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Edited by
Kenneth D. Lawrence
Ronald K. Klimberg

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Series Editors

Kenneth D. Lawrence
New Jersey Institute of Technology

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CHAPTER 1

A FORECASTING MODEL TO PREDICT THE AVAILABILITY OF STAFFING, EQUIPMENT AND FACILITY NEEDS FOR TELESANE SERVICES

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ABSTRACT

TeleSANEs are expert Sexual Assault Nurse Examiners (SANE) who use video-conferencing technology to ensure access to immediate and quality

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forensic nursing care in communities with little to no access to such expertise, and in communities in which low patient volume presents a challenge for SANEs to remain confident and competent. Patients who present for care post-assault generally represent a small proportion of emergency department case volume, yet they require specialized care and procedures that take several hours. Efficient and effective implementation of a TeleSANE program relies, in part, on being able to forecast the availability of trained nurses, telehealth equipment and facilities to respond to this episodic occurrence. In this chapter, we develop, apply, and evaluate a Monte Carlo simulation model that can be used to forecast TeleSANE nurse staffing, facility, and remote equipment needs, over a variety of potential scenarios, to help inform system performance and planning.

Keywords: Simulation, Nurse Staffing, Sexual Assault Nurse Examiners, SANE, TeleSANE

Introduction

Sufficient nurse staffing is a major challenge faced by hospitals. Nurse staffing costs can represent over 50% of the overall hospital costs (Kazahaya, 2005). Additional to the costs, in some situations there is a need to make provisions for immediate access to nurses or other clinicians with specialized training and expertise. The TeleSANE program utilizes Sexual Assault Nurse Examiners (SANE) to provide immediate access to forensic nursing care. In this chapter, we develop a predictive staffing simulation model as an effective tool for planning for these types of staffing needs.

In the following section, we provide a brief background of the TeleSANE program. The next section provides a review of the relevant literature. Subsequently, we discuss the predictive staffing simulation model we developed for the TeleSANE program. The later sections discuss model results and future directions.

Background to the TeleSANE Program

Individuals who experience sexual assault have unique medical, emotional and forensic needs requiring a trauma-informed approach to ensure their needs are met, that they are best supported to make informed decisions regarding their post-assault medical care and their involvement in the criminal justice system (Office on Violence Against Women, U.S. Department of Justice, 2013). Sexual Assault Nurse Examiners (SANE) are nurses who have received specialized training to respond to and care for patients who have experienced sexual assault. However, there are not

adequate numbers of SANEs nationally to meet the needs. Although exact numbers are unknown, the International Association of Forensic Nurses (IAFN) database shows that there are approximately 1063 programs that offer SANE care across the United States (IAFN, 2022).

To address inequities in access to SANE services, in 2012 the Massachusetts Department of Public Health's (MDPH) SANE Program was awarded funding from the U.S. Department of Justice, Office for Victims of Crime (OVC), to pilot the use of telehealth technology to support the care of patients who have been sexually assaulted in communities with little to no access to SANE services, or in communities in which low patient volume presents a challenge for SANEs to remain confident and competent. From 2012–2018 OVC funding was used to establish and operate the National TeleNursing Center (NTC). TeleSANE services were provided to patients in six military, tribal, rural, and community hospitals in three states (Arizona, California, Massachusetts), and the SANE or non-SANE clinicians caring for them. Evaluation findings from this national pilot indicate that there was high patient acceptance (86% overall and 97% in non-U.S. Navy sites), and site clinicians receiving TeleSANE clinical guidance reported a positive impact on their confidence in providing an effective examination, their ability to provide the patient with the best care and their sense of being supported by the TeleSANE (Walsh et al., 2019).

Due to the nascent use of telehealth for this patient population, the traumatic nature of sexual assault, and the fears and concerns that many patients have regarding their privacy and confidentiality, the NTC was initially established in three offices within a “brick and mortar” setting. The TeleSANE Center is staffed by one TeleSANE at a time, with a “back-up” list of TeleSANEs available for situations in which a second patient presents after an assault at another partnering hospital, known as a “remote site.” TeleSANE services are often utilized in communities with a lower volume of patients presenting for medical care following a sexual assault. Therefore, patient volume is generally lower in the remote sites, patient volume varies from 4–25 patients/year.

Although the need for TeleSANE services is episodic and low frequency, TeleSANE encounters generally require 4 to 5 hours of dedicated TeleSANE time and room/equipment deployment. TeleSANE Consults may also occur for situations in which a remote site clinician is seeking guidance but a patient does not meet the indications for a medical-forensic exam based on the time that has elapsed since they were assaulted, or the patient declines direct TeleSANE services. Consults are often more time-limited, generally require 1 to 2 hours, can often be conducted by phone, but may also require the use of a room and telehealth equipment.

When planning for the pilot, the goal was to minimize any potential wait times for patients. Additional expansion requires being able to forecast

future TeleSANE staff and room requirements based on expanding patient volume. The TeleSANE Predictive Simulation (TPS) Model was developed to help predict staffing and physical space requirements as the number of hospitals receiving TeleSANE support increase.

Literature Review

Operations research models have long examined resource allocation issues in hospitals. Many of these early operations research (OR) studies centered around analyzing bed occupancy and patient flows utilizing Markov and semi-Markov processes (Kao 1974; Young 1965). The OR studies included one of the major challenges facing hospitals, addressing the challenges of providing high-quality service with low operating costs. Satisfying these conflicting objectives with sufficient staff, when they are scheduled to provide superior care to an uncertain and time varying demand for service, requires decisions about forecasting demand, acquiring capacity, and deploying resources (Askin et al., 2007). Nursing staff costs typically represent over 50% of the total hospital costs (Kazahaya, 2005) highlighting the important focus of nurse staffing and scheduling in achieving hospitals' goals of providing high-quality service within realistic budgets. To anticipate staffing needs, managers attempt to predict the number of patients admitted and discharged based on the severity of their patient population. One of the common approaches to determine adequate nurse staffing is using minimum nurse-to-patient ratios (Yankovic & Green 2011). An extension of this minimum ratio approach is to use systems that adjust nurse staffing based on the severity of the patients. Several papers developed linear programming optimization models to provide guidance on staffing and scheduling nurses and other hospital personnel (Jaumard et al., 1998; Miller et al., 1976; Wright et al., 2006). However, static linear programming models, based on averages, do not address the variability of arrivals and service, extremely important information for providing TeleSANE nursing care, which queueing models can. Queueing models have been developed to determine staffing requirements in many time variable service systems; for example, in staffing call centers to provide timely and quality service (Gans et al., 2003) and in staffing emergency response systems to provide timely response (Green & Kolesar, 2004). Yankovic and Green (2011) developed a queueing model for hospital clinical units to provide information important for delivering timely responses to patient needs, and Chowdhury et al. (2018) developed a queueing model for a hospital emergency department to reduce wait and stay issues. The use of these queueing models for determining healthcare staffing requirements, however, have been rather limited. A few predictive

staffing simulation models have recently been developed to address the challenges stemming from the complexity and dynamics associated with predicting nurse staffing. [DeRienzo et al. \(2017\)](#) developed a nurse staffing simulation model of a neonatal intensive care unit and validated the model against historical data. [Johnson-Carlson et al. \(2017\)](#) developed a predictive staffing simulation model for proactively planning nurse staffing needs.

The following section describes the TeleSANE Predictive Simulation (TPS) model.

TeleSANE Predictive Simulation (TPS) Model

The Predictive Simulation Model developed for the TeleSANE program (TPS) is diagrammed in the sequential flowchart shown in [Figure 1.1](#). The model provides a Monte-Carlo simulation ([Ratick & Schwartz, 2009](#)) of a year’s anticipated activity. That year’s data is accumulated, after which the TPS model is run for a user specified number of years. As this model has universal application, the term TeleSANE will be referred to as Nurse in the subsequent sections of this model discussion.

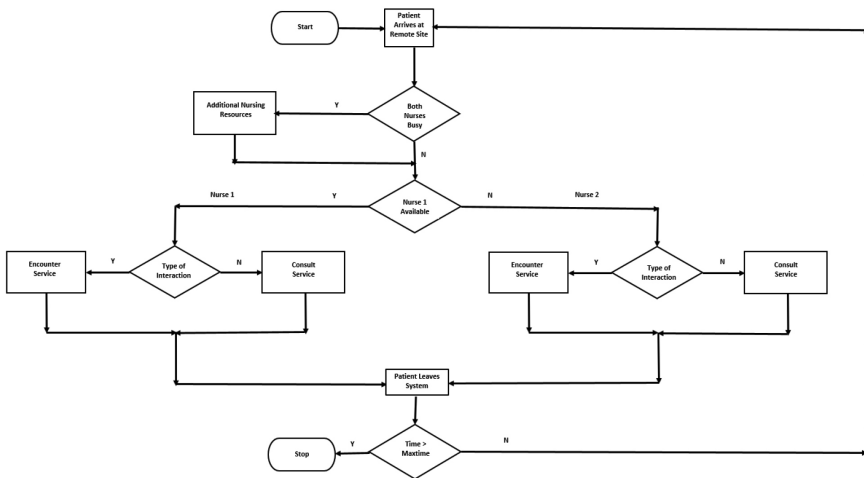


Figure 1.1. Flowchart of the TeleSane predictive simulation (TPS) model.

The TPS simulation first starts with the arrival of a patient at a remote site and a call to the TeleSANE Center’s Call Center. The model next determines if a nurse is immediately available to respond to the call and assume care of the patient. We simulated two active nurses. If both are busy, the Call

Center attempts to access additional nursing resources. These additional nursing resources include other TeleSANE trained nurses that are on duty or back-up list of nurses. The next step of the process is to determine if the call is going to be an TeleSANE Encounter or a TeleSANE Consult, as these require different amounts of time to complete.

Figure 1.2 shows the TPS interface that provides the user with seven step instructions to run the model, the type of input parameters required, and where these are to be input in the model Excel spreadsheet.

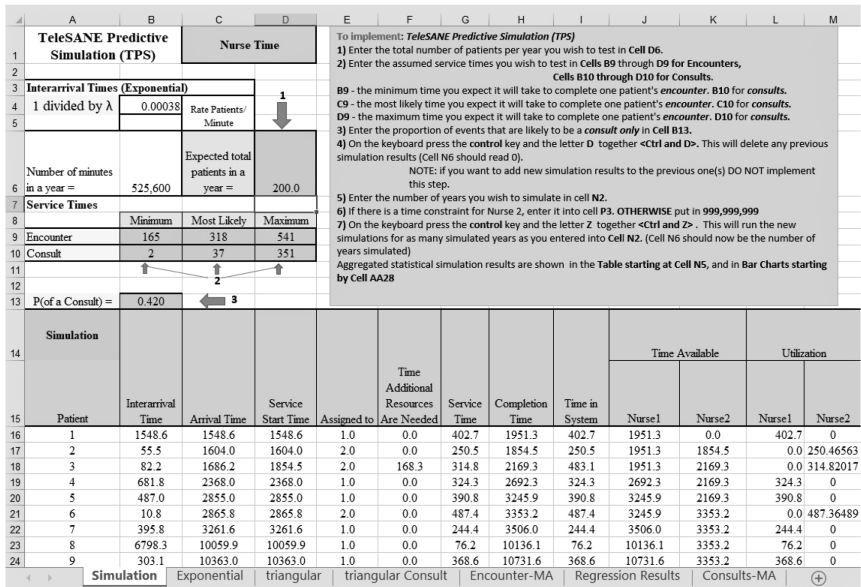


Figure 1.2. Input Parameters and Use Instructions for TPS.

Parameter values shown in Figure 2.2 (cells A1:D13) were obtained through analysis of one year's data from the TeleSANE program and the decision-maker's input. The arrival pattern of patients is random and independent. For this reason, the arrival rates follow a Poisson distribution. The corresponding interarrival times, the times between arrival of patients, follow an exponential distribution. The λ , the mean interarrival time, for the exponential distribution is calculated by taking the number of patients per year, cell D6, and dividing it by 525,600 (525,600 min/yr = 60 min/hr * 24 hr/day * 265 day/hr). The decision-makers have a significant amount of uncertainty regarding the future distribution of encounter and consult times, for that reason a triangular distribution was assumed for both sets of times. The triangular distribution is a continuous distribution defined by three values: the minimum, the maximum, and the mode (or most likely).

The proportion of events that are likely to be a consult only was based on the historical data and decision-maker's estimate.

Clarification of the 7-step instructions:

Step 1: The Total Number Of Patients expected per year allows for different patient intensities to be simulated (cell D6). Given the total expected number of patients per year, the interarrival rate (total number of patients per year/number of minutes per year) is calculated in cell B4.

Step 2: The triangular distribution requires three values: the minimum, the maximum and the mode (or most likely); for Encounters these are input into cells B9:D9 and corresponding times for Consults are input into cells B10:D10.

Step 3: The expected proportion of events that are likely to be Consults are input into cell B13 as a probability.

Step 4: The user has the choice to run a completely new simulation (for the specified number of years) or to add on to the previous simulation. To run a new simulation on the keyboard the user presses the **control** key and the letter **D** simultaneously **<Ctrl and D>**. This will delete any previous simulation results (Cell N6 should read 0). To add new simulation results to the previous one(s) the user is informed not to implement this step.

Step 5: The number of years the user wishes to simulate (up to 500) is entered into cell N2.

Step 6: If there is a time constraint for Nurse 2 (a second TeleSANE trained nurse to be simultaneously available with Nurse 1, in total minutes available for the year), that is entered into cell P3 (otherwise a very large number is added to cell P3).

Step 7: To run the simulation the user presses the **control** key and the letter **Z** simultaneously **<Ctrl and Z>**. This will run the new simulations for as many simulated years as was entered into **Cell N2**.

The simulated results of using these parameters are shown beginning on Row 16 of the Excel sheet shown in [Figure 1.2](#). Each simulated TeleSANE patient, provides information on the current "Interarrival Time" (in minutes), and the cumulative Arrival Time to that point in the yearly simulation, the Service Start Time, to which Nurse that specific TeleSANE call was assigned, the time additional resources were needed, the Completion time for that call, how long that call was in the system, and the calculated Time Available for Nurse 1 and Nurse 2. Also calculated is the utilization

of Nurse 1 or Nurse 2 for that Telecall. For example, as shown in Figure 10.2, given the 9 incoming Telecalls, Nurse 1 (primary on-call TeleSANE) was used for six of the 9 calls, and Nurse 2 for 3 of the 9 calls. The need for a second nurse can be seen by the short interarrival times for the call (see patients 2, 3 and 6). The need for additional resources is prompted by both the short call interarrival times, and the fact that Nurse 2 is busy (patients 2 and 3).

The next section describes the model results for four scenarios.

Model Results

The TPS model was run for a period of 500 years under four scenarios, as shown in Table 1.1. Two of the scenarios use the historical number of yearly pilot project patients of 86. Since incremental growth is expected in the TeleSANE program over the next year, the two other scenarios include 200 patients per year. The other criteria considered in these four simulations was whether or not there is a second nurse (N2) available, two of the scenarios; 86 and 200 Patients per year, have no second nurse (0 hours), and two have the second nurse available for up to 24,960 minutes per year ($24,960 \text{ min/yr} = 60 \text{ min/hr} * 8 \text{ hr/wk} * 52 \text{ wk/yr}$).

Table 1.1

The Four Simulation Scenarios

Scenario (500 Years)	# of Patients	# of hours for Nurse 2
(86 Patients; 0 Time for N2)	86	0
(86 Patients; 24,960 Minutes for N2)	86	24,960
(200 Patients; 0 Time for N2)	200	0
(200 Patients; 24,960 Minutes for N2)	200	24,960

Table 1.2 summarizes the results from the scenario with 86 patients/yr and no second nurse. In this scenario, Nurse 1 is utilized about 330 hours a year, which equates to a 16% of a FTE nurse (assuming a FTE = $2080 = 52 * 40$). The number of times additional resources would be needed under the conditions of this scenario are, on average, only 3 times a year (approximately 3% of the time), with a maximum of 10 times. The maximum amount of time averaged over all 500 years suggests these additional resources may be required for approximately 4 hours per year.