Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

IDENTIFYING THE OPTIMAL CONFIGURATION OF AN EXPRESS CARE AREA IN AN EMERGENCY DEPARTMENT: A DES AND METAMODELING APPROACH

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ABSTRACT

Annual Emergency Department (ED) visits have increased 44% over the last two decades while the number of EDs nationwide has fallen by 11%. This increase in demand has led to overcrowded EDs and increased length of stay, both of which have the potential to negatively affect patient outcomes and satisfaction. The University of Virginia (UVA) ED is considering process changes to the express care treatment area, an area that mostly treats low acuity patients, in an effort to reduce length of stay. We developed a discrete-event simulation model to assess the impact of changes to the express care area, including the number of treatment beds, hours of operation, and the types of patients sent to express care. Then, we developed a regression metamodel to analyze the impact of the proposed changes. The model findings suggest the current UVA ED express care settings are near optimal among the options considered.

1 INTRODUCTION

Over the last two decades, the number of annual emergency department (ED) visits rose 44% while the number of hospital EDs decreased by 11% (American Hospital Association 2015). The Affordable Care Act and expansion of health coverage may further increase ED visits (Smulowitz et al. 2014; Taubman et al. 2014). The increasing volume of patients has led to ED overcrowding which can affect patient outcomes and satisfaction (Hoot and Aronsky 2008; Niska, Bhuiya, and Xu 2010; Derlet and Richards 2000). The University of Virginia (UVA) Medical Center ED experiences length of stay times above the national average.

In an effort to reduce overcrowding, the UVA ED has introduced an express care treatment area to treat low acuity patients. However, the effect of this area on ED patient flow has not been studied. The UVA ED is considering process changes to the express care with the goal of improving length of stay for patients in express care and the ED as a whole, including reducing the number of beds in the area and opening earlier. The motivation for this study is to estimate the impact of changes using a simulation model before making changes in the ED.

The objective of this study is to identify optimal design parameters for better utilization of an express care area in an ED. Design parameters include express care hours of operation, capacity, and types of patients treated. We utilize discrete-event simulation (DES) modeling and regression-based metamodeling to assess the impact of implementing changes to the express care area. A full factorial design of experiments is used to create simulation scenarios. Improved operation of the area supported by data-driven decisions will help streamline patient flow in the ED and therefore alleviate ED overcrowding.

2 METHODS

2.1 Discrete Event Simulation

2.1.1 Model Description

We developed a DES model to investigate alternative operations of an express care area and patient flow in the ED. The model represents four different tracks of patient flow depending on the type and amount of resources required for patient care: adult patient track, trauma patient track, express care track, and pediatrics patient track. Typically, patients in each track are treated in a bed of a designated area by physicians and nurses working in that area. However, patients are often sent to other areas depending on the total ED census and the time of day. The simulation model incorporates the exceptional rules into the typical patient flow.

Figure 1 shows patient flow of the four tracks. Patients arrive at the ED either by walk-in or by ambulance. After a quick registration, if a patient is stable, he/she is triaged by a triage nurse. If not stable, a patient is placed in an appropriate ED bed immediately. Based on a patient's conditions and acuity, a triage nurse assigns an Emergency Severity Index (ESI), ranging from 1 (life threatening) to 5 (non-emergent), and determines the area to place the patient. When there is an available bed in the assigned area, a patient is placed in the appropriate bed. If there is no available bed, a triage nurse sends the patient to either the waiting room or a bed in another area, depending on the status of the patient and the ED system. A nurse initially examines a patient, and then a physician orders diagnostic tests and labs if needed after seeing the patient. Based on the patient's lab results and required treatment, a physician determines whether to discharge the patient or admit the patient to the hospital. Based on the disposition decision, a patient leaves the ED after receiving appropriate treatment or stays in the ED until there is an available inpatient bed in the unit where a patient is admitted.

In the adult area, bed availability is determined by current workloads of nurses working in each zone where 4 to 6 beds are assigned. The workload of a nurse is estimated by multiplication of the number of patients occupying beds in their zone with their acuity levels. If the current workload of a nurse is greater than a threshold (currently 10), the nurse does not take more patients even though there is an available bed in her/his zone unless special conditions are met (e.g. number of patients in the waiting room is greater than a threshold).

Our focus is to optimize the flow of the express care track and to evaluate impacts of the changes in the track on the entire patient flow in the ED. Currently, the ED has five beds in the express care area, which is open from 11 am to 11 pm. During the operating hours, one physician extender and one registered nurse see patients in the area. There is one attending physician from 1:30 pm to 11 pm in the unit, and an attending physician from the adult care area works in both areas between 11 am and 1:30 pm. Usually, patients with low acuity levels (ESI 4 and 5) are sent to express care, but some of patients with ESI 2 and 3 are also sent to the area. The capacity and processes of the express care unit were determined based on experiences of care providers and managers in the ED. The UVA ED is considering to change the capacity and operation of the area with the goal of decreasing length of stay of patients in the ED. To evaluate the impact of process changes to the express care area and other areas, we developed experimental models with various alternatives. The method of designing alternatives is explained in Section 2.2.

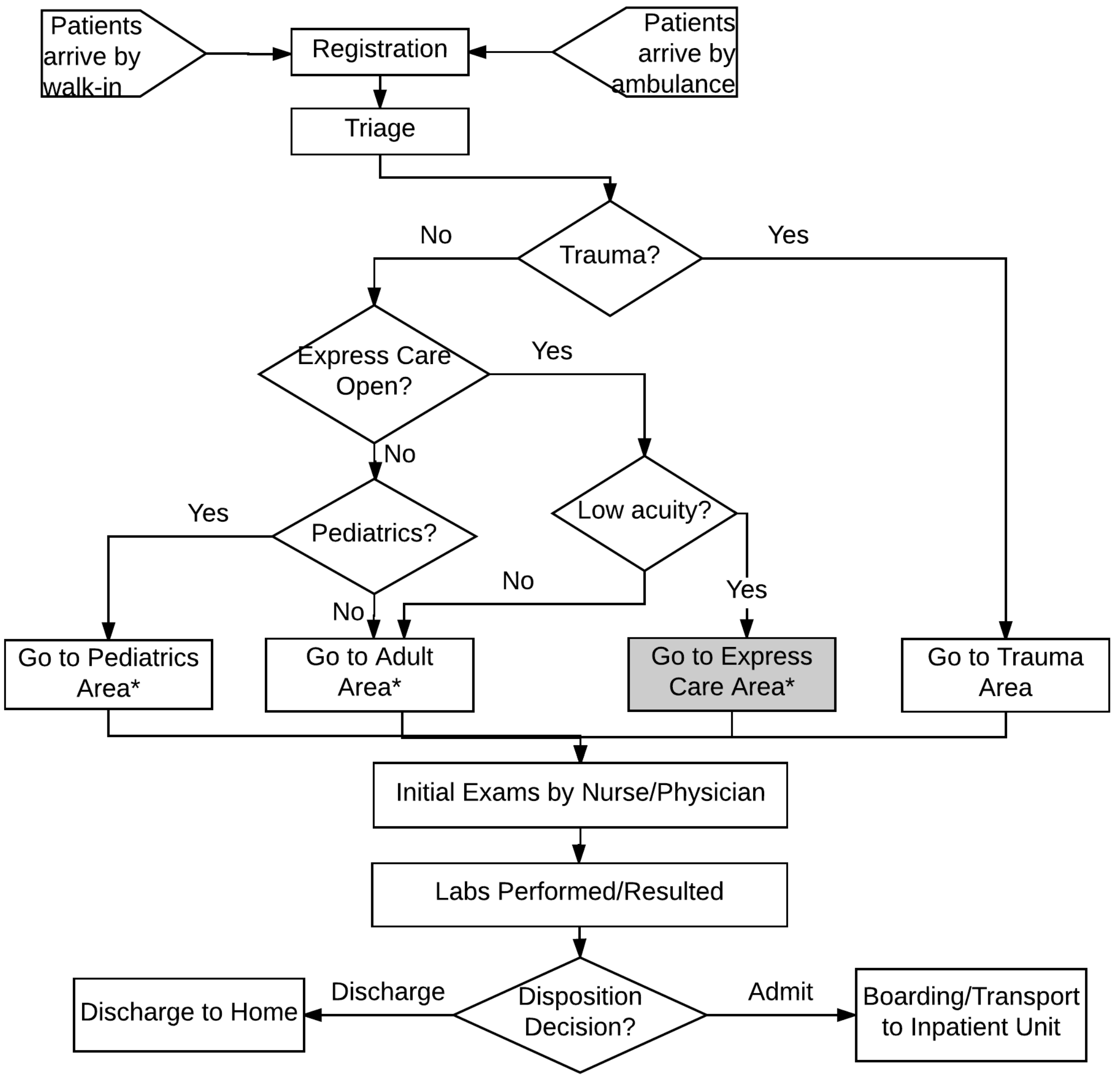

Figure 1. Patient flow through ED (*: When bed available).

2.1.2 Data and Parameter Estimation

To develop the baseline simulation model, we used the electronic medical records (EMR) of patients who visited the ED in 2014. Using the data, we estimated process times and other parameters associated with paths of patient flow for each of the four patient tracks. ED arrivals vary by time of the day. To reflect the time-varying arrival patterns, a non-homogeneous Poisson process was assumed, and a piecewise-constant estimation was used with one hour intervals (Law and Kelton 2006). Arrival patterns were estimated using patient arrival time stamps for the entire population, and track assignments were given to patients upon arrival in the ED based on the overall patient volume distribution for the four tracks.

2.1.3 Performance Measures and Validation

There are various metrics that reflect the degree of ED overcrowding and efficiency of patient flow. This study focused on two main time intervals, length of stay (LOS) and 'door to doctor' (DTD). LOS represents the total cycle time from patient arrival to departure, and DTD represents the time between patient arrival and the time the patient is seen by a physician. Although our focus was on the express care area, we analyzed the two performance measures for both the patients in the express care track (*Express LOS*, *Express DTD*) and patients in all four tracks (adult, trauma, express care, and pediatrics) (*Overall LOS*, *Overall DTD*) in order to evaluate ramifications of the express care alternatives on the ED as a whole.

The baseline simulation model was validated by comparing its results with the key performance measures of hospital data. The model was run for 14 days with 25 replications and a warm-up period of one day.

2.2 Regression-Based Metamodeling

Metamodels have been frequently applied in DES models to identify significant factors associated with performance measures, optimize system parameters, and conduct sensitivity analysis (Kleijnen and Sargent 2000; Kuhl 2005). Of various types of metamodeling, such as polynomial regression, neural networks, and Kriging, we used a first-order linear regression model to quantify the impact of factors on the performance measures.

The inputs of a metamodel were determined using a factorial design of experience. A factorial design is recommended to evaluate a feasible set of options when each factor has multiple dimensions (Karnon et al. 2012). We considered four design factors that may influence the operation of the express care area and patient flow in the ED: (A) the time to open the express care area, (B) the duration of operating hours, (C) the number of express beds, and (D) types of patients sent to the beds. Each factor has two levels, and Table 1 shows coded data.

Table 1. The 2^4 design for the express care area.

LEVEL	FACTOR			
	Open time (A)	Operating hours (B)	Number of express beds (C)	Patient Type (D)
Low (0)	10 am	12 hours*	4 beds	Hybrid*
High (1)	11 am*	13 hours	5 beds*	Only ESI 4 and 5

* Corresponds the current operation of the express care area.

Currently, the express care area is open from 11 am to 11 pm, but it can be open one hour earlier from 10 am to 10 pm. The operating hours can be extended from 12 hours to 13 hours, in which a physician extender and registered nurse will be staffed for the additional time. The express care area has 5 beds, but if a bed is removed from the area it can be used in the adult care area. The express care area was designed to see patients with low acuity levels (ESI 4 and 5), but in 2014, of patients who were sent to the area, 2% were with ESI 2, 14% were with ESI 3, 71% were with ESI 4, and 13% were ESI 5. About 15% of patients with ESI 4 and 5 were sent to the adult care area during the express care operating hours. This hybrid patient type can be changed to sending all patients with ESI 4 and 5 to the express care area during its open hours.

We performed a full 2^4 factorial experiment, and the experiment was replicated 25 times. Since each replication is independent and the order in which the runs are made was random, this is a completely randomized experiment. The inputs and outputs obtained from the simulation models were fitted to the metamodel. A separate regression model was developed for each performance measure.

3 RESULTS

The baseline simulation model was validated using the hospital data for 2014. Table 2 shows that the model outputs closely resemble the actual system. The time interval between disposition decision and departure for admitted patients indicates ED boarding time.

Table 2. Comparisons between hospital data (2014) and results of the baseline simulation model.

		Hospital data (2014) Mean (minutes) [std.]	**Simulation results** Mean (minutes) [95% CI]
Overall LOS		300 [230]	295.8 [294, 297.7]
Express LOS		175 [137]	167.5 [162.2, 168.5]
Overall DTD		40 [40]	38 [36.4, 39.6]
Express DTD		48 [41]	46 [44, 48]
Disposition decision to departure	Discharged patients	30 [10]	31.2 [30.8, 31.5]
	Admitted patients	271 [246]	273.8 [270.9, 276.8]

After validating the model, we developed 16 alternative models, each of which represents a treatment combination of the experiment. Using the regression metamodel, we analyzed the effects of the four factors on the four performance measures, respectively. Table 3 summarizes significant factors associated with each of the performance measure (α=0.05).

Table 3. Summary of significant factors for performance measures.

	Effect Estimate			
	Overall LOS	Express LOS	Overall DTD	Express DTD
Main factors	C D	A B C D	C D	A B C D
Two-factor interaction	AC AD BD	AC BC	AC AD CD	AC BC

The results indicated that the number of express beds (C) and patient type (D) significantly affect both overall patient flow in the ED and patient flow in the express care area. On the other hand, the opening time of the express care area (A) and operating hours of the area (B) influence only the flow of patients who are sent to the express care area.

The ANOVA in Table 4 summarizes the magnitude of the effects for *Express LOS*. While the main effects of all factors were significant, the effects of factors C and D were stronger than factors A and B. The regression model for predicting *Express LOS* is

$$y_{Express\_LOS} = 185.6 - 1.4x_1 + 1.2x_2 - 9.5x_3 + 9.4x_4 + 1.3x_1x_3 - 1.2x_2x_3$$

where the coded variables x_1, x_2, x_3, and x_4 represent A, B, C, and D, respectively. The regression model indicates that opening the express care area one hour earlier (10 am – 10 pm) slightly increases the average *Express LOS* by 1.4 minutes when the number of express care beds is 4 and holding other variables constant. When the number of express care beds is 5, the change in the open time does not have a significant effect on Express LOS. This may be because the demand for the express care service is lower between 10 am and 11 am than the demand between 10 pm and 11 pm. On the other hand, opening the express care area for one additional hour decreases the average *Express LOS* by 1.4 minutes, when the number of express care beds is 4 and holding other variables constant. The effect of the additional operating hour on *Express LOS* disappears when the number of express care beds is 4. When considering the cost of staffing the area for the additional hour, this improvement may not be practically significant. When reducing the number of express care beds from 5 to 4 and using the bed in another area, the average *Express LOS* is expected to increase by 9.5 minutes, holding the opening time (A) and operating hours (B) at the lower level and other variables constant. When operating the area for 13 hours, the effect of increased capacity on *Express LOS* slightly increases, compared to operating it for 12 hours. Similarly, when sending all patients with ESI 4 and 5 to express care during its open hours, the average *Express LOS* increases by 9.4 minutes, holding other variables constant. The 2-factor interaction plots shown in Figure 2 depict that the degree of impact of reducing the number of bed from 5 to 4 is greater when opening the express care area at 10 am compared to 11 am and when operating it for 13 hours compared to 12 hours.

The regression model for the *Overall LOS* indicated that the effect of the number of express beds (C) is similar to *Express LOS*. However, the effect of patient type (D) is the opposite, where the change in the patient type sent to the express care from the current practice decreases *Overall LOS* by 3.7 minutes.

Table 4. Analysis of Variance for Express LOS.

Source	Type III Sum of Squares	df	Mean Square	F	P-Value
Intercept	13787057.87	1	13787057.87	119034.591	0
OpenTime	780.117	1	780.117	6.735	0.01*
OperatingHour	546.854	1	546.854	4.721	0.03*
NumBeds	35877.793	1	35877.793	309.761	<0.001*
PatientType	35435.564	1	35435.564	305.943	<0.001*
OpenTime *OperatingHour	18.39	1	18.39	0.159	0.691
OpenTime * NumBeds	725.301	1	725.301	6.262	0.013*
OpenTime * PatientType	76.134	1	76.134	0.657	0.418
OperatingHour * NumBeds	529.021	1	529.021	4.567	0.033*
OperatingHour * PatientType	13.732	1	13.732	0.119	0.731
NumBeds * PatientType	139.802	1	139.802	1.207	0.273
OpenTime * OperatingHour * NumBeds	47.136	1	47.136	0.407	0.524
OpenTime * OperatingHour * PatientType	5.997	1	5.997	0.052	0.82
OpenTime * NumBeds * PatientType	24.409	1	24.409	0.211	0.646
OperatingHour * NumBeds * PatientType	0.172	1	0.172	0.001	0.969
OpenTime * OperatingHour * NumBeds * PatientType	4.37	1	4.37	0.038	0.846
Error	44476.401	384	115.824		
Total	13905759.06	400			

*α=0.05

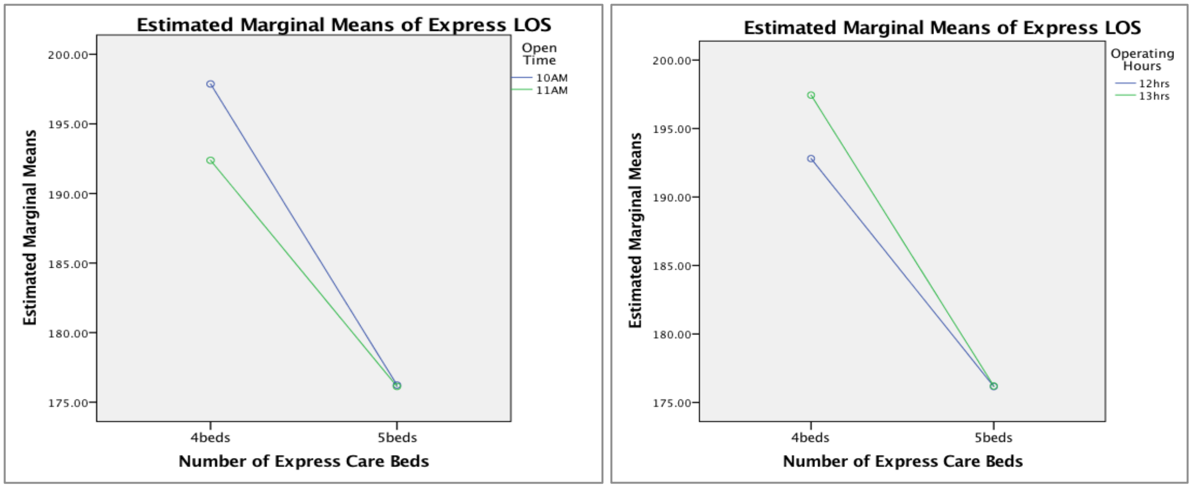

Figure 2. 2-Factor interaction plots for Express LOS.

The regression model for *Express_DTD* is as follows:

$$y_{Express\_DTD} = 64 - 1.2x_1 + 0.9x_2 - 10x_3 + 9x_4 + 1.2x_1x_3 - 1.1x_2x_3.$$

This result indicates that the direction and magnitude of effects of the four factors are similar between *Express LOS* and *Express DTD*. In other words, the efficiency that may be obtained from the changes are mostly attributed to the reduction in delays between patient arrival and first provider encounter.

Overall, the best parameters for *Express LOS* is (A) 10 am, (B) 13 hours, (C) 5 beds, and (D) hybrid patient type. However, the difference in the performance measure between the current settings and the optimal settings is only about 1 minute. This means that the current express care is operating almost at optimal level with respect to patient flow in that area. This configuration can also help reduce *Overall LOS* by 4 minutes.

The best parameters for *Overall LOS* is (A) 10 am, (B) 12 hours, (C) 5 beds, and (D) only ESI 4 and 5. The changes in the opening hour and patient type will help decrease the *Overall LOS* by 12 minutes. This configuration, however, will lead to an increase in *Express LOS* by 17.7 minutes. The optimal settings for *Express DTD* and *Overall DTD* are the same as those for their LOS.

In addition to the best parameters, we identified the worst cases that lead to the longest LOS. For the express care area, the configuration (A) 10 am, (B) 13 hours, (C) 4 beds, and (D) only ESI 4 and 5 yields 44.3 minutes longer *Express LOS*. However, this setting contributes to reducing *Overall LOS* by 5.8 minutes. For *Overall LOS*, the current setting, (A) 11 am, (B) 12 hours, (C) 5 beds, and (D) hybrid patient type, leads to the longest time.

4 CONCLUSION

This study developed a DES simulation model and investigated various alternatives to identify the optimal design parameters for better utilization of an express care area in an ED. The results showed that the current UVA ED express care settings are near optimal among the options considered. Contrary to our initial hypothesis, the replacement of one express care bed with one adult acute bed may not help improve patient flow in the ED. However, opening the area one hour early and sending all patients with ESI 4 and 5 during the operating hours may improve the overall patient flow. Even though the magnitude of the improvement is small compared to the total time patients spend the ED, the gain is still meaningful in that it can be achieved without spending additional resources. The impacts of the changes in the express care area operation may be different when the capacity of the ED increases or downstream processes change. Future analysis could consider additional resource configurations to see if further improvement could be realized. Our study also demonstrated that an improvement in patient flow in one area does not necessarily help the overall patient flow in the ED. This finding indicates that a holistic perspective is required when reengineering a system in order to improve the overall performance of a system. As shown in this study, a DES simulation approach and well-designed what-if scenarios are effective methods to support integrated decision making. Although the results are specific to this study institution, the DES and metamodeling approach can be applied to other EDs to reengineer their care areas.

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