# Simulating the Behavior of Building Occupants using Multi-agent Narratives: A Preliminary Study in a Generic Hospital Ward

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## Abstract

In architectural design it is of cardinal importance to anticipate how people will use a building prior to its construction and occupation. Conventional multi-agent simulation methods represent occupant movement and activities to assess the day-to-day performance of households and office buildings. In these environments, behavior is usually driven by individual schedules or comfort-related actions. In other kinds of settings, such as hospitals, airports, or factories, behavior is driven by codified sets of collaborative procedures which dynamically adapt to the spatial and social context. To address these building types, we propose a narrative-based approach whereby a variety of behavior patterns involving multiple occupants can be simulated and visualized. A scheduling method coordinates the narratives using Operations Research techniques. The method is demonstrated through a preliminary study, which involved collecting data in an existing hospital environment, modeling narratives computationally, and simulating them in an abstracted layout of a generic hospital ward.

## Introduction

One of the most important challenges faced by architects, engineers, and clients when designing a building is to anticipate the impact of a built environment on the behavior of its human inhabitants, and vice versa. This is a complicated task, due to the dynamic, stochastic, and context-dependent nature of human behavior. The behavior of building users, in fact, affects and is affected by environmental and social conditions, such as by the presence (or absence) of other people in space.

Failures in anticipating human-environment interactions can lead to severe consequences, such as underperforming spaces, diminished productivity, general dissatisfaction, and imbalances between expected and actual energy consumption. Instead, by effectively modeling and predicting the complex behaviors that are likely to occur when spaces are occupied, architects and engineers will be better able to maximize occupants' physical comfort, social well-being, and job performance, while minimizing their collective impact on the natural environment.

Occupant behavior simulation methods have been developed to predict human day-to-day influence on various sources of energy consumption, including HVAC systems, lighting, airflow and solar radiation through windows, and plug loads. In particular, simulating occupant movement and activities can lead to better predictions of internal loads calculations, and use of ventilation systems and electrical appliances (Feng et al., 2015).

Most of these energy-related occupant simulation models, however, have been applied to households or office buildings (as apparent from the comprehensive literature review by Gaetani et al. (2016)). In these settings, the activities performed can be described in the form of individual schedules, which discard dynamic group interactions. Collaborative activities, in fact, can take place only by scheduling the same activity in the same space for multiple participants.

In other types of settings, such as hospitals, airports, stations and factories, instead, behavior originates from the performing of structured sets of procedures which require collaboration among several actors, as well as the use of several spaces and specialized equipment. In such settings, activities cannot be scheduled beforehand, since their timing needs to adapt to the dynamic context in which they take place. Environmental factors (e.g. the building physical layout, the location of equipment), and social factors (crowding, under-staffing), have a significant impact on where people go and the activities they perform.

In an effort to make the analysis of such social and environmental factors more practical for design stakeholders, we propose a narrative-based approach whereby a variety of behavior patterns involving multiple occupants can be simulated and visualized. Narratives unfold in time and across multiple spaces, adapting to dynamic social and environmental conditions. A centralized scheduling mechanism dynamically allocates resources (e.g. actors, spaces and equipment) to the most urgent narratives at a given time. The method is demonstrated through a preliminary study, which involved collecting data in an existing hospital environment, modeling narratives computationally, and simulating them in an abstracted layout of a generic hospital ward.

*Table 1: Classification of occupant behavior models with examples.*

| Model Type | Occupant Presence | Occupant Actions |
|---|---|---|
| Fixed Profile | Appx G Occupancy (ASHRAE, 2004) | Appx G Lighting (ASHRAE, 2004) |
| Deterministic | Mahdavi and Tahmasebi (2015) | Buso et al. (2014) |
| Parametric Stochastic | Wang et al. (2005) | Haldi and Robinson (2011) |
| Non-Parametric Stochastic | Page (2007) | Widén et al. (2009) |
| Multi-Agent | Zimmermann (2010) | Langevin et al. (2014) |

## Review of occupant behavior modeling

Recent literature reviews by Yan et al. (2015), Feng et al. (2015), and Gaetani et al. (2016) collectively provide a nearly exhaustive overview of existing occupant behavior models and related issues. Here we offer a brief overview of existing occupant models with a classification scheme that combines five modeling types with two categories: presence and actions. Presence models focus on how people use and move through spaces, which determines when/where comfort levels need to be maintained and when/where actions can occur. Action models (also called adaptive behavior or user behavior models) focus on interactions with the building that directly affect energy use. Examples of such actions include adjusting windows and blinds, switching on/off lights, using appliances, and setting thermostats. The five types of occupant behavior models appear in Table 1 along with associated examples of presence and action models.

The current standard practice in energy modeling is to reduce occupant behavior down to fixed profiles. These profiles typically give aggregated hourly information about the degree to which a space, electrical appliance, or building system is used. The most prominent examples of these profiles are those found in ASHRAE (2004) and subsequent versions of Standard 90.1. While in widespread use, fixed profile models are unable to capture a number of behavioral patterns: those that occur within each hour, and those that differ from one day to the next.

The deterministic category of models is really a generalization that encompasses fixed profiles and other techniques that exploit occupancy-related data sets without introducing stochasticity. Mahdavi and Tahmasebi (2015) produce schedules of presence and absence by applying a calculated threshold to recorded occupancy data. Buso et al. (2014) use collected data to calibrate schedules for various sources of energy use. Human behavioral models based on simple deterministic rules, such as opening the window if the indoor temperature is above 25°C, also fall into this category.

Parametric stochastic models employ one or more standard probability distributions to reproduce observed behavioral patterns. The distributions are fit to the data through the selection of a relatively small number of parameters. A classic example of this approach is the work done by Wang et al. (2005), who investigate the feasibility of modeling occupant presence and absence using exponential distributions. Haldi and Robinson (2011) present a number of parametric statistic models describing occupants' use of windows and shading devices.

Non-parametric stochastic models, also known as data-driven models, use random processes but are not limited to standard probability distributions. Instead, non-parametric statistical techniques are applied to data that may originate from motion detectors, carbon dioxide sensors, video cameras, security-based systems, and/or diaries. Examples include the work of Page (2007) and Widén et al. (2009) for occupant presence and actions respectively.

The first four model types in Table 1 represent humans in an aggregated fashion, discarding information about the schedule of any particular individual. Multi-agent systems, instead, have been developed to generate more fine-grained individualistic representations of occupant behavior, often accounting for occupant movement and activities.

Agent-based models, for instance, are a specific kind of multi-agent system where each type of individual has an associated self-contained sub-model describing its response to other individuals and/or environmental stimuli (Yilmaz and Ören, 2009). Zimmermann (2010), Chen et al. (2016) and Langevin et al. (2014) present three agent-based models, the first two focusing on building performance simulation, and the third on occupant interaction with energy-related building systems. A different kind of multi-agent system is proposed by Goldstein et al. (2011) and Baptista et al. (2014). In both models the behavior of each building occupant is driven by a centralized scheduling algorithm, which accounts for both individual and shared activities. The model of Goldstein et al. (2011) also accounts for occupant locations.

The aforementioned multi-agent systems, however, have been mainly applied to describe the day-to-day occupant behavior in households or office buildings. In these types of settings, occupant presence and movement is usually driven by individual-oriented schedules, and occupant actions are largely motivated by a desire to maintain user-related comfort levels. In other types of settings such as hospitals, airports, and stations, movement and actions depend on a set of codified procedures that drive behavior across multiple spaces. In hospital environments, for instance, collaborative medical procedures drive the behavior of doctors and nurses, who make use of state-of-the-art technology to heal patients. In such settings, the following challenges arise. First, behavior can hardly be understood by analyzing individual behaviors since procedures are mainly collaborative, and they make use of multiple spaces and equipment units. Second, the unfolding of procedures in space depends on the presence (or absence) of other people in a given space, as well as on environmental conditions. Predefined schedules are limited in their ability to handle exceptional situations such as one in which a doctor or nurse is not currently available to perform a medical check.

The narrative-based model proposed in this paper aims to address these issues by recreating representative scenarios of occupant behavior, incorporating the description of collaborative procedures and their dynamic unfolding across spaces. This approach also uses a centralized scheduling algorithm, but captures shared activities in far greater detail. Multiple occupants can engage in a sequence of both consecutive and parallel tasks, performed over a succession of indoor spaces.

Table 1 helps us classifying our model in relation to the existing literature. Before doing so, it is worth mentioning that the table is somewhat over-simplistic in the sense that some modeling efforts do not fall neatly into one of the eight categories. For example, the research of Page (2007) covers not only occupant presence but also some work on window opening actions. A customizable machine learning method described by Goldstein et al. (2010) falls almost equally into both the non-parametric stochastic and multi-agent categories. Although the proposed narrative-based model incorporates activities such as examining a patient, the model does not currently incorporate a description of the actions performed in the examination procedure, which may have a direct impact on energy. We therefore classify our approach as a special kind of multi-agent occupant presence model, which incorporates a description of movement and activities.

## Multi-agent narratives

### Narrative-based models

Narrative-based models are specific types of multi-agent models in which occupant behavior is determined by narratives, computational entities that coordinate the movement and shared activities of multiple agents in space following specific rule-based scripts. While they share some fundamental characteristics with other multi-agent systems, such as the description of many agents interacting in an environment (Wooldridge, 2009), they differ from other types of models (e.g. agent-based model) in the degree to which agents are able to act autonomously.

In narrative-based models the behavior of agents is directed by the narrative rather than by individual responses to the surrounding environment. This feature makes complex collaborative behavior more manageable, since behavior rules are stored only in narrative entities, rather than being distributed across many agents. Narrative models can also store adaptation rules to the surrounding environment. For instance, if a patient cannot be found in his/her bed, a narrative entity can instruct a doctor and a nurse to wait, or to abort the procedure.

A scheduling mechanism coordinates the sequence of narratives to be performed, using context-dependent priority values. The scheduler assigns a higher priority to the most urgent or important narratives, and postpones narratives which for instance cannot be performed because some conditions are not satisfied (e.g. the doctor or nurse are busy).

The narrative-based model leverages relevant insights from other kinds of multi-agent systems adopted for pedestrian movement (Dijkstra and Timmermans, 2002), fire egress situations (Ozel, 1991; Chu et al., 2014), and human-environment interactions in public spaces (Yan and Kalay, 2005). In these models people movement and activities are modeled accounting for the dynamic influence of the spatial and social environment. The narrative-based model is also reminiscent of process-oriented simulations, which describe the behavior of systems by means of structured activity sequences that require a set of resources (e.g. people, equipment, and spaces) and take a certain (usually stochastic) amount of time (Heath et al., 2011).

Figure 1 summarizes the key components of the narrative-based model, which includes a centralized scheduler, the narratives, a description of a *space* where the behavior takes place, the *actors* involved in the behavior, and a series of *activities* performed. The role of these three elements in similar approaches have been described by Simeone and Kalay (2012) and Schaumann et al. (2015). Here we identify the specific information required by spaces, actors, activities, and narratives to support a newly proposed scheduling mechanism.

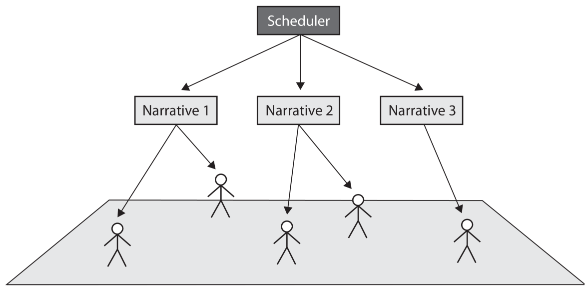


*Figure 1: System architecture*

### Elements of narrative-based models

Narrative-based models consist of a meaningful combination of three elements: the *space* (where?), the *actors* (who?), and the activities (what?). The infor-

*Table 2: Information required by spaces, actors, activities, and narratives (SP stands for Static Properties, DP for Dynamic Properties, and M for Methods)*

| Member name | Space | Actor | Activity | Narrative | SP | DP | M | Description |
|---|---|---|---|---|---|---|---|---|
| name | X | X | X | X | X | | | unique identification |
| geometry | X | X | | | X | | | form attributes |
| space function | X | | | | X | | | functional attributes |
| role | | X | | | X | | | role in an organization |
| related space | | X | | | X | | | space associated |
| duration | | | | X | X | | | expected duration |
| status | X | X | X | X | | X | | dynamic state |
| activity script | | | X | | | | X | performing rules |
| instructions | | | | X | X | | | sequence of procedures |
| priority function | | | | X | | | X | priority calculation |

mation required to model narratives can be collected using different methods, depending on the availability of the data, or the feasibility of the data collection procedures. Examples of such methods involve presence sensors, movement tracking devices (e.g. indoor GPS, RFID, or wireless systems), self-reporting digital diaries, as well as field observations, interviews, and questionnaires.

In this chapter we describe space, actor, activity and narrative models. Table 2 summarizes the information required by a narrative-based approach.

*a) Spaces*

Spaces constitute the setting for human behavior. The space model includes a description of *form* (e.g. a geometrical layout) and *function*, a list of attributes that can be attached to the model describing how the space can be used by its occupants. For instance, by describing a space as 'patient room', it is possible to constrain the behavior of agents to a discrete number of activities allowed in patient rooms, such as resting, eating, and checking on a patient's status. The space model also incorporates descriptions of the equipment used to perform activities. The equipment model includes any mobile furniture, electrical devices or any other kind of appliances that can be used by actors to perform an activity. Furthermore, each space has a status, which can be dynamically updated. Modeling spaces is the primary task of architects. In the simulation process, architects will be responsible to generate a geometrical layout, and to define the functional attributes of each space.

*b) Actors*

Actors are proxies for building occupants. They are characterized by a role related to the institution that occupies a building (e.g. doctor, nurse, or patient in a hospital setting), a space to which they are associated (e.g a doctor's office), and a status which may vary during the simulation (e.g indicating if a patient has been checked or not). Different from traditional agent-based systems, in our model actors have limited perceptual and cognitive abilities. Instead, their goal-oriented behavior is coordinated by the narratives that associate each actor with a set of activities to be performed in specific spaces. Actor models are defined by architects and engineers together with domain experts (e.g hospital managers). The information required to model actors can be based on data collected in existing settings, or projections about future building occupants.

*c) Activities*

Activities describe atomic behaviors that actors perform individually or collaboratively to achieve a goal. Activity examples include going to a certain location, talking with another actor, or working in an office. The narrative model can assign a specific duration to an activity (that can be extrapolated from data collected in existing settings), or use stochastic time values. In the case of activities that involve movement, the duration of the activity depends on the building layout as well as on other user- or context-dependent factors. The 'walk to' activity, in fact, uses a path-finding algorithm to drive actors' movement in space. Even though some activities, such as 'walk to' or 'talk to', can be applicable to most types of settings, others can be considered domain-specific. Their modeling therefore requires the assistance of domain experts which provide context-dependent knowledge.

*d) Narratives*

Narrative models consist of sequences of activities performed by one or more actors in space. Every narrative encapsulates the relevant information required to achieve a larger goal. Narratives are associated with a list of parameters (e.g. a specific list of spaces and actors), as well as a priority value that indicates the relevance of the narrative at a given time. A set of instructions describes the step-by-step preforming of the narrative to coordinate the actors' behavior. A priority function dynamically updates the priority value.

To avoid potential drawbacks of narrative descriptions that are too rigid, stochasticity and conditional statements can be inserted in the narrative instructions to allow for adaptation to contextual conditions. Conditional statements can relate to different aspects of the current state of the simulated environment. For instance, they can refer to an agent's state, environmental conditions, or to the presence or absence of other agents or equipment. For example, if a patient cannot be found in his/her bed, the narrative can instruct doctors to wait or to move on to the next patient. This decision can depend on the doctor's state (e.g. in a hurry), environmental conditions (e.g. noise in the room), or some probabilistic function.

Modeling narratives is a joint task between architects, engineers and domain experts. Since rules of human behavior in built environments pertain to the multiple domain of expertise, other types of experts could potentially participate in the definition of narratives, such as environmental psychologists, anthropologists and social scientists.

**Scheduling narratives**

A scheduling mechanism coordinates the activities performed over time by dynamically selecting narratives based on a priority value associated with each narrative. The priority value is generated by means of a priority function, which quantifies the desirability of a narrative outcome at a specific moment in time. These priority functions can take into account dynamic social and environmental conditions.

Our approach is inspired by optimization techniques used in Operations Research (Hillier and Lieberman, 2014) for airline crew and fleet scheduling, truck routing, political districting, and many other applications, most notably hospitals (van Essen et al., 2012; Konrad et al., 2013; M'Hallah and Alkhabbaz, 2013; Marques et al., 2014; Amaral and Costa, 2014).

In the case of hospital occupant behavior, we formulate the scheduling task as a Set Partitioning Problem (Garfinkel and Nemhauser, 1969). We begin with a set of $m$ actors, $ACTORS = \{actor_1, \ldots, actor_m\}$. An actor may be engaged in performing exactly one narrative at a time, though more than one actor may be involved in performing the same narrative. In mathematical terms, this means partitioning the set $ACTORS$ into subsets of actors that perform one narrative each. For example, a set of five actors (i.e. $ACTORS = \{actor_1, \ldots, actor_5\}$), who perform two tasks might be partitioned into a narrative involving two actors (e.g. $\{actor_1, actor_4\}$) and another narrative involving the remaining three actors ($\{actor_2, actor_3, actor_5\}$). In general, the possible narratives can be described by the list $NARRATIVES = [narr_1, \ldots, narr_n]$, where each narrative $narr_j$ is a subset of $ACTORS$. We then introduce a list of priority values $PRIORITIES = [priority_1, \ldots, priority_n]$, where higher priority numbers indicate more urgent narratives. Our task then is to choose a set of narratives that partition $ACTORS$ in a way that maximizes the sum of the priority numbers.

A number of methods are available to solve the Set Partitioning Problem. Whereas Linear Programming techniques can help calculate an optimal solution, a nearly optimal solution is sufficient for our purposes. We therefore adapt a "greedy" approach similar to the Set Cover greedy algorithm (Vazirani, 2003). The premise of our method is quite simple: first, sort all possible alternatives, and then pick the top alternatives which do not contain overlapping actors.

To illustrate the algorithm, consider an example with four actors and six possible narratives.

$$
\begin{aligned}
&ACTORS = \{\text{Liz}, \text{Bob}, \text{John}, \text{Dana}\}\\
&NARRATIVES = [\{\text{Liz}, \text{Bob}\}, \{\text{Dana}\}, \{\text{Bob}\},\\
&\qquad\qquad \{\text{Liz}, \text{Bob}, \text{John}\}, \{\text{Bob}, \text{John}\}, \{\text{Liz}\}]\\
&PRIORITIES = [6, 7, 4, 2, 11, 5]
\end{aligned}
$$

The meaning of each narrative is irrelevant here. But to provide context, one could imagine that the first narrative with Liz and Bob represents a conversation between a doctor and a nurse. The second narrative, involving only Dana, might represent a patient resting in bed. The third narrative might represent a nurse named Bob taking a break. The fourth might represent a doctor named Liz and a nurse named Bob checking a patient named John, and so on. The priorities in the list $PRIORITIES$ correspond to the narratives in the list $NARRATIVES$. A key point is that not all of these possible narratives can occur at the same time. Because each actor can participate in one narrative only at any given time, a subset of the narratives must be chosen. The choice is determined based on the priority of each narrative. The priority number of the conversation involving Liz and Bob, for example, is 6.

Applying our algorithm, we first sort the narratives by priority. The narrative involving Bob and John, with a priority value of 11, is the most urgent and therefore appears at the top of the list:

$$
\begin{aligned}
&narr_5 = \{\text{Bob}, \text{John}\}; \quad priority_5 = 11\\
&narr_2 = \{\text{Dana}\}; \quad priority_2 = 7\\
&narr_1 = \{\text{Liz}, \text{Bob}\}; \quad priority_1 = 6\\
&narr_6 = \{\text{Liz}\}; \quad priority_6 = 5\\
&narr_3 = \{\text{Bob}\}; \quad priority_3 = 4\\
&narr_4 = \{\text{Liz}, \text{Bob}, \text{John}\}; \quad priority_4 = 2
\end{aligned}
$$

Next, we choose narratives from the top down while avoiding conflicts. Narratives $narr_5$ and $narr_2$ are selected, but $narr_1$ must be avoided because Bob is already busy with $narr_5$. We move on to $narr_6$, which is selected, then stop because all actors are assigned. So the final narratives to be selected are:

$$
\begin{aligned}
&narr_5 = \{\text{Bob}, \text{John}\}; \quad priority_5 = 11\\
&narr_2 = \{\text{Dana}\}; \quad priority_2 = 7\\
&narr_6 = \{\text{Liz}\}; \quad priority_6 = 5
\end{aligned}
$$

When the set partitioning algorithm is incorporated into a simulation of human behavior, it must be reapplied at successive points in simulated time. Our simulation method performs the set partitioning after each task is completed, where each *task* is a single instruction in a narrative at which an activity is performed by a set of actors. Each time the algorithm is applied, the set of possible narratives stays the same but the priority of each narrative changes.

Priority functions relate to previous work on utility functions in economics (von Neumann and Morgenstern, 1944) and in Artificial Intelligence (Russell and Norvig, 1995; Mark, 2009). In this work we use intuitive principles to calculate priorities, as explained in the case study section.

One technique we employ is to increase by 50% the priority number of each narrative that is underway, but not finished. This ensures that a simulated occupant is likely to continue doing whatever he/she was doing before, unless his/her narrative ends or he/she is diverted by another narrative with an extremely high priority number (e.g. an emergency). Further research is needed to determine and validate a more rigorous convention for favouring the current narrative.

To produce realistic simulations covering many hours of simulated time, priority values would likely have to depend on the time of day, occupants' prior activities, and possibly other conditions. In future work, these values could be extracted automatically from empirical data. One could imagine profiles of default narrative priorities being developed in a manner analogous to how occupancy profiles are currently put forward, albeit with an extra processing step. The difference is that while occupancy profiles average away the complex social behavior patterns that typify how indoor environments are actually used, well-calibrated priority values have the potential to reproduce these patterns by guiding the selection of narratives.

### Simulation system

A simulation system is responsible for selecting and coordinating the execution of the narratives. The system is composed of three modules (Figure 2). A *scheduler* enumerates all the possible narratives to perform, assigns a priority to each narrative, and uses the algorithm described in the previous section to select which narratives to perform. A *coordinator* keeps track of which occupants are engaged in which narratives and initiates the possible selection of new narratives whenever any occupant completes the narrative instructions. A *performer* executes the narrative instructions.

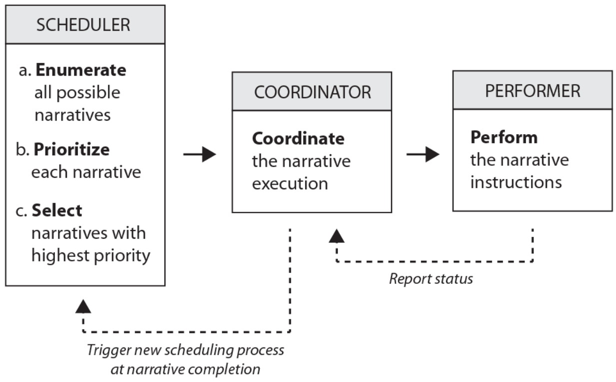


*Figure 2: Simulation system*

## Preliminary study in a hospital ward

We chose hospital environments as test bed for our approach, for the following reasons. First, the complexity of occupant behavior patterns makes different types of prediction very challenging both for architectural design and for energy modeling. The complexity largely arises from the multitude of actors performing collaborative activities across multiple spaces. Second, despite the complexity of the occupancy phenomena in hospitals, activity patterns are mostly driven from well codified medical and organizational roles and procedures. This formalization is useful for identifying, modeling, and simulating narratives. Third, human and building performance aspects are of primary concern in hospital design and operations. Such aspects involve staff efficiency and patient satisfaction, the use of spaces and equipment in time (including how much they are left unused), as well as saving costs from energy, light, appliances and ventilation systems. Hence, both architects and energy modelers would benefit from a model able to represent building use patterns in such settings.

The presented case study involves the following steps: (a) collecting data in existing hospital environments; (b) modeling representative narratives computationally; (c) simulating the narratives in an abstracted layout of a hospital ward.

### Data collection and analysis

We adopted two types of data collection methods. The first involved direct experience observations in an orthopedics department in Tel Aviv, Israel. Seven trained observers followed and tracked the behavior of one occupant each during the morning shift for six days distributed over a period of three weeks. The observers recorded the actors involved, the activity performed, the spatial location, the current hour, and the duration of the behavior (Table 3). This data collection method conformed to privacy regulations, which forbid the use of any movement tracking devices, cameras, or presence sensors.

The second data collection method involved extensive interviews and discussions with doctors, nurses and hospital managers. We integrated the previously collected data with domain-experts knowledge accumulated over decades of work experience in hospitals to extrapolate the description of narratives which tend to recur in different hospitals. Our assumption is that by leveraging experts' longstanding knowledge in the hospital domain it is possible to identify narratives that are likely to be performed in hospitals that are yet to be built.

The data collection process culminated in the orga-

*Table 3: Example of data collected by means of empirical observations*

| ID | Hour | Actor | Activity | Space | Duration |
|---|---|---|---|---|---|
| 1 | 9:53 am | doctor_1 | talkTo (nurse_1) | nurse station | 5 min |
| 2 | 9:58 am | doctor_1, nurse_1 | walkTo (patient_bed_1) | nurse_station | 1 min |
| 3 | 9:59 am | doctor_1 | talkTo (nurse_1) | patient_room_1 | 30 sec |
| 4 | 9:59 am | doctor_1, nurse_1 | talkTo (patient_1) | patient_room_1 | 7 min |
| 5 | 10:06 am | doctor_1, nurse_1 | walkTo (patient_bed_2) | patient_room_1 | 5 sec |
| 6 | 10:06 am | nurse_1 | talkTo (patient_2) | patient_room_1 | 4 min |

*Table 4: Example of narrative models*

| ID | Narrative | Duration | Actors | Activities | Spaces |
|---|---|---|---|---|---|
| 1 | change_shift | 20-30 min | nurses | walkTo, prep | med_room |
| 2 | prep_treatment | 20-30 min | nurse | walkTo, prep | med_room |
| 3 | treat_patient | 5-10 min | nurse, patient | walkTo, treat | patient_room |
| 4 | food_distribution | 2-5 min | volunteer | walkTo, give | patient_room |
| 5 | patient_check | 10-15 min | doctor, nurse, patient | walkTo, talkTo, use | patient_bed, nurse_station |
| 6 | go_to_bathroom | 5-30 min | patient | walkTo, use | bathroom |
| 7 | rest_in_bed | / | patient | walkTo, use | patient_bed |
| 8 | do_paperwork | / | doctor | walkTo, use | doctor office |

nization and abstraction of the collected data into narratives that were observed to recur from one shift to another. Table 4 displays some of the identified narratives, which are of different kinds. The first five narratives, for instance, tend to recur at certain hours of the day. The last four narratives, by contrast, can be performed at any time during the shifts. Some narratives have specific durations, while others do not.

## Modeling

In this study, we chose to simulate only a specific number of narratives, and namely the last four displayed in Table 4. The narratives are performed in an abstracted hospital ward layout with two doctors, three nurses, and nine patients. Each doctor has an individual office desk, nurses share one nurse station, and there are four patient rooms with a bathroom in each. Each narrative includes a set of procedures to coordinate the behavior of a group of actors. Figure 3 displays the steps of the 'patient check' narrative, performed sequentially until completion.

A priority function assigns a contextual priority value to each narrative. In this study we used three basic principles to model priorities. First, we provided different initial priorities to collaborative and individualistic behaviors. Specifically, narratives which require collaboration among actors (e.g. patient_check narrative) are assigned higher priorities. Second, we further prioritize narratives which have already started to reduce the chance of a behavior being interrupted. Third, we de-prioritize completed narratives to reduce their chances of being triggered again.

In this work, space, actor, activity, narrative models, and priority functions have been written using Python, a common object-oriented programming language. Narrative procedures are specified using YAML (Ben-Kiki et al., 2009), a human friendly data serialization standard similar to XML and JSON. A general-purpose simulator called PythonPDEVS (Van Tendeloo and Vangheluwe, 2015), developed independently of this work, has been used to coordinate the narratives, though different types of simulators can be used for the same purpose.

```yaml
patient_check narrative:
 parameters: [doctor, nurse, patient,
             n_station, p_bed]
 instructions:
  - [[doctor, nurse], walkTo, n_station]
  - [doctor, talkTo, nurse]
  - [[doctor, nurse, patient], walkTo, p_bed]
  - [doctor, talkTo, nurse]
  - stochastic:
    - probability: .6
      instructions:
       - [[doctor, nurse], talkTo, patient]
    - probability: .4
      instructions:
       - [nurse, walkTo, n_station]
       - [nurse, use, n_station]
       - [nurse, walkTo, p_bed]
       - [[doctor, nurse], talkTo, patient]
```

*Figure 3: Example of narrative instructions*

## Simulation

Figure 4 shows a snapshot of the simulation output. Actors are represented as dots, with color indicating the narrative they are engaged in (e.g. rest_in_bed, nurse_patient_check, patient_check). The legends to the right list all the narratives taking place, as well as the current instruction in each narrative. In the snapshot, for instance, we can tell from the light green

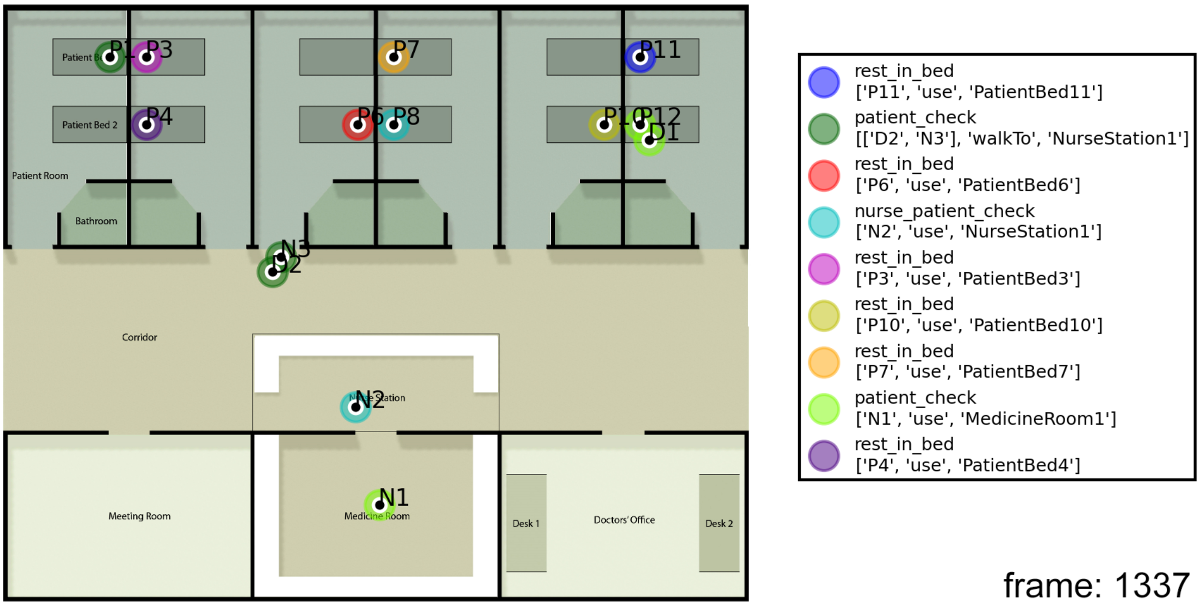


*Figure 4: Simulation output*

color that actors D1, N1, and P12 are engaging in a patient_check narrative. The current instruction indicates that the nurse N1 is using MedicineRoom1, searching for medicine that he/she will later bring back to PatientBed12 where the doctor and patient are waiting.

The proposed simulation approach exhibits a number of characteristics which distinguishes it from previous multi-agent methods in the building science domain. For example, occupants travel together as part of a complex activity involving multiple locations. In the multi-agent model of Goldstein et al. (2011), occupants may be scheduled to travel together incidentally, if it so happens they are selected for two consecutive activities in different locations. In the narrative-based simulations of Figure 4, doctors and nurses travel together because this common real-world behavior is explicitly modeled. We note that the human tendency to travel in groups, in certain situations, has previously been captured by Chu et al. (2014) in the context of building evacuation.

As seen in Figure 4, multi-agent narratives allow fine-grained tasks—such as the retrieval of medicine from a separate room—to occur as part of an encompassing behavior pattern. This introduces the potential for occupancy simulations to incorporate increasingly detailed descriptions of the complex behaviors that routinely unfold in real-world built environments.

## Discussion

The paper introduces a method to model, simulate, and visualize the behavior of building occupant in built or yet unbuilt environments. Compared to previous methods, the proposed narrative-based approach has the following advantages. First, it describes human behavior patterns from the perspective of a narrative, rather than that of the actor who performs it. This supports the encoding of rules to describe collaborative behaviors, as well as adaptations to dynamic social and environmental conditions. Second, it provides a dynamic scheduling mechanism which coordinates the performing of narratives over time using priority values, which adapt to the dynamic state of the world. Third, it supports the fine-grained description of representative scenarios that occur in buildings of the same kind, accounting for spatial and social factors. Simulations of this kind could then be used by architects and engineers to test multiple design options and observe how different physical layouts affect occupant behavior.

The main drawback of this approach, however, is the considerable amount of outstanding research required to develop, calibrate, and validate year-long narrative-based simulations. In particular, we acknowledge the cumbersome and time-consuming process of collecting data manually and modeling narratives. Because we focus on representative narratives that are shared among buildings of the same kind, this process need not be repeated for every design project. Rather, a team of experts would develop a set narratives for a particular building type. Architects would then integrate these narrative models with project-specific information, incorporating any additional data that might be available.

Another drawback of the approach is that its suitability for all building types, including offices and households, is unclear. It is possible that the algorithm used to schedule narratives in hospital environments may prove less effective in other types of settings, where behavior is less driven by optimization considerations. Nevertheless, hospitals and other process-driven environments such as factories, airports, and

train stations play a significant role in society, and deserve dedicated modeling approaches if necessary.
Future work may try to address the issues mentioned above. The algorithm could be tested not only in hospitals but also in different types of settings. Automated data collection methods could also be incorporated in the data collection phase to generate accurate inputs to narrative models. Additional research is also needed to ensure the various priority functions are appropriately scaled, are based on common guidelines, theories, and/or datasets, and vary appropriately over the course of simulated time to reflect typical morning, afternoon, and evening activities.

## Conclusion

We contribute early steps toward a tool that allows modeling and simulating multi-agent narratives in architectural design. The aim is to assist architects and engineers in displaying representative occupant behavior scenarios prior to building construction. These simulated scenarios may help architects evaluate different design options to maximize the productivity and improve the experiences of future occupants, while minimizing the impact on the natural environment.
A preliminary study demonstrates the data collection, modeling, and simulation process in a generic hospital ward. Preliminary simulation results demonstrate that the proposed approach holds the potential to assist architects in simulating and dynamically visualizing representative occupant behavior scenarios specifically tailored to the designed setting.
Narrative-based models could eventually be coupled with weather, heat transfer, light, plug load, and other types of energy models to simulate energy use while accounting for the dynamic aspects of human movement and activities in buildings.

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