CI	138.6	54.9
Time to PIA (mins) - High 95% CI	147.4	61.3
Time to PIA (mins) - % Difference	2.9	14.1
LOS - discharged (mins) - Model Average	448.1	179.8
LOS - discharged (mins) - Data Average	432.7	180.7
LOS - discharged (mins) - Low 95% CI	441.4	174.1
LOS - discharged (mins) - High 95% CI	454.8	185.5
LOS - discharged (mins) - % Difference	3.6	0.5

C ADDITIONAL ST. JOSEPH'S ED SCENARIOS' RESULTS

Figure 11 summarizes the results of Group 2 scenarios. Marginal effects are seen on ED performance metrics for these scenarios. Positive effects taper off as the number of added resources increases. Negative effects can be observed on gridlock and ED performance metrics at the most extreme increases. Negative effects can be attributed to the fact that and increase in number of patient stretchers/chairs leads to an increase of patients that require care at any given point. Since physicians and nurses are already highly utilized, no further gains can be made because of the staff constraint.

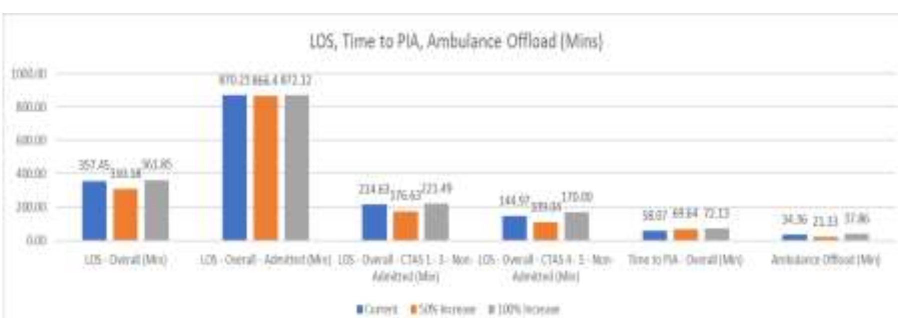

Figure 11: Group 2 scenarios summary

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AUTHOR BIOGRAPHIES

EVGUENIIA DOUDAREVA is a Ph.D. Candidate in the Department of Mechanical and Industrial Engineering at University of Toronto. She holds a M.A.Sc. and B.A.Sc. in Industrial Engineering from University of Toronto. Her research interests include optimization, discrete event simulation, and healthcare. Particularly, she is focusing on a generic approach to modelling the Emergency Department. Her email address is jenya.doureva@utoronto.ca.

MICHAEL CARTER is a Professor in the Department of Mechanical and Industrial Engineering at the University of Toronto (since 1981) and Founding Director of the Centre for Healthcare Engineering. His research focus has been in the area of health care resource modeling. He is on the editorial board for the journals "Health Care Management Science", "Operations Research for Health Care", "Health Systems" and "IIE Transactions on Healthcare Systems". His e-mail address is mike.carter@utoronto.ca.