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MINIMIZING FLOW-TIME AND TIME-TO-FIRST-TREATMENT IN AN EMERGENCY DEPARTMENT THROUGH SIMULATION

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ABSTRACT

Emergency Department management is a resource constrained environment that has gained attention in recent years. An in-depth literature review was conducted and two patient flow models, Virtual Streaming (VS) and Physician Directed Queuing (PDQ), were selected to be contrasted against a FIFO-baseline model using discrete event simulation. Scenarios were constructed by assigning doctors to 4-hour shifts. Model performance was ranked by finding the minimum aggregated time to first treatment (TTFT) of admitted patients and the length of stay (LOS) of discharged patients. The benefits from PDQ were seen largely by Emergency Severity Index (ESI) 4 and 5 patients and the benefits from VS were seen largely by ESI 2 and 3 patients. Results suggest VS for the patient mix used herein when the system is near capacity and the baseline when the system is not near capacity. However, trade-offs and improvements of these models are discussed.

1 INTRODUCTION AND MOTIVATION

A traditional Emergency Department (ED) is one that specializes in acute care and services patients using a process of medical triage. Medical triage is a systematic way for nurses or other medical practitioners to prioritize patients. The Emergency Severity Index (ESI) is often used to systematically triage patients based on patient acuity and resource requirements in the United States (Pitts et al. 2008). In these EDs nurses determine ESI levels for patients and, subsequently, these patients are seen according to the ESI level then using a first in, first out rule (FIFO). The ESI algorithm classifies patients using a five level scale. Patients classified as ESI 1 are in a critical, life-threatening state. Patients classified as ESI 2 are in a critical, but not life-threatening state. Patients classified as ESI 3, 4, or 5 represent patients in a non-critical state stratified by the amount of resources required for treatment.

The ED is the most important department in evaluating hospital performance (McClelland 2011). Pitts et al. (2008) reported that between 1996 and 2006 the number of EDs in the U.S. decreased 5% from 4,019 to 3,833 leading to overcrowding. This has led to the need for intelligent scheduling of resources. Improved resource management strategies are necessary to combat the increasing costs of healthcare and overutilization of EDs. Discrete Event Simulation (DES) has been shown to be a valuable tool in evaluating the performance of healthcare management strategies (Katsaliaki and Mustafee 2011). More specifically, DES has been proven to help in patient scheduling and admissions; patient flow; resource availability; resource scheduling, bed sizing and planning; and room and staff sizing (Jun, Jacobson, and Swisher 1999). In this study DES was applied to contrast patient flow methodologies for various staff sizes and schedules.

2 LITERATURE REVIEW

Several different triage systems are used worldwide to manage patient flow in an ED. Four of these systems stand out in literature: the Australian Triage Scale, the Canadian Triage Acuity Scale, the Emergency Severity Index, and the Emergency Triage System (also known as the Manchester Triage Scale) (Bernstein et al. 2003). Each of these triage systems make limiting assumptions that require validation. The literature is somewhat sparse on validation of these triage systems in practice.

The ESI classification, used predominantly in the United States, was introduced as a 3-level triage system; however, the 3-level system was proven to be unreliable (MacLean 2001; Gill, Reese, and Diamond 1996). Tanabe et al. (2004) validated a 5-level ESI triage algorithm that considers patient acuity and ED resource consumption. This ESI algorithm gained the support of the Emergency Nurses Association and the American College of Emergency Physicians (Emergency Nurses Association 2003). The 5-level ESI triage algorithm assigns an ESI level of 1 to patients in a life-threatening, serious condition—these include unresponsive patients or patients that are intubated or pulseless. An ESI level of 2 is assigned if the patient is in a high-risk situation, or is significantly confused or disoriented. ESI levels 3, 4, and 5 are assigned to patients in a non-critical state based on the number of required resources for treatment. Patients classified as ESI 3 require two or more resources; patients classified as ESI 4 require one resource; and patients classified as ESI 5 require no resources (Ashour and Kremer 2012).

The implementation of the ESI triage system does not seem to be thorough enough to deal with the increase of patients and the decrease of ED's. Saghafian et al. (2012) has shown that the triage nurse can classify patients into those admitted and those who will be discharged from the hospital. They argue that minimizing time to first treatment (TTFT) is the largest priority for admit patients and minimizing length of stay (LOS) is the largest priority for discharge patients. They introduce an extension of the ESI algorithm called Virtual Streaming (VS) and mathematically prove that VS minimizes LOS and TTFT.

Medeiros, Swenson, and DeFlitch (2008) studied the Physician Directed Queuing (PDQ) model. The PDQ model also utilizes ESI classification. The PDQ system uses an upfront fast-track group of nurses, medical technicians and an ED physician in a PDQ area. This PDQ area is physically detached from the larger ED and serves as the entrance and exit point for patients. In the PDQ area triage is performed. Also, treatment of some ESI 4 and ESI 5 patients is performed. Patients not treated in the PDQ area are sent to the larger, attached ED. PDQ was implemented at Hershey Medical Center for a month pilot study. This pilot showed an average reduction of 23% in LOS and 35% in TTFT across all ESI classes when compared to the previous year's same month (Medeiros, Swenson, and DeFlitch 2008). VS and PDQ are not the only systems developed to handle ED crowding. Chan et al. (2005) discuss other approaches similar to PDQ such as team triage (Wiler et al. 2010) and rapid entry and accelerated care at triage (REACT).

Other methods to improve ED performance rely on IT advancements and information sharing. One such program, InQuickER, is designed to handle same-day appointments utilizing the increasing prevalence of mobile device apps (InQuickER 2011). Another approach, the Urgent Matters Program, uses IT efforts to reduce ED waiting time and to enhance the overall quality of care (McClelland et al. 2011). Started in 2002 and funded by the Robert Wood Johnson Foundation, this program was designed to enhance flow in the ED. This program has managed to expand in to a number of collaborating hospitals and to build a solid library of tools directed at helping reduce waiting times in the ED. Some of these tools are e-newsletters, webinars, and national conferences.

Knowledge-based reactive scheduling systems have been introduced to reduce the waiting time of patients in the ED by focusing on the requirements of the EDs (Kiris et al. 2010). These systems track information such as a detailed patient priority, arrival time, flow time, and doctor load. The reactive scheduling system determines patients who have initial higher priority. Then the system seeks to reduce their waiting times and changes the number of doctors scheduled. As more patients arrive the queues are updated to reflect newly determined priority. Doctor loads are balanced throughout this process. A final approach to improved ED performance includes heuristic techniques. For example, Puente et al. (2009) implemented genetic algorithms to enhance the scheduling of doctors in an ED by automating shift schedule generation.

An ED is a complex environment. In order to produce meaningful results in such a complex environment, more than one objective must be considered. The flow of information (McClelland et al. 2011), the flow of the patients (Saghafian et al. 2012; Medeiros, Swenson, and DeFlitch 2008), and the classification system (MacLean 2001; Gill, Reese, and Diamond 1996; Tanabe et al. 2004) all influence the performance of an ED. ED management and staffing strategies should address these three flows and use the proper performance metrics. Bernstein et al. (2003) proposed the Emergency Department Work Index (EDWIN) to measure the performance and crowding in an ED and can be considered a viable candidate in tracking overall ED performance.

3 PROBLEM DESCRIPTION

There are many ESI-based ED management strategies in the literature. This research examined literature and selected two dissimilar ESI-based patient flow methodologies to gain insight on how they impact the quality of care. This study was completed to contrast and learn from existing ED strategies and to validate performance claims found in literature. The three models analyzed were VS, PDQ and a baseline.

ED performance is tied directly to economics and quality of care. This research focuses on a simplified view of the quality of care, as measured by a surrogate. The surrogate was developed noting that two groups of patients exist—admit patients and discharge patients. Admit patients (A) are those that will be admitted to the hospital after treatment in the ED. Discharge patients (D) are those that will leave the hospital after treatment. Saghafian et al. (2012) argued that for admit patients the time to first treatment (TTFT) is the most important performance measure because the patient will be admitted to the hospital. The authors also argued that for discharge patients minimizing the length of stay (LOS) is the performance measure of interest.

In this research, admit and discharge patients may be assigned ESI levels 2, 3 or 4, written as 2A, 2D, 3A, etc. Patients assigned ESI 5 are of low acuity and are discharge patients only. ESI 1 patients were not considered in this work because they preempt all other patients. Thus, there are seven patient types in this research. These seven patient types lead to seven minimization objectives: to minimize the TTFT for the three admit patient classes and to minimize the LOS for the four discharge patient classes. To reduce this problem to a single objective an overall model performance metric was developed by aggregating the appropriate average primary performance for each patient type. Models were evaluated using the performance metric and by varying the number of scheduled doctor-shifts used in a simulation.

4 METHODOLOGY

The Physician Directed Queuing (PDQ), Virtual Streaming (VS), and baseline simulation models were developed in Simio®. The models use a continuous work schedule of six 4-hour shifts. The first shift is from 0:00 to 4:00; the second shift is from 4:00 to 8:00, and so on to the last shift from 20:00 to 24:00. In each simulation run a shift schedule is given and the system is observed for 10 days after a day warm-up.

Experimentation was conducted by varying the number of doctors that are scheduled in 4-hour shifts between hours 0:00 and 24:00 and calculating the overall model performance metric described in Section 6. For completeness the TTFT and LOS of the patient classes were recorded. The total number of doctor-shifts was varied from 22 to 30 doctor-shifts in a day, where only even values were used. This range of doctor-shifts was determined during a pre-analysis of the system explained in Section 4.3.

The arrival rate distributions for the different patient classes were constant across the three models to obtain an accurate and fair comparison among the different sets of results. However, the doctor-shift schedules and facility layout were varied. Section 4.1 describes the assumptions made to build the models. Section 4.2 discusses the arrival rates by patient classification and number of patient-doctor interactions. Finally, Sections 4.3-4.5 describe the methodology behind the baseline, VS, and PDQ models, respectively.

4.1 Assumptions

Several assumptions were made to test the three ED management strategies. In all models patients are triaged before proceeding to treatment. During triage patients are assigned an ESI level and classified as admit or discharge without error. In the PDQ model the decision to enter the PDQ area is made.

Patient prioritization considered ESI level first in all situations. This ensured that the most severe patients received treatment first. The models use different dispatching rules to select who to treat first within the same ESI level. In the VS model, doctors treating patients who will be admitted in an admit queue prioritized patients that have not been treated yet. Doctors treating patients who will be discharged prioritize patients by shortest processing time (SPT). In the baseline and PDQ models, doctors use a first in, first out (FIFO) rule as a secondary dispatching rule and do not consider hospital admittance.

Doctors treat one patient at a time and were assigned at most seven patients at any time. Further, doctors were not assigned specific patients. This means, for example, that if there were two doctors, then fourteen patients could be in the ED and additional patients must be in a waiting room. It was assumed that doctors perform identically. Simulations sampled the processing times, the number of required patient-doctor interactions, and arrival rates from the distributions provided below.

Table 1 provides the treatment time distributions for the patient types used in this research. Testing is assumed to be exponentially distributed with a mean of 30 minutes and triage is assumed to be triangularly distributed with parameters (3,5,7) in minutes. The treatment times of interactions are uniform over the number of patient-doctor interactions. For example, if a patient with a total treatment time of 32 minutes requires four interactions then each patient-doctor interaction is eight minutes.

Table 1: Patient processing times.

ESI	Type	Distribution	Parameters (min)
2	Admits	Triangular	(29.1, 32.6, 36.1)
	Discharges	Triangular	(23.1, 24.2, 25.3)
3	Admits	Triangular	(50.7, 55.6, 60.5)
	Discharges	Triangular	(26.2, 31.9, 37.6)
4	Admits	Triangular	(22.6, 25.0, 27.4)
	Discharges	Triangular	(22.6, 25.0, 27.4)
5	Discharges	Triangular	(9.3, 9.8, 10.3)

4.2 Arrival Rates and Number of Visits

Figure 1 provides the distributions of patient-doctor interactions by patient class and the arrival rates used in this work. These rate follow non-stationary Poisson processes that were adapted from literature. In particular, arrival rates of ESI 2 and 3 patients, both admit and discharge, were taken directly from the original VS methodology (Saghafian et al. 2012). Rates for ESI 4 and 5 patients were adapted from published time study distributions (Graff et al. 1992). These rates were utilized to generate patients for the three models, as mentioned earlier. These rates show an overall patient mix of 39.5% ESI 2, 43.9% ESI 3, 14.2% ESI 4 and 2.4% ESI 5.

4.3 Range of Doctor-Shifts

Physicians are scheduled on four-hour shifts starting from midnight and continuing for 24-hours before repeating. A scenario refers to a configuration of doctors in the system. A crude queuing analysis was completed to suggest an acceptable range of physicians that should be scheduled by shift. The range of scheduled doctors per day was predetermined to keep the system as close to the system's capacity limits as possible. This was done to test how a particular setup performed for each total doctor-shift scheduled per work day. An acceptable range of doctors by shift was developed assuming independent shifts and all

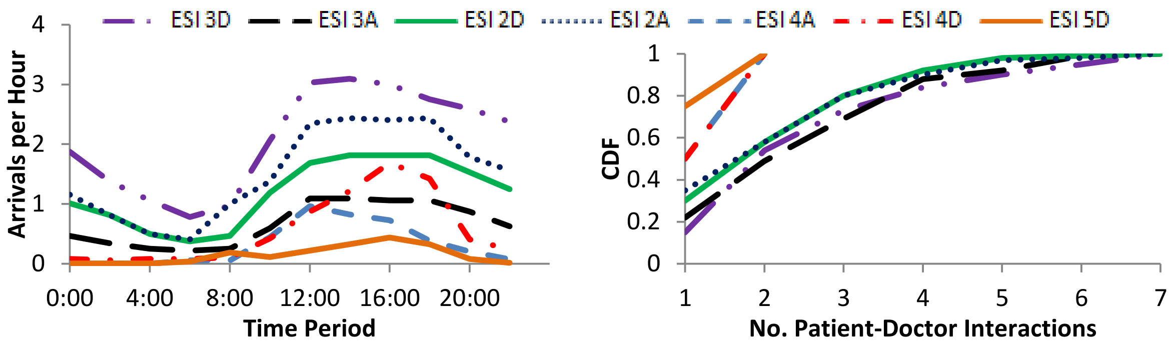

Figure 1: Arrival rates and patient-doctor interactions by ESI level.

patients have a processing time of 60 minutes. Table 2 was produced by aggregating the expected arrivals from Figure 1 and determining the minimum number of doctors needed over a four-hour period. Table 2 contains the minimum and maximum number of doctors to be scheduled in each four-hour shift considered in this research. The results in Table 2 do not account for the amount of time a patient spends in testing. A few preliminary runs of the baseline model showed that a minimum of 22 doctor-shifts are needed to keep the system from being over capacity. Additionally, no more than 30 doctor-shifts are considered to avoid low doctor utilization. This range was modified for the VS and PDQ models.

Table 2: Expected arrival and doctor ranges per shift.

Time of Day	Expected Arrivals	Min # Doctors	Max # Doctors
0:00-4:00	5.82	2	4
4:00-8:00	5.00	2	4
8:00-12:00	16.41	4	9
12:00-16:00	21.94	5	10
16:00-20:00	17.67	4	9
20:00-24:00	10.815	2	4

4.4 Baseline

The baseline model was developed to represent what is used in many hospitals throughout the United States. In the baseline scenario physicians treat patients according to ESI level using FIFO to break ties without further facility management or prioritization rules. Treatment occurs in the main ED queue. Patients may require additional testing which is done externally to the ED. Table 2 has the range of doctors per shift considered for the baseline model.

4.5 Virtual Streaming (VS)

VS utilizes a triage process and two virtual queues—one for admitted and one for discharged patients. The virtual streams are collocated, compete for the same resources, and are differentiated by the patient type that is treated in each stream. Figure 2 shows the virtual streaming (VS) system. Upon entering, patients are routed to triage for initial processing. After triage the patients are routed to either the admit queue or the discharge queue. Admit doctors prioritize new patients after considering ESI level. Specifically, if there is more than one patient of a given ESI, then the patient with the minimum number of visits completed will be selected. Discharge doctors prioritize patients by considering ESI level then the amount of treatment time required. Specifically, if there is more than one patient of a given ESI, then the patient with the smallest treatment time is treated first. FIFO is used to break any further ties in either queue. After treatment from a doctor, a patient may go to testing if more patient-doctor interactions are required. If no more interactions are required, then the patient leaves the ED to be discharged from care or admitted to the larger hospital.

Shift-to-shift variation of the number of scheduled doctors may occur. But, it is assumed that the number of doctors scheduled in admit and discharge queues are equal for any given shift. This was done to avoid prioritizing admitted patients over discharged patients or vice versa. If there ever exists a time when the admit queue has patients waiting and the discharge queue has idle doctors these doctors will treat a patient in the admit queue and vice versa.

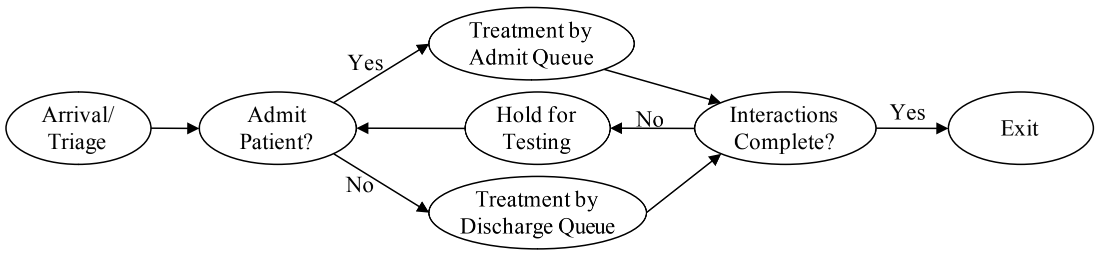

Figure 2: Flowchart for Virtual Streaming (VS).

4.6 Physician Directed Queuing (PDQ)

In the PDQ model, patients arrive and head to triage. During triaging it is decided if the patient will be treated in the PDQ area or sent to the main ED. Patients treated in the PDQ area may proceed to testing if further interactions are required or exit the system if treatment is complete. The patients that have not been eligible for the fast track and sent to the main ED are prioritized by ESI level with FIFO to break ties. Patients in the main ED may go to testing or leave the hospital if no further patient-doctor interactions are required. This procedure is summarized in Figure 3.

The PDQ area is designed to treat patients classified as ESI 4 or 5 only. The PDQ doctors prioritize patients by ESI level using FIFO to break ties. The PDQ area has at most one physician and, thus, a capacity of seven patients at any time.

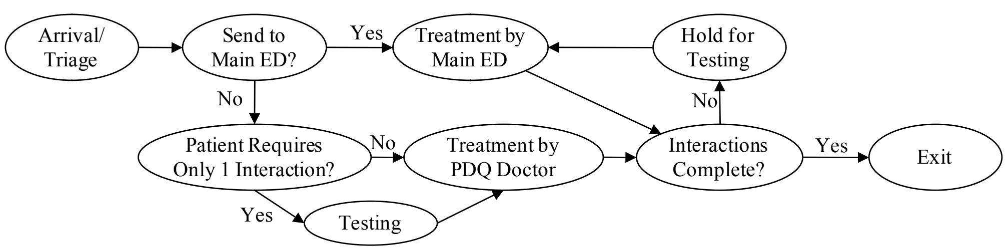

Figure 3: Flowchart for Physician Directed Queuing (PDQ).

5 EXPERIMENTATION

The baseline, VS, and PDQ models described above were developed in Simio® 4.68. Scenarios were developed by assigning doctors in each of the six shifts. All scenarios were replicated 30 times and average values for the problem objectives and half-widths were obtained. These statistics were calculated for patients that leave the system (disposed) during 240 hour runs with 24 hour warm-up periods.

In order to investigate the performance of the models the number of doctors in different locations was varied by shift. In VS experimentation the number of doctors in a shift is restricted to an even number. This restriction is used to not prefer admitted patients over discharged patients or vice versa. This leads to an even number of doctor-shifts per day. So, for simplification in comparison, only an even number of doctor-shifts per day were considered in the baseline and PDQ models. Additionally, the total number of doctor-shifts per day was kept between 22 and 30 doctor-shifts.

In the baseline model, the number of doctors in the main ED is changed between the bounds from Table 2 above. For this model 2,673 scenarios were simulated. For the VS model, the number of admit doctors was varied for different shifts between the bounds specified in Table 3. For this model there were $2^3 3^2 4 = 288$ different scenarios tested.

In the PDQ model the number of doctors in the PDQ area and the number of doctors in the main ED are varied. It is common that a fast track is open only during the hours of the day that correspond to when low acuity patients arrive at high rates (Wiler, Gentle, and Halfpenny 2010). This corresponds to between 8:00 and 20:00 in our model. The PDQ area is staffed by one physician during this 12 hour period. The upper and lower bounds on the number of doctors in the main ED during each time period are identical to the baseline scenario and shown in Table 2. The number of scenarios under the PDQ model is 2,916 different scenarios.

Table 3: Range of admit doctors in VS model.

Time Period	Min # Doctors	Max # Doctors
0:00—4:00	1	2
4:00—8:00	1	2
8:00—12:00	2	4
12:00—16:00	2	5
16:00—20:00	2	4
20:00—24:00	1	2

6 RESULTS AND DISCUSSION

Doctor layout in an ED is a multiobjective scheduling problem because it involves minimizing waiting time or flowtime for seven patient groups. Visualizing multiobjective scheduling problems is usually done by considering a representation of the Pareto frontier. Multidimensional Pareto frontiers are hard to visualize because they are not easily graphed. A simplified approach is used here. A weighted sum of the objectives is used to evaluate the performance of a scenario since all objectives are minimization with respect to time. Specifically, a weighted objective function in hours for a scenario with setup parameters X is computed in (1):

$$\Theta(X) = 0.395(LOS_{2D} + T_{2A}) + 0.439(LOS_{3A} + T_{3D}) + 0.142(LOS_{3A} + T_{3D}) + 0.024LOS_{5D} \quad (1)$$

where X refers to the doctor schedule used, T refers to TTFT, and the subscripts refer to the patient class that the performance characteristic is averaged over during a simulation run. In (1) the weights are the expected arrival proportions used in all experimentation. This aggregate objective can be thought of as a measure of a scenario's overall average waiting time.

The results from the experimentation were averaged across the 30 replications then aggregated using (1). For each ED management strategy the objective values in (1) were grouped by the number of doctor-shifts scheduled and ranked. This aggregation reduces the objective space to two dimensions so it can be visualized graphically. The minimum weighted objective is tabulated for all three ED management strategies by the number of scheduled doctors and a confidence interval is provided in Table 4. Plots of the weighted objective for are shown in Figure 4. Also, an overlay of the best performing scenarios by modeling methodology is shown in Figure 4. The doctor schedules are provided in Table 5 for the best performing configurations with respect to the overall average waiting time metric. The schedules of doctors for the all scenarios favored the busiest periods between 12:00 and 20:00.

The interest of this paper is in doctor scheduling in a resource constrained setting and the comparison of the baseline VS, and PDQ scenarios. Table 4 shows the average results calculated during experimentation; however, the exact values of these waiting times are not as important as the trends between the

Table 4: LOS and TTFT in hours for the best performing configurations by doctor-shifts per day.

D-S	Run Type	Total Wait	LOS 2D	LOS 3D	LOS 4D	LOS 5D
22	Base	34.9	4.8 (4.7, 5.0)	28.5 (25.7,31.3)	24.0 (21.5,26.5)	2.6 (2.6, 2.6)
	PDQ	31.2	29.8 (27.8,31.9)	39.5 (37.1,41.9)	30.3 (28.0,32.5)	3.5 (3.2, 3.8)
	VS	31.4	6.9 (6.7, 7.1)	27.0 (24.3,29.7)	16.8 (10.3,23.3)	4.9 (3.3, 6.5)
24	Base	24.3	2.8 (2.7, 3.0)	11.4 (10.2,12.6)	41.5 (33.6,49.4)	29.3 (23.4,35.3)
	PDQ	22.0	17.6 (15.8,19.4)	25.9 (24.2,27.6)	27.3 (25.2,29.5)	3.3 (2.9, 3.7)
	VS	22.8	7.7 (7.5, 7.9)	12.1 (11.1,13.0)	32.9 (24.0,41.8)	5.1 (3.7, 6.5)
26	Base	10.2	2.2 (2.0, 2.5)	5.5 (4.8, 6.2)	11.7 (9.0,14.4)	32.6 (24.3,41.0)
	PDQ	13.2	6.2 (5.1, 7.2)	14.0 (12.7,15.3)	16.4 (14.8,18.0)	4.1 (3.5, 4.8)
	VS	10.1	5.9 (5.5, 6.3)	6.5 (5.9, 7.1)	8.3 (5.8,10.8)	8.8 (5.2,12.4)
28	Base	4.0	1.2 (1.2, 1.2)	2.2 (2.1, 2.4)	4.3 (3.8, 4.8)	10.2 (7.5,13.0)
	PDQ	6.5	1.6 (1.4, 1.8)	4.5 (3.8, 5.2)	9.9 (8.2,11.5)	10.5 (7.2,13.8)
	VS	4.0	3.0 (2.9, 3.2)	2.7 (2.5, 2.9)	1.9 (1.7, 2.1)	1.6 (1.4, 1.9)
30	Base	2.5	1.1 (1.0, 1.1)	1.4 (1.3, 1.5)	2.2 (2.0, 2.5)	3.0 (2.4, 3.6)
	PDQ	3.1	1.1 (1.1, 1.1)	1.9 (1.7, 2.0)	4.2 (3.6, 4.8)	4.8 (3.9, 5.7)
	VS	2.9	2.4 (2.3, 2.5)	2.0 (2.0, 2.1)	1.3 (1.3, 1.4)	1.0 (0.9, 1.1)

D-S	Run Type	Total Wait	TTFT 2A	TTFT 3A	TTFT 4A
22	Base	34.9	4.3 (4.2, 4.5)	27.9 (25.3,30.5)	21.5 (17.2,25.9)
	PDQ	31.2	1.1 (1.1, 1.2)	14.1 (12.8,15.4)	0.7 (0.6, 0.8)
	VS	31.4	4.7 (4.6, 4.9)	24.8 (22.1,27.6)	15.2 (9.1,21.4)
24	Base	24.3	2.3 (2.2, 2.5)	10.8 (9.6,12.1)	41.5 (33.0,49.9)
	PDQ	22.0	1.1 (1.1, 1.1)	10.3 (9.7,10.9)	0.7 (0.6, 0.8)
	VS	22.8	4.6 (4.5, 4.8)	9.3 (8.3,10.2)	29.4 (20.9,37.9)
26	Base	10.2	1.8 (1.6, 2.0)	4.8 (4.1, 5.5)	11.4 (8.9,13.9)
	PDQ	13.2	1.0 (1.0, 1.1)	8.1 (7.5, 8.6)	0.9 (0.7, 1.1)
	VS	10.1	2.9 (2.7, 3.2)	3.9 (3.4, 4.3)	6.5 (4.5, 8.6)
28	Base	4.0	0.9 (0.9, 0.9)	1.7 (1.6, 1.9)	4.2 (3.5, 5.0)
	PDQ	6.5	1.0 (0.9, 1.0)	3.3 (2.9, 3.8)	2.3 (1.7, 2.8)
	VS	4.0	1.4 (1.3, 1.5)	1.4 (1.3, 1.6)	1.4 (1.3, 1.6)
30	Base	2.5	0.8 (0.8, 0.8)	1.1 (1.0 ,1.1)	2.1 (1.9, 2.4)
	PDQ	3.1	0.8 (0.8, 0.8)	1.5 (1.4, 1.6)	1.1 (0.9, 1.4)
	VS	2.9	1.0 (1.0, 1.1)	0.9 (0.8, 0.9)	0.9 (0.9, 1.0)

scenarios. This is because the results apply to the specific patient mix used and for a different patient mix the results may be different. With this in mind this paper focuses on relative trends among the scenarios instead of specific performance objective values.

Table 5 shows that the baseline model is outperformed by the VS model when the resources are heavily constrained (24 doctors or less). Specifically, VS simulations showed lower average waiting times for patients in ESI 3, 4, and 5 but higher average times for patients in ESI 2 than the baseline for 24 or 22 doctor-shifts. Thus, a trade-off exists between improving ESI 2 patients and improving ESI 3, 4, and 5 patients where VS performs better for the latter while the baseline performs better for the former. When the number of doctors scheduled is 26 or larger VS simulations performed about as well as the baseline with respect to the average total waiting time metric. The results from the seven objectives show that there exists a trade-off between the baseline and VS models for 26 or more doctor-shifts. VS performs as much as

Table 5: Corresponding doctor schedule by shift for Table 4 with PDQ area doctors in parentheses.

Doctor-Shifts	Run Type	Total Wait	0-4	4-8	8-12	12-16	16-20	20-24
22	Base	34.9	2	2	5	7	4	2
	PDQ	31.2	2 (0)	2 (0)	4 (1)	5 (1)	4 (1)	2 (0)
	VS	31.4	2	2	4	6	6	2
24	Base	24.3	3	2	4	7	4	4
	PDQ	22.0	2 (0)	2 (0)	4 (1)	7 (1)	4 (1)	2 (0)
	VS	22.8	2	2	4	6	8	2
26	Base	10.2	2	3	6	5	7	3
	PDQ	13.2	2 (0)	3 (0)	4 (1)	5 (1)	7 (1)	2 (0)
	VS	10.1	4	2	6	4	8	2
28	Base	4.0	3	2	5	8	7	3
	PDQ	6.5	3 (0)	2 (0)	4 (1)	8 (1)	6 (1)	2 (0)
	VS	4.0	4	2	4	6	8	4
30	Base	2.5	3	2	5	8	8	4
	PDQ	3.1	2 (0)	2 (0)	5 (1)	7 (1)	7 (1)	4 (0)
	VS	2.9	4	2	4	8	8	4

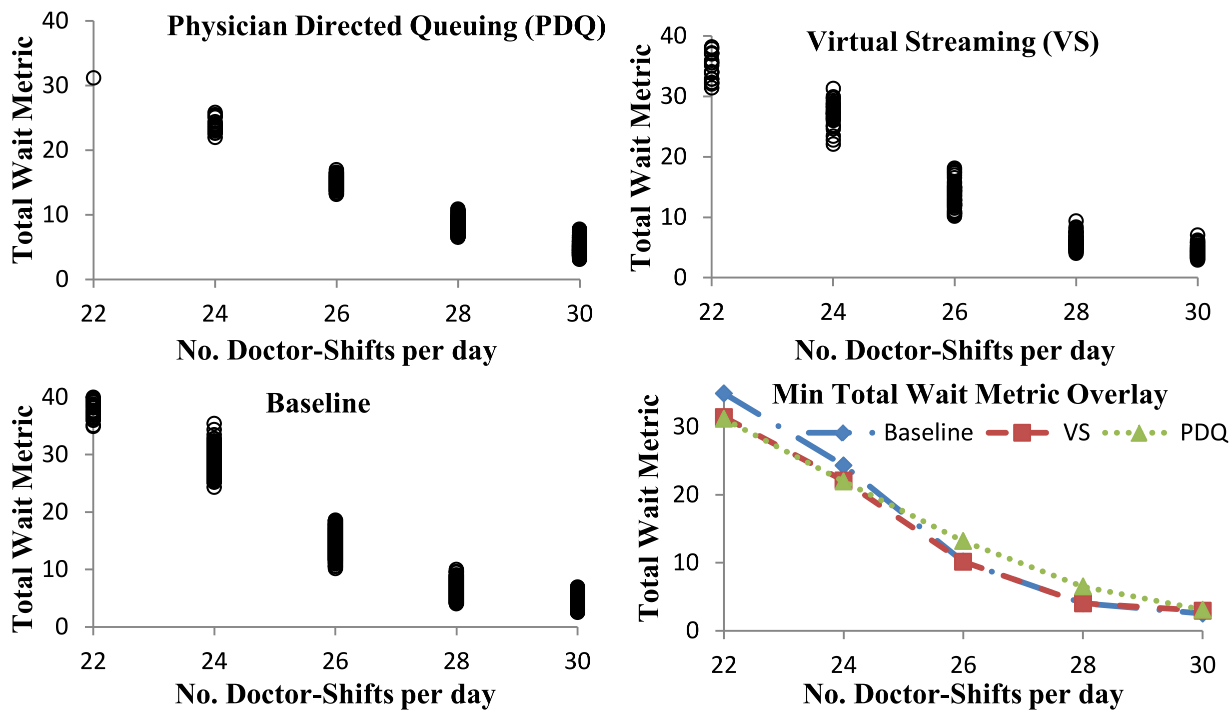

Figure 4: Total wait metric by methodology and minimum metric overlay.

a 300% reduction in average waiting time of ESI 5 patients compared to the baseline. VS performs 60% worse at most in average waiting time of ESI 2 patients compared to the baseline. This trade-off between ESI 5 and ESI 2 patients is not apparent in the the single objective because there are many more ESI 2 patients than ESI 5 patients. These results suggest that VS improves the average performance of EDs in highly resource constrained situations for our patient mix. This was expected because the assumptions concerning the objectives and patient mix used were based on the work that developed the VS method.

An interesting result is that PDQ has the lowest overall average waiting time when 22 or 24 doctor-shifts are scheduled and the highest overall average waiting time when 26 or more doctors per day are used. This suggests that PDQ is more valuable in highly resource constrained situations. Exploring the results for 22 and 24 doctor-shifts per day shows that PDQ performs the best for TTFT for ESI 2 and ESI 4 patients and the best for LOS for ESI 5 patients. These results suggest that the use of a separate queue for ESI 4 and 5 patients can benefit not only the ESI 4 and 5 patients but also the ESI 2 patients.

There exists a trade-off between using the PDQ model and using the baseline for this patient mix. The baseline benefits from pooled resources and outperforms the PDQ for LOS of ESI 4 and 5 patients when there are 26 or more doctors scheduled per day. This contradicts the original rationale for implementing PDQ. This contradiction may have occurred because PDQ was formulated for a patient mix that contained more than 50% ESI 4 and 5 patients. The patient mix in this research was less than 17% ESI 4 and 5 patients.

The best performing scenarios of the VS and PDQ models have similar overall total average waiting metrics for 22 and 24 doctors scheduled per day. The VS model performs better than PDQ when 26 and 28 doctors are scheduled per day and the two models perform similarly when 30 doctors are scheduled per day.

These results suggest that exploration of the seven objectives is necessary to fully contrast VS and PDQ across the number of doctors scheduled per day. The results show that PDQ tends to perform as formulated reducing the TTFT and LOS for ESI 4 and 5 patients. This reduction is most noticeable when comparing the results of 22 doctors per day. PDQ consistently had a lower TTFT for ESI 2 compared to VS. Conversely, VS had lower LOS and TTFT average values for ESI 3 than PDQ except when 22 doctors per day were scheduled. When there were 22 or 24 doctors scheduled per day VS had a lower average LOS for ESI 2 patients than PDQ.

The results, on the whole, suggest that the number of doctors scheduled per day greatly impacts the decision between VS, PDQ, and baseline models. Additionally, the trends herein are for a specific patient mix and a different patient mix may have different results.

7 CONCLUSION AND FUTURE WORK

A literature review of improvements to ESI in medical triage was conducted. Virtual Streaming and Physician Directed Queuing were selected as examples of two different modeling approaches and contrasted through simulation. Seven objectives were discussed, however, the results and trends in this work rely on the overall total average performance objective derived in (1) above.

VS and PDQ models showed improvements over a baseline model in highly resource constrained settings. In less resource constrained settings (30 doctor-shifts per day) the baseline showed the benefit of resource pooling. In this setting the baseline model performed well across all seven objectives and, in some instances, better than the VS or PDQ models. Thus, it is recommended that when 30 or more doctor-shifts are scheduled that the baseline is used.

When 28 doctor-shifts or fewer are scheduled using VS is recommended for this patient mix. VS is recommended because it performs the best or comparably to the other models when 28 doctor-shifts or fewer are scheduled. Conversely, the performance of the PDQ model shows marked advantage for ESI 4 and ESI 5 patients. PDQ was originally designed to handle systems that have approximately 50% of patients in ESI 4 or 5 where the modeled system has only ~17%. In order to fully test the utility of PDQ it is necessary to test other patient mixtures closer to 50% of the patients being in ESI 4 and 5.

Using the PDQ system improves flow of low acuity patients and using the VS approach favors ESI 2 and 3 patients. The decision to implement one of these two approaches needs to be made based on other factors by hospital management including the patient mixture historically seen and the associated development and operation costs. The PDQ development requires an up-front facility that can be staffed and provide a workspace for physicians. This may require a fixed construction investment from a hospital.

The VS implementation, as implied by the name Virtual Streaming, does only a logistic system to track where patients are located and how the streams are progressing.

It is expected that with more doctors, all systems perform better. The number of doctors was predetermined to be varied near the capacity limits for the system to predict if a particular setup performed better under highly constrained circumstances. The results presented are averages across all patients and aggregated into a single objective. It is recommended that additional experimentation is completed to investigate the variance of the VS, PDQ, and baseline models.

The Emergency Severity Index (ESI) is not the only approach presented in the literature or used in the United States to prioritize patients. It may be advantageous to repeat this procedure utilizing the expected processing time index known as the Park Index (Peck and Kim 2009). Additionally, future testing should consider using PDQ for hours outside the range of 8 to 20 to identify if any improvement in performance can be realized by doing so. This research used complete enumeration for the experimental designs of each model. The implementation of a guided search heuristic such as genetic algorithm may help reduce the computational burden in finding approximate Pareto frontiers. This could be helpful in understanding the tradeoffs between the PDQ and VS models in terms of the seven objectives simultaneously.

Lastly, a combined model that implements the benefits of both VS and PDQ should be explored. These two models are dissimilar in their approach and a hybrid may have resounding impact on the use of ESI for triaging and ED management as a whole. The success of a hybrid model may then be realized through the implementation of the process in an ED. It is clear that EDs operate under different settings. For this reason a hybrid model will need to be tested across multiple patient mixes and under any other appropriate assumptions. This paper was a first step in showing the need for an improved, hybrid ESI triage model. The paper used simulation to highlight the trade-offs between two specific models. The trade-offs discovered suggest that a combined approach, which may realize the potential benefits of both the strategies, should be explored.

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