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REAL-TIME NURSE DISPATCHING USING DYNAMIC PRIORITY DECISION FRAMEWORK

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ABSTRACT

The increase in medical treatment complexity can cause experienced nurses to have difficulty determining priorities among patient needs. Electronic health record systems will enable automated decision support to assist medical professionals in making these determinations. This article details a framework that uses a discrete-event simulation, programmed in Python, to determine how priorities should be assigned in real time based on characteristics of patient needs. The severity of patient needs is dynamic because severity increases over time until the need is addressed. The simulation framework is applied to a cardiac care unit with 14 patients, who collectively have 125 needs. Four different priority schemes are evaluated and their effectiveness compared under the assumption of an 8 or 9 nurse capacity. The results illustrate the importance of modeling the dispatching of nurses according to severity because, although fewer nurses result in longer average queue times, they can handle higher-severity needs effectively.

1 INTRODUCTION

In healthcare settings, nurses and other caregivers are confronted with a dizzying array to patient care tasks that range from life threatening to routine. These needs encompass call button requests, device alarms, machine maintenance, medication administration, and patient turning, among others. However, if some routine tasks are delayed long enough, patients may suffer serious adverse outcomes and the cost of their care may substantially increase. Examples of these types of tasks include ambulating patients to decrease their length of stay in the hospital or turning a patient to prevent bedsores. Today, nurses use ad-hoc or use implicit strategies for prioritizing care tasks which can lead to patients suffering from preventable conditions. As medical settings become more complex, especially with the increase in technology-enabled treatment systems, prioritization of care tasks will become more difficult and have a profound impact on patient outcomes and costs.

With the introduction of electronic medical record systems, the potential exists to create a task prioritization system that optimizes patient outcomes and reduces costs. The system would dynamically list required tasks in priority order based on an intelligent algorithm that considers severity of patient needs and other parameters. This system would operate as shown in Figure 1. It is meant to represent a ward (i.e., department) of a hospital that consists of a group of nurses who serve a group of patients. Patients require service when they press the nurse call button (which is immediately answered and assigned a reason such as a drink refill or assistance to use the toilet), require scheduled care (such as medications or turning over in their bed), or a device alarm sounds with a known reason (such as a device needing cleaning or a patient activating a fall warning device at the edge of their bed), among others.

This paper aims to develop a methodology for a decision support system (DSS), which assigns medical personnel to tasks that have time-dependent severities. A tool was developed to evaluate alternative priority assignment systems. This work included modeling of time-dependent severity functions and parameter estimation, along with the development of a discrete-event simulation to determine how priorities should be assigned in real time based on characteristics of patient needs. The main challenge was to model dynamic priorities that will change while a patient's need waits in a queue until the need is addressed. Various priority schemes were evaluated using input from an experienced nurse practitioner. We organize the remainder of this paper as follows. Section 2 presents the related literature. Section 3 details the methodology behind the severity profiles and the discrete-event simulation. Section 4 presents the determination of parameters for the severity functions and results of the simulation analysis that compares priority schemes. Section 5 concludes with future research directions.

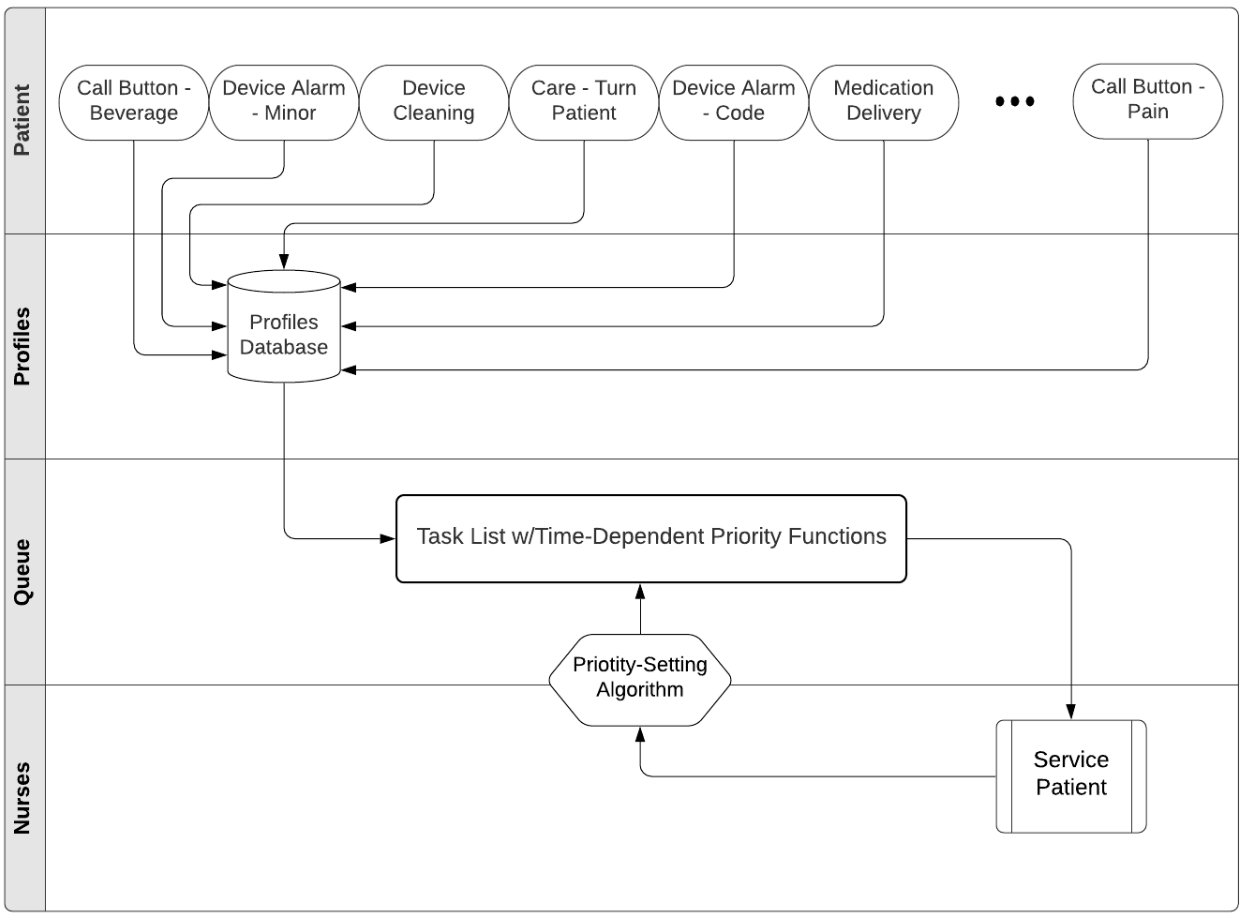

Figure 1: Priority dispatching framework.

2 LITERATURE REVIEW

Although the job of a registered nurse is fast-paced with unpredictable and heavy cognitive work loads, the few studies of interruptions and multitasking in health care have focused on physicians (Kalisch and Aebersold 2010). Sir et al. (2015) designed patient classification systems, which are commonly used in nursing units to assess how many nursing care hours are needed to serve patients. Bagheri et al. (2016) proposed a stochastic optimization model for nurse scheduling that accounts for uncertainties in the demand and stay period of patients over time. Kang et al. (2010) investigated alternative policies for dispatching ambulances to multiple call-types with priorities designed to maximize expected survival rates. Najafi et al. (2014) developed a dynamic model for dispatching and routing vehicles in response to a natural disaster that is capable of receiving updated information at any time and adjusting plans accordingly. The problem of continuous reallocation of patient responsibilities for nurses was addressed by Klemets and De Moor (2015), who developed a user-centered system using ubiquitous computing principles.

Queuing models have been applied extensively in healthcare settings. Bahadori et al. () used queuing models and simulation to show that patient waiting times can be reduced by multitasking and reallocating personnel to more time-consuming activities, such as filling prescriptions. Belciug and Gorunescu (2015) considered resource allocation in a hospital by integrating a queuing system compartmental model and an evolutionary-based optimization at a geriatric department in the UK. Vass and Szabo (2015) use a M/M/3 queue model to characterize the patient flow in the Emergency Department (ED) situated in Romania. Developing criteria for queuing system effectiveness has also been addressed by Almehdawe et al. (2013), who used a Markov chain approach to model the interface between a regional emergency medical services provider and multiple EDs that serve both ambulance and walk-in patients. Komashie et al. (2015) provided an integrated queuing model that links patient satisfaction, waiting time, staff satisfaction, and service time, while considering efficiency in a holistic care delivery setting.

Queuing models in healthcare and other settings often include priority-based queue disciplines. Sze (1984) described a queueing model of telephone operator staffing to reduce the cost of meeting its service criteria. Zhang et al. (2019) provided a new patient queuing model with priority weightings to optimize an emergency department, including a case study to illustrate the practicability of the proposed model. Hagen et al. (2013) examined several alternative queuing models for intensive care units including effects on wait times, utilization, return rates, mortalities, and number of patients served. Finally, a priority-based queuing model with a similar problem profile was developed by Schmidt and Gazmuri (2012) to dispatch products from two depots to geographically distributed clients.

Decision support systems are used extensively in healthcare settings. The applications include general and specific clinical settings, including procedures involving in-flight medical emergencies (Sene et al. 2018), identifying high readmission-risk patients (Huang et al. 2020), finding interim housing (Rakes et al. 2014), proposing ventilator settings (Akbulut et al. 2014), detecting diabetic retinopathy (Noronha et al. 2013), hypertension management in developing countries (Anchala et al. 2013), medical personnel identification (Zaffar et al. 2016), red eye detection (López et al. 2016), infectious disease diagnosis (Shen et al. 2018), and diabetes care management (Sim et al. 2017).

Our approach creates a priority-dispatching methodology based on the severity of patient needs and other parameters. This approach requires the integration of an intelligent algorithm to inform nurses of required tasks and their relative priorities. Embedded methodologies in other DSS applications include text-mining (Huang et al. 2020), and mixed-integer sequential goal programming modelling (Ang et al. 2018). The use of these DSS applications reduced readmission (Huang et al. 2020), reduced mistakes (Akbulut et al. 2014), improved quality of care (Lin et al. 2011), improved nurse scheduling (Ang et al. 2018), and improved job satisfaction (Kihlgren et al. 2016).

Simulation approaches have been used to support scheduling decisions in healthcare settings, with many of them applied to EDs. Prabhu et al. (2019) used a simulation model to test various physician to patient assignment policies to minimize the number of information handoffs and to reduce the workload at the end of a shift. Swan et al. (2019) compared a pod system to a unit-based design in an ED using a discrete-event simulation, showing that pod system maintained clinical quality while increasing resource utilization and maintaining patient flow requirements.

Simulation models have also been used to evaluate a system's sensitivity to changes in the input parameters in an ED (Furian et al. 2019). Garcia-Vicuña et al. (2019) applied a "management flight simulator" to support better admission and discharge discharge and admission processes. Tako et al. (2019) used simulation to evaluate the effectiveness of integrated community-based health and social care services. Pepino et al. (2015) proposed a prototype simulation of a hospital ward that evaluates task distribution among nursing and other clinical personnel. Walker et al. (2015) developed a simulation for planning the schedules of providers and the appointment for patients.

Simulation models can also help support real time decision making. Morrice et al. (2018) used simulation to design a worklife integrated practice unit that treats various medical issues and determines patient appointment schedules. Ceresoli and Kuhl (2018) developed a generalized simulator to analyze alternative outpatient healthcare clinic designs. Berg et al. (2018) presented a discrete-event simulation model based on the daily operations of an outpatient clinic where multiple specialties share resources including support staff, exam rooms, and ancillary providers.

3 METHODOLOGY

A discrete-event simulation model that mimics a hospital ward was created. In this setting, a group of nurses provide care to each patient in the ward without being assigned to a specific patient. Inputs include patient needs that require one of the nurses to complete. Some tasks, such as the administration of medications, must take place within a certain time frame and other tasks, such as machine alarms, will occur at random times. Available resources consist of nurses who would accomplish the required tasks. Task completion times have random duration, with distributions based on collected or published data. Tasks are dispatched according to a set of priority-based rules that include the severity of each patient's need.

3.1 Severity Profiles

The system includes a set of time-dependent severity profiles based on various patient types, as illustrated in Figure 2. Each profile is flexible to account for specific severity levels for events. Each patient need starts with a severity S_0. This severity linearly increases to a severity of S_1 at time T_1. The severity rating model is flexible, allowing for every type of severity. Some patient needs are initiated by the patient, for example when they press the nurse call button for assistance with sanitary needs. Other service needs are not initiated by the patient, such as when an elderly patient requires turning to avoid bedsores. In these cases, although a frequency of the service (e.g., every two hours) is known, the severity rating of the service need would be $S_0 = 0$ (or 1) at the earliest practical time at which the patient can be turned (e.g., 90 minutes). Some service requests have a severity function that is constant over time. In these cases, $S_0 = S_1$ and $T_1 = 0$.

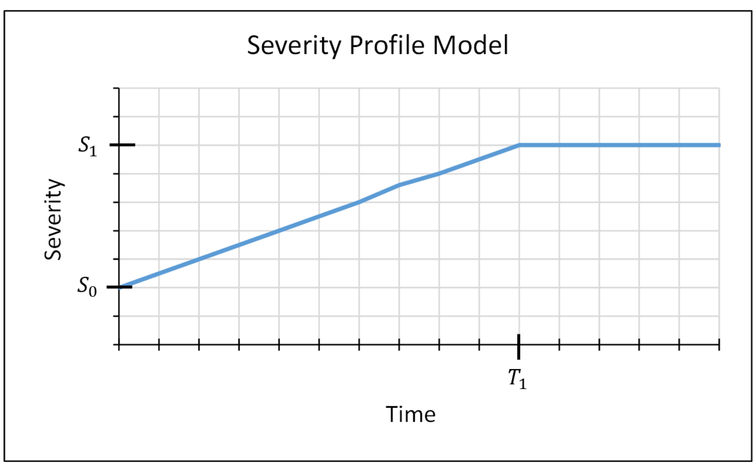

Figure 2: Severity model.

Several meetings were held with an experienced nurse who assisted with the quantification of severity ratings for the myriad of service types. They were asked to estimate severity at points in time based on the severity scale shown in Table 1. That is, they were asked to estimate the variables (S_0, S_1, and T_1) for a variety of patient service needs. The data collected during these meetings are shown in the results section below.

Table 1: Severity definitions.

Rating	Description
10	Imminent Death
9	Serious Condition or Extreme Pain
8	
7	Major Condition or Severe Pain
6	
5	Moderate Condition or Moderate Pain
4	
3	Minor Condition or Slight Pain
2	
1	Negligible Inconvenience

3.2 Python Simulation

There are many complexities that preclude the use of a closed-form analytical model to determine the best priority dispatching scheme. In particular, patients have needs that vary from one another, depending on their age, condition, and recent treatments. Given the lack of a closed form analytical solution, a discrete-event simulation was created to mimic the operation of a typical hospital ward. The events triggering action include the arrival of a patient need and the completion of service. System state changes occur based on these events and are controlled by the priority dispatching scheme. A particularly-important complexity is the continuous changing of priority over time, even while the patient need is waiting in queue for service.

A flowchart illustrating the logical flow of the simulation code is shown in Figure 3. The simulation conforms to a general framework, where a set of nurses provide care for a group of patients. Patients vary in their specific needs, and therefore each patient-need combination would be considered an entity. For example, if the hospital ward includes 15 patients, of which 10 were elderly, then 10 patients would need to be turned about every two hours to prevent bedsores. As such, the queuing system includes a finite population of patient needs that re-occur periodically, some at random times and some at pre-determined frequencies.

The simulation is initiated with a internal storage consisting of p patient needs and k nurses. The first arrival for each of the p patient needs is then generated, including its arrival time and service time (the time-between-arrivals and service time parameters are taken from a database of patient need parameters). The main simulation loop starts with the determination of the next event - either a patient need "arrival" or a service completion "departure."

If the next event is an arrival, the logic checks to determine if all nurses are busy. If so, the entity is added to the patient need queue. If any of the nurses are idle (they are assumed to be interchangeable relative to their skill sets, so that each nurse can address any patient need), a nurse begins service delivery. In this case, the start time, end time, queue time duration, and system time duration are tabulated. The logic continues by determining the next event.

If the next event is a departure, the queue is checked. If the queue is empty, then the simulation logic determines the next event. If the queue is not empty, then the severity of each member of the queue is

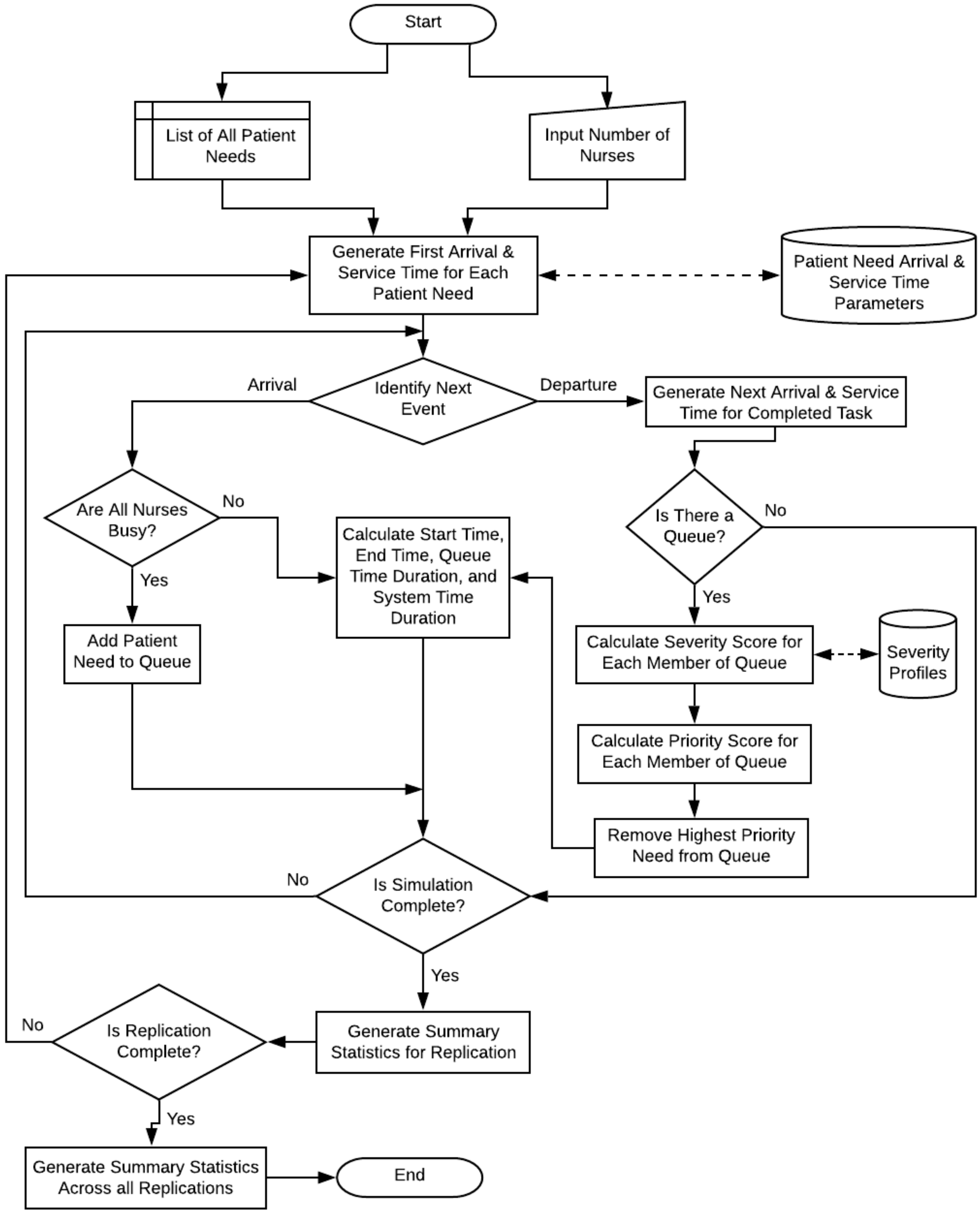

Figure 3: Simulation flowchart.

calculated based on its time in queue and severity function model parameters. Based on this severity, a priority is calculated using a specific priority scheme (discussed in the results section below). The highest priority entity is taken off the queue and service begins. In this case, the start time, end time, queue time duration, and system time duration are tabulated. The logic continues by determining the next event.

The simulation continues until the target number of simulated arrivals occurs. A "warm-up" period is included to eliminate instability that can take place at the beginning of the simulation, and a "warm-down" period is also included at the end of the simulation. A fixed number of macro replicates are simulated. Then, all summary statistics are calculated and graphical results are presented for analysis. The simulation output includes the distribution of queue time, displayed as a histogram, time series plot, and box plot. It also includes numerical summaries, including the average, median, and 95th percentile of queue times. These statistics are shown for each patient need to facilitate the analysis of the systems performance according to the severity of each need.

4 RESULTS

Key results are described in this section. Although the simulation represents a general framework for many types of hospital wards, the remainder of this section applies the simulation to a cardiac care unit (CCU) at a medium sized hospital.

4.1 Parameter Determination

Consultation with an experienced nurse practitioner provided information concerning parameter estimation for severity functions. Parameters were estimated for a hospital's CCU, where results are shown in Table 2. In the table, "TBA" is the average time-between-arrivals, "Random?" asks if the TBA is constant or variable, "Min ST" and "Max ST" are the typical minimum and maximum service times, and the other table headings have previously been defined. An example of a constant TBA is a routine visits to rooms, while an example of a random TBA is initiation of the bed exit alarm. In the simulation, random arrivals are assumed to vary according to a Poisson process (hence, the TBA would be exponentially distributed), and the service time distribution is assumed to be a shifted gamma, where 90% of service times were assumed to fall between the minimum and maximum values.

Two important considerations were revealed during interaction with the nurse practitioner. First, the patient-condition interaction can effect many of the severity rankings. Severity parameters will be higher for patients suffering from certain serious conditions. Second, some patient needs, such as pain medication, should be flexible and vary by patient as well as over time. For example, a patient that does not respond well to medication after 30 minutes may be subjected to a more aggressive treatment (e.g., IV administration) than originally planned. This circumstance may impact how severity is quantified. In both cases, the simulation is easily setup to include severities specific to each patient. However, in the results that follow we used the parameters from Table 2.

4.2 Simulation Results

To illustrate the operation of the simulation, inputs associated with the CCU were used. The simulation was developed in Python 3.7, a programming language that is offered free of charge by the Python Software Foundation. It incorporates packages NumPy, matplotlib, statistics, math, and sys. The NumPy random number generator is used to generate random numbers. It was run on a Lenovo ThinkPad Carbon X1 with Windows 10 Enterprise, Version 1903, OS Build 18362.900.

The number of micro-replications (i.e., iterations), macro-replications (i.e., replicates), and duration of warm-up period were chosen as follows. Welch's method (Welch 1983) was used to identify the warm-up period duration. Based on an analysis of moving average plots of queue times, 1,000 iterations were removed from the beginning and the end of the simulation output data. By calculating the standard error of average waiting time across replicates, the number of replicates was set at 10, and the number of iterations

Table 2: Example parameters for severity functions.

Patient Need	Code	No. Patients	TBA	Random?	Min ST	Max ST	T_1	S_0	S_1
Pain Medication	Meds	10	90	no	5	10	150	5	7
Sanitary Assistance	Sanitary	10	240	yes	5	20	15	3	6
Turn a Patient	Turn	10	105	no	10	20	150	1	5
Finger Sensor (Oximeter)	Oximeter	6	720	yes	5	8	30	2	4
Cardiac Sensor	C-sensor	4	600	yes	3	5	10	6	7
Respiratory (Rate) Sensor	R-sensor	4	720	yes	5	10	15	3	5
Bed or Chair Exit Alarm	Bed_alarm	3	600	yes	5	15	0	9	9
Routine Visits to Rooms	Visit	14	75	no	5	15	30	0	3
Indwelling Catheter	Catheter	4	360	yes	5	8	60	3	7
Eating Assistance	Eating	6	240	no	10	30	30	2	5
Bathing Assistance	Bath	12	600	yes	30	45	60	1	3
Mobility Assistance	Mobility	10	240	no	15	30	120	1	5
Hygiene (Oral Care)	Oral	10	360	no	10	15	90	1	3
Teaching Patients	Teach	8	360	yes	10	20	120	1	3
Discharge Instructions	Discharge	2	600	yes	30	45	30	3	6
Doing Procedures	Procedure	6	600	no	45	120	150	2	4
Bandage Changes	Bandage	6	600	no	15	35	60	5	8

per replicate was set at 25,000. Using these settings, the simulation took an average of about 40 minutes to run.

In order to compare various priority schemes, the following priority schemes were analyzed (their A-D code will be used later in this section to identify the priority scheme):

- **A.** The severity score at the time queue is analyzed.
- **B.** The product of severity score and time in queue.
- **C.** The severity score with preference given to entities in queue longer than 10 minutes.
- **D.** The severity score with preference given to entities in queue longer than 5 minutes.

To illustrate the simulation output, the parameters in Table 2 were simulated. Table 3 assumes 8 nurses serve patient needs and priority scheme A is implemented. The most important results concern how the dispatching of nurses relates to the severity of patient needs and the length of time a patient spends in the queue. For example, an analyst may wish to focus on the ability of nurses to serve higher severity patient needs in a timely manner. After running the simulation for the four priority schemes, the comparison graphs are shown in Figure 4. For example, for priority scheme A, the average waiting time for a patient needing to be turned is 7.6 minutes.

Tables 4 and 5 provide summary results comparing the CCU operation with 8 nurses to its operation with 9 nurses. It separates patient needs into those with lower severities (with $S_0 \leq 1$) and those with higher severities (with $S_0 \geq 5$). By separating higher from lower severity needs, an analyst can evaluate the system's performance relative to the various types of needs. For example, with 8 nurses and priority scheme A, the overall average queue time was 5.36 minutes (with a 95th percentile of 22.41 minutes). Although this response time may be unacceptable for higher severity needs, higher severity needs are in fact responded to in an average of 1.11 minutes (with a 95th percentile of 3.92 minutes).

The value of the simulation is evident when comparing the assignment of 8 versus 9 nurses for priority scheme A. With 9 nurses, the overall average queue time is reduced to 2.04 minutes (and the 95% percentile is reduced to 12.29 minutes). However, for high severity patient needs, the average queue time is only

Table 3: Simulation output example.

Event	% Demand	Queue Time Average	Queue Time Std Dev	Queue Time Std Error	Queue Time Median	Queue Time 95th%
Visit	27.80	6.40	7.18	0.03	4.80	20.59
Meds	17.90	3.14	3.34	0.02	1.87	9.01
Turn	14.30	6.27	9.09	0.05	3.01	25.43
Sanitary	7.00	2.86	3.01	0.02	1.60	8.06
Mobility	6.70	5.26	7.56	0.06	2.40	20.99
Oral	4.70	7.07	10.66	0.10	3.35	29.59
Eating	4.10	3.34	3.63	0.04	1.93	9.93
Teach	3.70	8.53	13.57	0.14	3.77	37.18
Bath	3.40	5.91	7.96	0.09	3.34	22.29
Catheter	2.00	3.01	3.09	0.04	1.86	8.40
Bandage	1.70	2.52	2.86	0.04	1.07	7.64
Procedure	1.60	3.37	4.02	0.06	1.71	10.40
Oximeter	1.50	3.68	3.83	0.06	2.59	10.37
C-sensor	1.10	2.74	2.91	0.05	1.49	7.78
R-sensor	1.00	3.05	3.17	0.06	1.91	8.66
Bed_alarm	0.90	2.84	3.00	0.06	1.53	7.89
Discharge	0.50	3.03	3.14	0.09	1.87	8.31

reduced by 30 seconds to 0.61 minutes. Therefore, a manager will likely be satisfied with a staffing level of 8 nurses.

The results would be interesting to an analyst who wishes to compare priority schemes. In all cases, the average and 95% percentile queue times are improved for lower severity patient needs. However, priority schemes B, C, and D are similar in regards to their affects on the system's performance.

Table 4: Comparison of average queue times.

	Average Queue Time (Minutes)					
Priority Scheme	Higher Severity Needs		Lower Severity Needs		All Patient Needs	
	8 Nurses	9 Nurses	8 Nurses	9 Nurses	8 Nurses	9 Nurses
A	1.11	0.61	8.12	2.65	5.36	2.04
B	2.43	0.99	6.51	2.30	5.12	1.94
C	2.92	0.96	6.74	2.17	5.41	1.90
D	3.06	1.23	6.91	2.24	5.28	1.93

Table 5: Comparison of 95th percentile of queue times.

	95th Percentile Queue Time (Minutes)					
Priority Scheme	Higher Severity Needs		Lower Severity Needs		All Patient Needs	
	8 Nurses	9 Nurses	8 Nurses	9 Nurses	8 Nurses	9 Nurses
A	3.92	2.92	31.77	14.08	22.41	12.29
B	7.96	4.36	23.28	11.57	19.20	9.91
C	11.78	4.65	24.85	11.18	17.91	10.86
D	8.81	6.23	27.88	10.30	19.91	8.74

5 CONCLUSION AND FUTURE WORK

In this research, we addressed the problem of dispatching nurses in real time based on a set of patient needs whose priorities are dynamic. A discrete-event simulation with events associated with patient request and

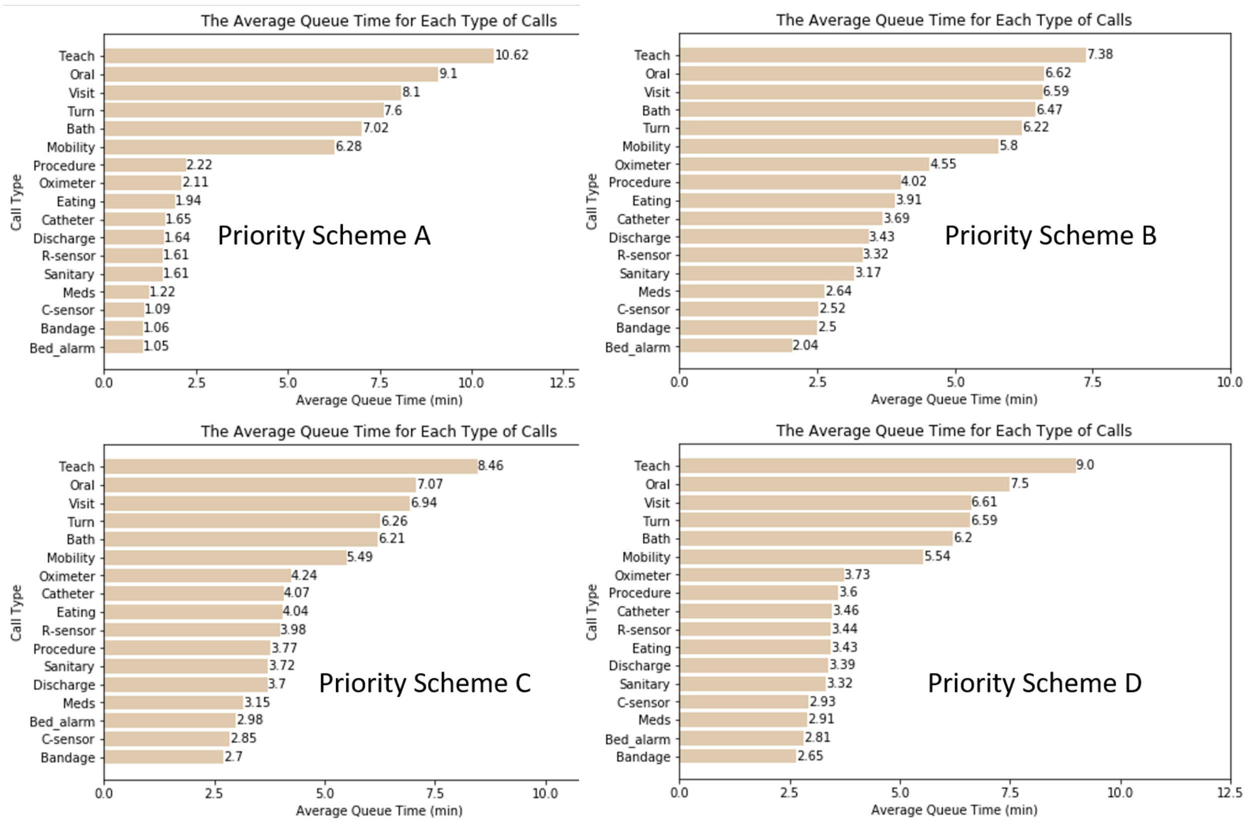

Figure 4: Average queue times (minutes) by patient need.

nurse availability was built. This effort required the quantification of severity for various patient needs that may increase while the patient awaits service. Potential future work could include analysis of systems where continuity of care is critical. For example, the allocation of 8 nurses or a subset thereof to specific patients can be compared to a system where every nurse satisfies every patient's need. In addition, it would be interesting to evaluate experienced nurses' actions using a machine learning approach. These results could inform future simulations regarding the setting of priority schemes.

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