Modeling and Simulation of Nuclear Medicine Patient Service Management in DEVS

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Abstract

Increased demand for specialized health care services has been identified as one of the causes of increased health care costs in the U.S. Nuclear medicine, a sub-specialty of radiology, uses relatively new technology to diagnose and treat patients. Procedures (tests) in nuclear medicine require the use of radiopharmaceuticals with a limited half-life and involve several steps that are constrained by strict time windows and require multiple resources for completion. Consequently, managing patient service in nuclear medicine is a very challenging problem with very little research attention. In this paper, we present a discrete event system specification (DEVS) simulation model for nuclear medicine patient service management that considers both patient and management perspectives. DEVS is a formal modeling and simulation framework based on dynamical systems theory and provides well defined concepts for coupling components, hierarchical and modular model construction, and an object oriented substrate supporting repository reuse. We report on simulation results based on historical data using both patient and management performance measures. The results provide useful insights regarding the management of patient service in nuclear medicine. While this work focuses on nuclear medicine, results will find generality in other health care settings.

Keywords: Simulation, DEVS, health care, nuclear medicine, patient service, scheduling

1 Introduction

Health care costs in the U.S. have increased quickly in recent years and now exceed those in other nations that provide similar, or better care for their citizens. Increased demand for specialized services has been identified as one of the causes of this trend in U.S. health care costs. Speciality clinics such as nuclear medicine, a sub-specialty of radiology, use appointment scheduling systems to manage patients. These clinics are affected by many factors such as patient behavior, staff experience, service time variability, equipment failures, and radiopharmaceuticals management, which have an impact on the way the appointment systems perform. This paper focuses on patient service management in nuclear medicine, which uses new technology to treat and diagnose patients. Nuclear medicine procedures/tests include PET CT scan, imaging test, heart stress and radiotherapy for lymphoma. Most of the tests require administering a radioactive isotope or radiopharmaceutical in order to take high quality images deep within the body and involve multiple scans during one day, or on multiple days. To successfully perform a nuclear medicine test, all the resources needed for each step of the test must be available at specific times. If the test is not completed successfully, the patient
must be re-scheduled for another day. Therefore, scheduling patients, radiopharmaceuticals and resources to accommodate unforeseen disruptions (no-shows, late radiopharmaceutical delivery, breakdown of equipment, etc) is a very challenging problem for nuclear medicine departments. Furthermore, the characteristics of patient and resource management in nuclear medicine make it a unique problem with little research work reported in the literature. The limitations imposed by the behavior and short life cycle of the radiopharmaceuticals, combined with the different types of patient arrivals, random disruptions and resource availability, make the management of patient service in nuclear medicine a complex problem.

The contributions of this research include the first (to the best of our knowledge) DEVS simulation model for nuclear medicine patient service management. The model represents an advance toward improving patient service in health care with innovations in the way the model is represented and implemented. The model incorporates both patient and resource scheduling algorithms within the simulation framework. This in essence provides a novel decision support system for assisting managers not only in patient and resource scheduling, but also in assessing their daily scheduling decisions and system performance. The simulation model enables system-level performance assessment, identification of potential bottlenecks, and integration of scheduling and patient flow analysis. We report a computational study to quantify important trade-offs among a patient and resource scheduling strategy currently used in a real nuclear medicine department and provide insights into the complexity of patient service management in nuclear medicine. While this paper focuses on nuclear medicine, we believe that results can be applied to many other systems that are not as complex as nuclear medicine, for example, diagnostic imaging areas such as magnetic resonance imaging (MRI) and computed axial tomography (CT scan).

In nuclear medicine, a typical test requires at least three resources: a radiopharmaceutical; technologist; gamma camera; and, sometimes, a nurse or EKG technician. Nuclear medicine equipment may cost up to a million dollars and therefore must be managed efficiently. The schedule for radiopharmaceutical delivery, injecting the patient, and scanning must adhere to a specified protocol since radioactivity decays over time. For example, a scan made too early before the radiopharmaceutical has diffused adequately, or too late after excessive decay has occurred, results in a poor image. If there is too much delay, the procedure must be terminated and repeated on another day, causing unnecessary exposure to radiation, poor utilization of resources, and increased cost. Furthermore, since relatively few pharmacies supply radiopharmaceuticals, the dosages and delivery schedules depend on the lead time (hours to days) required to supply the radiopharmaceuticals. A well designed system for patient service management in nuclear medicine has to consider goals of both patients and department managers.

A viable approach to address the challenging problem of managing patient service in nuclear medicine is modeling and simulation (M&S). In this paper, we consider a discrete event M&S approach for managing patient service in nuclear medicine. In particular, we use the discrete event system specification (DEVS) formalism [1] to derive a generic simulation model for a nuclear medicine patient service management that can be tailored to any real nuclear medicine department. DEVS is a formal M&S framework based on dynamical systems theory and provides well defined concepts for coupling components, hierarchical and modular model construction, and an object oriented substrate supporting repository reuse. Modular construction is one of the most important characteristics of DEVS because it allows the modeler to design and construct each model independently for optimal efficiency. As long as models adhere to
certain protocols, they can interact which each other. In this work, we consider both the patient and management perspectives. Both points of view are very important for developing patient and resources scheduling policies, and for evaluating the performance of patient service and resource utilization. Patients are concerned with the level of service offered by the department while managers are also concerned with using their limited resources effectively.

The rest of the paper is organized as follows. In Section 2 we review closely related work and provide preliminaries on DEVS in Section 3. We derive our simulation model and describe its hierarchical structure, operation and implementation in Section 4. We report on a computational study in Section 5 and end the paper with some concluding remarks and directions for future research in Section 6.

2 Related Work

Medical facilities dedicated to the diagnosis and treatment of diseases are becoming more critical in comprehensive health care systems. Mettler et al. [2] found that diagnostic medical procedures increased 5-to-6 fold whereas the U.S. population increased by approximately 50%. The increased demand for specialized services has been identified as one of the causes on increases health care costs in the U.S. [3]. Hospital-based imaging facilities such as radiology departments are highly specialized and each may provide an unique set of services to patients. The equipment used for the diagnosis of diseases are usually very expensive and finding an efficient way of scheduling patients on these resources is a complex and dynamic task [4]. Effective utilization of diagnostic facilities, which are used by almost every patient that enters a hospital, is a necessary condition for overall hospital efficiency [5].

Prior research on patient service management in nuclear medicine is very limited. Both simulation and optimization have been considered as viable approaches to patient and resource scheduling in radiology. Most work in the literature seem to focus on scheduling outpatients [6, 7] without a focus on the complexities of nuclear medicine. In fact, Gupta and Denton [8] identified the problem of scheduling in health care highly constrained environments as a current research open challenge. We refer the reader to recent surveys on outpatient appointment scheduling by Cayirli and Veral [9] and Gupta and Denton [8].

Discrete event simulation [10, 1] has been used frequently to study this problem over the past years; see Jun et al. [11]. This technique can be use to forecast the impact of changes in the system, to examine resource needs or to investigate the relationships between variables in a system [12]. An early paper by Walter [13], built a simulation model of a hospital radiology department to predict the effects of scheduling policies on the efficiency of the appointment system, as measured by the average patient queueing time and doctor idle time during the day. Kho and Johnson [14] developed a computer model that simulates patient flow through a radiology facility that was used to identify causes of congestion and low productivity and to predict effects of changes in the system. Johannes and Wyskida [15] developed a model for scheduling patients and clinical instruments in a nuclear medicine department that minimizes the equipment idle time. The authors used simulation to test the shortest-processing-time-first rule to schedule several patient classes in a nuclear medicine department. Only a limited number of procedures were studied and their heuristic assumes that the group of patients requiring service are known at the beginning of the day. Other work on the use of simulation to analyze staff allocations to improve patient flow in radiology departments include O’Kane [5], Klafehn [6], Centeno et al. [7], and Ramakrishnan et al. [16].
Several papers study variations of our problem using optimization techniques. For example, Conforti et al. [17] study optimization models for outpatient scheduling within a radiotherapy department, whereby patients have to visit the treatment center several times during the week. Green et al. [18] address the problem of scheduling randomly arriving patients of different types in an MRI facility. They formulate the problem as a finite-horizon dynamic program for an appointment schedule that allows at most one patient per period and a single server, where only one patient can be served at a time. The authors derive properties of the optimal scheduling policies. Patrick et al. [19] study a similar problem but they characterize patients with different priorities. Patrick and Puterman [20] consider the problem of scheduling patients in a CT scan department. They formulate an optimization problem that returns a reservation policy that minimizes the non-utilization of resources subject to an overtime constraint. Their approach assumes the use of a pool of patients that can be called to occupy unused time slots. The authors use simulation to demonstrate a reduction in outpatient waiting time. Standridge and Steward [21] propose a simulation model that includes a control logic for patient scheduling. The system presented by the authors schedules patients within a simulation framework. Vermeulen et al. [4] devise an adaptive approach to automatic optimization of resource calendars in a CT scan facility. They implement a simulation model for a case analysis to demonstrate that their approach makes efficient use of resources’ capacity.

Patient satisfaction in outpatient clinics may be difficult to quantify since it depends on the way patients perceive the service received. Several performance measures have been identified in the literature as the most commonly used for evaluating patient service satisfaction in health care clinics. Waiting time Type 1, is the time a patient waits from the time he/she calls for an appointment until the date of the appointment [22, 23, 24]. Waiting time Type 2 is the time a patient waits from the time he/she arrives at the clinic to the time when service is started [22, 25, 26, 7]. The percentage of time a patient requests for an appointment and is satisfied [18, 27] and the time the patient spends in the system [28, 29] were the last ones identified. Besides patient satisfaction, health care managers are concerned with the profitability of the business. In particular, nuclear medicine department managers understand that providing a high level of service to their patients is important for the business. But this requires improving other areas such as human resource overtime [25, 26], resource utilization [22, 26, 7], and patient throughput [16]. Those performance measurements have been used commonly in literature to represent the management’s perspective.

3 Preliminaries

To provide a mathematical foundation for the proposed simulation models, we first review some preliminaries on DEVS. The reader familiar with DEVS may skip this section. In this work we use the Parallel DEVS formalism [1] to construct the simulation model for a nuclear medicine department. Parallel DEVS is a revision of the classical DEVS formalism [30]. It uses a hierarchical approach to build complex models starting with the basic or atomic model, and then coupling the atomic models to create coupled (composite) models. An atomic model has to be in a defined state at any time and has input and output ports through which all interaction with the environment is mediated. External events arising outside the model are received through the input ports, and the model description determines how the model responds to them. All internal events arising within the model change its state and manifest themselves as events on the output ports to be transmitted to other models. Communication between
models is enabled via the couplings.

Unlike Classical DEVS, Parallel DEVS allows all imminent components to be activated and send their outputs to other components of the system. DEVS has a well defined concept of system modularity and component coupling to form coupled models. This leads to the property of closure under coupling which justifies treating coupled models as components and enables hierarchical model composition construct. Since several DEVS simulators have already been development and validated, the models developed in this work will be executed by the existing DEVS simulators. Consequently, the focus of this paper is on simulation modeling and not simulation algorithms.

Let $M$ denote an atomic model with a set of input ports $I\text{Ports}$, a set of input values (events) $X_p$, a set of output ports $O\text{Ports}$, and a set of output values (events) $Y_p$. We denote by $(p, v)$ the port-value pair. Then a basic Parallel DEVS is a structure defined as follows [1]:

$$DEVS = (X_M, Y_M, S, \delta_{ext}, \delta_{int}, \delta_{con}, \lambda, ta)$$

where,

$X_M = \{(p, v) | p \in I\text{Ports}, v \in X_p\}$ is the set of input ports and values, where $I\text{Ports}$ is the set of input ports;

$Y_M = \{(p, v) | p \in O\text{Ports}, v \in Y_p\}$ is the set of output ports and values;

$S$ is the set of sequential states;

$\delta_{ext} : Q \times X^b_M \rightarrow S$ is the external transition function, where $X^b_M$ is a set of bags over elements in $X_M$ and $Q$ is the set of total states;

$\delta_{int} : S \rightarrow S$ is the internal state transition function;

$\delta_{con} : Q \times X^b_M \rightarrow S$ is the confluent transition function;

$\lambda : S \rightarrow Y^b_M$ is the output function;

$ta : S \rightarrow R^+_0, \infty$ is the time advance function; and

$Q := \{(s, e) | s \in S, 0 \leq e \leq ta(s)\}$ is the set of total states, where $s$ is the state and $e$ is the elapsed time.

Note that a bag is a set with possible multiple occurrences of its elements. This allows Parallel DEVS to handle multiple inputs. Definition (1) can be interpreted as follows: At any time the system is in some state $s$ and if no external events occur, the system will not change state for a time $ta(s) \in [0, \infty]$. When this time expires the system outputs the value, $\lambda(s)$, and changes to state $s' = \delta_{int}(s)$. An output is only possible after an internal transition. If an external event $x \in X_M$ occurs when the system is total state $(s, e)$ with $e \leq ta(s)$, i.e., before expiration time, the system changes to state $s' = \delta_{ext}(s, e, x)$. The external transition function dictates the system’s new state when an external event occurs, while the internal transition function dictates the system’s new state when no events occurred since the last transition. The confluent function decides the next state in cases of collision between external and internal events.

The DEVS formalism includes the means to construct models from components. The specification includes the external interface, the components (DEVS models), and the coupling relations. Let $EIC$, $EOC$ and $IC$ denote the external input coupling, external output coupling and internal coupling, respectively. Then a coupled model $N$ can be defined mathematically as follows:
\[N = (X, Y, D, \{M_d \mid d \in D\}, EIC, EOC, IC)\]  \hspace{1cm} (2)

where,
\[X = \{(p, v) \mid p \in IPorts, v \in X_p\}\]
is the set of input ports and values and
\[Y = \{(p, v) \mid p \in OPorts, v \in Y_p\}\]
is the set of output ports and values. \(D\) is the set of component names, and for each \(d \in D\),
\[M_d = (X_d, Y_d, S, \delta_{ext}, \delta_{int}, \delta_{con}, \lambda, ta)\]
is a DEVS model with
\[X_d = \{(p, v) \mid p \in IPorts_d, v \in X_p\}\]
and
\[Y_d = \{(p, v) \mid p \in OPorts_d, v \in Y_p\} \hspace{1cm} (3)\]
The external input coupling, \(EIC\), connect external inputs to component inputs:
\[EIC \subseteq \{(\langle N, ip_N \rangle, (d, ip_d) \rangle \mid \text{ip}_N \in IPorts, d \in D, \text{ip}_d \in IPorts_d\} \hspace{1cm} (4)\]
The external output coupling, \(EOC\), connect external outputs to component outputs:
\[EOC \subseteq \{\langle (N, op_N), (N, op_N) \rangle \mid \text{op}_N \in OPorts, d \in D, \text{op}_d \in OPorts_d\} \hspace{1cm} (5)\]
Lastly, the internal coupling, \(IC\), connect component outputs to component inputs:
\[IC \subseteq \{(\langle a, op_a \rangle, (b, ip_b) \rangle) \mid a, b \in D, \text{op}_a \in OPorts_a, \text{ip}_b \in IPorts_b\} \hspace{1cm} (5)\]
We should point out that in DEVS no output port of a component may be connected to an input port of the same component, i.e., \(((a, op_a), (b, ip_b)) \in IC\) implies \(a \neq b\). In other words, no direct feedback loops are allowed for each component. Armed with the above characterizations, we are now in a position to derive several atomic and coupled DEVS models for nuclear medicine patient service management.

4 Simulation Model

The practical setting of a nuclear medicine department involves several resources, which include humans and equipment, procedures/tests and performance measures. We start by describing these entities in the context of model abstraction and then derive the corresponding atomic and coupled models that constitute the nuclear medicine simulation model.

4.1 Model Abstraction

We conceptualize a nuclear medicine department model involving human and equipment resources, stations, and patients. We classify these entities by considering their roles and the interactions they have within the model.
Human Resources

We distinguish between four types of human resources: technologists, nurses, physicians, and managers. We capture the behavior of each human resource by taking into account the expertise and experience. Human resources that have been executing their tasks for several years are expected to complete their tasks more rapidly compared to those human resources that have lesser experience. The set of activities each type of human resources can perform depends on the expertise. Table 1 lists some of the activities that can be performed by each type of human resource.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Technologist</th>
<th>Nurses</th>
<th>Physicians</th>
<th>Managers</th>
</tr>
</thead>
<tbody>
<tr>
<td>IV access</td>
<td>IV access</td>
<td>IV access</td>
<td>IV access</td>
<td>IV access</td>
</tr>
<tr>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
</tr>
<tr>
<td>administration</td>
<td>administration</td>
<td>administration</td>
<td>administration</td>
<td>administration</td>
</tr>
<tr>
<td>Draw doses</td>
<td>Draw doses</td>
<td>Draw doses</td>
<td>Draw doses</td>
<td>Draw doses</td>
</tr>
<tr>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
<td></td>
<td>Radiopharmaceutical</td>
<td>Radiopharmaceutical</td>
</tr>
<tr>
<td>preparation</td>
<td></td>
<td></td>
<td>preparation</td>
<td></td>
</tr>
</tbody>
</table>

In our simulation model we represent each human resource type as a separate atomic model, capable of receiving messages containing their schedules. A schedule includes times (and stations) when the human resource will serve patients. When it is time to serve a patient the human resource travels to the appropriate station according to the schedule. Travel time from the human resource’s office to each station is known.

Procedures/Tests

Nuclear medicine procedures/tests are essential in medical specialties such as cardiology, pediatrics and psychiatry. The procedures are usually requested by physicians by calling the nuclear medicine clinic to ask for an appointment for their patients. The procedures provide physicians with information about structure and function of the human body (diagnosis) but are also used for disease treatment. Table 2 lists several nuclear medicine procedures and their current procedural terminology (CPT) codes.

<table>
<thead>
<tr>
<th>CPT Code</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>78465</td>
<td>Cardiovascular Event (CVE)</td>
</tr>
<tr>
<td></td>
<td>Myocardial Imaging (SP-M)</td>
</tr>
<tr>
<td>78815</td>
<td>Positron Emission Tomography (PET)/</td>
</tr>
<tr>
<td></td>
<td>Computed Tomography (CT) skull to thigh</td>
</tr>
<tr>
<td>78306</td>
<td>MSB-bone imaging (whole body)</td>
</tr>
<tr>
<td>78315</td>
<td>MSC-bone imaging (three phase)</td>
</tr>
<tr>
<td>78223</td>
<td>GIC-Hepatobiliary imaging</td>
</tr>
<tr>
<td>78472</td>
<td>CVI-cardiac blood pool (muga)</td>
</tr>
<tr>
<td>78585</td>
<td>REB-Pulm perfusion / ventilation</td>
</tr>
<tr>
<td>78006</td>
<td>ENC-Thyroid imaging (upt. sing)</td>
</tr>
<tr>
<td>78195</td>
<td>HEE-Lymphatic imaging</td>
</tr>
<tr>
<td>78464</td>
<td>CVD-Myocardial img (SP-R ORS)</td>
</tr>
</tbody>
</table>

Each procedure images a specific organ and requires the administration of at least one
radiopharmaceutical. The number of steps for each procedure may range from 3 to 11. The duration of each step may vary depending on the experience of the human resource in charge, however it must be completed within the time window stipulated by protocol for the procedure. As an example, the CVE/SP-M procedure is described in Table 3. This procedure involves four steps and require the use of two different radiopharmaceuticals. This procedure takes a minimum of 95 minutes to complete and requires the involvement of at least two human resources. Table 4 shows the steps for the PET/CT procedure. In this procedure only one radiopharmaceutical is needed.

### Table 3: Procedure 78465: Cardiovascular Event (CVE) Myocardial Imaging (SP-M)

<table>
<thead>
<tr>
<th>Step</th>
<th>Activity</th>
<th>Time (min.)</th>
<th>Station</th>
<th>Human Resource</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I.V. Start</td>
<td>5</td>
<td>TRT 1, 2 &amp; 3</td>
<td>Technologists; Nurse; Manager</td>
</tr>
<tr>
<td>2</td>
<td>Stress EKG</td>
<td>30</td>
<td>Treadmill 1 &amp; 2; EKG Tech</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Patient Wait</td>
<td>30-60</td>
<td>Waiting room</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Imaging</td>
<td>30</td>
<td>Axis 1, 2, &amp; 3; P2000A &amp; B, P3000</td>
<td>Technologists; Nurse; Manager</td>
</tr>
</tbody>
</table>

### Table 4: Procedure 78815: Computed Tomography (CT) skull to thigh

<table>
<thead>
<tr>
<th>Step</th>
<th>Activity</th>
<th>Time (min.)</th>
<th>Station</th>
<th>Human Resource</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>IV Start</td>
<td>10</td>
<td>TRT 1, 2 &amp; 3</td>
<td>Technologists; Nurse; Manager</td>
</tr>
<tr>
<td>2</td>
<td>Adm. Radioph.</td>
<td>5</td>
<td>Meridian; TRT 1, 2 &amp; 3; Axis 1, 2, &amp; 3; P2000A &amp; B</td>
<td>Technologists; Nurse; Manager</td>
</tr>
<tr>
<td>3</td>
<td>Patient Wait</td>
<td>60</td>
<td>Waiting room</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Imaging</td>
<td>45</td>
<td>Axis 1, 2, &amp; 3; Meridian; P3000, P2000A &amp; B</td>
<td>Technologists; Manager</td>
</tr>
</tbody>
</table>

### Stations and Equipment

A nuclear medicine department has separate stations for performing specific procedures/tests. We conceptualize stations as spaces where patients are served by human resources. Every station has at most one type of nuclear medicine equipment. We classify stations based on the type of equipment in the station. Nuclear medicine equipment includes different types of gamma cameras and treadmills. Our simulation model incorporates an atomic model for each equipment, an atomic model that represents a room, and a coupled model for a station. The station coupled model represents both the room space and the equipment in the station. Before starting any activity at any station, the model has to verify that all the entities needed to perform the procedure have arrived. For example, to administer a radiopharmaceutical the human resource, patient and the radiopharmaceutical needed to perform this activity must be in the station. The time spent by these entities in the station will depend on the protocol for
performing the procedure/test, experience of the human resource, and on the type of equipment involved.

Patients

Patient service requests are usually managed by a call center. A receptionist is in charge of taking care of these requests by finding an appointment for the patient. In the simulation model we represent the call center by a scheduler atomic model. This atomic model is in charge of patients’ schedules. We also have a call generator atomic model that generates patient service requests during the simulation. Patients will always ask for one procedure and, in some cases, they will also provide a day of preference for the appointment. The scheduling of patients depends on the algorithm or rules available in a given nuclear medicine department. Schedule information is passed to all the models involved in the scheduling. First, human resources whose schedules were affected by the inclusion of a new patient are notified. Secondly, notifications are sent to the models that are in charge of generating patients and radiopharmaceuticals at the time of the appointment.

Performance Measures

Since our nuclear medicine patient service management approach involves both patient and management perspectives, we design the models so that important information pertaining to both perspectives is captured during each simulation run. We derive a transducer atomic model, which is responsible for collecting this information and for computing statistics of interest to the modeler. In particular, we use performance measures that have been seen in the literature. Table 5 gives the selected performance measures that we used to evaluate patient service satisfaction in health care clinics. Besides being concerned about the quality of service they provide to their patients, nuclear medicine managers have to watch for the profitability and operation of the business. Their main concern is to provide a high quality of service but also make the best use of the available resources. Table 6 gives the performance measures that are commonly used in the literature from a management’s perspective in health care clinics. We use these measures in our simulation model to assess system performance of a nuclear medicine department based on the patient and resource scheduling algorithm/rule used by the department. Such scheduling algorithm/rule is discussed in detail in Section 5.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waiting time type 1</td>
<td>Time patient wait from the time of calling for an appointment until the date of the appointment</td>
<td>[22]</td>
</tr>
<tr>
<td>Preference ratio</td>
<td>Percentage of times patient request for an appointment is satisfied</td>
<td>[18]</td>
</tr>
<tr>
<td>Cycle time</td>
<td>Time patient spent on the system</td>
<td>[28], [29]</td>
</tr>
</tbody>
</table>

4.2 Atomic and Coupled Models

We derive several atomic and coupled models to build the simulation model. We derive an atomic model for each of the following human resources: Manager (MANGR), Technologist
Table 6: Managers performance measurements.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equipments' utilization</td>
<td>Maximize utilization</td>
<td>[22], [26]</td>
</tr>
<tr>
<td>Human resources' utilization</td>
<td>Most adequate number of human resources while maximizing utilization</td>
<td>[26], [7]</td>
</tr>
<tr>
<td>Patient throughput</td>
<td>Number of patients served per day</td>
<td>[16]</td>
</tr>
</tbody>
</table>

(TECH), Nurse (NURSE), Receptionist (RCPST) and Physician (PHYS). Similarly, we derive an atomic model for Equipment (EQUIP) resources including Treadmill, Axis Gamma Camera, TRT Gamma Camera and P2000 Gamma Camera. We also derive an atomic model for nuclear medicine department rooms (ROOM) such as the Waiting Room, Treadmill Room, Axis Camera Room, TRT Camera Room and P2000 Camera Room. Note that the names of the rooms are based on the equipment inside the room. So by coupling the ROOM and EQUIP atomic models, we build a nuclear medicine department station (STATION) coupled model. We should point out that atomic models are generic representations of the different types of entities used in nuclear medicine. So in the simulation the models are instantiated with different attributes to represent the unique or different entities in nuclear medicine.

Next, we couple the above models to build a nuclear medicine department coupled model called NMD. To model call requests, patient arrivals, and radiopharmaceutical arrivals, we derive atomic models for Call Generator (CGEN), Scheduler (SCHED), Scheduled Patient Generator (PGENR), Radiopharmaceutical Generator (RPGENR) and Transducer (TRANSD). These models are coupled together to build an Experimental Frame (EF) coupled model. The overall simulation model results from coupling NMD and EF.

We are now in a position to provide mathematical descriptions of the models. However, due to space limitation we focus only on three atomic models, TECH, EQUIP, and SCHED, which are critical to the operation of a nuclear medicine department. In what follows, $\times$ denotes the cartesian product of sets and $\land$ denotes the logic AND operation.

**TECH Atomic Model**

We consider a TECH atomic model having input and output ports as shown in Figure 1. The model has three basic input ports, namely; “in”, “set”, and “update”, and two types of output ports, namely; “out” and “room$^x$”. The number of output ports of type “room$^x$”, $x = 1, \ldots, n$, depends on the number of rooms $n$ in the nuclear medicine facility. The TECH atomic models receives external input via the input ports and transmits output information via the output ports. The input port “in” is for receiving a message to make the model ready or active for work at the beginning of the simulation. A new schedule for the technologist is sent through the “set” port, while any updates to the schedule are sent through the “update” port. The “out” output port allows for transmitting information to the TRANSD atomic model. The rest of the output ports transmit information to the rooms associated with the technologist.

The TECH (technologist) atomic model has eight basic states, namely: idle, get_schedule, waiting, update_schedule, travel_to, travel_from, serve_patient and wait_here. We depict the behavior of the atomic model using the state (transition) diagram shown in Figure 2. Mathematically,
the TECH atomic model can be defined in Parallel DEVS as follows:

\[
DEVS_{TECH} = (X_M, Y_M, S, \delta_{ext}, \delta_{int}, \delta_{con}, \lambda, ta)
\]

where,

\[X_M = \{(p, v) | p \in IPorts, v \in X_p\}\]

is the set of input ports and values, where

\[IPorts = \{\text{"in"}, \text{"set"}, \text{"update"}\},\]

and for \(p = \text{"in"}; X_{\text{in}} = V_1\); for \(p = \text{"set"}, X_{\text{set}} = V_2\); and for \(p = \text{"update"}, X_{\text{update}} = V_3\). The sets \(V_1, V_2\) and \(V_3\) are arbitrary sets. The set

\[Y_M = \{(p, v) | p \in OPorts, v \in Y_p\}\]

is the set of output ports and values, where

\[OPorts = \{\text{"out"}, \text{"station1"}, \text{"station2"}, \cdots, \text{"stationn"}\}.\]

The sets \(Y_{\text{out}}, Y_{\text{station1}}, Y_{\text{station2}}, \cdots, Y_{\text{stationn}}\) are arbitrary sets. The set

\[S = \{\text{"idle"}, \text{"get_schedule"}, \text{"waiting"}, \text{"travel_to"}, \text{"serve_patient"}, \text{\ldots}\}\]
“wait here”, “travel_from”} × ℜ⁺ × V₁ × V₂ × V₃

is the set of sequential states.

**External Transition Function:**

\[ \delta_{\text{ext}}((\text{phase}, \sigma, \text{sched}), e, (p, v)) \]

= (“idle”, ∞, sched), if \( p == \text{“in”} \)
= (“get_schedule”, \( t_g \), sched), if \( \text{phase} == \text{“idle”} \land p == \text{“set”} \)
  \( \text{mysched} = \text{computeEventDelays}(\text{sched}); \)
= (“waiting”, \( t_w \), sched), if \( \text{phase} == \text{“get_schedule”} \)
  \( t_w = \text{getWaitDelay}(); \)
= (“update_schedule”, \( t_u \), sched), if \( \text{phase} == \text{“waiting”} \land p == \text{“update”} \)
  \( \text{mysched} = \text{updateEventDelays}(\text{sched}); \)
= (“idle”, ∞, sched), if \( \text{phase} == \text{“waiting”} \land \text{mysched} == \emptyset \)
= (phase, \( \sigma - e \), sched), otherwise.

**Internal Transition Function:**

\[ \delta_{\text{int}}((\text{phase}, \sigma, \text{sched}), e, (p, v)) \]

= (“travel_to”, \( t_t \), sched), if \( \text{phase} == \text{“waiting”} \land \text{travel} == \text{true} \)
  \( t_t = \text{getTravelDelay}(); \)
  \( \text{stationID} = \text{getStationID}(); \)
= (“serve_patient”, \( t_{pd} \), sched), if \( \text{phase} == \text{“travel_to”} \)
  \( t_{pd} = \text{getProcedureDelay}(); \)
= (“wait_here”, \( t_w \), sched), if \( \text{phase} == \text{“serve_patient”} \land \text{travel} == \text{false} \)
  \( t_w = \text{getWaitDelay}(); \)
= (“serve_patient”, \( t_{pd} \), sched), if \( \text{phase} == \text{“wait_here”} \)
  \( t_{pd} = \text{getProcedureDelay}(); \)
= (“travel_from”, \( t_f \), sched), if \( \text{phase} == \text{“serve_patient”} \land \text{travel} == \text{true} \)
  \( t_f = \text{getTravelDelay}(); \)
= (“wait”, \( t_w \), sched), if \( \text{phase} == \text{“travel_from”} \)
  \( t_w = \text{getWaitDelay}(). \)

**Confluence Function:**

\[ \delta_{\text{con}}(s, t_a(s), x) = \delta_{\text{ext}}(\delta_{\text{int}}(s), 0, x). \]

**Output Function:**

\[ \lambda(\text{phase}, \sigma, \text{sched}) \]

= (out, stats);
= (station_i, \( \text{msg}_i \)) if \( \text{phase} == \text{“travel_to”} \land \text{stationID} == i \), where \( \text{msg}_i \) is the message to send to the Station coupled model for station \( i = 1, \ldots, n \).
**Time Advance Function:**

\[ ta(\text{phase}, \sigma, \text{sched}) = \sigma. \]

Observe that the confluent function performs an internal transition before the external transition. In other words, no preemptions are allowed. The operation of the TECH atomic model can be described as follows. When an input is received on the “set” input port, the model transitions to the “get_schedule” state, where a `computeEventDelays()` method is called to retrieve the technologist’s schedule for the day. The model transitions to “waiting” state after obtaining the schedule. If an input is received on the “update” input port while the model is in the “waiting” state, a transition to the “update_schedule” state is performed and the method `updateEventsDelay()` is called to update the technologist’s current schedule. After completing the schedule update the model transitions back to the “waiting” state. The model goes into the “travel_to” state when its time to serve the next patient in the schedule, and remains in that state until the travel time to the patient location has elapsed. It then goes into the “serve_patient” state. The state “serve_patient” involves performing a procedure based on the nuclear medicine test prescribed for the patient.

As an example, suppose that a technologist has to perform the nuclear medicine test CPT Code 78465 (see Table 3) on a patient. This test involves the following activities: IV start (5 minutes), stress EKG (30 minutes), patient wait (30-60 minutes), imaging (30 minutes), and computer process (15 minutes). Let us assume that the technologist has to perform IV start and imaging on the patient, and that the duration of each activity is deterministic. Then the TECH atomic model would transition from the “waiting” state to “travel_to” state at the scheduled time and remain in that state for a delay of \( t_t \) minutes, which is the amount of time it takes to get to the IV room. Next, the model would transition to “serve_patient” for IV start for a delay of \( t_s = 5 \) minutes. After the delay elapses, the model would transition from “serve_patient” to “travel_from” for a delay of \( t_f \) minutes, that is, the amount if time it takes to travel from the IV room to the technologist’s office. Finally, the model transitions from “travel_from” to “waiting”.

Depending on the technologist’s schedule, the TECH model either remains in the “waiting” for some delay \( t_w \), or repeats the process if another patient has to be served. However, when its the scheduled time to travel to the imaging room, the model has to be in the “waiting” state, from where it would transition to “travel_to” for a \( t_f \) minutes delay, before moving to “serve_patient”. This time to model goes into the “serve_patient” state to perform imaging for a delay of \( t_{pd} = 30 \) minutes. Upon completion of the delay, the model transitions to “travel_from” for a delay of \( t_f \) for the imaging room, and finally to the “waiting” state to wait for the next activity in the schedule.

**EQUIP Atomic Model**

The EQUIP atomic model has one input port “in” and one output port “out” as shown in Figure 3. The EQUIP atomic model has two states, “idle” and “busy”. The behavior of this atomic model is depicted in Figure 4.

The model is initialized in “idle” state and transitions to the “busy” state if an input is received via the “in” port. A method is called to compute the amount of time the model will stay “busy” just before transition. This amount of time will depend on the task the equipment has to perform. Let us call this method `getTaskDuration()` and we will use it in expressing the model in parallel DEVS. When in “busy” state the model does not respond to any inputs,
implying that the equipment is busy. Once the amount of time has elapsed, the model returns to the “idle” state. As we mentioned earlier, the EQUIP atomic model is coupled to a Room (ROOM) atomic model. The coupling between these two models will be discussed later in the paper. The “out” port of the EQUIP atomic model is used to transmit information to the ROOM atomic model. We can now define EQUIP in Parallel DEVS as follows:

\[
\text{DEVSEQUIP} = (X_M, Y_M, S, \delta_{\text{ext}}, \delta_{\text{int}}, \delta_{\text{con}}, \lambda, ta) \tag{7}
\]

where,

\[X_M = \{(p, v) | p \in IPorts, v \in V_p\}\]

is the set of input ports and values, \(IPorts = \{\text{“in”}\}\), and \(X_{in} = V_1\) is an arbitrary set. The set

\[Y_M = \{(p, v ) | p \in OPorts, v \in Y_p\}\]

is the set of output ports and values, \(OPorts = \{\text{“out”}\}\), and \(Y_{out}\) is an arbitrary set. The set

\[S = \{\text{“idle”}, \text{“busy”}\} \times \mathbb{R}_0^+ \times V_1\]

is the set of sequential states.

**External Transition Function:**

\[\delta_{\text{ext}}((phase, \sigma, task), e, (p, v)) = \begin{cases} \text{“busy”, } t_p, \text{task}, & \text{if } phase == \text{“idle”} \land p == \text{“in”}, \\ t_p = \text{getTaskDuration(task)}; & \\ \text{(phase, } \sigma - e, \text{task), otherwise.} & \end{cases}\]

**Internal Transition Function:**

\[\delta_{\text{int}}((phase, \sigma, task), e, (p, v))\]
= ("idle", ∞, task), if phase == "busy" ∧ tp == 0

Confluence Function:

δ_{con}(s, ta(s), x) = δ_{ext}(δ_{int}(s), 0, x).

Output Function:

λ(phase, σ, task) = (out, msg) if phase == "busy", where msg is the message to send to the ROOM atomic model.

Time Advance Function:

ta(phase, σ, task) = σ.

SCHED Atomic Model

The SCHED atomic model is in charge of accommodating patients and resources into the system schedule. We allow the modeler to use or implement a scheduling algorithm of their choice.

The SCHED atomic model shown in Figure 5. It has one input port “call_in” and three types of output ports, namely; “patient_out”, “radioph_out” and “hres_x_out”. The number of output ports of type “hres_x_out” depends on the number of human resources available in the nuclear medicine facility. The information transmitted by these ports is used to update the human resources’ schedules. The ‘patient_out” and “radioph_out” output ports are used to send information to the Patient Generator (PGENR) atomic model and the Radiopharmaceutical Generator (RPGENR) atomic model, respectively.

![Figure 5: A basic SCHED (scheduler) atomic model](image)

The operation of the SCHED atomic model is depicted in Figure 6. The model has three basic states: “idle”, “update_schedule”, and “scheduling”. The model is initialized in the “idle” state. A transition to the “scheduling” state occurs when the model is in the “idle” state and a message is received at the “call_in” input port. A method, getPatientSchedule(); takes the information provided by the patient and performs the scheduling using the algorithm chosen by the user. If the scheduling is successful, the model transitions to the “update_schedule” state, where the schedules for the resources selected in serving the patient are updated. After completing the schedule updates, the model transitions to the “idle” state. Otherwise, if scheduling is unsuccessful, the model transitions from “scheduling” state back to the “idle” state.

Mathematically, the SCHED atomic model can be expressed in Parallel DEVS as follows:

\[ \text{DEV}_{SCHED} = (X_M, Y_M, S, \delta_{ext}, \delta_{int}, \delta_{con}, \lambda, ta) \]
Figure 6: State transition diagram for SCHED atomic model

where,

\[ X_M = \{(p, v) | p \in IPorts, v \in X_p \} \]

is the set of input ports and values, \( IPorts = \{“call_in” \} \), and \( X_{call_in} = V_1 \) is an arbitrary set. The set

\[ Y_M = \{(p, v) | p \in OPorts, v \in Y_p \} \]

is the set of output ports and values, and \( OPorts = \{“patient_out”, “radioph_out”, “hres_1_out”, “hres_2_out”, \cdots, “hres_n_out” \} \), where \( Y_{patient_out}, Y_{radioph_out}, Y_{hres_1_out}, Y_{hres_2_out}, \cdots, Y_{hres_n_out} \) are arbitrary sets. The

\[ S = \{“idle”, “update_schedule”, “busy” \} \times \mathbb{R}_{+0} \times V_1 \]

is the set of sequential states.

**External Transition Function:**

\[
\delta_{\text{ext}}((\text{phase}, \sigma, \text{call}_i), e, (p, v))
\]

\[ = \{“scheduling”, t_s, \text{call}_i\}, \quad \text{if} \ \text{phase} = “idle” \land p = “call_in” \]

\[ \text{appointment} = \text{getPatientSchedule} (\text{call}_i); \]

\[ = \{\text{phase}, \sigma - e, \text{call}_i\}, \ \text{otherwise}. \]

**Internal Transition Function:**

\[
\delta_{\text{int}}((\text{phase}, \sigma, \text{call}_i), e, (p, v))
\]

\[ = \{“update_schedule”, t_u, \text{call}_i\}, \quad \text{if} \ \text{phase} = “scheduling” \land search = true; \]

\[ = \{“idle”, \infty, \text{call}_i\}, \quad \text{if} \ \text{phase} = “update_schedule”; \]

\[ = \{“idle”, \infty, \text{call}_i\}, \quad \text{if} \ \text{phase} = “scheduling” \land search = false; \]

**Confluence Function:**

\[
\delta_{\text{con}}(s, \text{ta}(s), x) = \delta_{\text{ext}}(\delta_{\text{int}}(s), 0, x). \]

16
Output Function:

\[ \lambda(\text{phase}, \sigma, \text{call}_i) = \begin{cases} 
(\text{patient}_\text{out}, \text{patient}_i), & \text{if } \text{phase} == \text{“update\_schedule”}, \text{ where } \text{patient}_i \text{ is the message to send to PGENR}; \\
(\text{radioph}_\text{out}, \text{radioph}_i), & \text{if } \text{phase} == \text{“update\_schedule”}, \text{ where } \text{radioph}_i \text{ is the message to send to the RPGENR}; \\
(\text{hres}_i\text{\_out}, \text{msg}_i), & \text{if } \text{phase} == \text{“update\_schedule”} \land \text{hresID} == i, \text{ where } \text{msg}_i \text{ is the message to send to the atomic model for human resource } i = 1, \ldots, n. 
\end{cases} \]

Time Advance Function:

\[ ta(\text{phase}, \sigma, \text{call}_i) = \sigma. \]

We omit the mathematical definitions for the rest of the atomic models, CGENR, PGENR, RPGENR and TRANSD, and instead devote the rest of this subsection to explain some of the coupled models used to create the simulation model. All the coupled models are coupled according to the three types of connections (EIC, EOC, and IC) defined in Equations 3, 4 and 5, respectively. We start with the STATION coupled model. As shown in Figure 7, the model is created by coupling EQUIP and ROOM. STATION has three input ports, namely; “patient_in”, “radioph_in”, and “hres_in”. EICs exist between the input ports and the ROOM atomic model. Two ICs connect EQUIP with ROOM. Information is passed to EQUIP via ROOM when an input has been received on STATION’s input ports. The STATION coupled model has two types of output ports, “patient_out” and “hres\_n\_out”. The number of output ports of type “hres\_n\_out” depends on the number, n, of human resources in the nuclear medicine facility. The information transmitted by the output ports is used to notify when a patient or human resource has been released from the room. This only happens when the ROOM atomic model receives information from the EQUIP atomic model notifying the service performed on the patient has been completed.

![Figure 7: The STATION coupled model](image-url)
The next model is the NMD coupled model shown in Figure 8. This model is a representation of the nuclear medicine department (NMD) and is created by coupling the human resource atomic models (TECH, NURSE, RCPST, PHYSN, MANGR) to STATION. In the figure we only show human resource models TECH, NURSE and MANGR due to limitation in figure size.

![NMD coupled model diagram](image)

**Figure 8: The NMD coupled model**

The last coupled model is the Experimental Frame (EF) shown in Figure 9. The EF allows the modeler to specify the kind of experiments that should be performed on NMD to enable answering questions of interest. Therefore, the EF is coupled to NMD (as depicted by the arrows) to create the overall simulation model for a nuclear medicine facility. The figure shows the atomic models that are part of EF and the way they are connected. CGENR is an atomic model of a telephone call center and is in charge of generating telephone call messages for patient appointment requests. This model allows the user to specify the telephone call arrival rate and the associated probability distribution. The generated appointment requests are received and processed by the SCHED atomic model. SCHED allows the user to select an algorithm for scheduling patients (and the needed resources) into the system. The schedule information is passed from SCHED to the RPGENR and PGENR atomic models. RPGENR models the ordering and arrival of radiopharmaceuticals at the facility at the scheduled time. PGENR models the actual arrival of patients to the nuclear medicine facility at their appointment times. To compute the performance measures of interest (described in Section 4.1), we created the transducer (TRANSD) atomic model. The TRANSD atomic model collects information from NMD and computes performance measures of interest.

### 4.3 NMD System Entity Structure

A system entity structure (SES) is used to plan, generate and evaluate design of simulation-based systems. This is a scheme that organizes a set of possible structures of a system. A library of models is generated when all the components abstracted from the real system are implemented. The SES is used to classify these components by their characteristics and to organize them in a hierarchical composition. This representation allows the modeler to visualize the system as a whole. The goal of the SES is to synthesize a simulation model by traversing a model hierarchical structure. A SES represents not a single model structure, but a family of structures from which a candidate entity structure can be selected.
The SES for the NMD simulation model is shown in Figure 10. At the top level, the scheme shows the two major coupled models that define the system structure. The *Experimental Frame* (EF) branch is decomposed into three branches that are assigned to the *Transducer* (TRANS), *Generator* (GENR) and *Scheduler* (SCHED) atomic models. The double line under the GENR branch means specialization. The Generator model is categorized into specialized entities such as the *Patient Generator* (PGENR), *Call Generator* (CGENR) and the *Radiopharmaceutical Generator* (RPGENR). The NMD branch is decomposed into two branches: Human Resource (HR) and Station (STATION). The HR branch is decomposed into four branches, each define a different type of human resource existing in nuclear medicine. The *Technologist* (TECH)
can be specialized into Nuclear Radiology Technologist and EKG Technologist. The STATION branch is decomposed into two branches. A selection constraint, depicted as dotted arrow from Gamma Camera (GAMMC) and Treadmill (TREADM) specializes entities to ROOM. Specialization entities mean that those entities cannot be selected independently. Finally, GAMMC is specialized into image with SPEC capability (IMSPEC) and image (IMAG).

4.4 Model Implementation, Verification and Testing

We implemented the NMD simulation model in DEVSJAVA [31], a Java-based modeling and simulation software implementation of DEVS formalisms such as Parallel DEVS. We tested and verified each atomic and coupled model using DEVSJAVA Simulation Viewer Version (SimView) 1.0.4. SimView allows the modeler to visually inspect the behavior of each model created in DEVSJAVA. Atomic models were verified first because they serve as building blocks for coupled models. Every component is represented with their input and output ports. Couplings among the various models are also represented for coupled models.

SimView has the advantage of having several convenient functionalities that include allowing the user to start and stop the simulation at any time during the simulation run, fast-forwarding or slowing down the simulation, and being able to input user defined parameters created for model verification and testing by simply clicking on a model’s input port and selecting the desired option from the pop-up menu. To run a simulation, the user selects the appropriate model from the top menu on the SimView window and click the run button. During the simulation run the simulation clock is displayed on the window. Parameters and statistics of are displayed as well by positioning the mouse cursor on top of the model block.
5 Application

We applied the NMD simulation system to the nuclear medicine department of the Scott and White Health System in Temple, Texas. This nuclear medicine department is one of the largest fully-accredited nuclear laboratories for general nuclear imaging and non-imaging, nuclear cardiology and positron emission tomography (PET) scan in the country. This facility operates five days a week from 8:00 am to 5:00 pm, and is not open on weekends. There are sixteen full-time physician support staff budgeted in this department. Every member of the group performs specific tasks that depend on the staff specialty. The department has eight technologists and two EKG technologists. This staff group has several responsibilities that include the preparation and administration of the radiopharmaceuticals, drawing doses and imaging acquisition. Electrocardiogram (EKG) technicians perform stress exams for cardiac tests. A nurse assists with the radiopharmaceutical administration and drawing doses. The division manager can also assist with those activities in the absence of one of the regular staff. The department also has two full-time nuclear medicine physicians, two radiology residents, and a staff cardiologist.

There are seven gamma cameras (one Philips PRISM 3000, two Philips PRISM 2000, three Philips AXIS and one Philips Meridian). Five of these cameras are planar, and are capable of doing 2D whole-body imaging and 3D Single Photon Emission Computed Tomography (SPECT). The other two cameras are also planar, one is SPECT capable for a small field of view only and the other is for imaging only. The stress cardiac area comprises a nurse station and three stress rooms. Two of the stress rooms have treadmills. The third room is for chemical stress testing for patients who cannot walk on a treadmill. All three are equipped with EKG capability. In the PET facility, there is one PET imaging camera, three patient preparation rooms for I.V. starts and waiting time, and a radiopharmaceutical receiving room. Around 60 different procedures are performed in this department. Table 2 (Section 4.1) shows the procedures that were performed more frequently at the clinic during the year of our study.

Patient calls are answered by three receptionists. Patients may provide a preferred day in which they would like to come to the clinic. A search for an appointment is first done by trying to satisfy that preference. However, if an appointment is found where the patient waits more than a month to be served, the preference provided is disregarded and an alternative earlier appointment is provided. Resource scheduling is performed using a load balancing routine. Nevertheless some human resources (technologists) from the staff are fixed to specific stations. Human resources assigned to stations take care of the stations where the equipments utilized the most are located. Our nuclear medicine department fixes technologist 1 and technologist 2 to station Axis1 and station Axis2 respectively. The rest of the staff is scheduled to the other stations.

We conducted preliminary experiments to validate our simulation model and to gain management insights into the impact of the existing scheduling approach on patient service. The performance measures identified in the literature (Section 4.1) were used to quantify service levels based on both patient and management perspectives. We used the following configuration for the nuclear medicine department simulation model: 7 gamma cameras, 2 stress rooms, 1 PET positron camera, 10 technologists, 1 nurse and 1 manager. Based on historical data we assumed Poisson arrivals for the patient appointment calls of about 90 calls per day on average.

In our computational study, we used historical information regarding patients who were served at the facility during a particular year. Appointment calls were received every 7 minutes.
on average. About 70% of those calls were for outpatients, who made appointments in advance since they did not require to be served immediately. The patients in this class are expected to arrive on time to their appointments but on average 1% of the time they arrived late, 1% of the time they canceled their appointment, and 1% of the time they did not show up. The patients who required to be served immediately comprised the other 30%, half of which were inpatients who required to be served on the same day. The other half were emergency patients who needed to be served as soon as possible. To randomly generate a nuclear medicine procedure for each patient, we used an empirical distribution based on historical data for the procedures that were performed during that year.

5.1 Computation Results

This section reports the results of using simulation to investigate the behavior of the system in a variety of scenarios when the scheduling rules established by the nuclear medicine department to manage patients and resources are used. We conducted three sets of experiments that differ in the number of patient calls the clinic receives per day. The appointment call interarrival process is set to follow an exponential distribution. First we consider a scenario where the clinic receives a high volume of calls (HVC). In this scenario, the mean interarrival time for appointment calls is set at 5 minutes. For the second set of experiments we used historical data to obtain a mean interarrival time for each month of the year. In this scenario, the mean interarrival times represent the real volume of calls (RVC) received at the clinic during a year. The values of these mean interarrival times range from 6 minutes to 10 minutes. Finally, a 10 minutes mean interarrival time is used for the third set of experiments to observe the behavior of the system under a low volume of appointment calls (LVC). We made 20 replications for each simulation run and used a scheduling time horizon of 12 months with a warm-start period of 3 months. To maintain independence among the replications, we used different seeds for the random number generators in the simulation. All the computational experiments were conducted on a DELL Optiplex GX620 with a Pentium D processor running at 3.0GHz with 3.5GB RAM.

The simulation results are reported in the tables and figures below. All the results for the RVC set of experiments are within 15% of the actual results for that year, hence validating our results. Table 7 shows for each set of experiments the mean and standard deviation (STDEV) of the simulation CPU time, the total number of patients served, and patient throughput. The total number of patients served and the type of procedures performed determine the revenue to the department. The simulation times for the NMD system are small, a desirable property of the simulation model especially when quick answers regarding the patient service operations are needed. However, there is a noticeable difference between the HVC experiments and LVC experiments which can be explained by the fact that more entities are handled by the system when the interarrival times are lower. As expected the results show that the largest number of patients are served under the HVC experiment. Appointment calls will arrived more frequently and more patients are accommodated into the system.

The number of patients served per month for each experiment are reported in Figure 12. The results show a general trend of decreasing patient throughput throughout the year for the RVC set of experiments. This corresponds to the decrease in demand during that year based on the actual records.

The corresponding utilization of nuclear medicine equipment for the year is given in Table 8 and the mean values plotted in Figure 13. The graph shows that for the RVC experiments most
Table 7: Simulation time, patients served and system throughput

<table>
<thead>
<tr>
<th></th>
<th>HVC</th>
<th>RVC</th>
<th>LVC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>StDev</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPU Time (secs)</td>
<td>1213.09</td>
<td>27.09</td>
<td>685.45</td>
</tr>
<tr>
<td>Patients Served</td>
<td>16005.43</td>
<td>51.25</td>
<td>15020.30</td>
</tr>
<tr>
<td>patients/day</td>
<td>66.69</td>
<td>0.21</td>
<td>62.58</td>
</tr>
</tbody>
</table>

Figure 12: Number of patients served per month

of the equipment is utilized around 70% of the time. Higher of utilization of the equipments was achieved under the HVC experiments but the numbers were close to those in the RVC experiments.

Table 8: Equipment percent (%) utilization

<table>
<thead>
<tr>
<th></th>
<th>HVC</th>
<th>RVC</th>
<th>LVC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>StDev</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treadmill(1)</td>
<td>75.91</td>
<td>0.68</td>
<td>71.84</td>
</tr>
<tr>
<td>Treadmill(2)</td>
<td>75.98</td>
<td>0.61</td>
<td>71.85</td>
</tr>
<tr>
<td>TRT(1)</td>
<td>41.08</td>
<td>0.69</td>
<td>36.56</td>
</tr>
<tr>
<td>TRT(2)</td>
<td>35.17</td>
<td>0.69</td>
<td>32.15</td>
</tr>
<tr>
<td>TRT(3)</td>
<td>32.77</td>
<td>0.64</td>
<td>30.28</td>
</tr>
<tr>
<td>Axis(1)</td>
<td>80.11</td>
<td>0.49</td>
<td>77.04</td>
</tr>
<tr>
<td>Axis(2)</td>
<td>80.03</td>
<td>0.58</td>
<td>77.01</td>
</tr>
<tr>
<td>Axis(3)</td>
<td>84.63</td>
<td>0.69</td>
<td>78.78</td>
</tr>
<tr>
<td>P2000(1)</td>
<td>84.68</td>
<td>0.56</td>
<td>78.55</td>
</tr>
<tr>
<td>P2000(2)</td>
<td>84.51</td>
<td>0.67</td>
<td>78.69</td>
</tr>
<tr>
<td>P2000(3)</td>
<td>79.90</td>
<td>0.66</td>
<td>74.00</td>
</tr>
<tr>
<td>Meridian(1)</td>
<td>83.48</td>
<td>0.42</td>
<td>81.04</td>
</tr>
</tbody>
</table>

The utilization of human resources is reported in Table 9 and plotted in Figure 14. We included a load balancing routine so that assignment of human resources to patients is evenly
done. However, the manager decides on which human resources to fix to specific stations and thus load balancing is only done for those resources that are not fixed. Consequently, the utilization of Technologist 1 and Technologist 2 is relatively higher for all experiments. As mentioned earlier, these two technologists are fixed to specific stations (management’s preference) where most of the procedures were actually scheduled. Also, observe that on the contrary, the utilization of Technologist 8, Manager and Nurse are significantly reduced. The workload of these three human resources is taken up by Technologists 1 and 2.

Table 9: Human resource percent (%) utilization

<table>
<thead>
<tr>
<th></th>
<th>HVC</th>
<th></th>
<th>RVC</th>
<th></th>
<th>LVC</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>StDev</td>
<td>Mean</td>
<td>StDev</td>
<td>Mean</td>
<td>StDev</td>
</tr>
<tr>
<td>Technologist(1)</td>
<td>80.07</td>
<td>0.49</td>
<td>49.53</td>
<td>0.39</td>
<td>77.02</td>
<td>0.55</td>
</tr>
<tr>
<td>Technologist(2)</td>
<td>79.99</td>
<td>0.58</td>
<td>49.85</td>
<td>0.31</td>
<td>76.99</td>
<td>0.44</td>
</tr>
<tr>
<td>Technologist(3)</td>
<td>74.69</td>
<td>0.79</td>
<td>41.34</td>
<td>0.63</td>
<td>70.92</td>
<td>0.78</td>
</tr>
<tr>
<td>Technologist(4)</td>
<td>74.07</td>
<td>0.63</td>
<td>40.69</td>
<td>0.53</td>
<td>70.57</td>
<td>0.61</td>
</tr>
<tr>
<td>Technologist(5)</td>
<td>73.94</td>
<td>0.71</td>
<td>41.03</td>
<td>0.59</td>
<td>70.42</td>
<td>0.67</td>
</tr>
<tr>
<td>Technologist(6)</td>
<td>74.14</td>
<td>0.84</td>
<td>41.39</td>
<td>0.34</td>
<td>70.78</td>
<td>0.66</td>
</tr>
<tr>
<td>Technologist(7)</td>
<td>74.05</td>
<td>0.73</td>
<td>40.77</td>
<td>0.39</td>
<td>70.34</td>
<td>0.78</td>
</tr>
<tr>
<td>Technologist(8)</td>
<td>67.19</td>
<td>0.52</td>
<td>33.58</td>
<td>0.33</td>
<td>62.19</td>
<td>0.76</td>
</tr>
<tr>
<td>Technologist(9)</td>
<td>76.20</td>
<td>0.68</td>
<td>41.36</td>
<td>0.42</td>
<td>72.12</td>
<td>0.93</td>
</tr>
<tr>
<td>Technologist(10)</td>
<td>76.28</td>
<td>0.61</td>
<td>41.34</td>
<td>0.39</td>
<td>72.13</td>
<td>0.98</td>
</tr>
<tr>
<td>Nurse(1)</td>
<td>32.75</td>
<td>0.50</td>
<td>12.00</td>
<td>0.43</td>
<td>28.32</td>
<td>0.78</td>
</tr>
<tr>
<td>Manager(1)</td>
<td>49.58</td>
<td>1.37</td>
<td>17.05</td>
<td>0.61</td>
<td>41.06</td>
<td>1.08</td>
</tr>
</tbody>
</table>

Table 10 shows the average number of days a patient has to wait from the day of the call to the day of the appointment (waiting time Type 1). As expected, patients wait less under the LVC experiments with a waiting time of about three days. The HVC experiments reported an average wait of about 39 days, which is caused by the higher demand for service and for not
having the resources needed at the nuclear medicine department to satisfy such demand.

Finally, Table 11 reports on the preference ratio (Section 4.1), that is, the percentage of time the preference asked by the patient was satisfied. The HVC set of experiments reported a 9% of preference ratio which is significantly low. This result is explained by noticing that schedules are mostly full during the year and patients end up scheduled in the limited spaces available.

Table 10: Average waiting time days (Type 1) from patient call to appointment

<table>
<thead>
<tr>
<th></th>
<th>HVC</th>
<th></th>
<th>RVC</th>
<th></th>
<th>LVC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>39.24</td>
<td>StDev</td>
<td>0.33</td>
<td>Mean</td>
<td>7.72</td>
</tr>
<tr>
<td>Mean</td>
<td>2.76</td>
<td>StDev</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 11: Percentage (%) of time patient preference is satisfied

<table>
<thead>
<tr>
<th></th>
<th>HVC</th>
<th></th>
<th>RVC</th>
<th></th>
<th>LVC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>9</td>
<td>StDev</td>
<td>5.14</td>
<td>Mean</td>
<td>80.76</td>
</tr>
<tr>
<td>Mean</td>
<td>97.06</td>
<td>StDev</td>
<td>0.06</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6 Conclusion

Managing patient service in nuclear medicine is a very challenging problem with very little research attention. In this paper, we use the discrete event system specification (DEVS) formalism to derive a generic simulation model for nuclear medicine patient service management that takes both patient and management perspectives. DEVS is a formal M&S framework based on dynamical systems theory and provides well defined concepts for coupling components,
hierarchical and modular model construction, and an object oriented substrate supporting repository reuse. We implement and validate the simulation model based on a real nuclear medicine setting and report computational results based on a scheduling algorithm and several patient and management performance measures. The results provide useful insights into patient service management in nuclear medicine. For example, a higher demand for service can negatively affect the level of service provided to the patient if resources are not managed efficiently. Thus it is up to the nuclear medicine clinic to alter their resource capacity for a given demand and patient preferences in order to maintain a high level of service.

While this work focuses on nuclear medicine, we believe that results will find generality in patient service management in other health care settings. It also provides several future research directions. For example, the current simulation model can be extended to a stochastic one using stochastic DEVS (SDEVS), which allows for modeling atomic model state transitions as a stochastic process. One can also envision stochastic optimization algorithms for scheduling patients and resources, which can be based on mathematical programming or stochastic online optimization. Finally, the current work can be extended to a simulation-optimization setting, whereby the simulation model provides feedback to stochastic optimization scheduling algorithms with the objective of making optimal decisions based patient and the nuclear medicine management perspectives.

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References


