A COMPUTATIONAL MODEL FOR SIMULATION, VISUALIZATION AND EVALUATION OF MANDATORY AND OPTIONAL BUILDING OCCUPANCY SCENARIOS

A Dissertation

by

SAIED ZARRINMEHR

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee	Mark J. Clayton
Co-Chair of Committee	Wei Yan
Committee Members	Geoffrey J. Booth
	Xuemei Zhu
	Nancy M. Amato
Head of Department,	Robert Warden

December 2016

Major Subject: Architecture

ABSTRACT

Evaluating design decisions is an important factor in a post-positivist design process. Understanding how people move in space is an important part of the evaluation processes. However, making accurate predictions of occupants' movements is a challenge mainly due to the differences between individual occupants, their unique preferences in relation to environmental qualities, the types of scenarios with which they become engaged, and multiple dimensions of the environmental factors that affect occupants' decisions. This study suggests a model to simulate and visualize mandatory occupancy scenarios, which are task-based, and optional occupancy scenarios, which are attraction-based. The impact of environmental qualities is largely overlooked in existing simulation models in both of these scenarios. Existing simulation models for mandatory scenarios are often based on finding shortest or fastest paths and for optional scenarios mainly rely on the field of visibility. The original contribution of the simulation models that this study suggests is simultaneous consideration of environmental qualities, path simplicity, and visibility in addition to desires such as travel time or distance minimization. The integration of these models unlocks new potentials that the individual components do not include. The individual techniques that will be used to develop the occupancy simulation models are validated in the exiting literature experimentally. However, this study does not include conducting field studies to validate the integrated model. If the observed walking trails of humans are provided, the suggested models in this study can be validated through a fine-tuning process that reproduces the observed trails. The simulation results can finally

be used for evaluation purposes to help designers at the design phase and facility managers in after design phases to make informed decisions. This study provides a software solution that implements the suggested model to support its feasibility. This software uses a Building Information Model (BIM) to represent the built environment, an Agent-Based Model (ABM) to simulate the occupants, a list of research evidence to encode agent's reactions to the environment, a Discrete Event Simulation (DES) model to represent the tasks in mandatory scenarios, and the field of visibility (isovist) to simulate an occupant's viewshed. In this software, evaluation is a process of data query from the information collected by the agents during the simulations. The data query logic can be set according to the interests of designers or facility managers.

To my mother and father who sacrificed their lives for me.

CONTRIBUTORS AND FUNDING SOURCES

This work was supervised by a dissertation committee consisting of Professor Mark J. Clayton, as the advisor, Professor Wei Yan, as the co-advisor, Professor Xuemei Zhu of the Department of Architecture, Professor Geoffrey J. Booth of the Department of Landscape Architecture and Urban Planning, and Professor Nancy M. Amato of the Department of Computer Science and Engineering.

There are no outside funding contributions to acknowledge related to the research and compilation of this document.

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

CHAPTER I

THE NEED FOR EVALUATION OF BUILDING OCCUPANCY SCENARIOS

1.1 Introduction

This study proposes an integrated simulation model for the evaluation of design proposals from the perspective of an occupant's experience. Evaluation is an integral part of all rational design processes. The results of evaluating design alternatives create the basis for predicting performance, comparison, and selection. This research aims to produce a detailed transcript of a virtual occupant's predicted experience from considering mandatory and optional usage scenarios at the scale of the individual. The model will be implemented in the form of simulation software.

This research is based on an assumption that desirability of an environment is bound to the occupants' personal preferences, their positions in space and the activities with which they are engaged, which will be referred by "occupancy scenario". Use of an environment inevitably relies upon multiple occupancy scenarios. An occupancy scenario can be classified according to the type of activities that the scenario includes. Gehl (1987) divides activities into three categories including "necessary activities", "optional activities", and "resultant activities". Poor environmental qualities do not significantly change the "necessary activities", including predetermined walking activities such as shopping, going to work and other unavoidable daily trips. The poor environment, on the other hand, tremendously decreases "optional activities" as well as the chances to form the socially-oriented resultant activities. "Resultant activities" emerge where the presence of people offer opportunities for activities, such as street vending (Gehl, 1987).

A scenario can be understood as engagement with different sequences of activities that are either planned or not planned in advance. Walking for pleasure is an example of optional scenarios and nursing in a hospital is an example of a mandatory scenario. Unlike optional scenarios, a trip from a nursing station to patient rooms must happen regardless of the qualities that a nurse will experience in-between or the stress-inducing care delivery that he or she will become engaged with. Whether navigation is mandatory or optional, when it happens the occupant tries to make choices that maximizes pleasure and minimizes dissatisfaction (Helbing et al., 1997). Evaluation therefore, is the inherent component of navigating space (i.e. walking). However, navigating space is not always a part of occupancy scenarios. For example, the scenario of typing while seated includes one single activity that does not require navigation in space. The evaluation model in this study will account for occupancy scenarios both with and without spatial navigation.

Crowd simulation and pedestrian dynamics are well-established fields of research that have evolved to increase complexity and subtlety in predicting paths that people will take. Much of the earliest work assumed that people would choose the shortest paths for walking. Subsequently evidence was found indicating that people choose fastest paths over the shortest paths (Ganem, 1998). Although the differences between shortest and fastest paths might be subtle, the mechanism for calculating fastest paths needs to account for time as well as other physical characteristics such as acceleration, velocity and direction which are not necessarily needed to find the shortest paths. There is also evidence to strongly support that, in normal walking scenarios, people do not take the shortest or fastest paths; they rather choose the most satisfying paths (Helbing et al., 1997). It is impossible to understand the most satisfying path without knowing how an individual evaluates the potential desirability in his or her environment. The space in which we walk is much more that a neutral void and includes various range of qualities to which we are sensitive and engender reactions. Therefore, a change from modeling shortest or fastest path to modeling the most satisfying path inevitably requires the inclusion of evaluation of desirability at the very heart of a model.

With a model of occupancy scenario available at the design phase, designers can predict where the occupants spend their time and how they feel in relation to the local qualities that they experience. Designer can also have an idea about how often they become engaged with different activities and how they feel when engaged with these activities. The model that this study envisions may allow a designer to have a full transcript of occupants' evaluation and conduct queries to see where and how often the occupants will be pushed out of their comfort.

In spite of the significant importance of occupancy scenarios in design evaluation, the state of knowledge and practice in architectural design has paid little attention to them. This study formulates and tests a computational model for simulating occupancy scenarios and evaluating them. After completion of a thorough review of research and theory, a model to explain an occupant's behavior in an architectural space has been devised, a software prototype to explore validation of the model has been developed, and tests to determine whether the model produces results that are believable have been conducted.

Although a simulation and evaluation model for occupancy scenarios does not exist, most of the theoretical frameworks to put this model together are present. Three main components of the occupancy scenario include occupants with idiosyncratic preferences, their positions and the activities that they become engaged with. An agent-based system can represent the occupants. A model of pedestrian dynamics developed in BIM can represent the environment and the location, direction and velocity of the occupants. A dynamic or static schedule of activities can represent the activities. The sequence of activities can be predetermined using dynamic or stochastic methods according to the type of scenarios. This study suggests a model that integrates all of these elements together to create a comprehensive model for simulation and evaluation of the occupancy scenarios. The details of the implementation of this system are not unique and can be developed in different ways. Developing one operating model will support the feasibility of the idea which is introduced in this study.

Section 2 of this study shows that in spite of the differences in descriptive models of design process, evaluation is always considered to be an essential part of design process. In this section evaluation will also be reviewed as part of design computation. The review of the literature in section 2 will be concluded with finding the gap in literature, which will serve as the point of departure for this study. Section 3, includes the statement of the problem. In section 4 the research question will be introduced and a semantic network of its requirements will be created. Section 5 will suggest technical strategies for developing a model by which the requirements of the evaluation can be met. The scope of research will also be narrowed down in section 5 and the research hypotheses will be included in section 6. Then validation strategy will be discussed in section 7. Finally, this study will be concluded by a roadmap to develop a simulation and evaluation mode for mandatory and optional occupancy scenarios.

1.2 Background

The research stance in this study is based on a post-positivist worldview. A post-positivist view provides an empirical system of reasoning and unlike positivism it does not claim that objective truth (knowledge) is based on unchangeable foundation (Wang and Groat, 2013, Pages 32-33). From a critical realism point of view, which is a common form of post-positivism, our knowledge of reality is uncertain because "cause and effect" is our perceived understanding of reality. The main difference between positivist and post-positivist worldviews is the extension at which researchers consider their research valid. Within critical realism the validity of empirical knowledge is based on imperfect senses of observer by which he/she connects to the world (Bhaskar, 1997, Bhaskar et al., 1998). Otherwise, the search for "cause and effect" is the essence of both positivist and post-positivist research stances. According to the research stance taken in this study the studies that are based on other worldviews will be excluded from the review of the literature.

This research adopts a model of architectural design process that relies upon explicit evaluation of a design scheme to determine whether it is an appropriate solution. It is an exploration of modeling and simulating the behavior of building occupants using agents that model psychological state of the occupant, emotive qualities of the built environment, and the reaction of the two. A review of theory on design methods helps to clarify this base for the research. The state of the art background of the literature will be reviewed at three levels. At section 2-1 the role of evaluation in the design process will be reviewed.

Section 2-2 will narrow down the scope from design process, to computational design process. Finally, at section 2-3 the related literature for evaluation from an occupant's perspective will be reviewed. By the end of this section the gap in the literature will be revealed as the absence of an integrated model that simulates occupancy scenarios at microscale that evaluates the environmental qualities from the perspective of building occupants.

1.2.1 Evaluation in the Design Process

In a study of procedural design theories, Lang (1987) suggested a descriptive model of design praxis that included definition, analysis, synthesis, development, implementation, operation and evaluation phases. In this model, evaluation is a post-occupancy phase that is intended to establish a performance profile for buildings. According to Lang, evaluation is also present in all design tasks when a design decision is made. Evaluation at design phase serves description, comparison and prediction. Given a system of values and possible design alternatives, evaluation at design phase determines if any of those alternatives are good enough for the implementation or not. To predict how people interact with the design alternatives and evaluate their performance, positivist theories are needed. Lang (1987) believes that symbolic mathematical models can be used when positive theories are well developed to predict the performance of aspects of buildings.

Numerous other models for design process have been developed. In his book "How Designers Think", Lawson (1990) studied different accounts of design processes. After scrutinizing them, he identified three main components in the design process, which are analysis, synthesis and evaluation. Lawson's model allows for loops between any two components of the design process. The scope of design procedural theories is not limited to architectural or urban design.

Evaluation is not decision making. It rather provides the input to analyze design alternatives and make informed decisions. Most descriptive models of design process do not shed much light on the nature of evaluation in design process. Alexander (1964) has discussed some aspects of evaluation in a unique way. He defined design as an effort to make fitness between a form (i.e. the solution) and its context (i.e. the problem). He refers to the fitness between form and context as the "negative process of neutralizing the incongruities, or irritants, or forces, which cause misfit" (page 24). Design starts with a list of "potential misfits", which are not very different from the lists that designers write as design requirements. According to Alexander a potential misfit is a binary variable that describes fit and misfit that may occur between form and context. Potential misfits are not independent from each other and often interact. Considering the interaction among the potential misfits, the design problem can be understood as a topological graph. The interactions among potential misfits ask for simultaneous consideration of them (Alexander, 1964).

Evaluation also locates at the heart of evidence-based design, which is another major movement in design process. Evidence-based design is defined as "a process for the conscientious, explicit and judicious use of current best evidence from research and practice in making critical decisions, together with an informed client, about the design of each individual and unique project" (Hamilton and Leifer, 2009, page 239). Four levels of evidence-based practice have been suggested from simply using the evidence to developing new evidence and disseminating evidence (Hamilton, 2003). While there is an inclination to consider evidence-based design as a new field (Hamilton, 2009), all of its ingredients can be found in positivist and post-positivist research and design processes. Regardless of the novelty of evidence-based design, rigorous evaluation of design proposals against evidence is the essence of practicing evidence-based design at its bottom line (i.e. level 1).

1.2.2 Evaluation in Computational Design

The design processes that are assisted with computational simulation and prediction models are referred to as computational design. The use of computational techniques in design process grew rapidly along with the emergence of Computer Aided Design (CAD) technology which made it possible to represent the geometry of design alternatives digitally. The trend of computation advanced with the advent of Building Information Modeling (BIM) technology. The BIM technology allows for attaching non-geometric data to traditional CAD geometric objects and using an object-based data scheme to represent building components and their behaviors (buildingSMART, 2014). The rich data scheme of BIM often provides the required input for new evaluation mechanisms, including several types of simulations that predict some aspects of building performance. Quite early in the consideration of computational methods in architecture, there arose an intriguing question: can architectural design process be mimicked by a computer to make best possible decisions (Negroponte, 1970)? This question in its essence includes search for optimal answers which is inherited in Artificial Intelligence (AI) and Machine

Learning (ML). The discipline that tries to employ AI and ML to investigate the possibility of this question is referred to as design optimization.

Artificial Intelligence is concerned with constructing intelligent agents that take rational actions in a given situation. AI algorithms suggest strategies for generating solutions and searching in the solution space (Russell and Norvig, 2010). Evaluation lies at the very heart of all AI algorithms and is based on a series of facts which create a Knowledge Base (KB). Gero (1990) laid out a theoretical framework for the application of AI in design which is based on function, behavior and structure. In his model, function is the purpose of designing, behavior refers to expected and actual behavior of the designed artifact, and structure refers to the components of the designed artifacts and their relations. According to Gero a design prototype should separate function, structure, expected behavior, and actual behavior. He classifies the related design KB into relational knowledge between design components, qualitative knowledge, computational knowledge, and context knowledge all of which need to be stored in the design prototype. Gero considers design as transformations processes in which the functions are transformed to a structure. These transformations involve formulation, synthesis, analysis, evaluation, reformulation, and production of design description (Gero, 1990).

Evaluation in Gero's model is the measurement of the difference between expected behaviors and the actual behaviors of a structure (i.e. design prototype) (Gero, 1990). The implementation of Gero's model needed a system for the representation of design prototypes that can store the related KB domains. Clayton et al. (1999) proved that virtual product models can be designed in a CAD system to store information which physically describes building, its performance and design intents. The design process that they suggested includes predicting the behavior of the form and assessing its function. The suggested virtual product models easily stored or updated the results of prediction and assessment. The enriched product model suggested by Clayton et al. (1999) includes assessment as a part of product model.

Kalay defined evaluation as “measuring the fitness between achieved or stated performance to stated criteria” (Kalay, 1992, Page 399). Based on this definition, evaluation is applicable to a specific set of performance characteristics. The input, fitness and output are the three main components that are present in the evaluation as a process. Fitness comparison can also be considered as a form of evaluation in AI which can be based on heuristics. Comparison of design alternatives can be made by apportioning performance weightings to calculate relative scores or using more advanced ML techniques such as clustering and Pareto efficient frontier (Gero, 1980). While the applications of AI and ML in design were limited to the use of metaheuristic algorithms, mainly Genetic Algorithm, the discipline of design optimization is growing fast and is supported by several automated simulation and prediction models.

The main challenge in using intelligent algorithms to mimic design process and find the optimized solution is the number of involved variables. Adding more variables exponentially increases the solution space to the point that exhaustive search is impossible. In his book “The Science of The Artificial” Simon (1969) has addressed this problem. Simon asserts that although parts of the design problem can be described scientifically, designing in its essence includes taking actions that the related sciences cannot fully describe. In his view "design solutions are sequences of actions that lead to possible worlds satisfying specified constraints" (Simon, 1969, page 124). Simon suggests that these actions include heuristics that produce admissible design alternatives out of endless possibilities that exist. In other words, design actions (i.e. heuristics) encapsulate evaluation to reduce the endless possibilities to a limited number of admissible alternatives.

Admissibility is not comprehendible without evaluation embedded in it. Admissible heuristics or design actions are hidden in other theories of design. Examples include Hillier's theory where he claims design is possible with ideas to think with (Hillier, 2007), Alexander's pattern language theory where he claims they encapsulate the essence of design solutions (Alexander, 1979), or Steadman's inductive fallacy theory where he discusses design is not possible without preconceptions (Steadman, 1979). When design is combined with computational techniques, evaluation is acknowledged as a constraint satisfaction process which can be solved as an artificial intelligence or machine learning problem. However, it is very important to note that evaluation is also a silent part of the design actions without which design is not possible.

1.2.3 Evaluation of Occupancy Scenarios

This research focuses on evaluation of occupancy scenarios from the perspective of occupants by modeling the occupants. In the built environment people become engaged in many different activities. They can also navigate through space, experiencing different qualities in their surroundings. Within different occupancy scenarios, the level of desirability can vary according to the changes in the qualities that the occupants experience in their surroundings, the activities with which they become engaged, the psychological state of the occupant or the interactions among them. A predictive evaluation mechanism from the perspective of occupants has to acknowledge the navigation of occupants in space and the activities with which they become engaged. The existing gap of the literature is that while there have been numerous attempts to simulate occupancy scenarios or evaluate the environmental qualities, an integrated model that accounts for both of them does not exist.

Most evaluation models do not account for the type of scenarios that the occupants become engaged with at microscale. For example, research in walkability is based on evaluation of the built environment to find environmental factors that encourage people to walk by using statistical analysis of large samples of users of the environment (the metascale). Several studies have proven the health (Pate et al., 1995), socioeconomic (Litman, 2003) and environmental (Rabl and de Nazelle, 2012) benefits of walkable environments. As a result, a huge body of research has been developed to find the environmental correlates of walkability (Robert Wood Johnson Foundation, 2007). Evaluation of environmental qualities is central to walkability research. When searching for environmental correlates of walking, some studies have paid attention to the types of walking scenarios and the characters of group of people who become engaged with these scenarios. Examples of these studies include finding correlates of walking to school for low-income Hispanic students in Austin, Texas (Zhu et al., 2008). However, research in walkability does not account for microscale movements of occupants and formulating their individual and unique scenarios.

Space syntax is probably the most well-known evaluation model in design to explain occupancy scenarios. It predicts the patterns of use based on accessibility of each point in space using syntactic steps. The main methods to define syntactic steps are isovists (i.e. visibility polygons), convex spaces, and minimum visibility axial lines. Vantage points, convex shapes, or axial lines that are connected to each other create local connections. By adding the local connections a global graph emerges by which the degree of accessibility (i.e. integration) to the entire space can be measured (Hillier and Hanson, 1984). Several case studies have shown that integration largely determines the pattern of both pedestrian and vehicular movement; therefore space syntax was claimed to reveal the secret of natural movement (Hillier et al., 1993). Hillier believes design is only possible with configurational ideas to guide thinking. Syntactic steps, which can be computed and numerically represented, can explain configurational rules that are non-discursive (Hillier, 1996).

Researchers in space syntax have taken long paces towards combining distance and visibility indices to create new indices that correlate with some aspects of human behavior. In museums and exhibitions, high visual integration increases the chance of interaction (Peponis et al., 2004). In large facilities, such as airport terminals, design elements that are located in visually integrated areas effectively help people in way-finding (Braaksma and Cook, 1980). There is also a growing body of literature in the application of space syntax in the design of healthcare facilities (Sadek and Shepley, 2016) which will be exhaustively reviewed later in this study. As a theoretical model for evaluation, space syntax takes no account of any environmental quality other than those related to the geometry of void (vs. mass) space. Additionally, the theory does not rely on simulating the scenario of occupancy and merely relies on the indices that are claimed to justify the aggregated behaviors.

The transition from aggregated results of space syntax or walkability research to active models at a microscale demands a model of occupants that can account for their unique preferences and scenarios. Agent-based systems provide the required functionalities of the occupant model. An agent is an encapsulated computer system that is situated in some environment, and is capable of taking flexible, autonomous actions to meet its objectives. After adopting an agent-oriented view of the world, most problems need to involve multiple agents to represent their decentralized nature, multiple loci of controls, or multiple competing interests (Jennings, 2000). Each building occupant can be simulated with an agent that mimics the occupant's behavior. Agents can be tuned to have shared or unique objectives. This makes agent-based models suited for modeling the differences among the occupants.

There had been several attempts to simulate occupants with agent-based systems. Yan and Kalay (2006) developed a multi-agent system to simulate the goals, social traits, perception and physical behavior of the users. In his model the environment is represented via geometric modeling and motion control. This model accounts for environmental qualities in a sense that when exploring the environment on their own volition, the agents that have a desire to sit choose a spot exposed to sun or covered by shadow according to their unique preferences. Yan and Kalay's model integrates a path-planning system with a behavioral system to simulate occupancy scenarios. The agents in their model are tuned to follow different unique scenarios. They follow an efficient path planning system that finds the shortest paths.

Other researchers developed models of occupancy scenarios that do not include path-planning or navigation systems. Simeone and Kalay (2012) have provided an alternative definition for mandatory occupancy scenarios, which was named “human behaviors.” In their modelling approach, events are a representation of how one or more people interact with a built environment to reach objectives defined by their specific tasks and objectives (Simeone and Kalay, 2012, page 527). In a later study, they further developed the concept of events and defined it as a combination of three elements including the actors that populate a setting, the activity they do, and the space they use (Schaumann et al., 2015). Events in their studies are designed to collect information from the engagement of occupants with activities and the interactions among them. In their study, events follow a complex scheduling system. One event can include several other events (i.e. nested events) and events can be arranged sequentially, in parallel, or in a selective way (Schaumann et al., 2015).

Navigation in space is an important part of a model that simulates and evaluates occupancy scenarios. Two main approaches can be taken to create a navigation system. One approach is to create a path planning system. In this approach a path is extracted via various techniques. The concern of path planning is often to find the shortest paths. Examples of path planning systems include the travelling salesman problem in which the goal is to find the shortest path that passes through all of the given destinations. When exact solutions for path planning cannot be found or finding them is computationally expensive, solutions for problems such as traveling salesman, can be found through applying different types of heuristics (Applegate, 2006). When used for navigation on foot, path planning systems ignore the microscale mechanisms that are physically involved in the act of walking. The dynamic features of walking which are absent in path-planning include location, velocity, acceleration, orientation, and collision. The transition from shortest paths to fastest (Ganem, 1998) or most desirable (Helbing et al., 1997) paths should inevitably account for the dynamic features of walking. Models of pedestrian dynamics are the alternatives for path-planning which are based on physics of motion. Pedestrian dynamics includes different techniques to simulate the motion of people who walk on their feet based on rules of physics (Schadschneider et al., 2011).

The discipline of urban and architectural design had so far stayed away from pedestrian dynamics and when needed mainly relied on finding the shortest paths. However, the theoretical framework for modeling occupancy scenarios had been drawn before, but not implemented. Schadschneider et al. (2011) suggested strategic, tactical and operational levels of modeling pedestrian behaviors, in which pedestrian dynamics is actually the lowest level in the hierarchy (i.e. operational level). At operational level, which is the lowest level, performing activities will be determined in relation to geometric obstacles. At the tactical level activities will be scheduled, and activity areas and routes will be chosen in relation to network topology and timetables. At the strategic level activities will be chosen. Schadschneider et al. (2011) believe that processes at the strategic and tactical level are usually considered to be exogenous to pedestrian simulation and demand information from other disciplines. Design decisions and the occupancy scenarios, as described earlier in this study, are indeed the decisions that are made at strategic and tactical levels.

An occupancy model that uses pedestrian dynamics as described by Schadschneider et al. (2011) was never implemented. When describing a predictive model of walking behavior using space syntax theory, Batty (1997) acknowledged the difficulty of developing a model of pedestrian dynamics that incorporates environmental conditions. Helbing et al. (1997) also hoped for a model of pedestrian dynamics that work on space syntax. A model of pedestrian dynamics that incorporates environmental qualities, simulates and evaluates the occupancy scenario can fill the gap which was addressed by these works and integrate the disciplines of pedestrian dynamics and design.

1.3 Research Problem

One of the main concerns of designers with a post-positivist stance is to enhance desirability of occupancy scenarios at the design phase. The design concerns obviously can include many other concerns such as structural integrity, weather and climate amelioration, thermal comfort, regulatory compliance (Rush, 1986). The scope of this study is limited to occupants' experiences only. Within this scope and with respect to the mobility of the occupants in space, occupants experience different desirability levels in relation to the environmental qualities that they experience and the activities that they become engaged with.

In a post-positivist stance the evaluation criteria for each environmental variable or activity that the occupants become engaged with is the outcome of a research. During a research process, researchers use different strategies to isolate dependent and independent factors from the rest of the world to investigate the existence of possible relationships between them. During design, however, such isolation can never exist. Indeed the whole purpose of design is to combine and integrate all of the factors together in the form of a design proposal (Wang and Groat, 2013). When evaluation criteria are developed in isolation, how could they inform designers about the overall desirability from an occupant's perspective? Without an objective and verifiable model for integrating different dimensions of evaluation, designers have to rely on their subjective interpretations, which is not necessarily always correct. The research question in the next section investigates the possibility of creating this integrated model which was also recognized as the gap in the literature in previous section.

1.4 Research Question

This research is organized around the following question:

Can a model be created so that researchers can explore informative evaluation of building designs from the standpoint of occupancy scenarios?

Developing this model has many requirements that should be fulfilled. In this section the requirements for a model that addressees the research question will be discussed. Since the research question requires the existence of a model, these requirements will be classified in relation to the input, the process and the output of the model. In the next section a semantic network will be proposed that maps the accumulated requirements to techniques or strategies that fulfill them.

1.4.1 Model Input Requirements

The input requirements of the model include a series of variables and a Knowledge Base

(KB) that includes the criteria for evaluation. Some variable are associable to space and some other variables are associable to the activities that the occupancy scenario includes.

Variables

Environmental Variables

One of the main features of building occupants is their mobility in space. Figure 1-1 shows an occupant in a walking trip. This trip is similar to many of the trips that we take on daily basis. Figure 1-1 also shows a variable that is distributed over the walkable space. This variable can be temperature, daylight intensity, smell or whatever that an occupant can feel in space, can sense, and possibly may inspire a reaction. If different levels of desirability (i.e. comfort, pleasantness or satisfaction) can be defined in relation to this color-coded variable, then this trip provides a unique pattern of changes in desirability which, accordingly, provides a unique experience. Because these types of variables are bound to space, they will be called *environmental variables*.

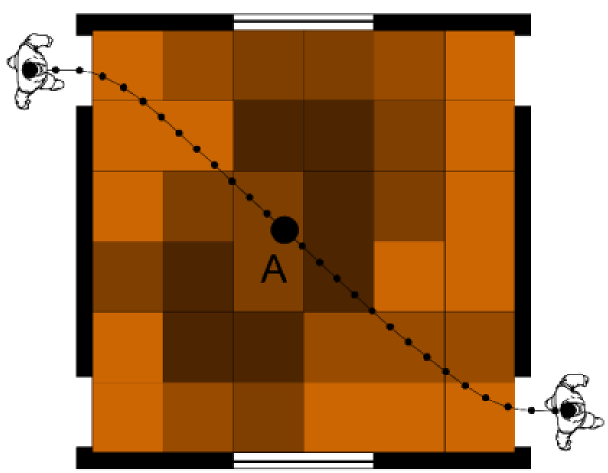

Figure 1-1: The trip shown in this figure will expose the traveler to a unique variation in the color-coded quality.

The experience of environmental variables is based not only on location, but also on the time span of experience. In Figure 1-1 let's assume that the occupant stops at point A and stays still for 2 seconds. In that case this occupant is constantly experiencing the same variable with no changes in it. Accordingly, the desirability level remains constant. This shows that for the evaluation of the environmental variables the knowledge of occupants' locations and the time that they spend in those locations are all important.

Sometimes it is not only the direct physical contact to the environmental variables that matters. Several studies have highlighted the significance of visual contact as well. For example, a study shows that after surgery, patients with a view of nature took fewer pain relievers and recovered faster than those with a view of a brick wall (Ulrich, 1984). Let's assume that having a view to a window affects the occupants' satisfaction because of the visual qualities that it offers. The influence of the view quality from each window depends on the existence of a line of sight within the occupant's cone of vision to the window. Figure 1-2-1 and Figure 1-2-2 show an occupant taking the same trip shown at Figure 1-1, but at two opposite directions. It is obvious that the direction shown in Figure 1-2-1 offers a better chance of looking at window 2, whereas in the opposite direction (see Figure 1-2-2) window 1 has a higher chance of being seen. In that case the input to the evaluation system also needs to include the view direction of the occupant.

Table 1-1: Evaluation input requirements of environmental variables.

1. *The environmental qualities that an occupant experiences in different locations*
2. *The location of an occupant in space*

Table 1-1 Continued

3. *The time that an occupant spends in different locations*
4. *The occupant's viewshed and direction*

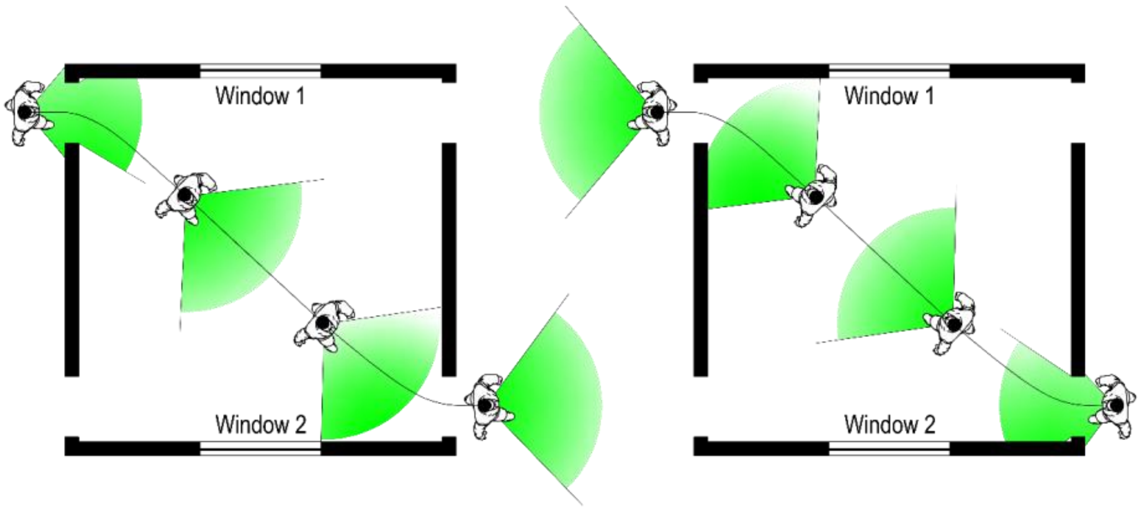

Figure 1-2-1 Figure 1-2-2

Figure 1-2: While some variables, such as view to a specific window, are bound to space, to evaluate their effects on an occupant, the occupant's direction is needed in addition to his or her location.

Activities

Occupancy scenario also includes activities which are not necessarily bound to space. For instance, walking is itself an activity and exhaustion from walking after a long walk is independent from the desirability of other environmental qualities. In optional occupancy scenarios an occupant will stop when he is exhausted from walking and will probably avoid taking long trails that ask for a continuous walking activity. In mandatory scenario, due to the significance of the activities, the chance for giving up walking from exhaustion is less. Therefore, in addition to the activities, the type of scenarios that include the activities is also important.

Unlike walking, some other activities are bound to space and have a time period of engagement. For example, buying milk is bound to the specific locations in grocery stores and takes a certain amount of time. Engagement in these activities also can be de desirable or undesirable. Delivering critical care to a patient is probably not very desirable for a nurse. Table 1-2 extends Table 1-1 to include the evaluation input requirements for this new class of variables.

Table 1-2: Evaluation input requirements of activities.

5. *The activities with which an occupant becomes engaged*
6. *The duration of an occupant's engagement with an activity*
7. *The type of occupancy scenario*
8. *The occupant's cognitive understanding of space*

Knowledge of Desirability

Knowledge of Desirability (KD) is the Knowledge Base (KB) defined in relation to the input variables and provides the evaluation criteria for both environmental variable and activities. If an environmental variable is quantifiable then the related KD can also be understood numerically. For example, a numeric range can describe whether fitness is achieved or not. The fitness of desirability can depend on multiple variables. For example, light levels can be numerically measured by illuminance which is the amount of light falling on a surface. However, the desirability from light level for an occupant also depends on the activities that he or she is engaged with. While 50 lux is acceptable for parking and walking on sidewalks, the intensity light level needed for reading and drawing is 500 lux (Williams, 1999). Whether desirability is defined in relation to multiple variables or a single one, at least when it is quantifiable, the KD is explicit and can be understood numerically. This example indicates that sometimes a series of variables need to be clustered and integrated to evaluate desirability.

Some environmental variables resist quantification and so does the expression of the knowledge of their desirability. For example, a general and agreed-upon definition for beauty does not exist. The study of such concepts is usually narrowed down to some specific features that can be defined and measured objectively. In case of beauty, for example, Berlyne (1963) and Salingaros (2006) refer to organized complexity and Ulrich (1984) discusses the restorative views. The attempt to push the boundaries of clearly defined factors into qualitative factors never comes to its end. Accordingly, there is always a need for non-explicit knowledge for evaluation of qualities.

The occupants' personal preferences will also affect desirability. For example, according to American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) while thermal comfort depends on air temperature, metabolic rate, clothing insulation, radiant temperature, air velocity, and relative humidity, this type of comfort is also subjective (ANSI/ASHRAE, 2013). Table 1-3 extends the evaluation requirements of this section.

Table 1-3. Desirability of a space.

9. *The desirability criteria of environmental variables*
10. *The desirability criteria of engagement with activities*

Table 1-3 Continued

11. The subjective judgment of individual occupants

12. The variable clusters that together determine one dimension of desirability

1.4.2 Process

When the input variables of the evaluation model are determined, the evaluation is comparing the variables against their related KD to measure the fitness. Measurement of the overall desirability without a criterion that puts all of the desirability of all of the variables together is a challenge for the output of the model. Table 1-4 updates the evaluation requirements.

Table 1-4. Fitness measurement.

13. The determination of the value of the desirability input variables

1.4.3 Model Output Requirements

While environmental variables are bound to space, some activities are mainly bound to time and can be completely dissociable from space. The two sides of evaluation pose a challenge to its representation because insightful evaluation needs to report when desirable or undesirable experiences occur in time domain and where they occur on space domain. For example, a 2D map can only represent environmental variables and their corresponding evaluation in space domain. Using a map is not the most effective way to represent an occupant's engagements with different activities and the time frequency of the desirability that is associated to them. A time series model probably serves the latter more efficiently, but fails to have any spatial indication. Another challenge that is latent in evaluation is the existence of several dimensions for evaluation, whether for activities or environmental variables. A comprehensive knowledge of desirability that accounts for all of environmental variables and activities does not exist for determining the overall desirability of an occupant for a given space and time location. These challenges are added to the list of evaluation requirements in Table 1-5.

Table 1-5. Evaluation output.

14. The representation of desirability in relation to environmental variables

15. The representation of desirability in relation to engaged activities

16. The integration of multiple dimensions of evaluation results

The requirements of the research question are distributed in different tables of this section. The next section will try to see if there are existing conceptual models that fulfill these requirements.

1.5 Research Strategy

This research adopts a model-based strategy. With this approach the main focus of this study will be to develop an explanatory model (Wang and Groat, 2013). The model that is proposed for evaluation of occupancy scenarios is computational and uses an object-oriented programming paradigm. Model-based reasoning is a research methodology commonly used in AI which is based on the interaction between human and computers. Computational scientific discoveries include a heuristic search through the space of hypotheses to find well-fitting hypotheses and a heuristic search through the space of sets of hypotheses to find coherent models (Phillips et al., 2002). Such computational models take advantage of the power of both computers and humans. They are based on heuristics of human, which computers lack, and speed, accuracy and the ability to manipulate rote facts of the computers. Hypotheses are the building blocks of a computational model, which integrates a collection of hypotheses into a coherent and plausible model (Phillips et al., 2002). The developed model then will be used for generation and testing of hypotheses, prediction and inference (Magnani et al., 1999).

This section investigates the plausibility of the existence of a coherent model. The implementation of the model as the main body of this research will be discussed in the next parts of this study. For the moment, the main question is if the building blocks of the computational model for the evaluation of the occupancy scenarios exist. To answer this question a semantic network will be used which is formed out of the decomposition of the research question into smaller requirements and look into the related literature to find relevant models or hypotheses for them. For this purpose all of the evaluation requirements from the previous section are collected in Table 1-6. These requirements are reordered and grouped into different categories to identify different conceptualized components of the model. Table 1-6 also shows the building blocks of the computational models that are proposed for each group of evaluation requirements.

Table 1-6. A semantic network that maps the conceptualized components of evaluation model to the modelling requirements.

MODEL	Requirements of an Evaluation Model	Conceptualized Components
INPUT	The environmental qualities that an occupant experiences in different locations	**Concept of Environmental Model**

Table 1-6 Continued

MODEL	Requirements of an Evaluation Model	Conceptualized Components
INPUT	The variable clusters that together determine one dimension of desirability	
	The desirability criteria of environmental variables	**Concept of Evaluation Criteria**
	The desirability criteria of engagement with activities	
	The type of occupancy scenario	**Concept of Occupancy Scenario**
	The activities with which an occupant becomes engaged	
	The duration of an occupant's engagement with an activity	
	The subjective judgment of individual occupants	
	The occupant's cognitive understanding of space	
	The location of an occupant in space	**Concept of Pedestrian Dynamics**
	The time that an occupant spends in different locations	
	The occupant's viewshed and direction	
PROCESS	The determination of the value of the desirability input variables	**Concept of Measurement of Desirability**
OUTPUT	The representation of desirability in relation to environmental variables	**Concept of Occupancy Events**
	The representation of desirability in relation to engaged activities	
	The integration of multiple dimensions of evaluation results	

1.5.1 Environmental Model

I will limit the scope of environmental qualities to those that can be numerically explained. Some qualities can be objectively measured or subjectively translated to numeric scales. The process of transforming qualitative measures to numeric measures does not fit the scope of this study. The qualities that can be numerically explained are referred by "spatial data." Section 6.4 of the appendix included detailed discussions about designing the data structures for spatial data.

For occupancy scenario a model of the built environment is needed that can include multiple layers of spatial data. The entire area in which an occupant can walk are referred by "walkable field." The boundaries of the walkable field are edges that a building occupant cannot cross such as edges of physical barriers or voids in the floor. Since requirement 4 from previous section also asks for knowledge of an occupant's viewshed, this environmental model should include information about the visual barriers too. A cellular data grid has been used for storing different layers of spatial data in its cells. The model environment also uses polygons for representing walkable fields, visual barriers and physical barriers. The environmental model is capable of interpolating spatial data and exchanging data with external applications such as Microsoft Excel. Data interoperability allows for merging a cluster of spatial data into one variable in an external application before importing them into the environmental model.

To create an environment for study, a Building Information Model is used. BIM is an object-based data scheme and each of its object classes represents one type of building components and its behaviors (Lee et al., 2006). BIM has evolved from Computer Aided Design (CAD) system which is a drafting technology and consists of vectors, associated linetypes, and layer identifications. The advent of 3D modeling turned the focus from drawings and 3D images to the data itself and BIM emerged (Eastman, 2008). While the occupant scenario evaluation environment does not demand using all of the capabilities that BIM offers, BIM semantics makes it much easier for conducting queries that lead to automatic extraction of a walkable field as well as physical and visual barriers. Section 6.2 of the appendix provides more detailed information about BIM adoption in this study.

1.5.2 Evaluation Criteria

For each layer of spatial data a criterion is needed for predicting its respective desirability. The model uses solid research evidence to predict desirability. The use of solid research evidence fits the post-positivist research stance of this study. Since in this computational evaluation model each layer of spatial data is coupled with an evaluation criterion, an object-oriented data structure for spatial data has been employed to allow for storing spatial data with a mathematical function for its evaluation. For example, Figure 1-3-1 shows the spatial distribution of daylight intensity over the walkable field. Experimental studies have provided evidence implying that light intensity between 500 and 1000 lux is appropriate for performance of visual tasks that need medium contrast (Williams, 1999). Figure 1-3-2 shows the desirability associated to the light intensity distribution according to this evidence. Indeed, daylight intensity is only an example of the environmental quality and coupling a desirability function to data will work with any type of spatial data such as distance from physical barriers and temperature.

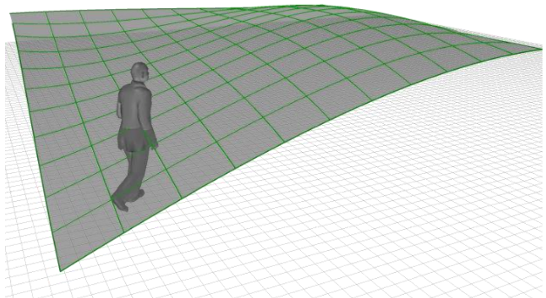

Figure 1-3-1: Spatial distribution of light intensity

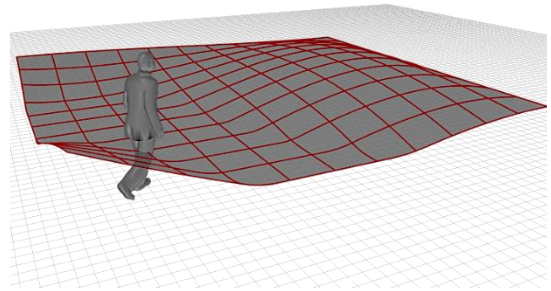

Figure 1-3-2: The desirability associated to the light intensity.

Figure 1-3. Spatial data can be coupled with a function to measure its desirability.

1.5.3 Occupancy Scenario

Occupancy scenario is an agenda for engagement with activities for each individual. The agenda can dynamically change in optional scenarios according to the preferences of the occupant or can be fixed in mandatory scenarios. There is a continuous range of scenarios between optional and mandatory occupancy scenarios from the combination of these types. In each of these scenarios the level of cognitive knowledge of the environment can also vary from minimum to complete awareness. Moreover, when occupants are not familiar with their environment, in the course of time their level of awareness of the environment will increase as they gradually learn about it. A continuous range between mandatory and optional occupancy scenarios, different levels of awareness from the environment, and the process of acquiring environmental awareness, together create numerous possibilities for occupancy scenarios and their modeling. Out of these possibilities, computational evaluation models for mandatory and optional occupancy scenarios have been devised. This study will exclude the scenarios in which occupants become engaged with resultant activities (Gehl, 1987) from its scope.

In mandatory scenario it has been assumed that the occupants are completely familiar with the environment and the qualities that it offers. The proposed computational model for mandatory scenario will account for the engagement of the occupants with several types of activities. As a case study the scenario of nursing will be modeled for mandatory scenarios. For optional occupancy scenarios, on the other hand, it has been assumed that the occupants have no cognitive knowledge of the environment and the decisions that they make are based on the desirability of the qualities that they perceive in their immediate surroundings. Within the scope of this study the occupants will only become engaged with the walking activity during occupancy scenario. The scenario of walking in a shopping mall has been used as a case study for modeling optional occupancy scenarios. These choices will narrow down the scope of this study and leave alternative types of scenarios to be modeled in future studies.

An agent-based model has been used for modeling desirability of environment from an occupant's perspective during the occupancy scenario. Because of adopting an agent-based approach, in the rest of this study the terms occupant and agent will be used interchangeably. While proposing to use an agent-based system, the interactions between agents have been excluded from the scope of this study. The occupancy scenario will be encoded in agents (i.e. occupants) and they will respond to environmental qualities. The agents include evaluation functions, which might be unique for each agent. The environment and the occupancy scenario context are the input to an agent, which is then an input to the simulation. The walking trail and desirability are the output of the simulation system.

1.5.4 Pedestrian Dynamics

Pedestrian dynamics is a well-developed field within physics, computer science and traffic engineering for modeling how an individual (either human or robotic) walks through a space. It provides a set of theories and techniques for deriving the behavior of people under occupancy scenarios. Models in pedestrian dynamics are mainly developed for simulating evacuation. Schadschneider et al. (2011) classified the available pedestrian dynamic models in three categories: fluid-dynamic and gas kinetic models, cellular automata, and social-force models. The main characteristics of these models are to explain pedestrian dynamics in models that are microscopic vs. macroscopic, discrete vs. continuous, deterministic vs. stochastic, rule-based vs. force-based, and high vs. low fidelity. Fluid-dynamic and gas kinetic models are based on similarities between crowd motion and the behavior of particles in liquids and gas (Schadschneider et al., 2011). These models are macroscopic and of low fidelity which makes them not suited for our modeling purpose. Models that are based on cellular automata are also discrete both in time and space meaning that the location of the agents should fit within an underlying cellular structure in fixed time-steps. Since the accuracy of an agent's physical location is critical to the proposed model, using a cellular automaton will not be an appropriate choice as well.

From the three different classes of models for pedestrian dynamics, social-force models fit the requirements of the proposed evaluation model. In this model a field of forces will control the behavioral changes of agents. The forces are calculated based on several different personal and environmental factors. According to Helbing and Molnár (1995) the behavioral changes of agents are formed in a process that starts with environmental or personal stimuli. The perception of the environment and the personal goals will then be mentally and psychologically processed to create motivations to act upon. Finally, a physical action is taken based on the motivations. While in most of the works that employed social force models, the forces are generated for collision avoidance and approaching a destination, this three level process promises much more than that and perfectly fits the requirements of evaluation as described earlier in this chapter. According to Helbing and Molnár the invention of social force model dates back to the beginning of 1950s when Lewin (1951) claimed that behavioral changes are guided by social fields. Whether forces are pre-calculated in a field or are dynamically updated, generalized force models appeared to be successful for modeling the interactions between pedestrians (Helbing et al., 2002), simulating the dynamic features of escape panic (Helbing et al., 2000) or even evolving human walking trails where there is no agent-to-agent interaction (Helbing et al., 1997).

Both fluid-dynamic and cellular automata models focus on the behavior of an agent in a crowd which is not necessarily within the scope of this study. Force models, on the other hand, are deterministic, continuous and of high fidelity. Therefore, it is desirable to adopt a social force model approach to determine the location, direction and velocity of the agents (i.e. occupants) which are required for creating the evaluation model. Applying forces has also shown to be a successful strategy to avoid colliding with moving obstacles as well (Rodriguez et al., 2007). The main concern in crowd simulation is not merely modeling the movement of people in a way that they do not collide with each other as well as with barriers. Applying more forces and using roadmaps look like a promising strategy to capture the real features of the walking scenarios. For example, previous research has shown that forces can be used to hold a group of people together while navigating an environment (Bayazit et al., 2004, Bayazit et al., 2002).

1.5.5 Measurement of Desirability

When a layer of spatial data is available and its corresponding evaluation criterion is translated into a mathematical function, the desirability of the spatial data from an occupant's perspective is computable if the occupant's location is known.

1.5.6 Occupancy Events

The purpose of the evaluation model is to create insightful evaluation results. The challenges for creating insightful results are that the results of evaluation belong to the separate domains of time and space and several variables are involved in each domain. This study proposes creating private databases in each agent and collecting information as they perform their occupancy scenarios. The information that the agents collect include time, location, direction, velocity, and their evaluations from the environmental variables which they experienced and the activities that they became engaged with. Designers who use this model can conduct queries into the agents' databases and capture the information in which they are interested. Programmatically, the information that the designers are interested in will create an event that will be captured during the simulation. For example, a designer can create an event for passing though the heat of sun and conduct a query to figure out when an agent will have to pass through the heat of sun, how often it occurs and how likely it is in general to occur. Events are well known for their application in all of the computer programming languages. By associating changes to events, programmers can trigger other actions (MSDN, 2016). Knowing where, when and how likely is an event to occur provides insight for designers at the design phase. The events that are proposed can search into multiple fields of information in an agent's database and create an integrated transcript of evaluation.

1.6 Hypotheses

Based on the research questions, strategies and the determined scopes of this study the following two hypotheses have been used to structure this investigation:

1- Simulation software can model and evaluate mandatory occupancy scenarios.

2- Simulation software can model and evaluate optional occupancy scenarios.

1.7 Research Validation and Reliability

1.7.1 Model Reliability

The main question that concerns the validation of this study is to prove an agent that can mimic the behavior of a building occupant. A study of the evolution of walking trails supports that pedestrians generally take into account detours and the comfort of walking to minimize the cost and effort to reach their destination (Helbing et al., 1997). Therefore, the walking trail of one individual represents how he or she has balanced the efforts to reach a destination. This study proposes creating a force-based model of pedestrian dynamics in which the desirability of activities and environmental variables are parametrized. In the proposed model, agents take paths that offer maximum desirability. With the variations of the parameters the agents make different choices and accordingly different walking trails will emerge. Within this setting the question of validation and reliability is whether we can find a setting for the parameters that reproduce the trail of a human occupant of a real building. This study proposes using a meta-heuristic algorithm (i.e. simulated annealing) for fine-tuning the parameters in a way that the artificial agents reproduce the walking trail of building occupants. Obviously the extent to which the model is valid depends on the reliability of meta-heuristic algorithm and the documentation of trails of human occupants. In other words, it can never be claimed that the artificial agents perfectly mimics the behavior of a real occupant, although extending the number of annealing iterations always improves the results.

1.7.2 Statistical Validity of Evaluation Results

After the fine-tuning process the agents can be released in the virtual environment to perform the occupancy scenario and collect information. The mandatory and optional occupancy scenarios will be designed based on the existing literature. A complex scenario, like that of a nurse, includes several random factors and various repeating pattern of activities. The result of data query from agents will therefore be influenced from randomness, repeating patterns of activities and the initial location of the agent. How can valid and stable statistical results be obtained from a model that essentially contains randomness? The strategy for obtaining statistical significance is based on setting the simulation run-time. This study proposes setting the running time for the simulation in a way that the probability of an event's occurrence statistically converges.

1.8 Research Outline

Chapter 2 of this study included a comprehensive review of the literature for mandatory and optional occupancy scenarios. The modeling strategies and the scope of the research will be determined in this chapter. Chapter 3 will show how a mandatory occupancy scenario can be simulated, how the simulation can be validated and visualized, and finally how its results can be used for making insightful and accurate evaluations. The same process will be included in Chapter 4 for optional occupancy scenarios. The scenario of nursing will be used as a test-case for mandatory scenario and the scenario of walking in a shopping mall will be used as a test-case for the optional scenarios. As described before, in the mandatory scenario it would be assumed that the agents are fully familiar with the environment and in the optional scenario it would be assumed that the agents have absolutely no previous knowledge from the environment. This study will be concluded in Chapter 5 where the research contributions will be summarized and checked against the objectives that have been set for this research. The focus of this study is to highlight the contributions of the models which will be developed in design phase and management of existing facilities. While the software development proves the feasibility of the ideas, the details of implementation will not fit within the scope of this study. This study includes an appendix which discusses the main strategic ideas behind the implementation, including BIM adoption, interoperability, class level diagrams of the major data structures, and calculation of the field of visibility.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

The purpose of this section is to understand the occupancy scenarios in a way that micro-scale simulation models can be created for them. In previous chapter it was discussed that a simulation model which leads to insightful evaluation should integrate models of built environment, evaluation criteria, occupancy scenario, and pedestrian dynamics. This chapter takes a closer look at each of these elements in the existing body of the literature. By the end of this chapter a set of objectives will be identified for the optional and mandatory simulation models to achieve. The confirmation of achieving these objectives will be set as the goal of the next two chapters in which the simulation models will be developed.

From Gehl's (1987) definition we know that undesirable environmental conditions will not stop the occupants from walking to address necessary tasks in mandatory occupancy scenarios. Nonetheless, in optional occupancy scenarios where walking is for the sake of pleasure, people simply prefer not to walk when environmental conditions are not desirable. Apart from this general idea for classification, Gehl (1987) did not suggest a descriptive model for occupancy scenarios. A number of studies attempted to present a descriptive model for mandatory occupancy scenarios. In this section, these works will be reviewed to create a model for scenarios. Interestingly, these works have mainly focused on understanding nursing scenario at healthcare facilities. The descriptive models for optional scenarios, on the other hand, are rare compared to mandatory scenarios. Since the scope of mandatory occupancy scenarios is limited to nursing in healthcare facilities, in Section 2 the background of modeling and simulation in healthcare facilities will be reviewed. In Section 3 of this chapter the background of the optional occupancy scenarios will be reviewed. Section 4 discusses the background of the navigation models in the literature of pedestrian dynamics. Finally, in Section 5 the gaps in the literature will be summarized and the simulation objectives will be set.

2.2 Simulation of Occupancy Scenarios in Healthcare Facilities

An analysis of the academic literature on simulation and modelling in health care identified simulations as the prominent method which is used in planning and resource utilization (Brailsford et al., 2009). The rich background of simulation techniques in healthcare literature can be found in the literature review by Mustafee et al. (2010). The scope of these simulation applications varies from very large scale suited for policy makers to the small scale of propagation of contagious diseases. They classified the existing simulation models to four categories based on their modeling techniques which include Monte Carlo, Discrete Event Simulations (DESs), system dynamics, and Agent-based Models (ABMs). Monte Carlo methods are based on repeatedly taking random samples to achieve numerical results (Doucet et al., 2001). Discrete event simulation (DES) technique is used to model the operation process of a system using a discrete sequence of events (Robinson, 2004). System dynamics is a simulation process that tries to understand the complex systems based on the interactions of its components with each other. The status of the components will be updated and visualized in small time steps (Sterman, 2001). ABMs use encapsulated software entities that are situated in some environment and are capable of taking flexible and autonomous actions to meet their individual objectives (Jennings, 2000, Bonabeau, 2002). Since this study is concerned with simulation of occupancy scenarios the application of Monte Carlo simulation and systems dynamics will be ruled out. A closer look at ABM and DES will, however, be necessary.

2.2.1 Discrete Event Simulations (DES)

Robinson (2004) classified the simulations that model the process of time into three categories: time-slicing and Discrete Event Simulation (DES), and continuous time. In the time-slicing approach the state of the operation of a system is updated after fixed time-steps. Time-slicing approach is inefficient because the state of the system will not necessarily change in every time-step. Also, the changes cannot always be counted in whole numbers of the fixed time-step. “In discrete event simulations only the points in the time at which the state of the system changes are presented. In other words the system is modelled as a series of events, that is, instants in time when a state change occurs” (Robinson, 2004, Page 15). In continuous simulations the state of the system changes continuously through time. Examples include movement of fluids or fast moving objects. Computers cannot simulate continuous changes, therefore, discrete small time-steps will approximate continuous changes (Robinson, 2004, page 25).

A simple citation analysis reveals a huge number of published works that employed DES models in healthcare systems. Therefore, the best approach to understand the applications of DES in healthcare is to identify the contexts of its applications. There are also numerous open source and commercial software and programming libraries for DES some of which, such as MedModel (ProModel Corporation, 2015), are uniquely adapted to applications in healthcare facilities. A review of the applications of DES in healthcare systems shows that DES was generally used as a forecasting tool to assess the potential impact of changes on patient flow, to examine asset allocation needs, and to investigate the complex relationships among different system variables (such as the rate of patient arrivals or the rate of patient service delivery) (Jacobson et al., 2006).

2.2.2 Agent-Based Model (ABM)

In a generally agreed upon definition an agent is characterized as "an encapsulated computer system that is situated in some environment and is capable of taking flexible, autonomous action in that environment in order to meet its design objectives" (Jennings, 2000, page 280). According to this definition, agents are problem solving entities with well-defined boundaries, embedded in a particular environment, fulfill a specific purpose, autonomous, and exhibit flexible behaviors in pursuit of their objectives (Jennings, 2000). In a description of agent-based software engineering, agents are also recognized for reactivity, proactiveness, and social ability (Wooldridge, 1997). Agents are able to perceive their environment and respond to the changes in a timely fashion. They do not simply act in response to the changes, but also can take the initiative to make changes. Finally, agents are capable of interacting with each other (Wooldridge, 1997).

Mustafee et al. (2010) classified the simulation techniques used in healthcare based on their contexts of applications. Their systematic review did not include any application of simulation techniques for modeling the occupancy scenarios. Their review only reported two applications of ABMs none of which were related to the simulation of occupancy scenarios. This proves the novelty of ABMs at the time of the review. In a more recent review of using ABMs in hospitals Friesen and McLeod (2014) also identified that the applications of ABMs was still relatively new. They suggest ABMs as a viable alternative for traditional analysis. According to Friesen and McLeod when designing an ABM for hospital applications, the choices of system attributes should be made in relation to the context and the objectives of the model which include computational efficiency, representation of the environment and its visualization, selection of the agents, charachterestics or profiles of the agents, rules that govern the interactions among agents, interventions and validations. Their review of the the literature shows that the applications of ABMs in hospitals have generally focused on patient safety, economic indicators, staff workload and scheduling, and patient flows. They have also identified a number of studies that applied ABMs for simulating nosocomial infections.

2.2.3 ABM vs. DES

While applications of ABM is rapidly growing across many different deciplines, the community of Operational Research (OR) is mainly using DES models because of wide availability and experience of OR community with DES software (Siebers et al., 2010). On ther other hand, developing an ABM demands a considerably long time to develop one's own code according to the nature of a given problem (Friesen and McLeod, 2014). A list of features that makes a problem a good candidate for the application of ABM was suggested in a panel discussion at UK Operational Research Society’s Simulation Workshop (Siebers et al., 2010). This list suggests that ABM should be employed when structural change in a process needs to be a result of the model, rather than an input to the model. The list also suggests the application of ABM for problems which naturally represent agents, interactions among agents, spatial aspects for agents, learning, and adaptation. The attributes that define the differences between DES and ABM include being process oriented (top-down) vs. individual based (buttom-up), using passive enteties vs. active enteties, and operating at macro-scale vs. micro-scale (Siebers et al., 2010).

Although the applications of ABMs in hospital design is growing, the existing models serve a variety of different purposes which understandably do not require navigation in space. A closer look at the works which were reviewed by Friesen and McLeod (2014) shows that only three of them have integrated path-plannning mechanisms, which in all of the cases are primitive (Ruohonen et al., 2006, Ong et al., 2008, Laskowski et al., 2011). Additionally, nearly all of the models do not deal with the fine building details. Many of the models have remained at the level of a theoretical discussion and have not been implimented or their state of implimentation is not clear (Friesen and McLeod, 2014). Only, a handfful number of simulation models were integrated with building models. These models, which will be reviewed next, have also remained at a prototype level or are reported as works in-progress.

2.2.4 Applications of ABM and DES in Modeling Occupancy Scenarios

According to Ekholm and Fridqvist (1996) understanding the organization of user activities is an indispensable part of building design process and the user activities should be understood at different levels systematically. Ekholm (2001) highlighted the significance of developing CAD-based software for modeling the organization of user activities and developed a prototype for such models in ArchiCAD. Ekholm (2001) made a list of suggestions for further development of the prototype which includes, but is not limited to the illustration and accommodation of user activities in a building.

In an attempt to develop a model for activity workflow, Simeone, Schaumann and their colleagues conceptualized using DES in several published papers (Schaumann et al., 2015, Simeone and Kalay, 2012, Simeone et al., 2013b, Simeone et al., 2014). They have not described the level of implementation of their suggested model and in all of their publications reported the state of implementation as a work-in-progress. Several of their publications indicates that the so far implemented model is not integrated and uses Autodesk Revit as a Building Information Model (BIM), Unity or other gaming engines for 3D visualization, and some scripts developed in C# programming language.

In the model suggested by Simeone, Schaumann and their colleagues activities provide a set of actions and procedures that direct agents toward the accomplishment of individual or group tasks. In their models an event is a combination of three elements including the actors that populate a setting, the activity they do, and the space they use. Events also include pre-conditions, a set of performing procedures, and post-conditions. Pre-conditions specify the requirements for an event to be triggered. If the preconditions are satisfied a set of performing procedures guides the execution of an event's activity component. Post-conditions include updating the states of the model components after the execution of the event (Schaumann et al., 2015, Simeone et al., 2013b). One event can include several other events (i.e. nested events) and events can be arranged sequentially, in parallel, or in a selective way. Each event can also be triggered stochastically (Schaumann et al., 2015). Events in their studies are designed to collect information from the engagement of occupants with activities and the interactions among them. A picture of using this information for evaluation was drawn in a later study as a work in-progress (Schaumann et al., 2016)

A number of studies have highlighted the importance of "activity sequences" to understand the workflow of nurses in hospitals (Cornell et al., 2010, Nanda et al., 2015). Nursing scenario includes multiple different activities that should be taken in a sequence. For example picking up medicine from medicine rooms, delivering medicine to a patient, and documenting the delivered care form an "activity sequence". Compared to this simple approach, the DES model which was suggested by Simeone, Schaumann and their colleagues represents a more realistic structure for modeling and simulating because it creates a more complete narrative of the use processes in buildings (Schaumann et al., 2015, Simeone et al., 2013b, Simeone et al., 2014).

2.2.5 Summary

Most of the models that either employed ABMs or DESs are concerned with the interactions between the people who are involved in different processes in hospitals. DES techniques are suitable for creating an integrated model of activities that include the involvement of different people and resources as a collection of events. While the activity agenda can be considered as an isolated input to the simulation, the performance of the activities includes spatial navigation and interactions with environment and other occupants. A DES by definition cannot account for details of navigation and interactions of agents because these features require continuity of time. An ABM, on the other hand, can account for both changes in time and the differences among the people. Therefore, several existing models combine both DES and ABM (Friesen and McLeod, 2014). In this study the strategic goal of modeling will also be to develop a hybrid combination of DES and ABM.

A simulation in which the ABM is merely for the performance of a program that is modeled by a DES includes the lowest possible level of integration between the DES and ABM and lacks some degree of realism. For example, existing evidence indicates that in an Intensive Care Unit (ICU) the visible patients receive better care and will be visited with more frequently (Cai and Zimring, 2012). In an ideal model of nursing scenario visibility bridges the gap of isolation between ABM and DES by allowing choosing and prioritizing tasks on the fly. In fact this idea was acknowledged before but was not suggested because of its high computational cost (Schaumann et al., 2015). In the model which will be envisioned for implementation, agents will be equipped with a visibility mechanism that allows them to detect changes in their cone of vision.

The state of the art of the literature also shows spatial navigation in simulations of occupancy scenarios of hospitals are either primitive or completely absent. When navigation exists it is limited to a simple static path planning algorithm. While the need to use elaborated building models have been introduced in some studies, an occupancy model that integrates with a building model does not exist yet. The literature also highlighted the significance of visualization and simulation performance when ABM is employed in a simulation.

2.3 Simulation of Optional Occupancy Scenarios

Unlike mandatory scenario, in optional scenarios there is no predefined activity agenda.

The occupants simply walk towards attractions that they notice in their surrounding environment. Compared to the large number of works that exist in relation to mandatory occupancy scenarios, studies on optional occupancy scenarios are rare. The related area to optional occupancy scenarios can generally be classified to research in walkability and space syntax. In this section a closer look at these two approaches will be taken to find modeling strategies.

2.3.1 Walkability

Scientific evidence indicates that walking as a physical activity will enhance both physical and mental health of the public (Pate et al., 1995). Only 30 minutes of walking per day has numerous significant health benefits (Ogilvie et al., 2007). The benefits of walking are not only limited to maintaining health, but also healing effects are attributable to walking. Physically active life-style decreases the risk for coronary heart disease, colorectal cancer, obesity, and osteoporosis (Sherwood, 2000). From the psychological view of point, walking decreases stress and depression level and increases emotional well-being, energy level, self-confidence, and satisfaction with social activity (Sherwood, 2000, Paluska, 2000). Walkable streets are viable means of treating depression and anxiety and improving mental well-being in the general public (Fox, 1999). The benefits of walking in streets cover a large spectrum of mental and physical health, social environment well-being, sustainability, and transportation. Now, it is important to ask "what makes an environment walking-friendly?"

To answer the question of "what makes an environment activity-friendly?" the dominant methodology is to find the environmental correlates of active-living in relation to different socio-economic classes of society. For example the study of Zhu et al. (2008) conducted a study to find the correlates of walkability to school for low-income Hispanic communities in Austin, Texas. *Active Living Research* (Robert Wood Johnson Foundation, 2016) website presents classified reviews of the related literature and environmental audit toolkits that have been developed and refined through numerous studies. In many of these studies, some environmental factors such as mixed land use pattern, often emerge as significant correlates of walkability (Lee and Moudon, 2006, Owen, 2004, Renalds et al., 2010).

As it was discussed in previous chapter the research in walkability is concerned with environmental correlates of active living environments and their impacts on different socio-economic classes of society. These studies are typically conducted at large scale and are not simulation-based. Developing a micro-scale simulation, which is the concern in this study, can help address the gap of knowledge in this field of research.

2.3.2 Space Syntax

Space syntax is a theoretical model for prediction of the pattern of use and include different software solutions such as Depthmap (Turner, 2001). The basis for calculation and prediction of use pattern are syntactic steps which can be in three different forms: isovists (i.e. visibility polygons), convex spaces, and axial maps. The theory suggests filling the void space of the environment with isovists, convex shapes or the minimum possible axial lines in a way that each point in the void space at least has a view to one axial line. A pair of isovists that have an overlapping area, two convex spaces that are directly accessible to each other, or two axial lines that intersect create local connections. When the local connections are added together a global structure emerges. The journey from local to global is the key idea in space syntax analysis. The resulted global structure can be modeled by a topological graph. In this graph different properties such as the degree of accessibility (i.e. integration) to the entire space can be measured numerically (Hillier and Hanson, 1984). Several case studies have shown that integration largely determines the pattern of both pedestrian and vehicular movement; therefore space syntax was claimed to reveal the secret of natural movement (Hillier et al., 1993). Since this model inherently does not consider an explicit model of the activities, it should be classified as a model for optional occupancy scenarios.

The applications of convex spaces and visibility axial maps are often limited to large scales in which the micro-scale analysis of the field of visibility (i.e. isovist) is computationally very expensive. Isovist is the key idea of visibility in space syntax and is defined as a set of all visible points from a vantage point in space with respect to an environment (Benedikt, 1979). Figure 2-1-1 shows an example of an isovist in a building. The idea of isovist did not become popular until the theory of space syntax was introduced (Hillier and Hanson, 1984). Figure 2-1-2 shows that the floor plan can be divided to a grid of vantage points. Each vantage point will be connected to the others that are visible from it. Figure 2-1-3 shows how the connections can populate the entire space to create the global structure of the visibility graph.

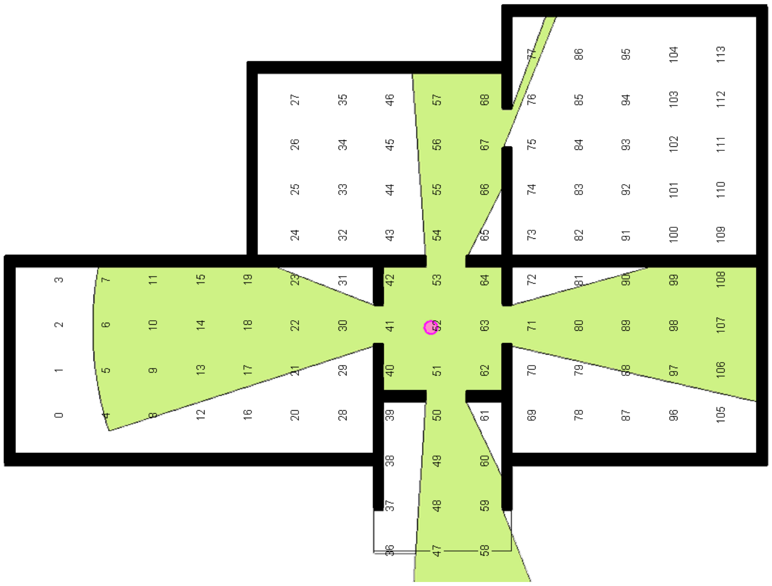

Figure 2-1-1: Isovist from a vantage point

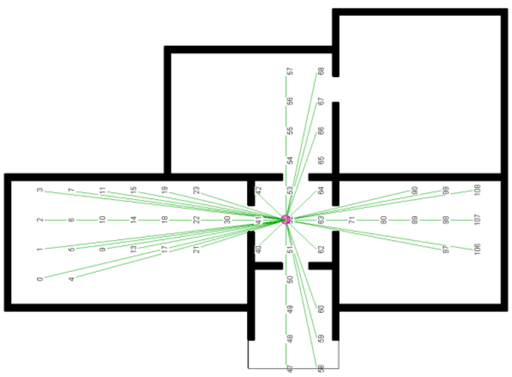

Figure 2-1-2: The local connections of a vantage point

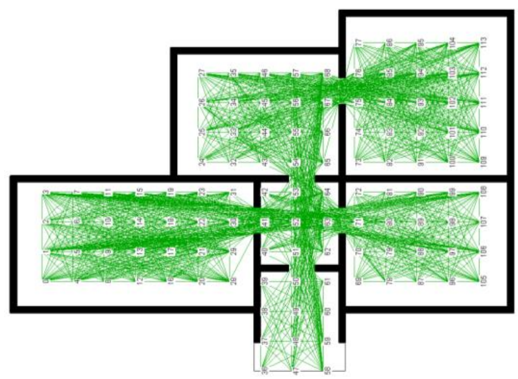

Figure 2-1-3: The global visibility graph

Figure 2-1: This figure illustrates how local connections create a global visibility graph.

Visual integration and connectivity are two of the most popular and commonly used space syntax indices. Connectivity is a local index that shows the number of local connections. If the global graph is a linked graph each two pairs of vantage points are accessible from each other. The shortest path from one vertex to each of the rest of the vertices can be measured and averaged to create the integration index of that vertex. Therefore, integration is considered as a global index. This is of course only one way for measurement of integration and Depthmap as the most popular space syntax software include other methods of measuring integration too (Turner, 2001). It is important to note that integration and connectivity are both based on visual accessibility in the visibility graph.

The methods for measuring integration and connectivity are also very similar in convex space and axial map analysis. Convex spaces are used to describe the transition of movement from one space to another when occupants move through buildings. The methods that are based on this syntactic measure create the accessibility graphs from partitioning the space to convex shapes and creating a graph in which the vertices represents a convex shape and the edges represent the direct physical accessibility between the partitioned spaces (Peponis et al., 1997). An axial map, on the other hand, is a method of creating a graph with fewest and longest lines of sight that cover the convex spaces (Hillier and Hanson, 1984). In its respective graph each node represents an axial line and each edge represents the intersection between two axial lines. A study shows that the axial map can explain the spatial cognition (Penn, 2003).

In museums and exhibitions, high visual integration increases the chance of interaction (Peponis et al., 2004). In large facilities, like airport terminals, design elements that are located in visually integrated areas effectively help people in way-finding (Braaksma and Cook, 1980). Hillier believes design is only possible with ideas to think with, which in the latest chapter of “Space is the Machine” (Hillier, 1996) he calls them preconceived ideas. The geometric properties of the isovist and the properties of the visibility graph create numerous spatial indices which space syntax advocates believe can explain non-discursive design ideas.

Path simplicity (vs. angularity) is another important concept in space syntax analysis. Pedestrian path choice is the main focus of many different disciplines including architecture, pedestrian dynamics and cognitive science. In Section 4 of this study it will be discussed that models of pedestrian dynamics are mainly concerned with finding shortest or fastest paths. Research in environmental psychology, however, has added new features to path planning which makes a path planning model more complicated. Out of numerous path choosing criteria which is available in the literature, the experiments in a study show that selecting one criterion seriously under predicts the chosen paths. In a lab environment, however, minimizing distance, time or turns could provide reasonable explanations. This study also suggests that the path selection criteria may change according to the changes in the environment (Golledge, 1995). An experiment in a virtual environments also support the idea that given different choices, people choose a path that is best aligned with their direction of movement (Dalton, 2003). Other studies have shown that the distances that people perceive in environments are often different from the real distances and depend on the features of the path. In a number of cases the difference between perceived and real distances was modeled using exponential functions (Wagner, 2006). There are also statistical models to explain the lateral deviation of the centers of attention from walking direction or the distances of centers of attention from the observer (Wagner et al., 1981).

Several studies in space syntax have focused on analysis of angularity. Turner (2000b) points out that while integration has shown to correlate with movement in many studies, it takes no account for the changes in angles. He suggested a new model in which the route decisions are based on the sum of the angular deviations rather than the number of turns. He also proposed a method for the measurement of the “angular mean depth” for axial lines and visibility graphs. In another study Turner and Dalton (2005) used the same idea to suggest a path choice model for vehicular movement which is based on paths with minimum angular changes for each pair of origin and destinations in a network. A more recent study shows that this methodology has more significant correlation with movement pattern compared to integration in transport network analysis (Turner, 2007).

Space Syntax and Care Delivery Scenarios

A systematic search in peer-reviewed journals and conference papers results in large number of publications that tried to draw connections between space syntax and healthcare design which include two literature reviews (Haq and Luo, 2012, Khan, 2012). Along with other spatial variables, many of these studies reported that effectiveness of care delivery positively correlates with visual integration of patients’ location (Hendrich et al., 2009b, Hendrich et al., 2009a). The extensive review of these works is obviously out of the scope of this study. What concerns this study is to know “Can space syntax be considered an appropriate model for evaluation of nursing scenarios?”

Space syntax originally was never claimed to be a simulation model for mandatory occupancy scenarios by its theorists. Batty (1997) explains that the results of space syntax analysis show aggregate traffic pattern of the pedestrians and is different from active-walker model. Only in an optional occupancy scenario when people are not preoccupied by other inevitable tasks, the natural attraction that Hillier's theory addressed can be the key element of choice. Obviously, nursing scenario is not an optional walking scenario. This of course was not a hidden fact from all of the researchers who conducted these studies (Cai and Zimring, 2012). The findings of space syntax applications in nursing scenarios can still be understood and acknowledged in a narrower scope. Even in mandatory scenarios when traveling from one location to another is mandatory, the occupants compromise between the goals of the scenario and the spatial qualities that they experience. When compromising is acknowledged as a fact, along with visibility factors one could expect to see the impact of other environmental qualities such as interrupting noise which existing evidence supports its impact on the performance of nurses (Shepley and Davies, 2003). Space syntax measures, nonetheless, are purely configurational and take no account for environmental factors that cannot be explained configurationally (Penn and Turner, 2001).

Many of the studies in healthcare attempt to use space syntax software for visibility. Some of these studies report results from which the conflict between task-driven behavior and natural attraction of space is revealed. For example, Lu and Zimring (2012) have found that nurses are more likely to put themselves in positions that offer best views to the patient beds rather than best connectivity. In a review of literature Lu and Zimring (2012) found three outcomes for improved visibility in healthcare facilities which include improved patient safety, reduced staff walking distance and time, and improved patient satisfaction. They introduced "targeted visual connectivity" as new visibility measure which shows the number of preselected patients from any place in the ICU layout. Figure 2-2 shows targeted visual connectivity prepared based on their idea using Sala script in Depthmap software. The hotter colors show higher number of partial visibilities to patient beds. Interestingly, their observed nurse locations shows that targeted visual connectivity is more strongly correlated with the density of all staff members compared with generic visual connectivity. This study supports that the nursing objectives in a mandatory scenario can significantly override the natural attraction of space introduced by Hillier et al. (1993).

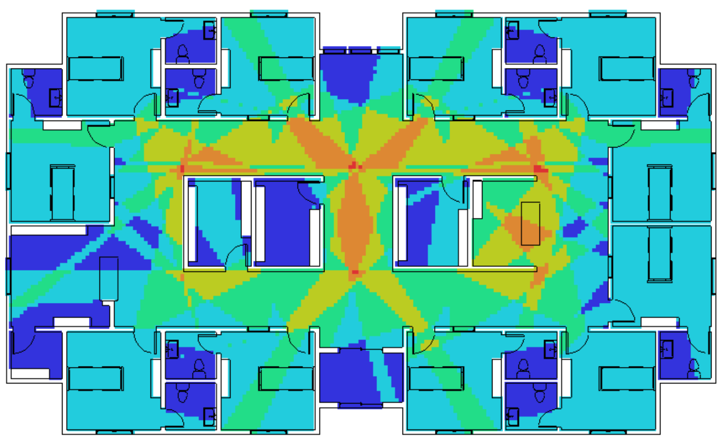

Figure 2-2: The color code shows the number of visible patient beds in the floor.

Space Syntax and ABM

Space syntax has also been integrated with an agent-based model to simulate occupancy scenarios. The idea behind this simulation is very simple. Agents choose a random destination in their cone of vision and take a fixed number of steps towards that destination. If taking steps towards the destination is not possible or the number of steps are completed the destination will be updated. The aggregation of the trail data of the agents have shown a meaningful correlation with the observed flow of people in a case-study (Penn and Turner, 2001). The simplicity of this model is surprising.

Some other works that are classified as applications of space syntax attempt to push the boundaries of space syntax software to an ABM that simulates mandatory scenarios. For example, to evaluate the visibility of a nurse while navigating space Choi (2011) selected the circulation areas in the corridors of a ward and used Depthmap software to measure step visibility from the circulation area. Figure 2-3 was produced in Depthmap based on the same idea to illustrate the concept. The resulting map was then used to find correlation between number of patient falls and direct visibility. This novel application is based on two simple assumptions. First, the possibility of being in each point of the specified circulation area is supposed to be the same. The frequency of a nurse's trips to different destinations might be different. Even when the frequencies are the same the choices of walking trails may be different. In that case even the aggregate of presence in the corridor is not evenly distributed. Second, when potential visibility exists it would not be clear if the direction of visibility to patients will fit within the viewshed of a nurse. For this type of analysis not only the location of a nurse, but also his or her direction matters. There is not adequate reason to support these two assumptions. A model that integrates ABM and DES will not have to be based on these assumptions and thus will be more suited to serve the same purpose.

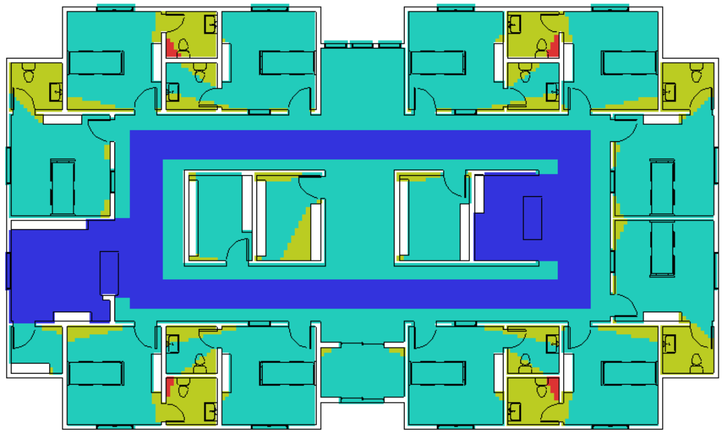

Figure 2-3: Visibility step map from corridors of a ward in Depthmap software.

Space Syntax and DES

There are a number of works that attempted to combine DES with space syntax as well. In a project to re-engineering the Emergency Department of a hospital, a group of designers and researchers developed a DES model to find the optimal site allocation in master planning. The configuration of the suggested model was then analyzed using least visibility axial lines and the results indicated improved connectivity and integration (Morgareidge et al., 2014). This novel approach, however, does not suggest a computational model to automatically integrate the results of DES and space syntax. Another example of integrating space syntax, DES, and ABM can be found at a much larger scale for e-mobility analysis (ElBanhawy et al., 2013). In this study the street network of the inner urban core of Newcastle-Gateshead was analyzed and transformed to an axial maps. The network includes charging points for electronic vehicles which include queues for the drivers (i.e. agents) to charge their vehicles.

2.3.3 Summary

Research in space syntax has highlighted the significance of the configuration of space as a whole and invented methods for the calculation of it through spatial indices such as connectivity and integration. This area of research is exclusively explored by research in space syntax. While almost all of the existing occupancy simulation models have excluded visibility analysis, space syntax offers an alternative model which is mainly based on visibility. It produces layers of spatial data that correspond to the aggregation of the trails in optional walking scenarios and are claimed to be the natural attractions of space. The results of space syntax are not based on simulations which use active-walkers and are mathematically derived.

Space syntax exclusively accounts for configurational properties and does not include other environmental data or occupants' preferences. Meanwhile, researchers in other areas, such as walkability, have pointed to the significance of many environmental variables that strongly correlate with human behavior. Given a design layout, methods like space syntax can calculate visibility, but adding user behavior simulation can help find more meaningful visibility for occupants in the environment. The integration of space syntax with environmental qualities is an ongoing challenge which has not been addressed yet. The existing literature in space syntax has also highlighted the significance of the path simplicity and supported that by observations which add a new layer of complexity to the modeling of navigation systems.

In spite of the limitations, space syntax has a great advantage for calculating visibility. For visibility analysis the isovists are calculated for the underlying grid and are used for many types of analysis later. Within this approach the heavy computation cost of calculating visibility fields is paid only once and later checking visibility is only looking up into a table with minimum computation cost. The only limitation of this approach is the discretization effect of the grid which can be handled by choosing an appropriate resolution.

While the application of space syntax in healthcare design is rapidly growing, there is not enough theoretical support for this type of analysis in mandatory occupancy scenarios. In fact, some of these studies reported other factors, such as view to the patients, correlate with the pattern of presence in space more strongly than standard space syntax indices such as connectivity and integration. The boundaries between the application of space syntax theory and the application of space syntax software in the body of research are not clear. The studies that used space syntax for analysis of healthcare facilities, ideally need an ABM in which agents are capable of detecting changes in their cone of vision. However, such models do not exist and require extensive programming knowledge and time for developing software applications. On the other hand, space syntax software is a tool for visibility analysis that is freely accessible and easier to use than other existing tools such as GIS (ArcMap, 2016). The existing Lean instructions that give significant value to having a line of sight to the patients (Grunden and Hagood, 2012) further pushes researchers to use space syntax tools for visibility analysis.

2.4 Navigation Models

Navigation models either rely on path planning algorithms or use Pedestrian Dynamics Models (PDMs). Path-planning and pedestrian dynamics serve two different purposes. The purpose of path-planning algorithms is to find the shortest path, whereas the purpose of a PDM is simulate the dynamic features of navigation and interactions of agents with each other as well as the environment in the course of time. PDMs are the intersection of three scientific fields including agent-based computing, the social sciences, and computer simulation. Social sciences include evidence about social entities and computer simulation concerns the study of different techniques of simulation (Davidsson, 2002). Path-planning, on the other hand, aims at finding the shortest paths and either uses exact algorithms such as variations of Dijkstra (1959) algorithm or a variety of methods that are based on heuristics, such as traveling salesman problem (Applegate, 2006). The literature shows that combining path-planning and pedestrian dynamics is possible. For example, Nishinari et al. (2004) combined this shortest path technique with a cellular automaton that stochastically determines the interaction between walkers.

Plath-planning has been the center of attention of some studies in healthcare which focused on the measuring the traveling distance of nurses. Nurses have been observed to walk between 8260 in intensive care wards and 6260 meters in a general ward (Bauer and Knoblich, 1978). Another study identified that nurses spent 29% of their time walking (Burgio et al., 1990). Based on the idea that if nurses spend less of their time walking they will have more time for the patients, a number of studies focused on strategies to minimize walking time and distance. Previous works have considered task frequencies (Pati et al., 2015, Pati, 2012) and layout configurations (Shepley and Davies, 2003) as factors that influence walking distance and time. Decentralized nursing stations and hybrid combinations of centralized and decentralized nursing stations have been shown to significantly reduce nurses' walking time and distance (Pati, 2012, Pati et al., 2015). A number of other studies also tried to minimize travel distances by optimization techniques

(Nanda et al., 2015) or employed a multi-objective optimization technique to minimize walking distance along with other environmental factors (Su and Yan, 2015). All of these studies indicate that modeling navigation in space is gaining rapid attention in the discipline of healthcare design. However, the existing models in these studies are entirely based on path-planning on network approximations of a 2D floor. These models have accuracy limitations which is critical in optimization scenarios.

2.4.1 Path-Planning on Networks

All of the path-planning systems use a network of paths for path finding. The network is a topological graph which is linked and includes all possible destinations. The linkedness of the graph suggests that at least one path exists that connects every two pairs of destinations together if the edges allow for bidirectional connections. The most well-known applications of path-planning is in motion planning for robots. The goal in motion planning is to find a path for a robot between any two points in Configuration Space (i.e. C-Space) such that it does not collide with barriers. The approaches for finding a collision-free path in robotics are classified into two domain: classic vs. heuristics (Masehian and Sedighizadeh, 2007). In the roadmap approach the connectivity of the robots free space (C_{free}) is captured in the form of a network of one-dimensional curves lying in C_{free} or its closure. Once constructed, the roadmap is used as set of standardized paths and path planning is reduced to a search in a graph to find a path that connects an origin to a destination (Latombe, 1991, page 153). Classical approaches for creating the roadmaps include visibility graph, retraction, freeway method, and silhouette. Other methods for motion planning which Latombe (1991) did not classify them within roadmap approaches include cell decomposition and potential fields. Due to the complexity of the path planning problem, which is NP-complete (Canny, 1988), some approaches employ probabilistic or heuristic methods for speeding up the process. According to the diversity of the heuristic methods that are employed in heuristic approaches, the classification is difficult. An example of these approaches include an algorithm to take random candidate nodes which are uniformly distributed on the constrained surfaces (Amato and Wu, 1996). In architecture, Taneja (2013) have extensively discussed navigation models that are based on network topologies and their applications in map-matching.

A detailed discussion of how the network topology or roadmap is created does not fit within the scope of this study. What concerns this study is the application of any of these models that approximates a continuous 2D floor with a network and their accuracy for measuring distances. In robotics the paths extraction and creation of the roadmaps should be subject to further operations such as smoothening (Amato and Wu, 1996) and consideration of kinematic constraints (Dawen and Amato, 2004) to create paths that are practically useable for robots. These operations are missing from the works in architecture which were mentioned before.

Figure 2-4 shows a network in a building floor. This model is produced by an automatic algorithm that covers the floor with a grid of nodes and connects each node to its sounding nodes. The nodes that are inside the physical barriers and the connections that intersect with barriers will be removed. Although the network topologies can be very different, all networks have some characteristics in common. First, they discretize the continuous walkable area. The choice of path in the floor will always be limited to the paths that can fit to the network. Figure 2-4 shows how a change in the network will result in the emergence of different shortest paths which are highlighted in blue and how these paths are different from the unique shortest path which is highlighted in red. Even when finding the shortest paths is technically possible, when taking a detour to avoid barriers the shortest path will overlap with the edges of the barriers. This means that technically what is generally referred to by "shortest path" is practically impossible to follow.

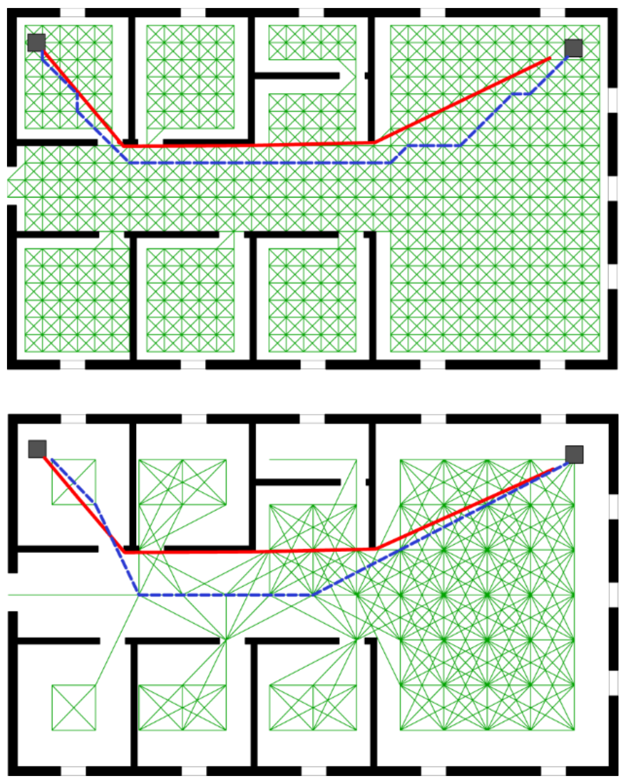

Figure 2-4: Different network topologies will result in different paths that are discretized.

Another limitation of using networks for modeling navigation is ignoring the dynamics of walking. Physically, it is not possible to walk on the edges of a network. The movement of human body follows the Newtonian rules of physics. An occupant's location in space is influenced by its desired velocity, acceleration forces and physical abilities to control these forces. The impact of physical characteristics of an agent in the formation of the walking trail is illustrated in Figure 2-5. In this figure the agent walks from one side of a wall to the other side of the wall with an acceleration of 8 ft/s^2 and maximum velocities of 12 ft/s. This trail, which was recorded using the software solution of this study, shows the complex and asymmetrical geometry of a trail. Path-planning models that are based on discretized networks cannot capture the trail shown in Figure 2-5, regardless of the topology of the network.

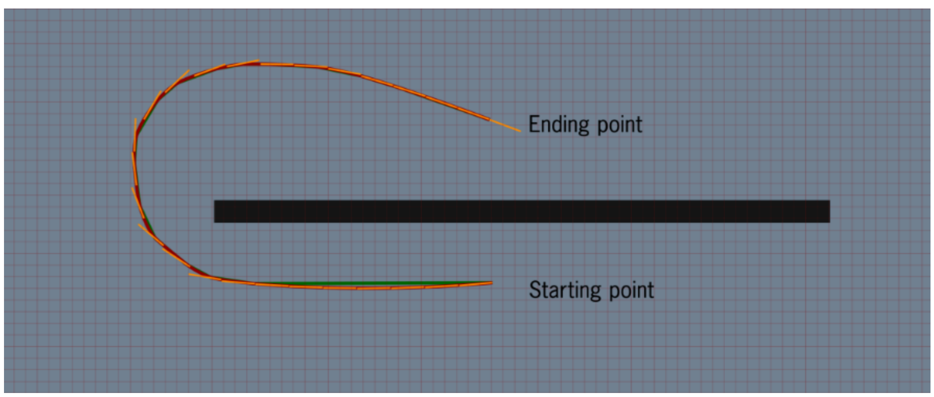

Figure 2-5: The walking trail of an occupant in a continuous floor using Newtonian rules of physics.

Path-planning also ignores the dynamics of interacting with barriers. A physically-based model of walking should also involve factors such as friction, resistance as well as elasticity and plasticity of body when colliding with other objects. A simulation that accounts for physical characteristics should include rigid body simulation and a physics engine, which are not embedded in path-planning models. As a result modeling the navigation system should be physically-based.

2.4.2 Pedestrian Dynamics

Unlike Path-planning which is concerned with finding the shortest paths Pedestrian Dynamics Models (PDMs) are concerned with the dynamics of walking, interactions among agents, and interactions of agents with the environment. Path planning is only the first step in creating models of pedestrian dynamics. This research, according to its scope, is not concerned with physical interactions among the agents; the dynamics of walking and interaction with the environment are, on the other hand, at the center of focus of this study. It is also concerned with continuity of the 2D floor area. The literatures suggest different classifications of PDMs and their properties which can be helpful for choosing the appropriate modeling strategy.

Schadschneider et al. (2011) classified the existing PDMs into three categories: fluid-dynamic and gas kinetic models, cellular automata, and social-force models. Fluid-dynamic and gas kinetic models are based on similarities between crowd motion and the behavior of particles in liquids and gas. These models assume the occupants move in a generally the same direction and overlook their individual goals and purposes. These models are macroscopic and of low fidelity which makes them not suited for this study. A cellular automaton includes a spatial configuration of cells that represent autonomous entities that interact with each other based on a limited number of rules. In Architecture, these models were used to explain the dynamic interactions from which natural forms or self-producing structures, such as city forms, emerge (Batty and Longley, 2014, Batty, 2005). Models that are based on cellular automata are also discrete, both in time and space domains, meaning that the location of the agents should fit within an underlying cellular structure in fixed time-steps. Since the accuracy of an agent's physical location is critical in this study, using a cellular automaton will not be an appropriate choice as well. The social-force model is a deterministic continuum model in which interactions between pedestrians are implemented by a field of forces (Schadschneider et al., 2011). Based on this classification only social-force models include high fidelity and continuity with which this study is concerned.

Helbing et al. classified the PDMs into normal and panic categories based on their intended application (Helbing et al., 2002). Normal behavior's main characteristics include choosing the fastest route to reach a destination, selecting the most comfortable speed, and keeping a certain distance from other pedestrians as well as barriers. Panic behavior is, however, quite different. Individuals tend to develop blind actionism; they move considerably faster; moving patterns are uncoordinated; interactions become physical in nature; at bottlenecks, jams are built up which may lead to dangerous pressures and fatal injuries; injured turn into obstacles and worsen the situation. Both normal and panic models can account for individual as well as crowd behaviors. However, most of the features of panic situations are caused by the interactions of individuals in a crowd (Helbing et al., 2002). The panic behaviors are not generally agreed upon and studies have represented different ideas about panic in crowd incidents (Keating, 1982, Rogsch et al., 2010). This paper, however, is neither concerned with crowd nor with panic situations which are at the center of attention of many PDMs.

Helbing et al. suggest a generalized force model of interactive pedestrian dynamics which successfully reproduces pedestrian behavior in both panic and normal situations (Helbing et al., 2002). Based on this idea a field of forces will be generated on the walkable field that will lead a traveler to a destination. In a social-force model a field of forces will control the behavioral changes of agents. The behavioral changes of agents are formed in a process that starts with environmental or personal stimuli (Helbing and Molnár, 1995). The perception of the environment and the personal goals will then be mentally and psychologically processed to create motivations to act upon. Finally, a physical action is taken based on the motivations. While in most of the works that employed social force models, the forces are generated for collision avoidance and approaching a destination, this three level process promises much more than that and perfectly fits the requirements of evaluation as described earlier in Chapter 1. According to Helbing and Molnár the invention of social force model dates back to the beginning of 1950s when Lewin (1951) claimed that behavioral changes are guided by social fields. Other studies have suggested a different definition for social-force models that is based on desired velocity of agents (Chraibi et al., 2013).

Generalized force models appeared to be successful for modeling the interactions between pedestrians (Helbing et al., 2002), simulating the dynamic features of escape panic (Helbing et al., 2000) or even evolving human walking trails where there is no agent-to-agent interaction (Helbing et al., 1997). In architecture these models were used to determine the effect of design decisions and exploration of potential improvements (Rodriguez et al., 2012, Zarrinmehr et al., 2013). Social-force models also preserve the continuity of walkable fields. In this model the application of forces defines the mechanism for agent-to-agent and agent-to-environment interactions. Therefore, dealing with a crowd is not required for the application of this modeling technique. Consequently, unlike gas kinetic and cellular automata, social-force model seems more promising as a navigation system for occupancy scenario.

Pedestrian dynamics have also been studied based on the emergence of crowd behavior based on the actions of individuals in the crowd. It should be noted that this behavior is not the result of flocking in which self-organizing forces are directly applied (Reynolds, 1987). When employing social force model pedestrians spontaneously decrease the chance of collision by aligning themselves into lanes (Hoogendoorn and Bovy, 2001). Social force model also describes the oscillation of pedestrian stream when they try to pass through the bottlenecks at opposite directions (Helbing and Molnár, 1995). Batty (2003) further studied randomness and emergence of patterns in pedestrian modeling techniques that use multi-agent systems. In his study randomness was applied to the velocity of agents on coarse scales in which the agents' random choices are constrained by the locational geometries. At fine-scale when a force-based model was employed randomness was applied to repulsion and attraction forces. This study showed that ordered patterns (i.e. fractal shapes) emerge in the crowd out of the actions that the agents take individually or collectively (Batty, 2003).

US National Institute of Standards and Technology (NIST) has reviewed and classified the evacuation models according to availability to the public, modeling method, purpose, whether or not they use a grid structure, individual vs. global perspective of the crowd members, behavior, movement, fire data, CAD model, visualization and validation (Kuligowski and Peacock, 2005). This review, which was not updated since 2005, includes

30 simulation models out of which 18 models only simulate the movement aspect of the crowd or attempt to model behavior implicitly by assigning certain response delays or occupant characteristics that affect movement throughout the evacuation. The need for behavioral theories and a list of "behavioral facts" that should be considered in evacuation models are discussed in details in another study (Kuligowski and Gwynne, 2010).

The main classifications of the models of pedestrian dynamics that exist in the literature do not cover all of the existing models. For example Yan and Kalay (2006) developed an agent-based system to simulate the goals, social traits, perception and physical behavior of the users. In their model the environment is represented via geometric modeling and motion control. The environment is divided into a cellular gird (i.e. tiles) that allows for storing information including sun vs. shadow. This model accounts for environmental qualities in a sense that when exploring the environment on their own volition, the agents that have a desire to choose a spot exposed to sun or covered by shadow according to their unique preferences. Indeed in this model agents' preferences and environmental quality determine the destination of an agent. When an agent finds its destination, an optimized A* algorithm is responsible for path planning (Yan and Kalay, 2006).

2.4.3 Validation of Pedestrian Dynamics Models

The validation techniques that are discussed in the literature are mainly concerned with the crowd modeling and there are very few works that spell out validation criteria for individual occupants. The empirical results include phenomenological description of collective effects in a crowd that any valid model should be able to reproduce them. These effects include jamming and clogging, quasi-periodic density variations in space and time, lane formation in counter-flow, oscillations in counter-flow at bottlenecks, formation of collective patterns at intersections, and representation of non-adaptive behavior in crowd disaster when crowd members show unpredictable and irrational behaviors (Schadschneider et al., 2011). An experimental study by Helbing et al. (2005) also confirms the emergence of the described phenomena. Experimental studies in the area of crowd behavior are rare due to the potential hazards that can be associated to them. In this study social force model is used to simulate the effects of different layouts and suggest design solutions.

The existing validation categories of evacuation models according to the NIST (Kuligowski and Peacock, 2005) include 1 model that is validated against code requirements, 14 models that are validated against fire drills or other people movement experiments/trials, 3 models that are validated against literature on past evacuation experiments (flow rates, etc.), 4 models that are validated against other models, and one model with was validated by a third party. Out of 30 reviewed models, 10 models have no indication of validation which shows a significant flaw in the existing modeling strategies (Kuligowski and Peacock, 2005).

For individual occupants the literature includes a study that compared the observed trail patterns on grasslands with the simulation results as a method to validate a simulation model. Helbing et al. (1997) in this study simulated the evolution of walking trails in grass lands. Each point on a grassland has a level of comfort to walk on it which increases as that grass in that point retreats and that point becomes part of a trail. This comfort deteriorates with the recovery of the grass. When the grass is homogeneously distributed over the grassland, the trails start to emerge along the shortest routes because it is only the desire to minimize the length of the routes that rules path planning. What makes the paths to evolve is the attractiveness of each point on the grassland that depends on the proximity of that point to the other points of the trail system that are visible to it. The evolution continues until a balance is reached between minimal trail-construction cost (i.e. walking on grass) and maximal comfort (i.e. attraction of points and the desire to reach keep paths short) (Helbing et al., 1997).

2.4.4 Summary

Simulation of the navigation model includes a path-planning system and simulation of the dynamics features of walking. This study is concerned with a path planning model that preserves the continuity of the floor (i.e. C-Space). The physical component of the simulation demands a physics engine to simulate the barriers and the occupants as rigid bodies. Among the existing pedestrian dynamics models, social force model fits the requirements of this study which are simulation at micro-scale, preserving the continuity of floor, and high fidelity of the individuals' behaviors. The choice of a force-based model is also consistent with the application of an agent-based model which was decided in Section 1 of this study to simulate individual occupants. The validation technique that will be used in this study is based on the comparison of the trail model that is produced in the simulation with the trail model that is observed in real world.

2.5 Conclusion: Summary of Findings

The results of the literature review in this chapter can be used to choose the strategies which will be used for the development of the simulation model in the next two chapters.

Furthermore, the review of literature has narrowed down the scope of research and determined a set of objectives which the developed models should account for. In this section the findings from the literature will be itemized and their context of application (i.e. mandatory and/or optional occupancy scenarios) will be determined.

2.5.1 Agent-based Model (ABM)

The simulation of the both mandatory and optional occupancy scenarios requires to represent the occupants' unique differences and goals.

- *ABM will be used to simulate the individual occupants in both mandatory and optional scenarios.*

2.5.2 Discrete Event Simulation (DES)

The simulation of mandatory scenario requires modeling the tasks that are assigned to individual occupants.

- *DES will be used to plan the tasks and activities in a scenario.*
- *The DES that simulates the activities of a nurse should allow for:*
    - *Prioritizing the tasks*
    - *Detecting some tasks visually.*

2.5.3 Visibility

The studies that were reviewed in the context of nursing scenarios have highlighted that in mandatory scenarios occupants' decisions are influenced by what they see. In optional scenarios, space syntax studies show that visibility determines the pattern of movement in space.

- *Agents in MOSM should be capable of visually detecting changes in their environments and react to them.*
- *Visibility will be limited to the cone of vision of the agents.*

The literature suggests pre-calculating isovists as a collection of cells in a cellular grid is an efficient technique by which the cost of calculation of the field of visibility in real time can be avoided.

2.5.4 Path Planning

A path planning system need to be chosen that preserves the continuity of the floor.

- *For mandatory occupancy scenarios the potential field model will be chosen for path planning.*

As literature has suggested the performance of this choice in terms of speed of calculation is not the best. However, creating a grid also allows for storing spatial data, and processing the spatial data using filters. Also, using a cellular grid allows for modeling the isovists (i.e. the field of visibility) as a look-up table of cells. When using this data structure, checking visibility of a target can be approximated by checking the containment of the target cell in the loo-up table. Checking visibility with the cellular model of field of visibility is faster than the polygonal model and does not require the computational cost of ray-tracing.

- *For optional occupancy scenario, the path planning should be limited to the visibility area of occupants.*

- *Angular simplicity of paths is also another factor that should be considered in both mandatory and optional occupancy models*

2.5.5 Walking dynamics

Simulation of navigation should preserve of the continuity of the walkable floor and be physically-based. These factors are not found in path planning systems.

- *A force-based model was chosen for the simulation of the agent behaviors. In addition to an agent-based model, this selection of this model demands:*
    - *Rigid body simulation of agents*
    - *Rigid body simulation of barriers*
    - *A physically-based model of movement which considers the kinematics of human body.*
    - *Collision Detection*

2.5.6 Validation

Validation of the occupancy scenarios is a key feature which is largely absent in the related literature. A mechanism for verifying the fitness of the simulation model and its results is, therefore, needed.

- *The technique for validation of model is based on the comparison of the simulated trail of the artificial agents and the observed trails of humans in real world.*

2.5.7 Visualization

Several studies have pointed to the necessity of visualization of the occupancy scenarios from the review of the evacuation models to the application of the agent-based models.

Visualization offers chances for verifying the model and the simulation process. Visualization is not necessary for either mandatory or optional occupancy simulation models. However, it enhances the understanding of the problems by the designers and may provide clues for them to find solutions.

- *The simulation should be capable of visualizing the occupancy scenarios in both 2D and 3D formats.*

2.5.8 Environment Model

The environmental model is an important component of agent-based models. Also, a rich environmental model will lead to a more informative visualization. The review of the literature in this section showed that the environmental models in healthcare simulations are either primitive or simply do not exist.

- *A mature BIM model will be suggested as a model of the environment in 3D format.*
- *A 2D model of the environment will be extracted from the BIM at the eye level of the occupants.*

This chapter showed that all of the ingredients that an occupancy simulation model needs exist in isolation but a model that integrates all of them together has not been suggested. The main limitation of Space syntax, path planning algorithms, and pedestrian dynamics is that they do not account for the desirability of environmental qualities. Space syntax is limited to configurational analysis; path planning algorithms are mainly concerned with speed and efficiency of creating roadmaps; pedestrian dynamics is mainly applied on crowd safety and evacuation model. This is a limitation of the current state of the application of these models which have not explored the full potentials that they offer. The most important contribution of this study in terms of modeling is the integration of these models to unlock new potentials that they already include. An integrated model will enhance the level of realism of existing simulations. The ability to enhance the level of realism is significantly important for validating the model and using its results for evaluation of the occupancy scenarios.

CHAPTER III

SIMULATION, VISUALIZATION AND EVALUATION OF NURSING SCENARIOS

3.1 Introduction

One original contribution of this study is to create an integrated model for simulation, visualization and evaluation of mandatory occupancy scenarios. The simulation component accounts for visibility from an occupant's vantage point, activity workflow, priority of the tasks, and an occupant's unique desires in relation to path simplicity and environmental qualities when navigating space. The simulation features are integrated from diverse disciplines including architecture, computer science, traffic engineering, and physics to create accurate and insightful ideas for decision-makers. The visualization component allows for visualizing spatial data in 2D and 3D formats within a detailed building model and animating the occupancy scenarios in 2D and 3D formats. The evaluation component allows for the filtering a large body of multi-dimensional information which is captured during the simulation of the occupancy scenario to check where, when, and how often specific events occur so that the decision makers can suggest informed changes at the building design phase or in planning activities in existing buildings.

Mandatory occupancy scenarios describe how a building occupant becomes engaged with a series of activities that should be performed as parts of a job description or to address some tasks. Nursing is the ideal representation of mandatory occupancy scenarios. A scenario defines a behavioral context for an occupant. The performance of a scenario may or may not require navigation in space. If the activities in the scenario need to be performed in different locations, then navigation in space will also be a part of the scenario. Whether navigating in space is needed or not, the scenario dictates the way that an agent is exposed to the environment and frames the agent's experience of the environment.

A comprehensive review of literature in the previous chapter showed a number of shortcomings for the existing simulation models of occupancy scenarios. Discrete Event Simulation (DES) models were extensively used for simulation of the mandatory scenarios, specifically for modeling activities in hospitals. Using DES is an ideal modeling strategy for the simulation of the functional aspects of the scenario. However, it inherently lacks the visibility analysis. Numerous studies used Space Syntax software for visibility analysis. Space syntax by definition cannot be used in mandatory occupancy scenarios, because walking towards natural attractions of space is not the only determining factor in mandatory occupancy scenarios. It lacks the mechanism of simulating individual occupants who navigate space purposefully with different objectives in mind. A number of works that tried to combine visibility analysis with an Agent-based Model (ABM) or Discrete Event Simulation (DES) used space syntax software. These choices were made in the absence of a model for simulating mandatory occupancy scenarios that account for visibility.

The review of the literature also informed us that many models integrate DES and Agent-based Models (ABMs) to account for differences between occupants and their objectives. Spatial navigation systems in the existing models are limited to rudimentary path-planning systems. However, more sophisticated and physically accurate models of walking can be found in models of pedestrian dynamics. In pedestrian dynamics, on the other hand, only a handful of works, have considered desirability of environmental qualities as a factor that influences occupants' choices in path planning and the models are basically concerned with collision avoidance and simulation of crowd evacuation.

While individual models or theories exist for analyzing visibility, planning activities, simulating the differences between individual occupants, and visualizing the occupancy process an integrated model that accounts for all of these features does not exist, although it has been conceptualized. Developing an integrated model has so far remained a challenge. The Mandatory Occupancy Scenario Model (MOSM) which will be developed in this chapter promises to fill the gaps between these models and create an integrated model that simulates and visualizes an occupant's behaviors at micro-scale. Yet, as discussed in Chapter 1, the ultimate purpose of MOSM is not merely to serve as a simulation and visualization tool. It allows designers and facility managers to evaluate desirability of occupancy scenario from the occupants' perspective. MOSM allows for training artificial agents to mimic the behaviors of humans in real buildings. MOSM includes a parametric model of each agent's preferences that determines their walking behavior. The training operation in MOSM fine-tunes the parameters so that the artificial agents follow the footsteps of the observed real building occupants. With a trained agent in an elaborated building environment MOSM is capable of rendering a picture of how often and where the occupants will be pushed out of their comfort zones. This picture can be of immense value for designers who are concerned with building design at the design phase or for facility managers who are concerned with the assignment of activities and space planning (i.e. occupancy scenarios).

While the scope of this chapter is narrowed down to the nursing scenario, MOSM can be generally applied to any other mandatory scenario as well. It includes a Discrete Event Simulation (DES) to create a descriptive model of the activities and the workflow. It includes an Agent-based Model (ABM) to simulate individuals who are involved in the scenario. Each agent (i.e. nurse) has a unique preference that influences his or her evaluation system. It includes a model for walking dynamics which is based on Newtonian physics and allows agents to find their most desirable paths as opposed to the shortest or the fastest paths. It includes an efficient visibility analysis mechanism that allows the agents to check their targets and act upon that. MOSM also includes a detailed Building Information Model (BIM) for the representation of the work environment. This environment will be used for visualization of data, animating the occupancy scenario, and checking the agents' views during the simulation of a scenario.

Sections 2, 3, and 4 of this study will explain the simulation framework. Section 2, describes the activity model, task model, and a decision making model which integrates DES, ABM and visibility analysis. In Section 3 a technique will be developed to create a navigation model which accounts for an occupant's preferences in relation to different layers of spatial data and path simplicity. In Section 4 the physical characteristics of the agent model will be described. A validation technique will be discussed in Section 5 by which an agent can be trained to follow the trail which is recorded from a real agent. The simulation model will be tested in a case-study in Section 6. In this section the effects of environmental qualities in an occupant's behavior will be measured and the reliability of the simulation results will be discussed. Section 7 of this chapter will explain that a filtering mechanism can be used to acquire data from agents and use this data to evaluate the performance of the scenario. Finally, this chapter will conclude by comparing the achievements with the promises that were made.

3.2 Mandatory Occupancy Scenario Model (MOSM)

The descriptive model for nursing scenario is suggested based on the lessons learned from the literature review in Chapter 2. On one hand, it is clear that a combination of a Discrete Event Simulation (DES) and an Agent-based Model (ABM) would ideally serve the simulation purpose. However, the existing models are missing an essential component which is visibility analysis. On the other hand, the visibility analysis models, which have been limited to space syntax tools, inherently lack the mechanism for simulating mandatory scenarios and completely ignore the effect of environmental qualities. The modeling strategy used in MOSM combines ABM and DES to simulate the use processes and engagement with activities. DES is used for modeling the operation of a system using events that repeat in the course of time. According to this strategy, DES lacks the ability to simulate the changes that occur in a system in-between the events (Robinson, 2004). DES is the desired choice for coordinating between different events that occur. ABM, on the other hand, is useful for simulating the changes in a continuous process. This section explains a DES model of mandatory scenarios in a way that it can be consistently merged with an ABM that simulates the behaviors of building occupants (i.e. nurses) at micro-scale level. The components of the developed model are defined at three levels: activities, sequences, and scenario. Activities determine the small scale behaviors of the agents. Sequences include an ordered collection of activities that fulfill an objective. The scenario includes a framework for engagement with the sequences to address all of the occupancy objectives. Section 6.7 of the appendix includes technical details for the implementation of the occupancy scenario.

3.2.1 Activity Model

Activities that occur at particular times are the main components of the DES. The level of details in activity models determines the level of realism (vs. abstraction) of the occupancy scenarios. In this study the properties shown in Table 3-1 are attributed to the activity model. Each activity has a unique name that identified it from other activities in an activity repository. The activity engagement area is determined by the boundaries of a polygon. Figure 3-1 shows a floor plan of a hospital in which a number of activity areas are highlighted. These areas include the bedside areas of patients, an area behind the counter in a nursing station, and the areas next to the shelves in the medication supply room and storage room. When engaged with an activity there is a preferred engagement target which determines the body position. The physical engagement target is also another attribute of the activity (Figure 3-1). During the simulation the body position will be randomly selected within the activity area and the body orientation will be set according to the physical engagement target. The engagement time with an activity is a random variable between maximum and minimum duration time. A Probability Density Function (PDF) is needed to generate the duration time. Finally, this activity area needs a mechanism to be physically accessed from any location in the walkable field. The potential field, which is a part the activity model, will make navigation to the activity area possible.

Table 3-1: Attributes of the activity model

1. Name
2. Area
3. Physical engagement target
4. Duration:
    - 4.1. Minimum duration time
    - 4.2. Maximum duration time
    - 4.3. Probability Density Function (PDF)
5. Potential Field

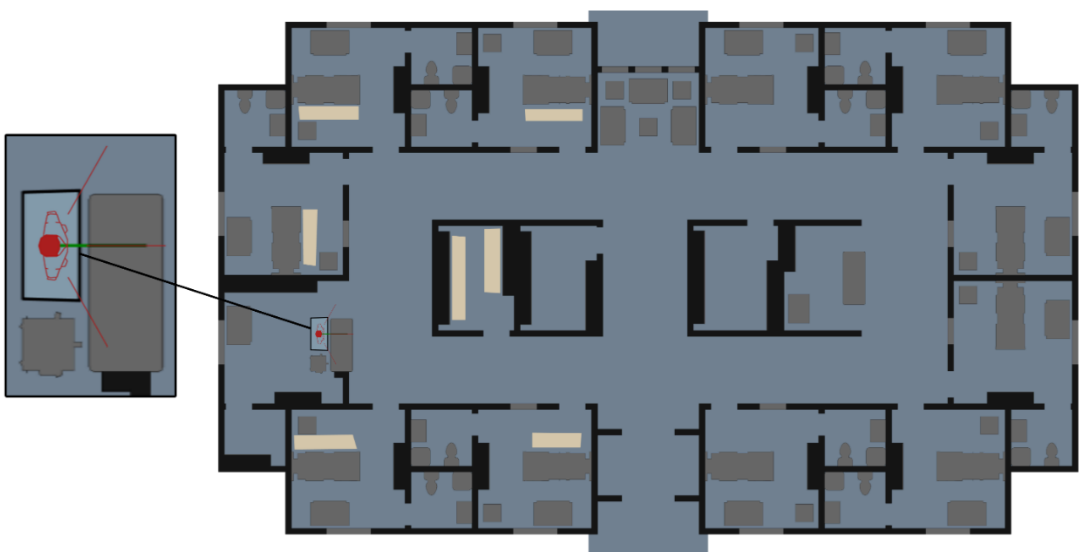

Figure 3-1: Visual representation of the activity area and the physical engagement target in MOSM.

The conceptual activity models can include some level of abstraction which will make them more general, thus reusable in different tasks and among different agents. One may consider delivering medicine to a patient a different activity from cleaning or checking that patient's general health condition because of the difference in the nature of these activities. Although these two activities serve different purposes, they share the same location and probably include similar physical behaviors. These activities can be abstracted to "care delivery" to generalize the simulation model at the expense of losing some degree of realism. Although abstraction is not required, MOSM stores the activities in a database that can ne globally accessed and shared in different tasks and among different agents. This is necessary because some activities may demand the simultaneous engagement of multiple agents such as physicians and staff.

This activity model only accounts for the types of activities which are bound to specific areas. In an emergency department of a hospital, for example, critical care might be delivered to a patient on a mobile bed at the doorways of a hospital where an ambulance drops off a patient. Mobile activities cannot be simulated with this activity model.

3.2.2 Sequence Model

A sequence is a list of activities that an objective will be achieved after their completion. Each sequence has an average activation time that will be used to simulate its activation. When the state of a sequence is active, the agent must get engaged with it. After the termination of the engagement with an active sequence, its state will change into inactive and the next cycle of activation starts. A sequence also includes a priority factor, which is the time when this sequence is expected to be addressed. When multiple sequences are active, this factor determines its priority in relation to the others. Sequences are defined into two different types according to their relationship to the agents (i.e. nurses) who get engaged with them. Expected sequences reoccur in a pattern that is predictable and known by the agents. When their occurrence time is passed, expected sequences are automatically detected. Unexpected sequences will not be automatically detected by the agent, unless a visual connection is established with them. Table 3-2 lists the properties of the sequence model. The existence of the fifth item in this table determines the difference between expected and unexpected sequences. This section explains the difference between expected and unexpected sequences and provides reasons for the arrangement of the activities in an ordered list.

Table 3-2: Attributes of the sequence model

1- An ordered list of activities
2- An average reoccurrence time interval
3- Priority factor (i.e. occurrence time)
4- Activation state:
   4.1. Active
   4.2. Inactive
5- Visual trigger
   5.3. Visual target
   5.4. Visibility field

Expected and Unexpected Tasks

Awareness is the key element for an agent (i.e. nurse) to react to tasks. It can be achieved with or without visual contact. For example, the tasks that are routinely expected to be repeated, such as delivering medicine to patients or regularly checking their health conditions, do not need visual awareness. Similarly, when electronic devises report a patient’s health conditions, visual awareness is not needed. Unless an agent (i.e. nurse) is making a mistake, addressing the tasks that the nurse is aware of their need for attention will not be missed. However, some tasks demand visual detection to come to the attention of a nurse. Figure 3-2 visualized an example of this type of sequences which will be triggered with visual detection of a patient on his or her bed. In this example, upon detecting the need for care, a nurse goes to the most conveniently accessible medical supply room to pick up the required medicine, delivers the medicine to the patient, and finally goes to the most conveniently accessible nurse station for documentation.

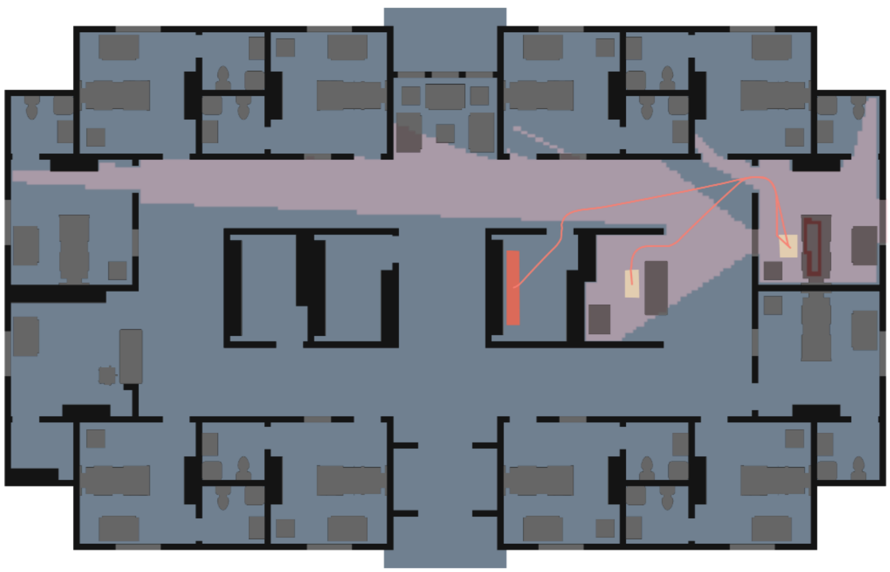

Figure 3-2: A sequence of activities that demand a visual contact to be triggered.

In critical conditions when a patient cannot communicate with nurses, the care delivery task has to wait until it is visually detected. The delay in care delivery can be associated with high risk levels. Therefore, existing Lean instructions for hospital design give significant value to patient visibility to reduce the risk of patient mortality (Grunden and Hagood, 2012). Figure 3-2 highlights the area that is visible to a patient. The visual awareness cannot be gained in this area unless a nurse is oriented in a way that the patient's body locates in his or her cone of vision. This depends on both the location and direction of the nurses in the ward, which are in return dictated by performing the tasks that are already known. Previous studies that used space syntax model overlooked the impact of engagement with existing tasks and body orientation in their analysis of visually detecting the patients (Choi, 2011, Lu and Zimring, 2012). These studies are based on the assumption that during a long term use the effects of position and direction will be neutralized by the aggregation of the data. There is not convincing evidence to support this vital assumption.

Visibility test was ignored in some studies that even conceptualized modeling an occupancy scenario due to the heavy computational cost which was believed to associate with it (Schaumann et al., 2016). However, measurement of the visibility to an area can be done in a very efficient way. A visibility target, such as the patient lying on the bed in Figure 3-2, is a polygonal area and a line of sight to any point inside this area will inevitably intersect with the boarders of the polygon. Therefore, visibility to the target can be simplified to visibility to any point in its edges. This polygon can be rasterized using a cellular grid and the field of visibility (i.e. isovist) for each of the cells on the polygon's edges can be calculated. Each isovist includes a visibility field which is a set of cells. The union of the isovists' visibility fields will result in a collection of cells (i.e. visibility area) from which a view to the target can possibly exist. In Figure 3-2, the unified cells are highlighted in pink. If a cell that includes the occupant's head is not included in this area, having a line of sight to the target is impossible and no further action will be needed to test visibility. However, if the occupant's head is located in this area, at least one isovist that include the occupant's head can be found. The visibility area uses a HashSet data structure to create a collection of cells. The time complexity for checking inclusion in this collection type is an $O(1)$ operation (msdn.microsoft.com, 2016).

Each cell in the visibility area includes a list of references to the isovist vantage points on the visual target's edges from which that cell is visible. If the cell that includes an occupant's head is located within the visibility area, an iteration to all of the vantage points from which this cell is visible will be needed to check if the line of sight locates within the occupant's cone of vision. This check is a simple dot product test of two vectors to measure the cosine of the angle between the occupant's direction and direction of the line of sight. Therefore, in the worst case when the iteration through all of the isovists on a visual target's edge will be needed the order of time complexity will need an $O(n)$ operation. In Figure 3-3 the color code is applied to the cells within the visibility area based on the number of isovist references that they include. The distribution of color hues implies that in a typical visibility test often the number of iterations is much lesser than the number of isovists on the edges of the visual target. By pre-calculating the isovists and the creating the visibility area to a visual target, the visibility test can be made very efficient and ray-tracing can be completely avoided during the simulation.

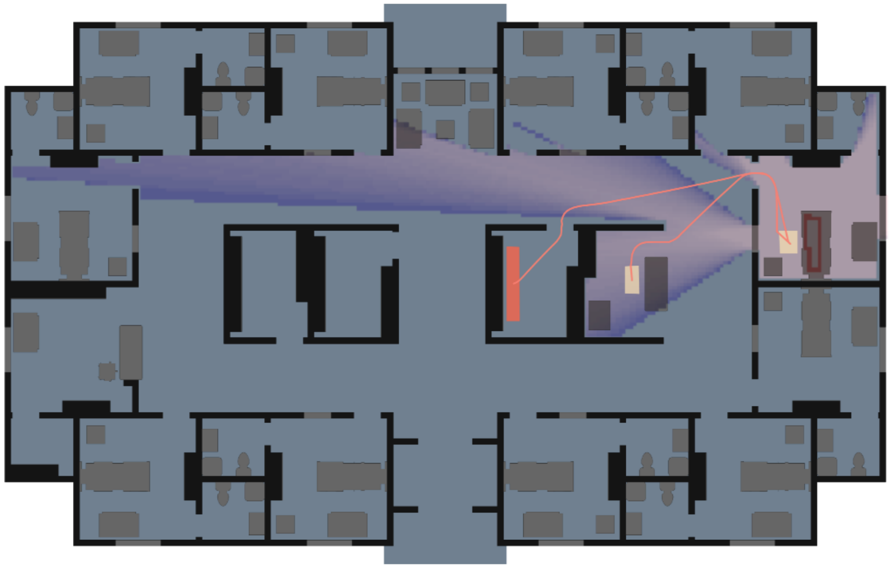

Figure 3-3: The color codes in the field of visibility reflect the number of isovist vantage points on the edges of the visual target that are visible from each cell.

Tasks as a Sequence of Activities

Previous studies suggested techniques for codifying different types of dependencies between the activities using pre-conditions and post-conditions (Schaumann et al., 2015, Simeone et al., 2013b). The fulfillment of pre-conditions, which can include the completion of other activities or certain environmental conditions, determines whether other activity can be executed. The post-conditions are the changes which are marked in the system or the other activities that are triggered after the execution of one activity. Pre-conditions and post-conditions tie the activities that serve an objective. The ties between the activities can be visualized using a precedence diagram. Figure 3-4 visualizes a nursing task which is composed of multiple activities and includes all different types of dependencies among the activities. Possible dependency types between the activities include deterministic, probabilistic and parallel connections.

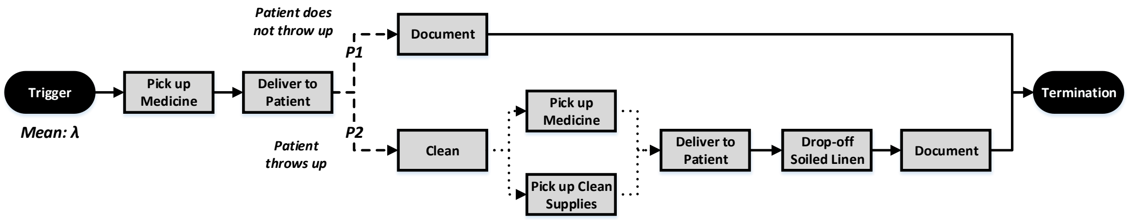

Figure 3-4: A series of activities that address an objective in a nursing scenario. These activities represent deterministic, probabilistic, and parallel dependencies between the activities.

Delivering medicine to a patient is an activity which needs to be preceded by picking up medicine from the medical supply room. In Figure 3-4 these connections are represented by solid arrows. However, the rest of the process depends on the patient's reaction. After the delivery of the medicine if the patient stays in normal health condition the nurse goes back to the nursing station for documentation. If the patient throws up, a very different chain of activities will follow. In Figure 3-4 the probabilistic connections are shown with dashed arrows. The activities after throwing up can be taken include initial cleaning, picking up new medicine and clean supplies, delivering them to the patient, dropping-off the soiled linen, and finally going to the nursing station for documentation. In the rest of this process picking up new medicine and picking up clean supplies should be done after initial cleaning and before delivering those to the patient but not in a specific order. In Figure 3-4 the dependency to more than one activity that can be executed in parallel is represented with doted arrows.

Figure 3-4 shows a typical task model in a DES. Although this model efficiently describes the process of executing activities, it poses a challenge for its integration with an ABM simulation and makes the simulation process complicated. Parallel connections, which are very common in DES models, are the source of a significant challenge for using the task models in an ABM. A nurse as a single individual cannot get engaged with more than one activity at a time if the activity locations are different. Therefore, the activity schedule in Figure 3-4 should be transformed to a sequence of activities. With respect to the dependencies between the activities, creating a linear sequence is possible by any arbitrary arrangement of parallel activities.

Since a task is independent from other tasks, it can be triggered in time intervals that follow an exponential distribution (Ross, 2014). Because of the probabilistic dependencies a simulation which is merely based on taking an exponential random number becomes more complicated and demands more complex statistical models such as a Bayesian Network for the selection of the probabilistic activity branches. Creating activity sequences is also suggested for decomposing a task with probabilistic connections into multiple sequential sub-tasks with deterministic connections.

Figure 3-5 shows that a complex task model with different types of connections between the activities can be transformed to multiple sequential task models which only include deterministic connections. The red arrows in this figure illustrate the possibilities that exist for sequentializing parallel branches in Figure 3-4. The probability for the occurrence of these sub-tasks can be easily calculated by a simple multiplication according to rules of conditional probability. Each of these sequences will be treated as independently.

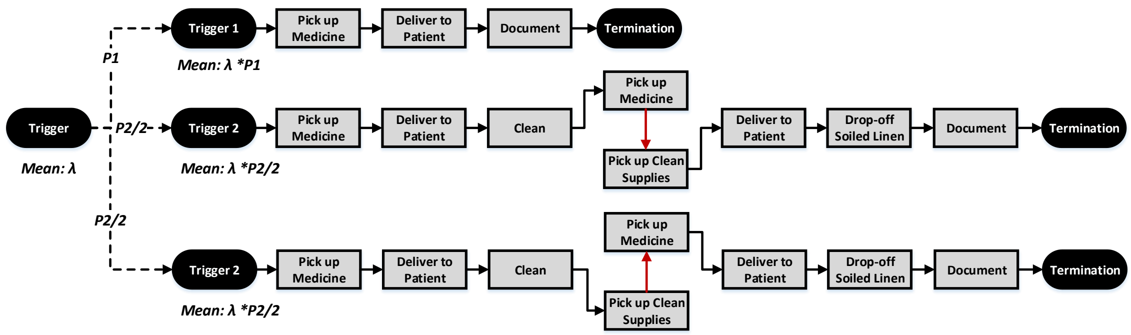

Figure 3-5: The parallel and probabilistic connections which were shown in Figure 3-4 can be removed to transform that task into three simple tasks which only include deterministic connections and are operable in an Agent-based Model (ABM).

When the nurse is engaged with a task and the workflow includes parallel connections, ideally the best sequence should be decided based on the convenience of accessibility. For example, according to the example shown in Figure 3-4, if the nurse is closer to the medical supply room compared to the clean supply room, the best sequence should include picking up medicine before picking up clean supplies. Therefore, the suggested strategy to create activity sequences out of a DES model imposes a limitation which can be improved in future studies.

After creating a linear arrangement of activities from the precedence diagram, the arrows that represented the order of the activities, not only represent the dependencies, but also indicate navigation in space from one activity area to the next one. This will be possible by means of a potential field which is embedded in each activity. The next section will explain how potential fields are generated and how they work. Figure 3-6 shows the user interface in OSM for creating and editing the activity sequences out of a collection of activities.

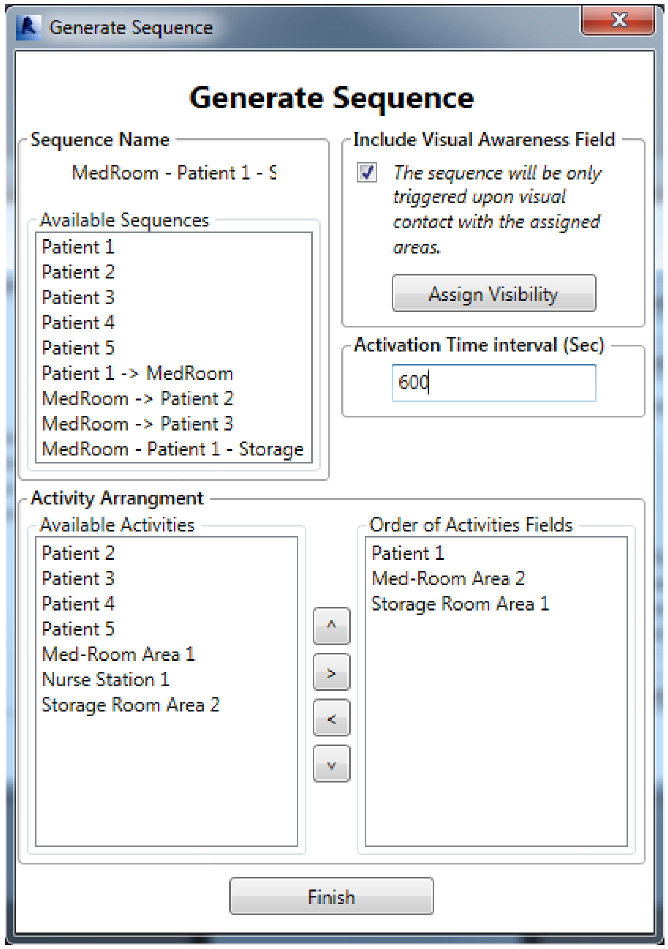

Figure 3-6: Activities can be selected from a database and arranged to create a sequence of activities that fulfill an independent objective.

3.2.3 Scenario Model

The scenario model is the core of agent model and algorithmically describes the use process for the agent. The operation of the algorithm is based on the activity and sequence models which were described so far. Therefore, in addition to the use process, a scenario includes a collection of sequences which are independent from each other and a list of stations. Table 3-3 shows the properties that a scenario includes. Since a scenario is included in the agent model, this table also represents some of the components of the agent model. The agent model includes other properties that will be explained in the next section.

Table 3-3: Attributes of the scenario model

1-	Use process algorithm
2-	A collection of independent sequences
3-	A collection of stations

In the suggested model the tasks are defined with two different types of priorities: normal vs. critical and activation time. The normal sequences are tasks which are associated with low risk levels and a nurse expects their activation. Critical sequences, on the other hand, are tasks which are associable with high risks and the nurses do not expect and cannot anticipate their occurrence. Nurses can only visually detect the existence of the critical sequences. Because of the critical conditions of patients, sometimes they are unable to communicate their need for care with the caregivers. Therefore, these sequences are associated with high risk levels. The simulation algorithm separates the normal and critical sequences and stores them in two different queues. A nurse is fully aware of the activation time and need for engagement with the sequences that are in the normal queue. On the other hand, the sequences that are in the queue of “critical sequences” are not known to the nurse. “Critical sequences” only come to the attention of a nurse after the establishment of a visual contact. When a critical sequence is detected it will be given priority to all normal sequences. However, both types of sequences have their own priority levels which are their expected occurrence time. In both queues the sequences are prioritized based on their expected occurrence time. The simulation has a time component with which the scenario proceeds. The expected occurrence time of all normal and critical sequences will be calculated using a random exponential distribution with respect to their average activation times. The state of activation of each sequence in both normal and critical queues is determined via comparing their expected occurrence time with the simulation progress time. If the simulation time passes the expected occurrence time of a sequence that sequence is considered active.

The above decision-making model is based on the framework suggested by Robinson (2004) in which the events in a DES model are classified into two categories: B (bound or booked) events and C (conditional) events. B events are state changes that are scheduled to occur at a point in time. C events, on the other hand, depend on conditions in the model. According to this classification, in the nursing scenario the tasks that do not need visual detection are B events and the tasks that require visual detection are C events which will be triggered according to the establishment of a line of sight. Robinson suggests a three-phase simulation approach that accounts for B and C event types. In the suggested framework when C events are found during the execution of known B and C events and before the termination of the simulation all of the found C events should be executed (Robinson, 2004, Page 19). According to the nature of C events in a nursing unit, when C events are found they will be given priority to all of the B events which are due.

Figure 3-7 visualizes the use process algorithm for a nurse. Upon start the algorithm loads the data models shown in Table 3-1, and creates the normal and critical sequences. Upon beginning the simulation time will be assigned to zero and two reference variables will be defined to represent the "current sequence" and the "current activity" with which the nurse is engaged. The references to these variables will not be assigned in the initialization process.

In each time-step the operations starts with a visibility test. If the visual triggers of an active critical sequence is detected, that sequence is no longer unknown. The detected critical sequences will be removed from the queue of critical sequences and added to the queue of normal sequences. In the normal sequences they will be given the highest possible priority to make sure that the critical sequences will be given priority over all normal sequences. The process continues with checking the reference for the "current sequence". If the current sequence is not assigned, the queue of normal sequences will be checked to see if the first sequence in the queue is active or not. If there is no active sequence, the nurse has no task to address and goes to the most conveniently accessible nursing station. Or, if the nurse is already in a nursing station, he or she will remain there until a sequence becomes activated. This is not the only way of accessing the nursing stations. If a task requires an action in a nursing station, the algorithm will also take the nurse to a nursing station.

If an active sequence is found, it will be set as the reference for "current sequence" and the first activity in the sequence will be set as the reference for "current activity". When the current sequence and current activity both are assigned, the simulation checks the state of engagement of the agent with the current activity. If the agent is not engaged with current activity, it will navigate to the current activity area. If the agent (i.e. nurse) is engaged with current activity and the engagement time is not finished, the agent will continue the engagement with the current activity. If the agent (i.e. nurse) is engaged with current activity and the engagement time is finished, the algorithm will update the current activity to the next activity in the current sequence. If the current sequence is finished, the references for current sequence and current activities will be cleared. The next expected occurrence time will be calculated for the sequence and it will be re-added to normal or critical queue according to its type. Finally, the time-step will be updated and checked against the simulation time. If the simulation time is passed the simulation terminates.

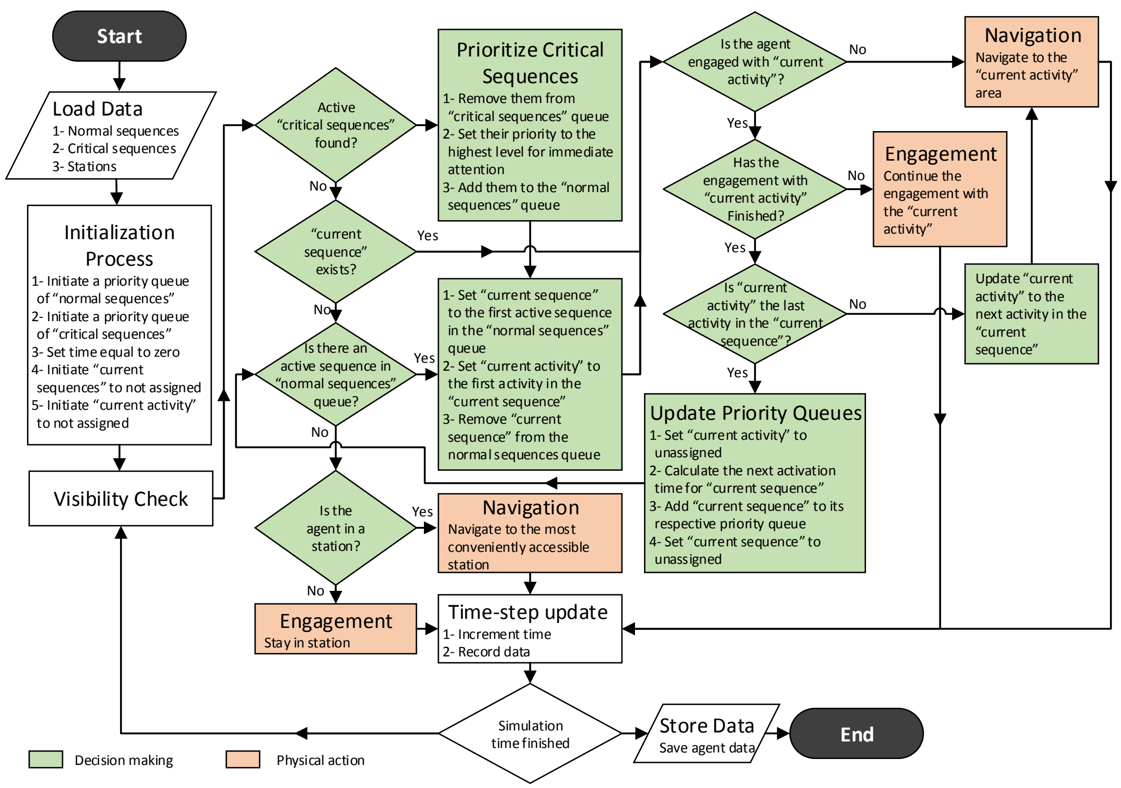

Figure 3-7: Use process algorithm.

During the performance of the scenario, the agent can collect and record the information about its engagements with the activities, its locations, and visual contacts. This information is the transcript of the simulation and can be used later to conduct queries. This process will be explained later in the evaluation section of this study. When the simulation is finished the data will be stored.

The simulation model in Figure 3-7 includes three types of processes. The parts of the algorithm which are not color-coded include the initialization, termination and the time-step update operations. The parts that represent decision making are highlighted in green. The parts of the algorithm that are highlighted in orang specify the physical actions that an agent takes. In the model suggested by this simulation it is assumed that the actions include engagement with an activity or navigation to an activity area. The level of details that the model implements for engagement with activities includes determining the physical orientation and the location of the agent. Navigation, however, has not been described yet and the next section will suggest the details of the navigation model to complete the Mandatory Occupancy Simulation Model (MOSM).

In summary, the algorithm and the data models that were explained so far combine visibility analysis, ABM and DES together. The sequences in this algorithm can be flexibly set to include any other task that is not related to caregiving to patients. While the context of this chapter is limited to nursing scenario, the model that was so far explained can be used for simulation of many other mandatory scenarios, such as the scenario of a waiter in a restaurant. Figure 3-8 shows that with this model even a patrolling sequence can be created to detect critical tasks.

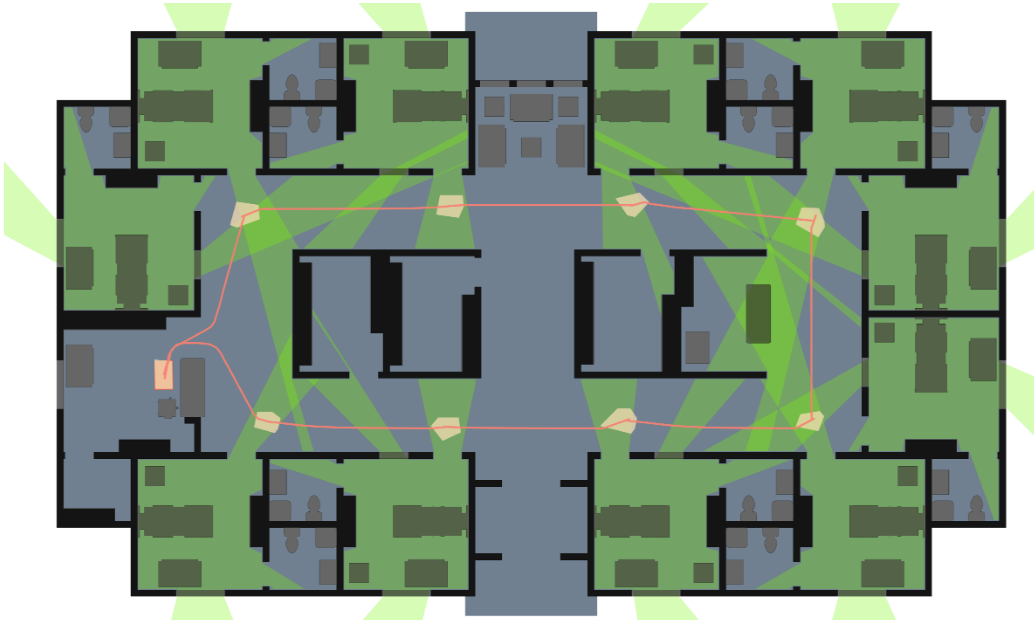

Figure 3-8: A sequence created for visually patrolling the ward.

This model has some limitations too. First, the activity model is always assigned to a location. In the emergency care department the processes of caregiving to a patient with critical health conditions starts right after the ambulance stops at the door when the patient is on a mobile bed. While most activities are generally bound to space, mobile activities demand a more flexible activity model. Also, the occupants can adjust the scenarios to maximize their convenience or efficiency when they are involved with different tasks. The described model does not include the process of adjusting the scenario.

3.3 Navigation Model

During the performance of a scenario an occupant (i.e. nurse) is required to walk to different activity areas and get engaged with different activities. The review of the literature in Chapter 2 discussed that navigation system should also be integrated within the simulation model. The use processes algorithm in Figure 3-7 specifies how the integrated model works. The navigation system should be concerned with the items which are listed in Table 3-4. The review of literature in Chapter 2 also identified social-force models as a viable candidate that preserves the continuity of the walkable floor and simulates the dynamics of walking and interacting with barriers. The inclusion of these items in the navigation system demands a physics engine capable of detecting collisions and simulating of rigid bodies. These features are independently implemented and added to MOSM software. The physics engine implementation is optimized for real-time visualization. The main modeling challenge is to create a force-based model that accounts for environmental qualities and activities.

Table 3-4: The goals of navigation model

1. Preserve the continuity of the walkable filed
2. Simulate the dynamics of walking
3. Simulate the dynamics of interacting with barriers
4. Account for the agent's unique preferences in relation to:
    4.1. Environmental variables
    4.2. Walking

Environmental variables, as described in detail in Chapter 1, are spatial data to which occupants have specific preferences and show reaction. Examples of these environmental variables include temperature, smell, sound, sun/shadow or having a line of sight to an area. All of these variables can change in each point of the walkable area and can be numerically explained. This study excludes the environmental variables that cannot be numerically explained and does not include the process of quantification. Each environmental quality has its own unique desirability. Desirability can also be attributed to walking as an activity. There is obviously a desire to make it short and there is research evidence to show that it is preferred to be straight. Given multiple paths to choose from people choose a path that is aligned with their direction of movement (Dalton, 2003). There is also evidence that people choose the fastest paths in normal walking scenarios (Helbing et al., 2002). Although the literature did not discuss the relationship between the straightest path and the fastest path, there is an obvious physical relationship between the two of them. Assuming that human body is capable of producing a force at a constant rate that accelerates the body, a path with less turns will become the fastest path too. After these clarifications about desirability, the challenge can be restated as "*finding a path that is most desirable in relation to different environmental variables, is short and is straight*". Integrating desirability with path planning and pedestrian dynamics have largely been absent in the mainstream modeling trend which was reflected in the literature. The few works that have considered the desirability as a part of their models deserve a closer look. An impressive application of desirability is in modeling the evolution of human trail systems. Each point on grassland has a level of comfort to walk on it which increases as that grass in that point retreats and that point becomes part of a trail. This comfort deteriorates with the recovery of the grass. When the grass is homogeneously distributed over the grassland, the trails start to emerge along the shortest routes because it is only the desire to minimize the length of the routes that rules path planning. What makes the paths to evolve is the attractiveness of each point on the grassland that depends on the proximity of that point to the other points of the trail system that are visible to it. The evolution continues until a balance is reached between minimal trail-construction cost (i.e. walking on grass) and maximal comfort (i.e. attraction of points and the desire to reach keep paths short) (Helbing et al., 1997). Hartmann (2010) also developed the cellular automata pedestrian dynamics model in which the distance was weighted according to the differences in spatial qualities.

The notion of cost of walking was introduced by Helbing et al. (1997) to explain discomfortness of walking on grassland. The evolution of human trail systems does not include the interactions among pedestrians. Hoogendoorn and Bovy further expanded the concept of cost in the context of the interactions of agents with each other as well as barriers in a number of studies (Hoogendoorn, 2003, Hoogendoorn and Bovy, 2003, Hoogendoorn and Bovy, 2001, Hoogendoorn and Bovy, 2004). In these studies the cost of walking denotes applying unpredicted controlling forces that are required to maintain a planned path when the interactions with other pedestrians as well as obstacles make deviation from the planned route unavoidable. The cost also includes the behavioral influences on the pedestrians. These series of studies are based on the assumption that pedestrians optimize some predicted pedestrian-specific utility function, representing a trade-off between the utility gained from performing activities at a specific location, and the predicted cost of walking subject to the physical limitations of the pedestrians and the kinematics of the pedestrian (Hoogendoorn and Bovy, 2004). Hoogendoorn and Bovy employed a differential game model based on optimal control theory to calculate the cost of control where pedestrians may or may not be aware of the walking strategy of other pedestrians (Hoogendoorn, 2003, Hoogendoorn and Bovy, 2003).

While modeling cost by Helbing et al. (1997) and Hoogendoorn and Bovy (2004) provides substantial insight for this study, they are based on assumptions that are not applicable to this study. Unlike a field of grass in which the grass recovers when the trail changes, the changes in the environmental qualities during occupancy scenario simulation time are barely significant and modeling the changes are out of the scope of this study. Also, modeling the interactions among pedestrians in a crowd is not one of the goals of creating the navigation model as discussed earlier. In this study it would also be assumed that the occupants have full awareness of the distribution of the environmental qualities in the environment. This cognitive map of the environment can be gained via visual diagnosis or previous experiences. The few studies that have considered desirability and cost in navigation models, regardless of the context of their application, support the fact that human walking trail represents a trade-off between different desires and costs. The trail does not represent the trade-off of interaction with other agents in a crowd. However, for a single agent it encapsulates the balance of desirability. This evidence will be used later for validation of both mandatory and optional navigation models.

3.3.1 Evidence-based Potential Fields

One common technique to calculate the field of forces that determine the navigation system in pedestrian dynamics is to create a potential field. A potential field is a field of scalar values. In the simplest scenario when we are only concerned with the distance to a destination, the scalar values increase as the distance from the target increases. To reach to the destination a walker takes the direction in its immediate surrounding that has the minimum value in the scalar field (Hartmann, 2010). In mathematical terms, the scalar values create a potential field and the steepest gradients of the potential field determine the destination-seeking forces. Figure 3-9 visualize a typical potential field in MOSM software using color codes and a topographic mesh with contours. This potential filed is practically not very useful because the gradient forces will push the occupant uncomfortably close to the physical barriers. To demonstrate this inefficiency of this potential field the gradient paths are visualized in Figure 3-10. A gradient path is the trajectory of interpolated gradients that start from one origin in the field and ends in the destination area of the field, which has the lowest potential. Existing crowd simulation models that are based on potential fields have a solution for this problem which can be extended to consider the impact of any environmental quality.

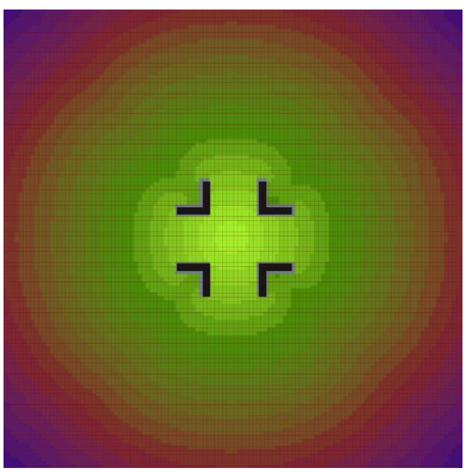

Figure 3-9-1: Visualization of a potential with color codes.

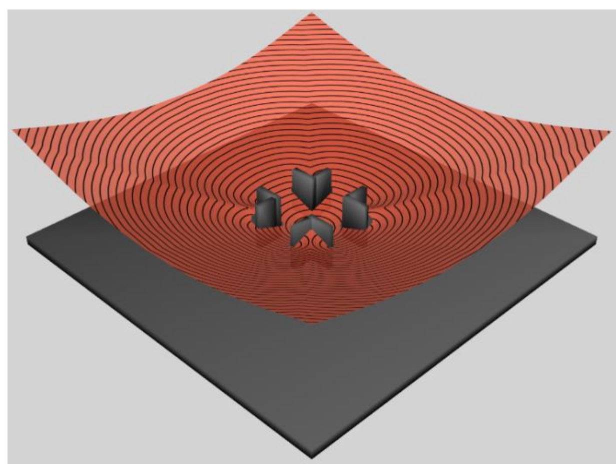

Figure 3-9-2: Visualization of a potential field with a topographic surface.

Figure 3-9: The visual representation of a potential in which the scalar values that merely represent the distance to the destination.

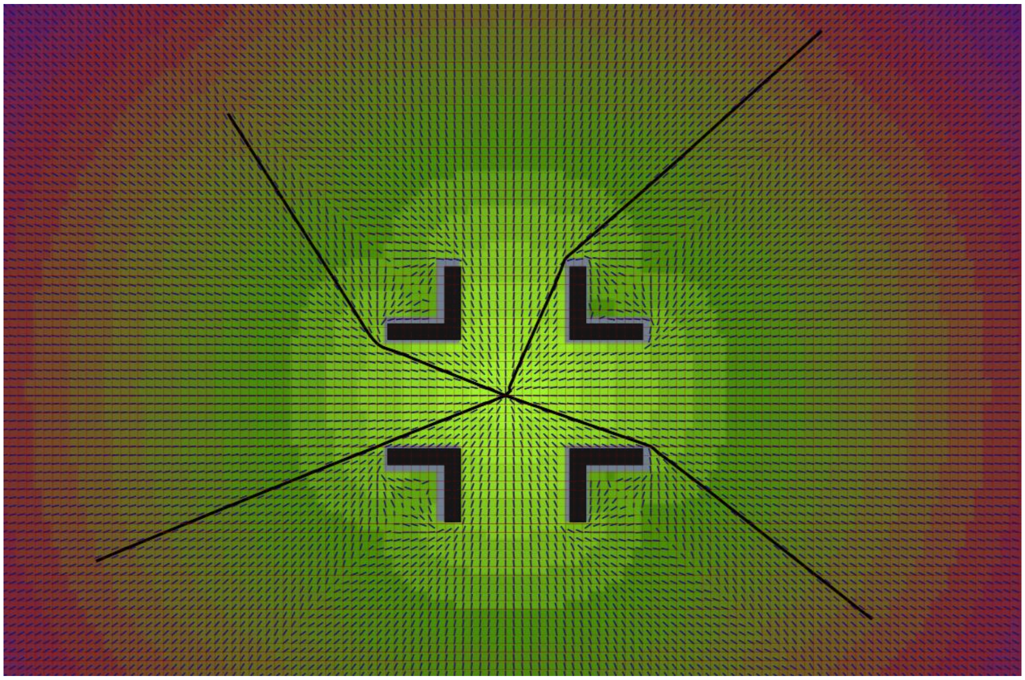

Figure 3-10: When the potential field represents the distances only, the gradient forces will push the agent to collide with barriers.

To avoid collision with barriers a repulsion force can be added to the force that is derived from the potential field. Alternatively other potential can also be added to the field. The first alternative is not very efficient at bottlenecks were the repulsion and the gradient forces that push the occupant at two opposite directions. This limitation, however, does not exist in the second alternative. Several studies that use potential fields for simulation of social or behavioral forces include mechanisms for adding the desires of keeping distances from barriers (Helbing et al., 1994) or maintaining desired speed (Helbing, 1991). We argue that the idea of aggregating potentials can be used to include the desirability of environmental variables and maintaining paths straight when walking.

Potentials are equivalent to the cost (vs. desirability) for environmental variables and will be used interchangeably in the rest of this study. For example, in Figure 3-9 higher potentials correspond to higher cost and lower desirability when the goal is to reach a destination. To make an aggregation of potentials first we need to convert environmental variables to their corresponding potentials. As discussed in Chapter 1, OSM software should include a mechanism to store environmental variables and their knowledge of desirability associated to them. The mechanism of storing data relies on a cellular grid on the floor (i.e. walkable field). The knowledge of desirability, on the other hand, is a mathematical function that is used to convert spatial data (i.e. environmental variable) to its cost. For instance, when navigating space, occupants want to keep their distance from physical barriers. Distance from physical barriers is an environmental variable like x which is always greater or equal to zero. The potential or cost associated to x that can be a mathematical function such as $f(x) = -\mathrm{x}$ for any x value, which means always increasing the distance from barriers increase desirability. This does not seem a reasonable assumption, because always after a certain distance from barriers the desirability should not change. Let's say we want the desirability to be constantly zero after certain distance, like A, and we want it to smoothly reach a maximum value, like B, at the edges of the barriers. Then we can use the formula $f(x) = B\left(1 - \sqrt{x/A}\right)^2$ for x values that are smaller than A and $f(x) = 0$ for x values that are greater than A. The second function is a Bezier curve; however, there are still numerous other ways for creating a smooth transition from maximum to minimum cost. Obviously, the cost functions cannot be arbitrary set and should always be evidence-based. Figure 3-11 illustrates the environmental variable on the layout shown in Figure 3-9 and Figure 3-10 and the costs that are derived with the two different functions which were discussed.

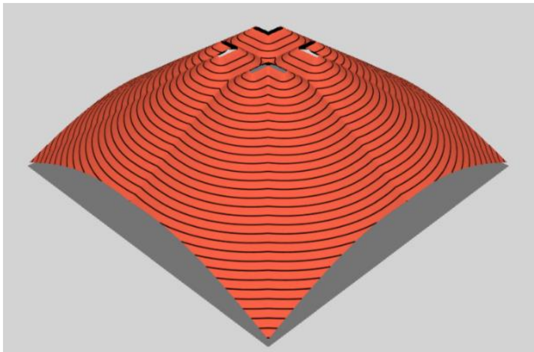

Figure 3-11-1: The cost of walking in proximity to the barriers always decreases along with the distance.

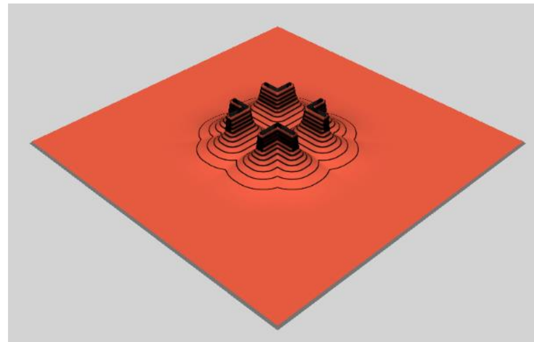

Figure 3-11-2: The cost of walking in proximity to the barriers gradually decreases and reaches its minimum at a certain distance. Then, it constantly remains zero.

Figure 3-11: Two different cost functions for an environmental variable which represents the distance from the physical barriers.

3.3.2 Integration of Static vs. Dynamics Potentials

For environmental variables which are bound to locations, a cost function can determine their corresponding potentials. This idea cannot be applied for the activity of walking length or maintaining the walking trajectory because these are based on the activity of walking which cannot be bound to space. A potential field which is merely the aggregation of the cost of different layers of environmental variables does not result in gradient forces that push an occupant to its destination. Naturally one would expect the potentials to be at their minimum at the destination area to make sure that the gradients will always direct the agent to the activity area. The potentials should grow along as the distance from the destination area increases and should also account for the static costs.

The method that will be suggested for the calculation of the potential field is based on the idea of using a floor graph. To create this graph, each cell on the walkable field will be connected to a number of its surrounding cells if the connection line does not intersect with any barrier. Figure 3-12 shows a graphic representation of this graph for a neighborhood of 5*5 cells drawn in OSM software. This graph is not used for path calculation, but serves as the basis for calculation of the potential field. Each edge in the graph can be subdivided within the cells through which it paths. The subdivision lengths of the edge are the weighing factors of the static costs of its intersecting cells (see Figure 3-13). The total cost of each edge of the graph is the summation of its length and the static costs that it includes. After replacing the static cost of the edges with the Eclidian distance between them in the graph, a simple Dijkstra algorithm (Dijkstra, 1959) can be used to calculate the potentials of the field. However, standard Dijkstra algorithm does not account for the desire to keep paths straight.

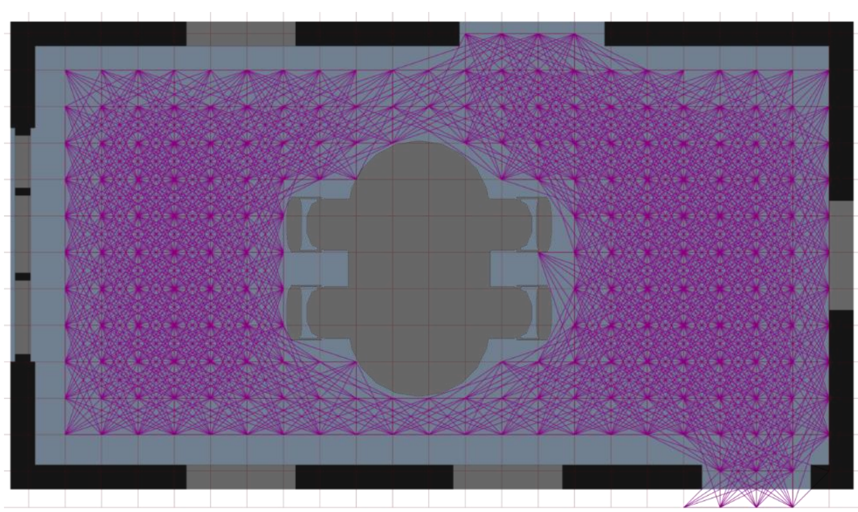

Figure 3-12: A graph on the floor in which each cell on the floor is connected to each cell in its 5*5 neighborhood range that is visible to it.

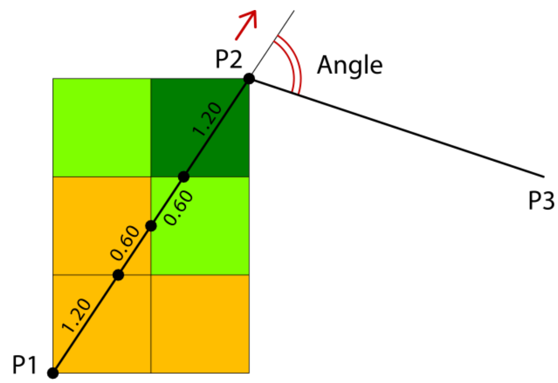

Figure 3-13: The static cost of edge from vertex P1 to P2 can be calculated based on the static costs (i.e. potentials) in the cellular floor.

A new feature can be added to the Dijkstra algorithm to account for the angular deviation of the paths. Each graph vertex includes a scalar value to represent its corresponding potential and a normalized 2D vector. Initially the potential values for the origin vertices are set to zero and the potentials for the rest of the nodes are set to positive infinity. The direction vectors are not assigned to any of the vertices at the initial phase. The origin vertices are stored in a binary heap to keep them dynamically sorted based on their potentials with an efficient computational cost (i.e. log(n)). In each iteration the vertex with the lowest potential, like P_2 in Figure 3-13, will be removed from the heap and stored in a collection which is called “labeled.” Next, the potentials for accessing the vertices that are connected to P_2 but are not labeled will be updated and all of them will be added to the binary heap. For example, we can assume that P_2 has a vector assigned to it that points to P_1, which is a labeled vertex. P_3 is also a connection of P_2 in the graph that is not included in the labeled collection. The cost of accessing P_3 from P_2 is the static cost of the P_2P_3 edge plus the cost of the angle between the normal vector of P_2, which is illustrated with a red arrow, and the normalized direction of P_2P_3 vector. The new potential of $P_3$is the potential of P_2 plus the cost of accessing P_3 from P_2. If the new potential of P_3 is smaller than its existing potential, its potential will be updated. Along with updating the potential of P_3 its direction vector will also be updated to the normalized direction of P_2P_3 vector. This process continues until the heap becomes empty.

3.3.3 Discretization and Rasterization Effects

With the modeling strategies that were explained both the dynamic and static costs can be integrated into one potential field. This approach introduces two limitations which are the rasterization effect of the cellular structure on a continuous floor, and the discretization of directions of movement with the predetermined directions that are imposed by a graph. To avoid the rasterization effect, the size of the cells in the cellular structure should be reasonably chosen. After choosing the appropriate size, a 2D Lagrange interpolation model will be used for interpolation and differentiation of the potential field. Lagrange interpolation was preferred over other interpolation types, such as NURBS, B-Spline and Bezier models, because the original data points will be kept within the data after interpolation.

The angular discretization effect can be enhanced with increasing the neighborhood range of the graph. This strategy also complies with the order of complexity of the Dijkstra algorithm in which adding to the number of edges only linearly increases the cost of computation (Fredman and Tarjan, 1987). As shown in Figure 3-14 when creating a neighborhood some of the edges that are connected to a vertex will follow the same directions. Among the connections with the same direction, we can keep the shortest connections and remove the others. This will significantly increase the computational performance while having no effect on both static and dynamic cost calculation. Figure 3-14 shows that if a neighborhood's range includes 5 cells, this technique will remove 37.5% of edges. This percentage will increase for larger neighborhood ranges (e.g. 41.25% for neighborhood rage of 9). Through this method a neighborhood template will be developed. In this template the weighting factors that are defined in relation to the cells and edges are also loaded. In fact, the graph which was illustrated in Figure 3-12 is only visualized, but never created. The creation of this graph is computationally expensive because of numerous collision tests that it includes. Storing this graph in the memory can also consume significant memory resources according to its resolution. A neighborhood template that includes all of the weighting factors, can serve the same purpose with no memory cost. This neighborhood template is designed and calculated based on the relative indices of the cells and can easily be translated to any cell origin. Even it would not be needed to check the collisions of the edges and the barriers. All of the cells inside the barriers will be assumed to have the static potential of positive infinity. Using all of these techniques will decrease the order of computational complexity of increasing the size of the neighborhood range.

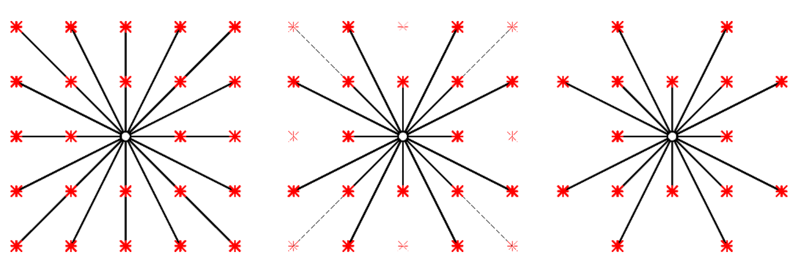

Figure 3-14: Neighborhoods can be simplified by removing the overlaying edges and leaving the shortest ones.

Even after employing Lagrange interpolation, the problem of rasterization exists. Increasing the range of the neighborhood template also cannot fully resolve the effects of discretization particularly because the distribution of the angles in the neighborhood size can never be unbiased when a cellular structure is used. However, the effect of these limitations will become much more reasonable. To further remove the discretization and rasterization effects, OSM software includes a mechanism for applying a Gaussian filter on spatial data. The Gaussian filter can also be used to change the cost or desirability of one point in space based on the desirability of its surrounding. For these types of applications, the range of a Gaussian filter's affection should be limited to the immediate surroundings that are visible and perceivable. Normal Gaussian filters that are used in image processing and filtering do not consider the visibility effects. For this reason OSM has a special filtering mechanism in which the filter will be clipped by the field of visibility (i.e. isovist) of each point. Figure 3-15 shows how this type of filter does not transmit the changes from one side of a wall to the other side which is not visible.

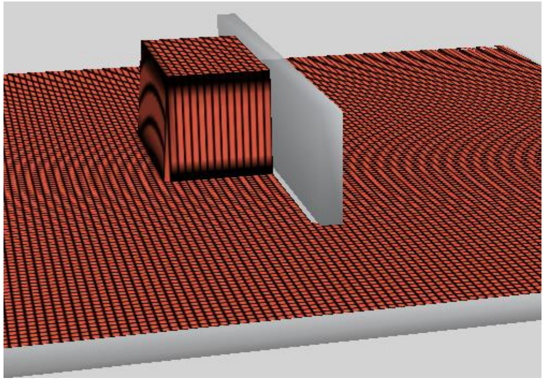

Figure 3-15-1: Original Data

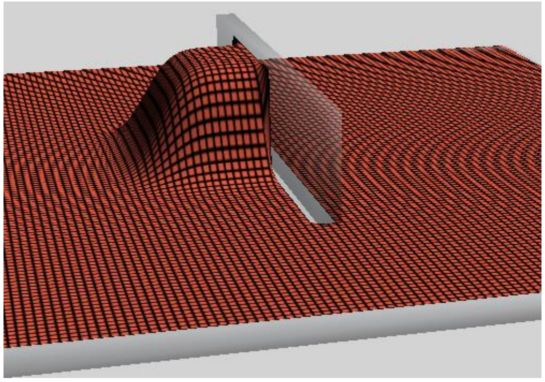

Figure 3-15-2: Filtered Data

Figure 3-15: Applying a Gaussian filter that is clipped by the isovists will limit the changes of data to one side of a wall.

3.3.4 Trade-off between Different Layers of Desirability

This section demonstrates the effects of adding dynamic and static costs to potential fields. Figure 3-16-1 and Figure 3-17-1 both illustrate potential fields which have been generated based on two desires: being away from the wall as a barrier and reaching the destination. The potential field which is illustrated in Figure 3-16-2 is also affected by the desire to keep the paths straight in addition to the previous desires. This desire is dynamic in nature. On the other hand, the potential field which is illustrated in Figure 3-17-2 is influenced by the static desirability which is color-coded in Figure 3-17-3. The gradient paths shown in Figure 3-16-3 illustrate the trajectory of forces from the same origin to the same destination. A comparison between the two trajectories shows how an agent who desires to keep its path straight will trade it for the length of the path. Similarly, the gradient paths in Figure 3-17-3 show how the length of the path will be traded for the desirability of the color-coded static quality. The desirable quality which is color-coded in green attracts the agent whereas the undesirable quality which is color-coded in red and dark blue hues repels the agent.

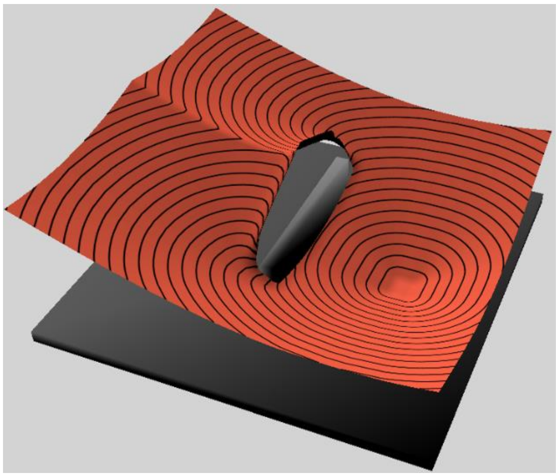

Figure 3-16-1: This potential field is influenced by the desires to reach the destination and being away from the barriers.

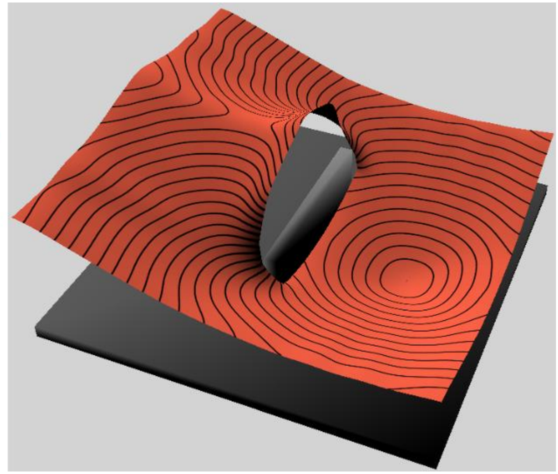

Figure 3-16-2: This potential field is influenced by the desires to reach the destination, being away from the barriers and keeping the path straight.

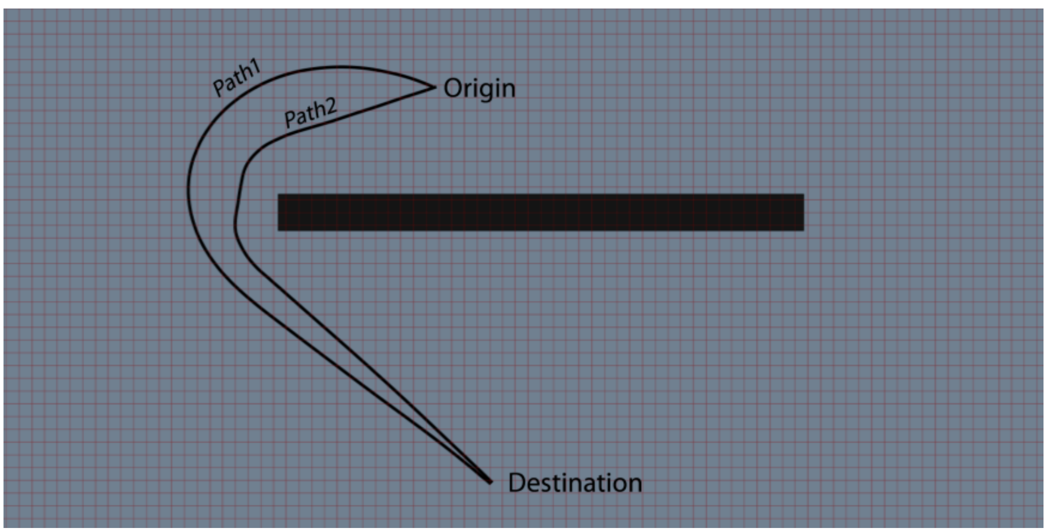

Figure 3-16-3: The force trajectories in the two potential fields.

Figure 3-16: This figure illustrates the effect of adding the desire to keep paths straight to a potential field.

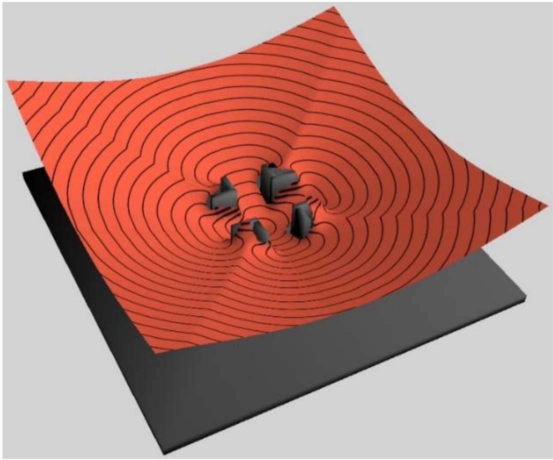

Figure 3-17-1: This potential field is influenced by the desires to reach the destination and being away from the barriers.

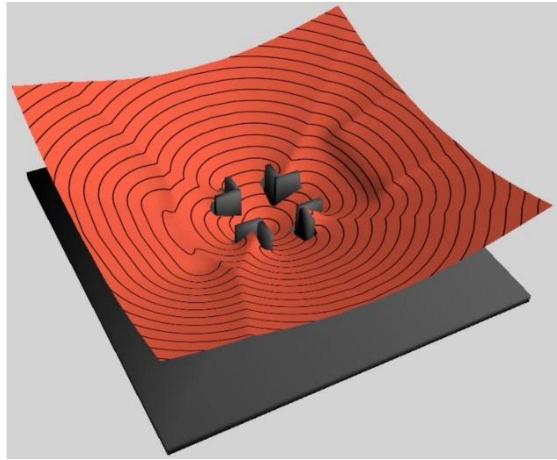

Figure 3-17-2: This potential field is influenced by the desires to reach the destination, being away from the barriers and the quality which is color-coded in Figure 3-17-3.

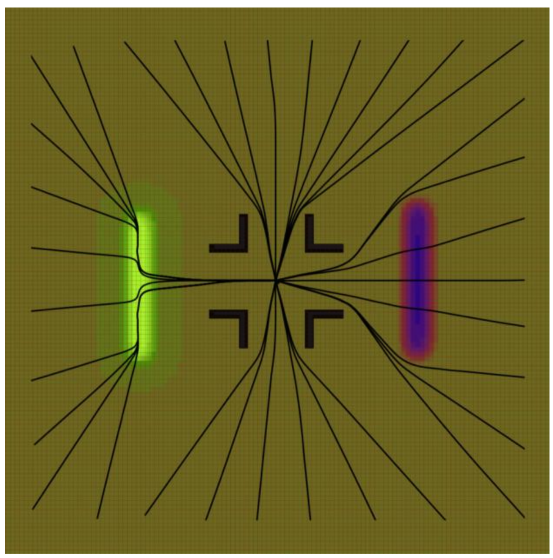

Figure 3-17-3: The trajectory of the forces that are influenced by the color-coded desirability.

Figure 3-17: This figure shows the effect of adding a generic static quality to the potential field.

By now the nature of potential fields and the reason for their inclusion in the activity model has become clear. When the goal is to simulate the interactions among the members of a crowd, the potential field needs to be dynamically updated. The normal occupancy scenario is not concerned with the interactions among the members of a crowd. Therefore, a potential field can be used for navigating the space to reach an activity area. To avoid collisions between different agents and barriers, which may happen in rare cases, repulsion forces are directly added to the force which is derived from a potential field through differentiation. Figure 3-18 shows the dialog window for creating an activity that includes the required information for the generation of the potential fields. Figure 3-19 shows the potential that belongs to the activity shown in Figure 3-1. This potential field is influenced by the static quality which is illustrated in Figure 3-20. Figure 3-20 also shows the impact of the generic static quality on the formation of the force trajectories. It shows that a quality can also serve as a permeable barrier. It should be noted that the paths which are illustrated in Figure 3-20, Figure 3-17-3 and Figure 3-16-3 are not the walking trails, but rather the force trajectories of a continuous gradient field. To find its way to the activity area an agent acts like a ball that rolls down the topography of the potential field under the force of gravity.

The potential field model which was so far explained, suggests a mechanism to find the most desirable paths as an alternative for the shortest or the fastest paths. The suggested model for integrating qualities in the potential fields applies force to the agents which changes their velocities in accordance to the qualities that they experience in their immediate surroundings. The magnitude of the steepest gradient vector in a potential field shows the magnitude of the destination seeking force which is applied to an agent. A comparison between the contours in Figure 3-19 and Figure 3-20 shows that when the cost of the color-coded quality increases, the slope of the potential field also increases. The closer topographic contours indicate that the destination seeking force which is applied to the agent also increases to let the agent rapidly pass this undesirable area. On the contrary, when the quality is desirable the slope decreases and the magnitude of the destination seeking force decreases, which lets the agent to spend more time in desirable areas.

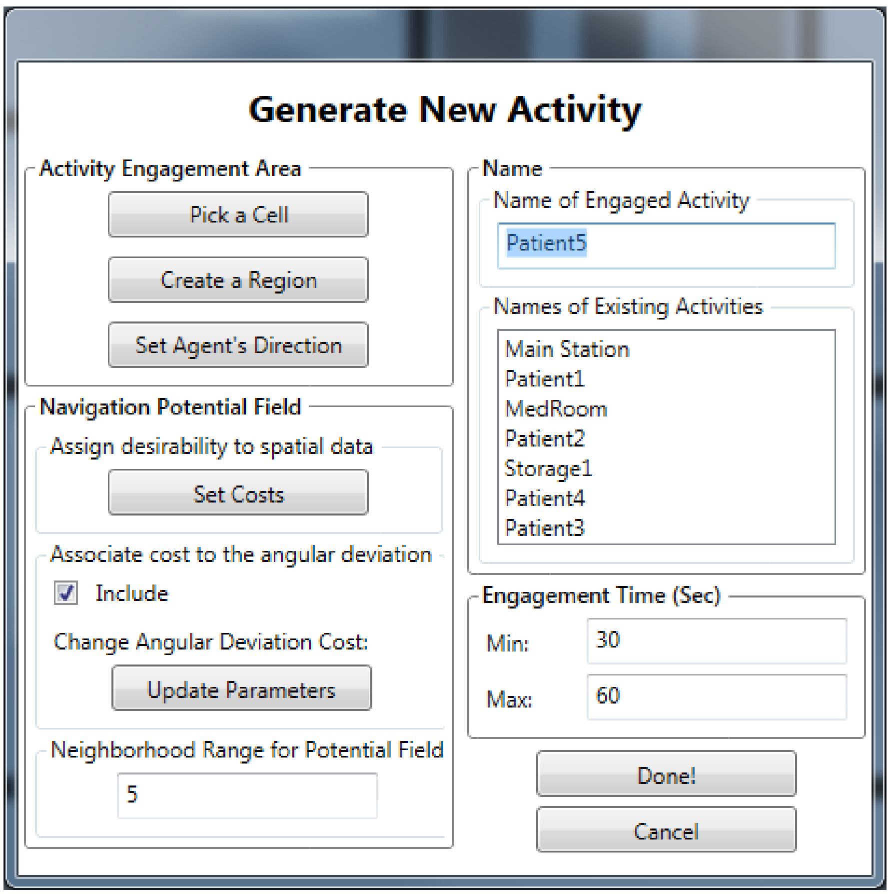

Figure 3-18: Activity generation dialog in OSM software.

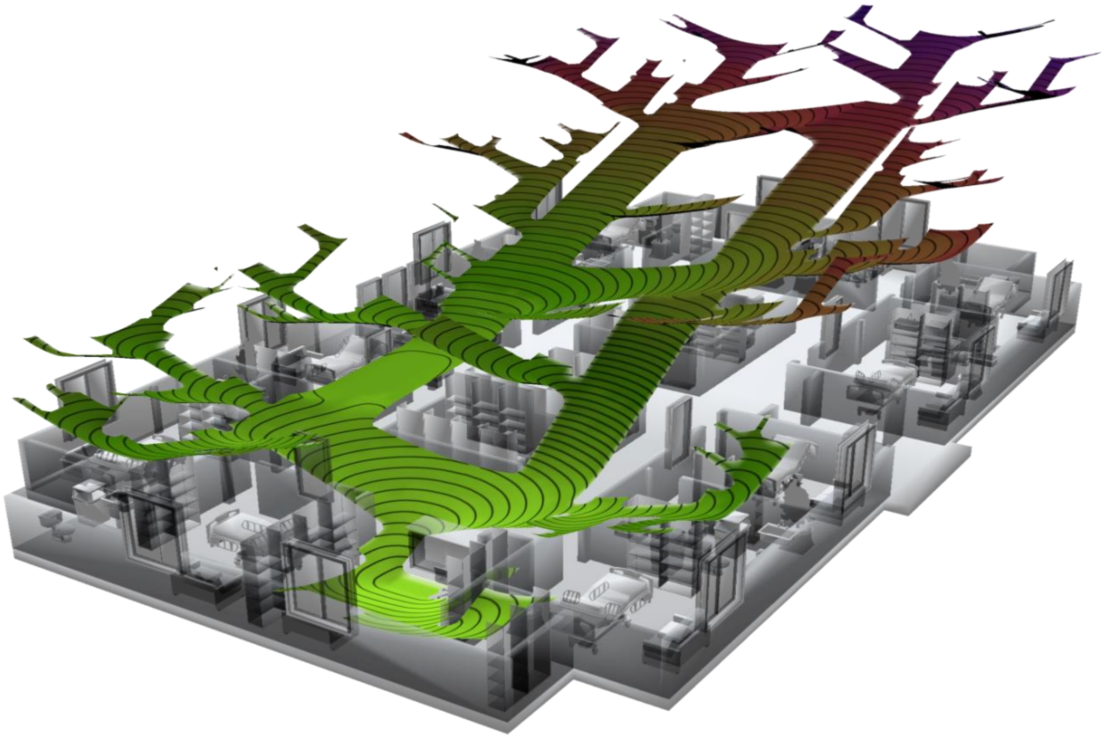

Figure 3-19: The topographic presentation of the potential field for the activity shown in Figure 3-1.

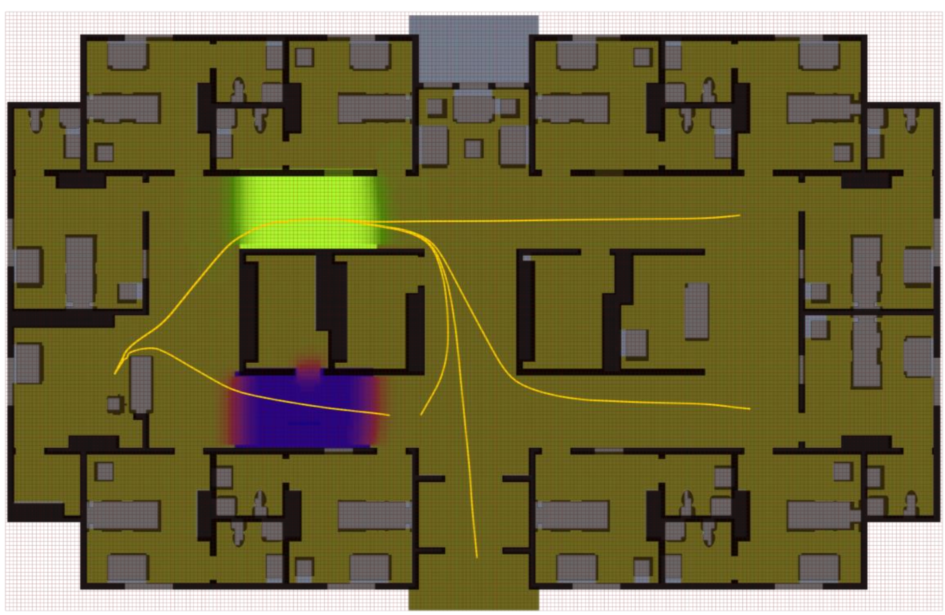

Figure 3-20: Qualities can serve as attractions or permeable barriers.

3.3.5 *Parameterized Potential Field*

The mechanism for the calculation of the potential fields which was explained in the previous sections was based on two assumptions which are not always true. The first assumption is that the existing research evidence can be used to derive cost functions which can numerically determine the desirability of the data. Research outcomes do not often numerically explain the desirability. Some studies may even be limited to supporting the existence of a relationship. For example, Helbing et al. (1994) used a potential field in which the potential of proximity to the barriers monotonically changes, similar to Figure 3-11-1 which employed $f(x) = -$x as the cost function. A close look at the models of pedestrian dynamics shows that almost all of them make numerous assumptions that are based on expert opinions. Like any other hypothesis, the presumptive cost functions will be acceptable if the models successfully reproduce the observed phenomena. OSM is also based on the same principle. The second assumption was that the potentials of different layers do not interact and can simply be added together.

The cost functions in OSM software are made parametric. Parameters are variables that include a name, value as well as lower and upper inclusive bounds. The users of the OSM software can define new parameter and integrate them with cost functions. Parameterization allows for fine-tuning and altering the cost functions. Parameters are defined globally in the scope of OSM software. Figure 3-21 shows the "Parameter Setting" dialog window in OSM software. Different cost functions can share the same parameters. Through sharing parameters dependencies among the cost calculation methods can be defined. For example, A and B are two parameters in the cost function of $f(x) =$

$B\left(1-\sqrt{x/A}\right)^2$ which was used in Figure 3-11-2 to calculate the potentials. Figure 3-21 and Figure 3-22 show how this function can be parameterized and visualized in OSM.

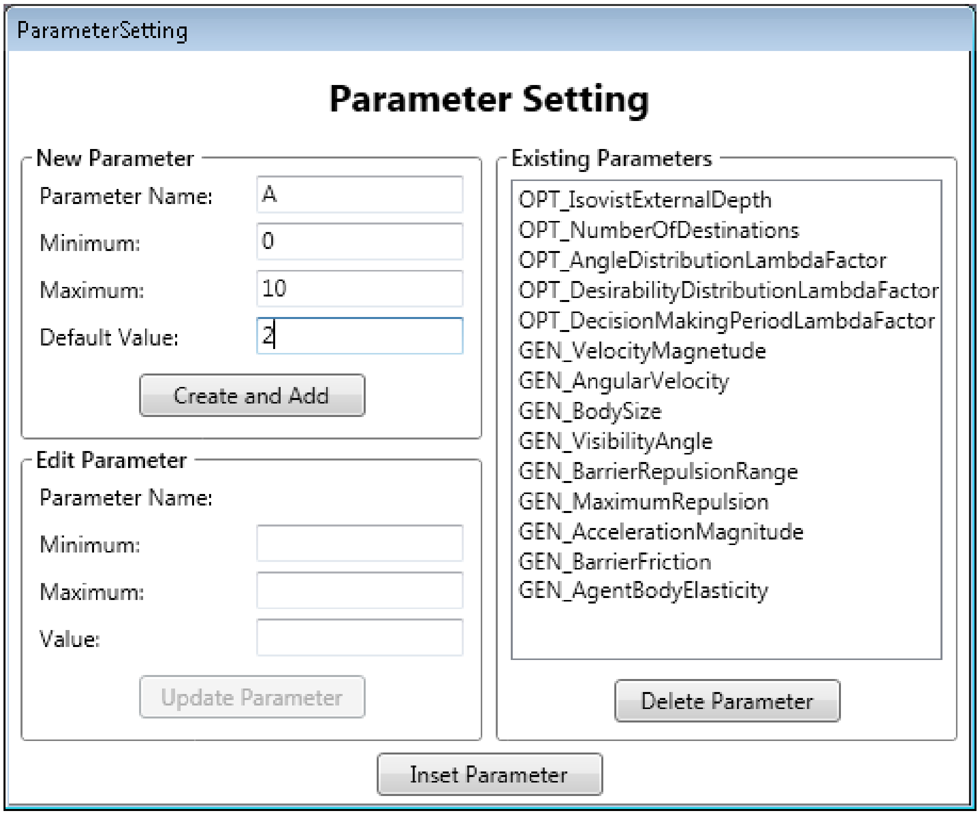

Figure 3-21: Parameter setting dialog in OSM software.

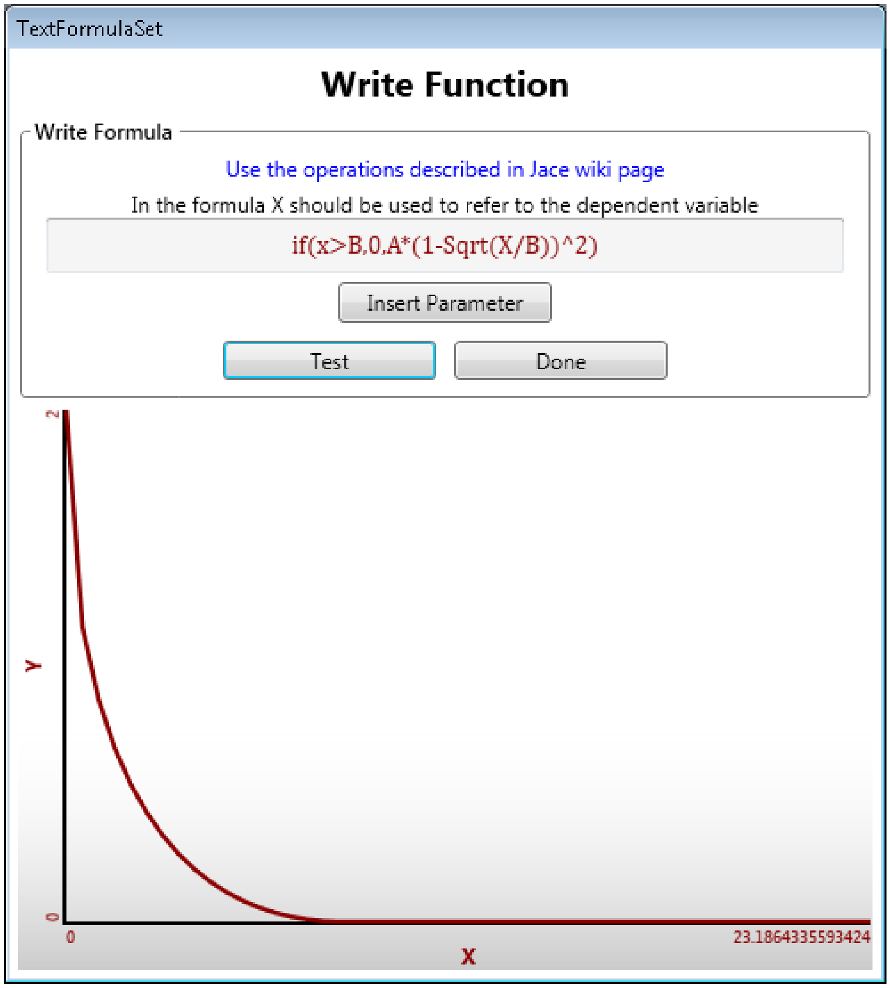

Figure 3-22: A cost function in OSM that includes parameters A and B.

To create a navigation model that accounts for the different layers of desirability and the interactions among them a data model is needed to represent desirability.

3.4 Physical Model of Agent

An agent in the suggested simulation model represents the nurse and acts to perform nursing tasks which are assigned to it. The scenario model which was algorithmically illustrated in Figure 3-7 is encoded in the agent model and determines its decision making process and its physical actions. The previous sections described both the scenario and the navigation system. This section describes the physical and visual representation of an agent which are shared between Mandatory occupancy Scenario Model (MOSM) and Optional Occupancy Scenario Model (OOSM) that will be discussed in the next chapter. The implementation details related to the agent model in OSM are discussed in Section 6.6 of the appendix. These details include the common data structures between all agent models in OSM and a hierarchy of inheritance from which different agent models in OOSM and MOSM are derived. Table 3-5 represents the physical attributes of the agent model which includes body size, safety buffer, visibility angle, location, velocity, angular velocity, direction, and acceleration. The agent also includes a collision analyzer system that keeps track of the closest barrier to the agent, the distance to the closest barrier, and the repulsive force that pushes the agent away from the barriers. Some of these attributes are parametrically controlled and can be randomized within the range of the pertinent parameter's variability. The rest of the attributes dynamically changes and are not parameterized.

Table 3-5: Physical attributes if the agent model.

	Attributes	*Parametrically Controlled*
1-	Body Size	✓
2-	Body Mass	✓
3-	Body Elasticity	✓
4-	Safety Buffer Circle	✓
5-	Visibility Angle	✓
6-	Location	×
7-	Direction	×
8-	Velocity	×

Table 3-5 Continued

	Attributes	*Parametrically Controlled*
9-	Maximum Velocity Magnitude	✓
10-	Angular Velocity	✓
11-	Acceleration	×
12-	Collision Analyzer	×

Two types of forces are applied on the agent: the navigation forces and the repulsion forces. The navigation forces are forces that push the agent to its destination, which according to our model is the steepest gradient of the potential field. The repulsion forces are applicable when the agent gets too close to physical barriers or other agents and there is a chance for collision. Since the potential field model which was described before includes the desirability to be away from the barriers, the navigation forces will never push the agents to collide with barriers. However, since the potential field does not account for the velocity of the agents, collisions are likely to occur when the agents walk with high speed and cannot control the velocity to maneuver around the barriers. Whether repulsion forces exist or not the agent always tries to orient itself along with the navigation force. Changes in navigation forces can be abrupt, but the rate of changes in an agent's direction is limited to its ability to physically make a turn, which is the angular velocity of an agent. Figure 3-23 shows the how an agent's direction can be updated according to the direction of the navigation force and angular velocity from A_1 to A_2 in two consecutive time-steps.

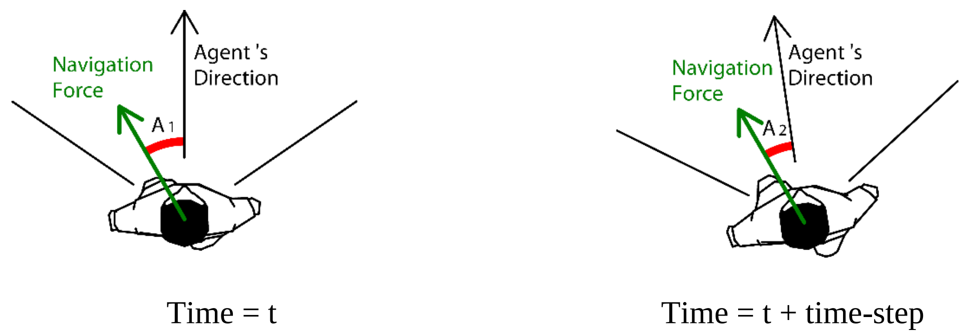

Figure 3-23: The agent orients itself to the navigation force which is derived from the potential field.

The simulation will update its state every 16.66 milliseconds (e.g. 60 Hz screen update frequency). At each time-step first the forces that are derived from an activity's potential field and the forces that repel the agent from other agents and the closest barrier are calculated, summoned and put into action. These forces will update the physical attributes of the agent. If collisions are detected, the physical attributes will be updated at collision points and the remainder of the time-step after collision will be calculated and recursively used to update the state. After collision, when calculating the collision reaction forces, the impact of an agent's body elasticity and the friction of the barriers will be considered. During the simulation, if the agent's velocity magnitude exceeds the maximum velocity magnitude, it will be reduced to the maximum allowed magnitude.

The described method is based on Euler forward integration method which is exposed to cumulative numerical errors. If the accuracy of the agent's location and direction is critical, the simulation model allows for using Runge–Kutta numeric integration method (RK4) as an alternative to Euler forward integration method to enhance the accuracy of the numeric integration.

Analyzing collisions is handled with the help of the cellular structure which covers the floor. Upon loading the model a reference to the closest barrier will be stored in each cell. Finding the closest barrier is then a search between the four surrounding cells that include the location of the agent. This strategy makes collision detection completely scalable and efficient. The repulsion forces will be applied only if the trajectory of the repulsion force is within the viewshed of an agent. In other words, the agent will never be repelled by forces or barriers that are not visible to it such as a wall which is behind an agent.

Figure 3-24 represents the visual representation of an agent in OSM software. The real-time visualization of the occupancy scenario visualizes an agent's body and the kinetics of walking (see state 2 in Figure 3-24). The real-time visualization also includes options for visualizing an agent's safety buffer, cone of vision, closest barrier, the trajectory of the repulsive forces, assigned color-codes, and the line of sight to visual targets if a line of sight to the visual targets exist and fits within the agent's viewshed. Figure 3-24 visualizes an agent in states 2 and 3 with all possible visualization options. The visibility target area is highlighted in yellow. The green area on the floor shows the area of the walkable field in which having a line of sight to the visual targets is possible. However, only in state 3 the line of sight fits within the agent's cone of vision and the target can be considered visible.

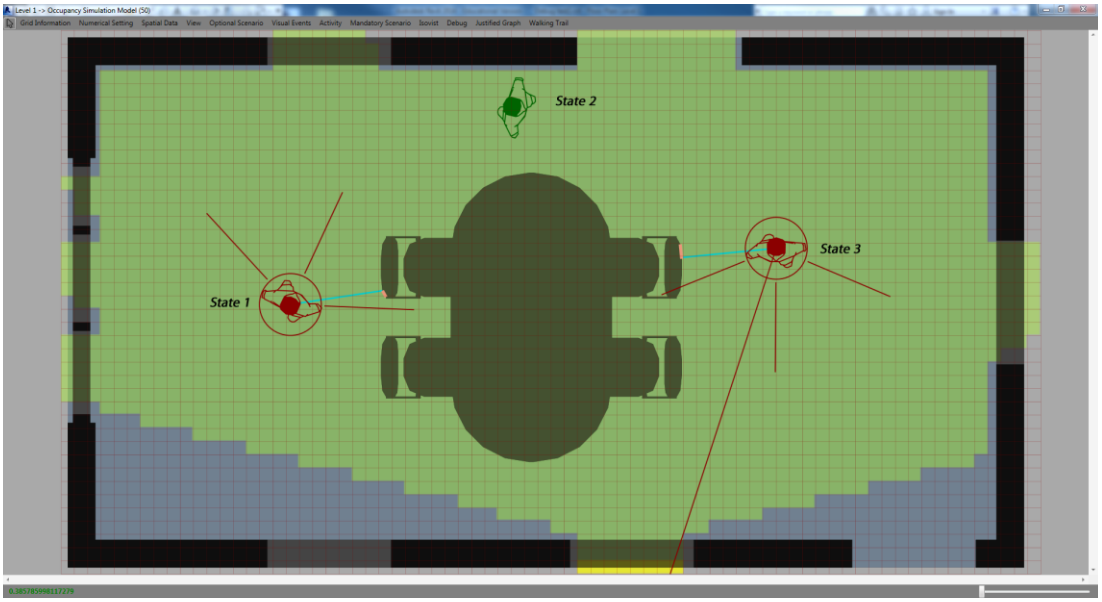

Figure 3-24: Visualization of an agent in OSM software.

3.5 Validation

This section provides a model for training the agents in a way that they can reproduce the walking trail of a human in a real building. This study does not include observation to record the walking trail of nurses. However, the format of the required data which can be used for training will be explained. This section also concludes the simulation framework.

3.5.1 Trail Model

Trail model is the basis of the training process. Observations often include information at discrete time intervals. The trail model is a parametric interpolation model in which the time parameter determines the location, velocity and the direction of the agent along the trail. The trail model is created from the observed trail data which contains records of an agent's physicals states and is stored in a file. The physical state is not limited to the location of the agent. It also includes the direction and velocity of an agent which are recorded at a given time. The trail data file includes seven numbers for each physical state from which the six first numbers determine the location, velocity, and direction vectors and the last number represents the time when the physical state was recorded. To estimate the physical states at any time in-between the recorded states a cubic Lagrange polynomial interpolation is used. This interpolation type is chosen to keep the original physical states intact after interpolation. Figure 3-25-1 shows a graphic representation of an interpolated trail. In this figure the green polygon connects the locations of the agents in the recorded trail data file, the red curve represents the interpolated trail, and the golden line segments are the normalized interpolated directions of the agent. For clarity of visualization the velocity vectors are not visualized but they also exist in all of the interpolated physical states. While the trail data file only includes information about five physical sates, the trail model includes thirteen states which were captured through interpolation at equal time intervals. Since an interpolation spline is not necessarily included in the convex hull of the data points, a strategy is needed to limit the data points to the convex hall while keeping the trail differentiable. OSM software also allows for flexibly balancing the physical states between cubic interpolation and the original trail location Figure 3-25-2.

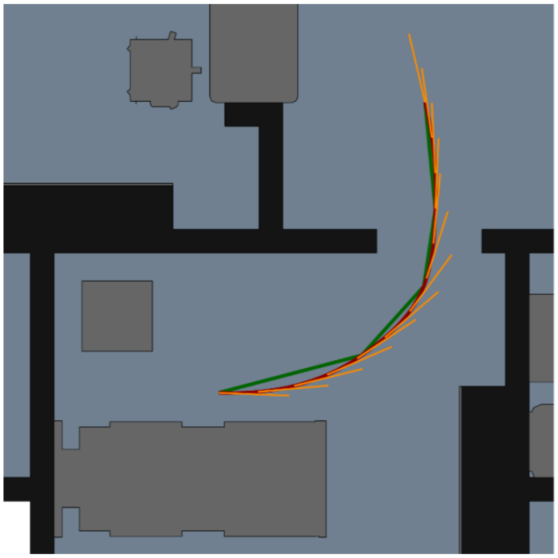

Figure 3-25-1: Interpolation of physical states across time using a cubic Lagrange polynomial interpolation.

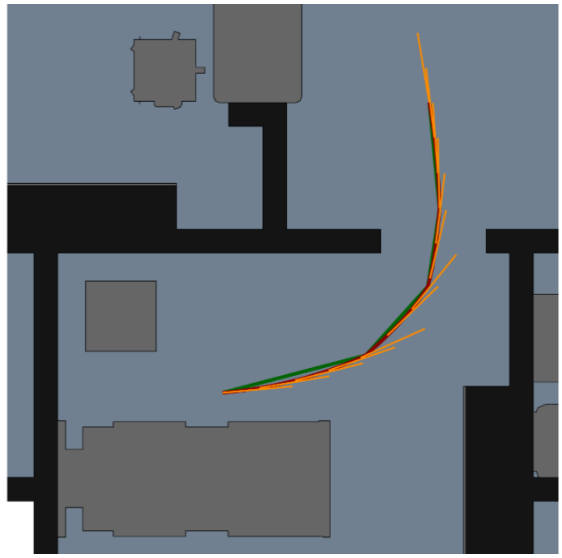

Figure 3-25-2: Balancing the states between cubic interpolation and original data

Figure 3-25: Visual representation of an agent's trail data in OSM software.

3.5.2 Fine-tuning Parameters

As discussed in chapter 2, previous studies indicate that a walking trail represents the trade-off between different desires of an agent (Helbing et al., 1997, Hoogendoorn, 2003). An agent's choices of navigation in the simulation model that was described so far depends both on the algorithm and the parameter values that are involved in the generation of the potential fields, barrier repulsive forces, and an agent's physical attributes. The only parts of the simulation model that can be subject to changes are the parameters that are involved and their values. Updating a parameter can influence the cost functions of the spatial data which are included in the generation of the potential field, the agent's physical attributes and the barrier repulsion forces. Therefore, our goal for training can be set to fine-tune the parameter values by which a recorded human trail can be reproduced. As the scenario model described, an agent may change its destination if a new task with higher priority comes to its attention. Therefore, different parts of a recorded trail may belong to potential fields that pertain to different destinations. The trail data which will be used in the training process, does not account for changes in the destination. The recorded data should include a nurse's physical states in a trip to a known destination until that nurse reaches the destination area and stops there to engage with an activity.

The idea of fine-tuning the parameters is based on using a Simulated Annealing (SE) algorithm to evolve the parameters values. The application of this idea requires measuring the fitness of any parameter setting against the trail model. The red path in Figure 3-26 shows a trail model which can be constructed from a real nurse's observed states traveling from a patient's bedside to the nursing station. The color-coded background shows a potential field and the dark path shows the path which was generated with respect to this potential field and the physical attributes of the agent. The differences between these paths are not limited to the locations of the agent, but also include the differences in time, direction and velocity. The fitness model must account for all of the differences. The solution that we propose is based on subdividing the trail model at equal time intervals, like T. This subdivision will result in an array of physical states which are expected to be reproduced by the ideal setting of the parameters. The agent will be released at the beginning of each sub-trail with the physical state that is captured from the trail model for the time interval of T. When the parameters are set correctly the agent should be in the next expected physical state in the array. If the agent is not in the expected physical state, the difference between the agent's physical state and the expected physical state can be calculated. All of the aspects of physical states are 2D vectors and the squared of the difference between similar vector components can be used as fitness residuals between two different states. Therefore, the objective of the SE algorithm is to minimize the sum of the fitness residuals along the path.

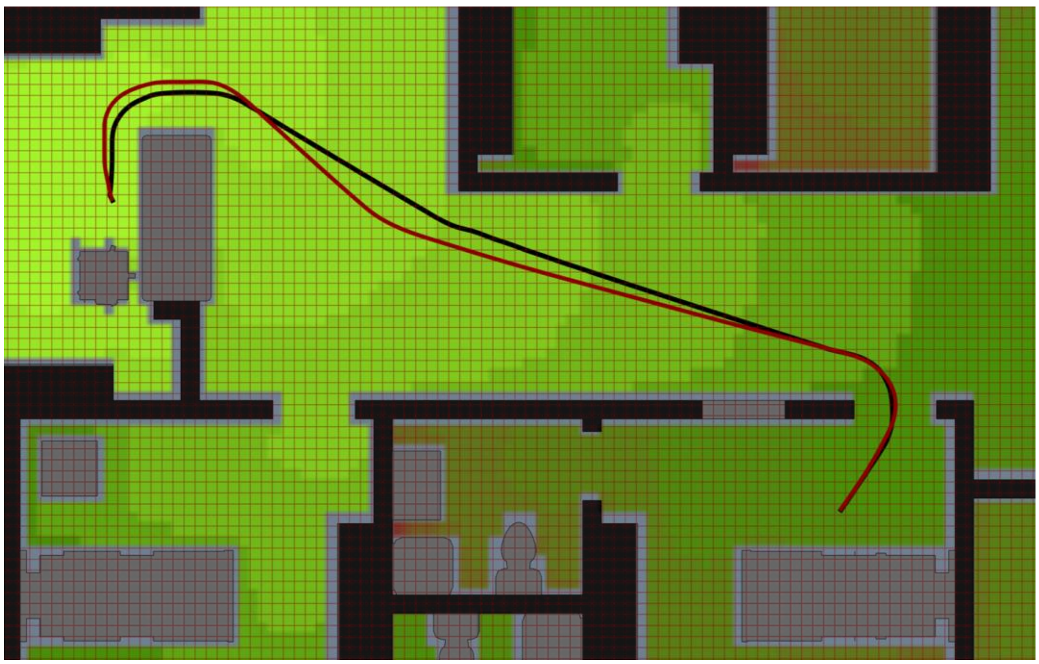

Figure 3-26: The red trail is a recorded trail and the dark trail is generated with an arbitrary setting of parameters.

All of the parameters that are involved in the spatial data cost functions will be automatically selected and included in the fine-tuning process. The parameters that determine barrier repulsion and agent's physical attributes can be also added to this list. The fine-tuning process is dynamically visualized in the OSM software. Figure 3-27 shows a screenshot of the annealing process in which the maximum energy was set to 15. The SE algorithm was set to minimize the maximum energy to zero in 10000 iterations.

This picture illustrates the annealing process after 3000 iterations. The dark-blue line segments show the best fitness values which were found until iteration 3000.

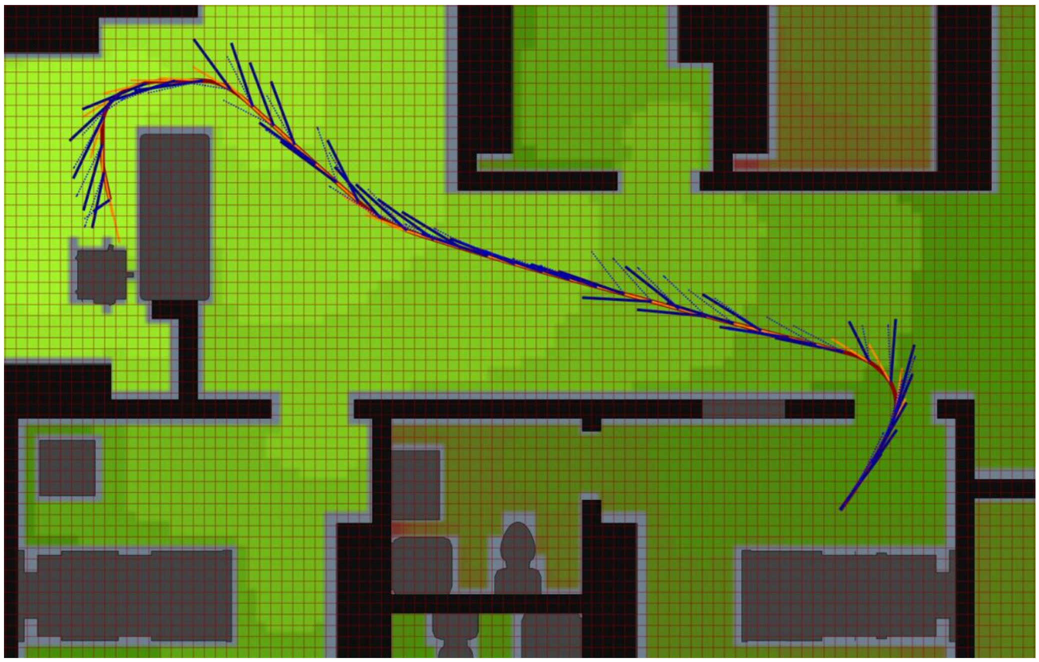

Figure 3-27: A screenshot of the parameter fine-tuning process with Simulated Annealing algorithm.

After fine-tuning of the parameters the agent is expected to mimic the walking behavior of the nurses in a real building. This expectation, however, has some limitations. The process of fine-tuning can be subject to over-fitting. With increasing the number of parameters, the chances for finding a well-fitted parameter setting increases. However, using an excessive number of parameters also increases the degree of freedom of the model which adverses the predictive value of the model. Currently the training process only includes the extraction of a model and does not include strategies to avoid over-fitting.

3.6 Case Study

By now the description of the simulation model is completed. In this section the simulation model will be put in use in a case-study. The case-study is a ward which was illustrated before. This ward includes eleven single patient rooms, two medical supply rooms and a laundry room (see Figure 3-28). This case-study will be used for evaluation of the nursing scenario in an acute care unit. In addition to the building model, an instance of a scenario model is also needed for simulation. Since this study is by nature a model-based research for the demonstration of the model, a scenario will be fabricated. The next two subsections will support some of the choices which are made in the design of the scenario from the literature. However, many of the choices are made arbitrarily for the purpose of the demonstration of the model. The underlying idea of model-based research is that the suggested model in this study is flexible to work with any scenario, including those which are supported by observations and unique circumstances of a particular case.

Figure 3-28: The layout of a ward which includes 11 single patient rooms, two medical supply rooms and a laundry room.

3.6.1 *Design of Nursing Scenario*

Nurse–Patient Ratios

A scenario is also concerned with the number of patients which are assigned to a nurse. Some U.S. states include legislations which mandate minimum hospital patient-to-nurse ratios according to different types of care (Tevington, 2011). A study of 168 acute care hospitals in Pennsylvania reports an average hospital-level staffing of 5.7 patients per nurse. This study suggests that staffing in hospitals with poor care environments is lower (6.0) than in hospitals with mixed and better environments (5.8 and 5.3) (Aiken et al., 2008). A review of literature indicates that several studies, in spite of their differences, show associations between increased staffing and lower odds of hospital related mortality (Kane et al., 2007). In this case-study, the scenario of nursing for an acute care unit will be simulated for a nurse who delivers care to 5 patients. The patients to whom care will be delivered are located in rooms which are highlighted in orange in Figure 3-28.

Activities and Sequences

Studying the behaviors of nurses has been motivated by maximizing the time that nurses spend carrying out direct patient care (Dearmon et al., 2013), minimizing the cost of patient care (Williams et al., 2009) and efficiently using educated nurses whose numbers are estimated to decline in future according to the American Association of Colleges of Nursing (Rosseter, 2014). With these motivations the studies that focused on understanding the workflow of nurses mainly report the proportion of their engagement time with different activities. In these studies, which are called time and motion research, the activities are classified in different categories. The classification methods change from one study to another. Generalized categories which are used dismiss the details of the nursing workflow. For example, Williams et al. (2009) presented four categories of nursing activities that was followed by many subsequent studies. “Direct care” is the hands-on interaction and/or care provision with specific patients. “Indirect care” includes activities related to a specific individual patient but not hands-on care (e.g. team meetings, patient documentation and telephone liaison). “Unit-related” activities pertain to the normal daily management of the ward environment (e.g. ordering supplies, ensuring a clean and safe environment). Finally, “personal time” activities facilitate nurses to work more confidently and productively (e.g. rest periods, continuing professional development and staff appraisal) (Williams et al., 2009, Page 2099).

Cornell et al. (2010, page 366) found more than 70 categories of activities in the Institute for Healthcare Improvement’s Transforming Care at the Bedside protocol. They recognized that existing studies classified what nurses do to 5, 12, or 17 categories. Table 3-6, which is by no means exhaustive, shows the diversity of the categories which were used in a number of time and motion studies that attempted to understand the nursing workflow in different types of healthcare facilities. The existing time and motion studies do not have the detailed information about the location and duration of activities. They also do not reflect the dependencies between the activities, in a way that a DES does, to create activity sequences.

Table 3-6: Reports of time and motion studies of nurse's behaviors in healthcare unites.

Authors (Year)	*Care Type*	*Time Proportion*	*Scenario Design Considerations*
Hendrich et al. (2008)	Medical-surgical	Documentation: 35.3% Medication administration: 17.2% Care coordination: 20.6% Patient care: 19.3% Nursing practice: 7.2%	Nurses spent only 20 to 30 seconds in any one spot
Williams et al. (2009)	Neuro-rehabilitation	Direct patient care: 46% Indirect patient care: 25% Unit-related: 10% Personal time: 19%	Proportions of direct care fluctuated throughout the day
Cornell et al. (2010)	Medical-surgical	Assessment/treatment: 18.5% Communicating: 12% Personal time: 11.4% Electronic charting: 10.1% Others: 7%	The duration of 40% of the activities was less than 10 seconds.
Munyisia et al. (2011)	nursing Home	Communication: 48.4% Medication management: 18.1 Documentation: 17.7%	Nurses were multi-tasking in 27.6% of their time

Table 3-6 Continued

Authors (Year)	*Care Type*	*Time Proportion*	*Scenario Design Considerations*
Abbey et al. (2012)	Intensive Care Unit	Direct care: 40.5% Indirect care: 32.4% Personal: 21.9% Unrelated: 5%	Nurses undertook two activities simultaneously for 43% of the study timeframe
Dellefield et al. (2012)	Nursing Home	Direct Care: 31% Indirect care: 59% Unproductive activities: 10%	
Mallidou et al. (2013)	Residential Long-term Care Unit	Personal care: 52% Other: 23% Paperwork: 6% Networking: 6% Personal time: 4%	One-to-three minute activities consumed about 35% of the time spent in personal care
Gholizadeh et al. (2014)	Intensive Care Unit Critical Care Unit	*Observation* Direct dare: 32.74% Indirect care: 24.9% Personal: 42.30% *Self-reporting* Direct dare: 40.52% Indirect care: 28.84% Personal: 30.41%	Self-reporting and observations show significant differences

Table 3-6 Continued

Authors (Year)	*Care Type*	*Time Proportion*	*Scenario Design Considerations*
Tamilselvi and Regunath (2014)	Medical ward	Basic Care: 6.2% Complex Care: 66.8% Administration: 4.1% Clerical: 9.9% House Keeping: 1.7% Supplies and Equipment: 2.4% Non Productive: 8.7%	
Antinaho et al. (2015)		Direct care: 38% Indirect care: 17%	

Although time and motion studies cannot be used to create an instance of a scenario, these studies have some indications which influence the design of a scenario. They show that the pattern of spending time with patients is significantly influenced by the technology used in healthcare facilities. For instance, a comparison between nursing activities before and after the installation of the third-generation of ICU information system showed that the percentage of time ICU nurses spent on documentation decreased more than 30% and half of the saved time was spent on patient assessment and direct care (Wong et al., 2003). Table 3-6 shows other considerations that concerns the design of a scenario. These considerations include fluctuation of activity times throughout the day (Williams et al., 2009), short duration of most activity engagements (Cornell et al., 2010, Hendrich et al., 2008), and multi-tasking (Munyisia et al., 2011, Abbey et al., 2012).

Table 3-7 shows six different types of sequences that are used in this scenario. These sequences can be classified to three different categories: visual patrolling, regular care delivery and unexpected care delivery. “Visual patrolling” and “regular care delivery” include expected sequences which reoccur with a known pattern. Nonetheless, sequences which are classified within “unexpected care delivery” need visual detection to come to the attention of a nurse. Unexpected tasks are also likely to be noted during the performance of all other expected tasks when visual contact to patients is established. Visually patrolling the hallway is included in this scenario to increase the chance of detecting the unexpected tasks.

This study does not include multi-tasking of activities. This is a general limitation of all of the approaches that employ a DES model for simulation of the workflows. The simulation of multi-tasking will be easier, when an ABM is employed, since the agents can make decisions to combine the tasks in a continuous time domain according to their locations and the task loads. Simulation of multi-tasking is envisioned in the future of this work.

The scenario includes there different types of expected sequences which are designed based on the idea of sequentializing which was discussed in Section 2-2. These types of sequences include different combinations of care delivery to a patient which can be preceded by picking up medicine from the most conveniently accessible medical supply room and followed by documentation at the most conveniently accessible nursing station.

Each combination is expected to happen in an hour, which indicates that three times of regular care delivery would be expected for each patient in an hour. Unexpected care types include two different types of care deliveries. Type 5 sequence is the reaction of a nurse when a patient who has thrown up is visually detected. These sequences include picking up medicine, delivering the medicine to a patient, picking clean supplies, cleaning and changing in patient room, dropping of soiled linen, and documentation at nursing station. Finally, Type 6 sequence includes picking up medicine, delivering the medicine to a patient and documenting it. For each patient sequence type 5 and type 6 are considered independent and expected to reoccur every two hours, indicating that in one hour one of these the sequences may occur.

Since it is assumed that this scenario includes acute care delivery, the nurse who is delivering care to 5 patients will respond to the need of unpredicted care type of all of the patients. This assumption is due to the need for immediate reaction to this type of care.

Table 3-7: Different kinds of sequences which are used in the case of study.

Sequences	*Average Activation Time*	*Activities*
Visual patrolling		Every 30 minutes
Type 1		30 minutes
Regular care delivery		Every 20 minutes
Type 2	Medicine pick up Delivery to patient Documentation at nursing station	60 minutes

Table 3-7 Continued

Sequences	*Average Activation Time*	*Activities*
Type 3	Patient Visit Documentation at nursing station	60 minutes
Type 4	Patient Visit	60 minutes
Unexpected care delivery		Every 60 minutes
Type 5	Medicine pick up Delivery to patient Clean supply pick up Delivery to patient Dropping-off the soiled linen and sheets Documentation at nursing station	120 minutes
Type 6	Medicine pick up Delivery to patient Documentation at nursing station	120 minutes

In Figure 3-29 the location of 30 activities that are included in the sequences of the scenario are highlighted. Table 3-8 classifies these activities to 6 different categories and includes information about their engagement areas and engagement times. All of the sequences in Table 3-7 are created out of these activities.

Table 3-8: Activities that are used in the scenario.

Activity	*Engagement Area*	*Minimum Time*	*Maximum Time*
Documentation	Behind the counters	10	20
Patient treatment	Patients' Bedsides	10	20

Table 3-8 Continued

Activity	*Engagement Area*	*Minimum Time*	*Maximum Time*
Medicine pick up	In front of shelves in medical supply room	4	10
Clean supply pick up	In front of shelves in the laundry	4	10
Dropping-off the soiled linen and sheets	In front of shelves in the laundry	4	10
Patrolling	Patients' doorways in the hallway	1	2

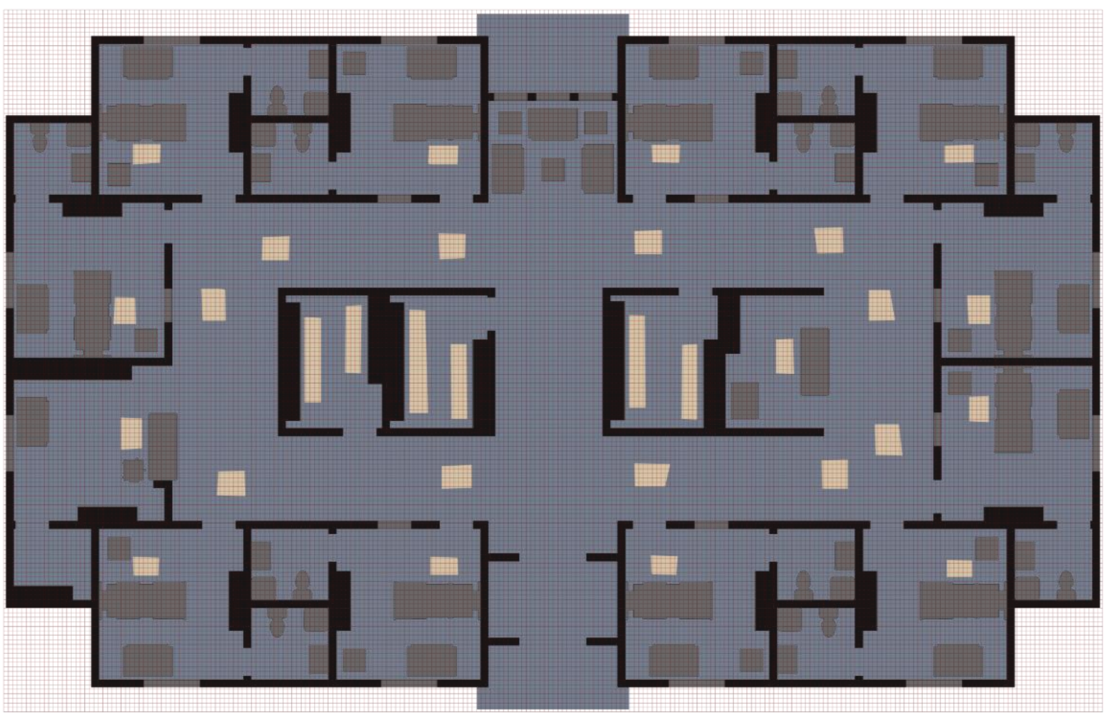

Figure 3-29: All of the activity areas that are used in the scenario.

3.6.2 Simulation Results

The scenario can be simulated in real-time to visualize the performance of the scenario. The real-time simulation includes a control panel which allows for agent's physical characteristics, such as maximum velocity magnitude, maximum acceleration magnitude, angular velocity magnitude, body size, body elasticity and visibility angle. It also includes options to control the barrier repulsions. If these parameters are not fine-tuned in a training process, the navigation control panel allows for visually tuning them. The navigation control panel also offers different options for visualization which include visualization of agent's body, cone of vision, capturing visual events, body safety buffer, 3D view of the agent, highlighting destination areas, closest barrier to the agent, barrier repulsion force trajectory and visualizing the detection of unexpected tasks. Figure 3-30 shows the real-time visualization of the scenario in OSM when a throw-up sequence is visually detected. The scenario also includes an attractive scene in the north side and a view to this scenery will also be captured when a line of sight in agent's cone of vision exists.

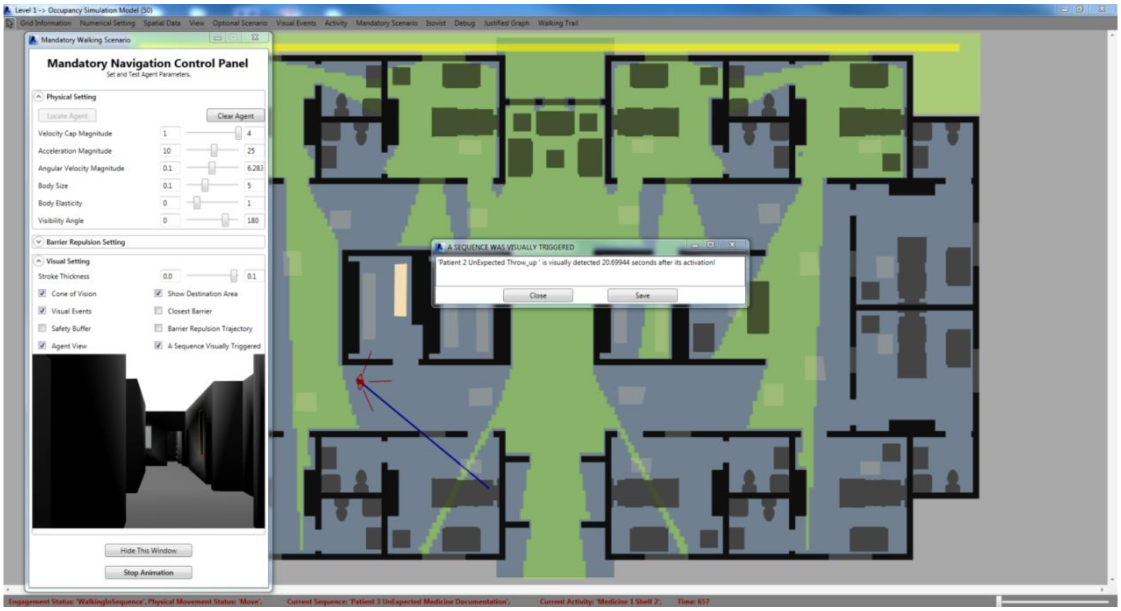

Figure 3-30: Visualizing the performance of the scenario in real-time.

The simulation of the scenario does not have to be in real-time. Removing the visualization of the performance of the scenario allows for increasing the speed of the simulation. In offline (vs. real-time) simulation the agent's locations and the information that it collects will be recorded in a separate thread for a given simulation duration and time-step size. The walking trail data will be recorded as a layer of spatial data, which shows the Probability of Agent's Presence (PAP) in different locations of the ward as dictated by the scenario. The simulation results also include a transcript of walking activity engagement and chances for visually detecting the unexpected tasks. Figure 3-31 shows the PAP of the scenario in the ward and Table 3-9 shows the simulation transcript for different durations of simulation. The only environmental quality that has influenced the navigation in this scenario is the desire to avoid the physical barriers. The results in this table were captured using a fixed time-step of 17 milliseconds. The simulation model in average needs 5.12

seconds to simulate an hour of occupancy scenario (i.e. 40734 time-step update operations in a second). This simulation uses a single thread does not involve GPU in the processing. These results were obtained in a computer with following specifications: CUP Intel i7-3770 @ 3.40 GHz, 16.0 GB RAM, and 64-bit Windows 7 OS.

Table 3-9: Simulation results for different durations of time.

Simulation Feature	***Simulation Results***								
Simulation Duration (H)	4	10	24	54	84	126	168	200	400
Walked Distance (Ft/H)	4165	4218	3831	3680	3886	3913	3867	3932	3818
Walking Time (PST)*	27.58	27.66	25.32	24.31	27.72	25.86	25.55	25.97	25.19
In Nursing Stations (PST)*	43.70	44.29	48.27	49.85	47.07	46.89	47.75	46.87	48.18
Engaged with Any Activity (PST)*	28.71	28.05	26.40	25.84	27.22	27.25	26.70	27.15	26.63
Chance for Visual Detection (PST)*	2.32	2.14	2.70	2.82	2.68	2.78	2.45	2.43	2.66

* PST = Percentage of Simulation Time

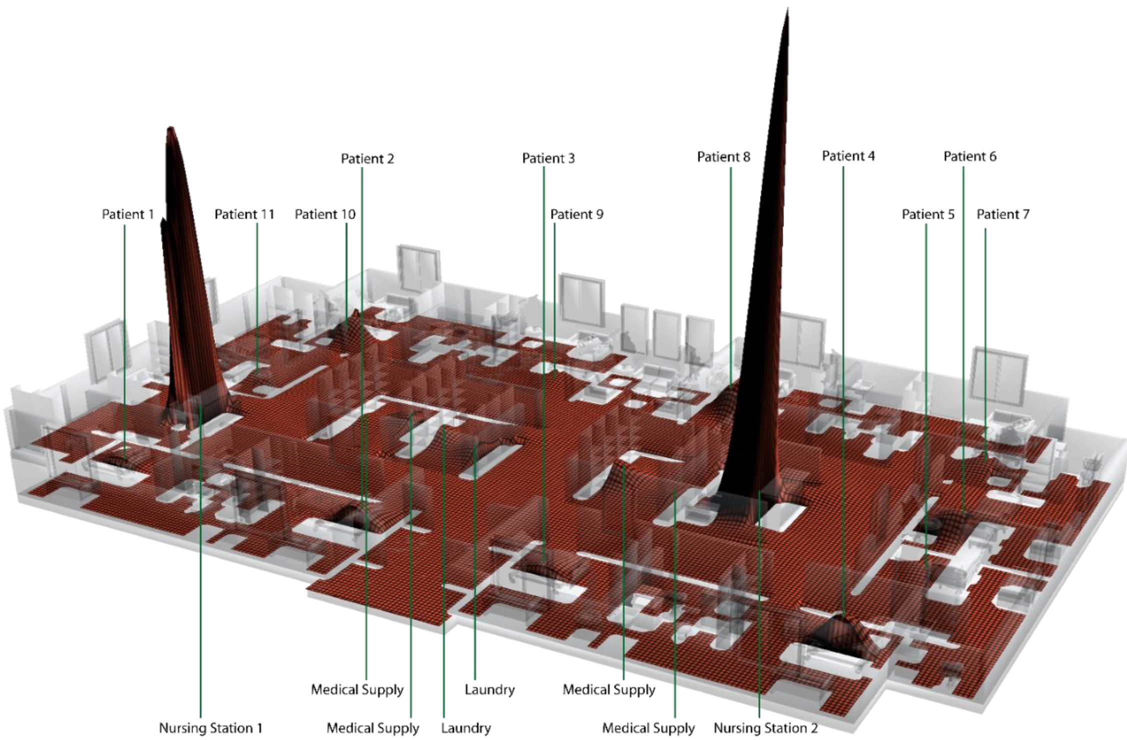

Figure 3-31: The aggregation of the recorded walking trail which shows the Probability of Agent's Presence (PAP) in space.

3.6.3 Reliability of Results

The scenario includes numerous random variables from different types. Therefore, the results of the simulation are expected to reflect the randomness as well. For instance the throwing-up sequence, which is expected to repeat every two hours with an exponential distribution, may not even occur during a 4 hours of simulation time. The detection of unexpected sequences also depends on the performance of the expected sequences. The patterns and the outcomes of an agent's interactions are inherently unpredictable (Jennings, 2000). However, as the time for the simulation increases the aggregation of the randomness variables will stabilize the results. For instance, Table 3-9 shows how

"Walked Distance" stabilizes as the simulation time increases. Table 3-10, shows the correlations between the PAPs which are resulted in different simulation durations. The agent will not walk on a large portion of the floor during the simulation and including these parts in the correlation analysis will falsely increase the correlation value. The correlation analysis in Table 3-10 only includes the cells that at least in one of the simulation results have a non-zero PAP value. The high correlation values in this table suggest that unlike "Walked Distance" the PAPs are significantly unchanged from 4 hours simulation to the 400 hours. This proves that to capture reliable results each field of simulation data should be tested individually in different durations to make sure that the results are stabilized.

Table 3-10: Correlations between Probability of Agent's Presence (PAP) for different simulation durations

Hours	***4***	***10***	***24***	***54***	***84***	***126***	***168***	***200***	***400***
4	1								
10	0.9961	1							
24	0.9926	0.9963	1						
54	0.9881	0.9878	0.9964	1					
84	0.9980	0.9979	0.9979	0.9941	1				
126	0.9974	0.9991	0.9980	0.9923	0.9996	1			
168	0.9950	0.9954	0.9989	0.9979	0.9989	0.9981	1		
200	0.9953	0.9968	0.9994	0.9968	0.9992	0.9989	0.9997	1	
400	0.9944	0.9953	0.9992	0.9981	0.9987	0.9980	0.9999	0.9998	1

3.6.4 What-If Analysis

The results of the scenario are affected by the desirability of the environmental variables that are included in the activities' potential fields, the building layout, and the tasks that are assigned to an agent. Changes in any of these items will change the results of the scenario. In this section, a generic quality which is shown in Figure 3-32 will be added to the generation of the potential fields of the activities while everything else will remain unchanged. A comparison between the results shows a poor correlation (0.7554) between PAPs resulted for 12 hours of simulation with and without the added data. As expected this comparison shows that even in a building that does not offer various choices for path selection, the environmental qualities can change the pattern of navigation and the likelihood of agent's presence in space. Figure 3-33 visualizes the changes in the navigation pattern and shows that these changes can even influence the chances for visually detecting the unexpected critical care delivery to patients in rooms 1, 3, 5, 7, 9, and 11. Therefore, environmental qualities, design and building layout can actually influence the performance of care delivery. While the affection of environment on the scenario even intuitively makes sense, the simulation model which was developed in this chapter is capable of accurately measuring the consequences of changes (i.e. what-if analysis) and thus making more informed decisions. In the next section the techniques for querying data from the agent will be discussed in more details.

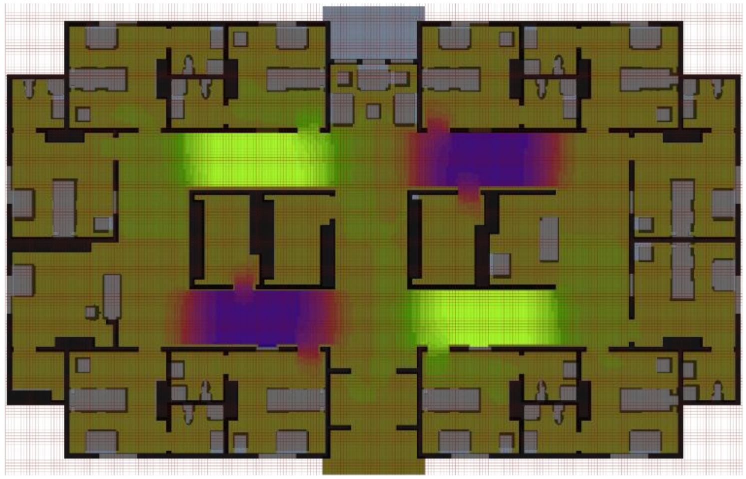

Figure 3-32: The potentials of a generic quality which was added to generation of activity potential fields.

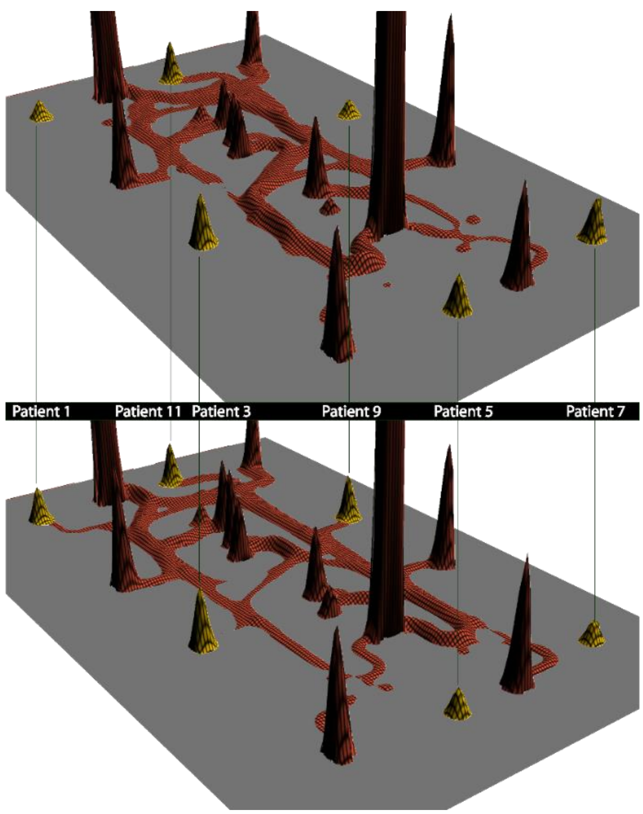

Figure 3-33: The difference in navigation pattern and PAPs before (on the top) and after (on the bottom) adding the generic data shown in Figure 3-32.

3.7 Evaluation

During the performance of the scenario the agent will experience different environmental qualities, engage with different activities and visually connect with different targets. As discussed in Chapter 1, these actions will influence the satisfaction of the occupant. The results of the simulation in previous section do not reflect all of the attributes of an agent's states (i.e. physical, engagement and visual). However, with the developed simulation model, accurate information about the agent's physical state, activity engagement state and visual state is available to us. These states can be subject to query to extract insightful and narrowed information. Some example of data query includes:

1. How often an agent will have a line of sight to a beautiful scene with a restorative effect?
2. What is the likelihood of engagement with care delivery at the bedside of a specific patient?
3. Where will the agent be pushed out of its comfort zone in relation to one layer of environmental variable?

These questions might be of interest for designers at building design phase when the building layout can be changed or for facility managers who design the occupancy scenarios in buildings that are already built. Both designers and facility managers would like to maximize the chances of occurrence of some states and minimize the chances of occurrence of some other states. Data query can answer when and where certain states take place or what the overall likelihood their occurrences are. For example, if design constraints does not allow for always having a good view and desirable temperature, a designer might want to make sure that at least one of them is desirable in the absence of the other one.

3.7.1 Data Query Mechanism

Data query mechanism suggests an integrated evaluation criterion for filtering agent states during the simulation of the occupancy scenario. The integrated criterion includes a Boolean logic and a collection of evaluation functions. Agent states include three types of variables in relation to spatial data, activity engagement, and visibility targets. An agent state can include multiple variables from each type. Data query should include a criterion for the evaluation of each variable type. Evaluation in relation to environmental variables is defined based a range of variation that can include or exclude a scalar value. For example, temperature comfort zone has a range of variation which can determine if the temperature at an agent's location is comfortable. Evaluation in relation to activities can answer whether an agent is engaged with a particular activity. Similarly, evaluation in relation to a visibility target can question if the agent has a line of sight to the target. The evaluation of each type of variable will result in a Boolean (i.e. true or false) variable.

Figure 3-34 shows the process of filtering the states. Given multiple instances of spatial data, visibility targets and activities, the first step is to select the variables that are desired to be included in the filtering process. Variability ranges should be defined for each field of spatial data which is included in the filtering process. Since there can be multiple instances of each variable type, a Boolean logic is needed to integrate the multiple variable evaluation results into one variable. The Boolean logic in which is shown in Figure 3-34 applies an "AND" operation to selected spatial data, an "OR" operation to selected visibility targets and an "OR" operation to selected activities. Finally, an "AND" operation is used to integrate the results from the three different groups. The Boolean logic for filtering the states which is shown in Figure 3-34 is isolated in Equation 3-1. This logic which is the core of data query can be changed depending on interests in state query. In the equation S is the agent state, $E(VT)$ is the evaluation of a visibility target, $E(SD)$ is the evaluation of a spatial data layer (i.e. environmental variable) and $E(AE)$ is the evaluation of an activity's engagement. OSM software allows for the recording the filtered data with a given frequency which is based on a fixed-number of time-steps.

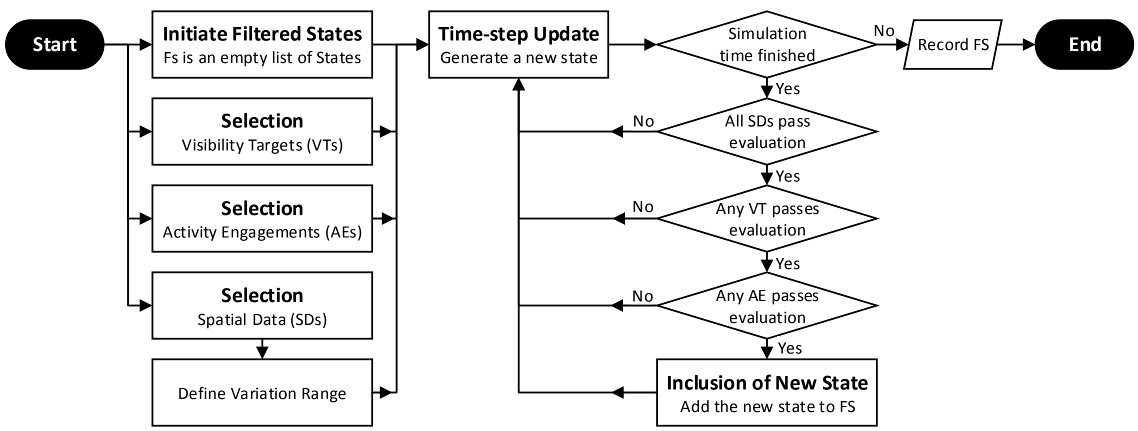

Figure 3-34: The process of data query in the simulation.

$$\exists\, E(VT \in S) \land \forall\, E(SD \in S) \land \exists (AE \in S)$$

Equation 3-1: An example of Boolean logic for data query.

3.7.2 Evaluation Results as Events

The agent states that are filtered through the process which is illustrated in Figure 3-34 do not have a structure. For the convenience of processing the filtered states and giving reference to them, a simple data structure, called "evaluation event" will be created to hold the states that pass the evaluation filter. An evaluation event occurs when the state of an agent passes the evaluation filter, continues as long as the agent states pass the evaluation filter, and terminates when the agent state no longer passes the evaluation filter. Each evaluation event, therefore, has a time span and includes a number of filtered states which are ordered sequentially. Evaluation events are the results of evaluation process and can serve different purposes which are listed in Table 3-11. Defining evaluation results as events that occur in the course of occupancy time enables us to analyze the frequency and likelihood of their occurrence in addition to the places where they occur. Therefore, evaluation events include slices of a scenario where the states pass a combined query filter.

Table 3-11: Purposes of data query from agent's states in occupancy scenario.

1-	Likelihood of an evaluation event
2-	Location of an evaluation event
3-	Frequency of an evaluation event

3.7.3 Informed Interventions

In this section the theoretical model for capturing and analyzing evaluation events will be put in practice. Several examples of event capturing and analysis in this section will demonstrate how the simulation model can inform designers or facility manager. Let's start with creating a simple event that only catches visibility to the multiple targets. Figure 3-35-1 shows that the visibility targets for this evaluation event include patients 9, 10, and 11. The chance of visual contact to these targets exists from the area which is highlighted in green, but visual contact is not guaranteed from this area and depends on agent's orientation. Figure 3-35-2 shows the PAP of this event. The transcript of this event at MOSM is also illustrated in Figure 3-36. The chance for visual contact to any of the patients in this evaluation event is 10.32%. For the analysis of the frequency of the evaluation event's occurrence the event was transformed from time domain to the signal domain using Fourier transformation. The frequency analysis in Figure 3-36 shows the amplitudes of signals with green lines. The signal amplitudes are significant for very low and very high frequencies. Since very high frequencies can be attributed to the noise level. After applying a low-pass filter the signal domain will merely include Dirac delta function which shows that this event is meaningfully periodic in the time domain.

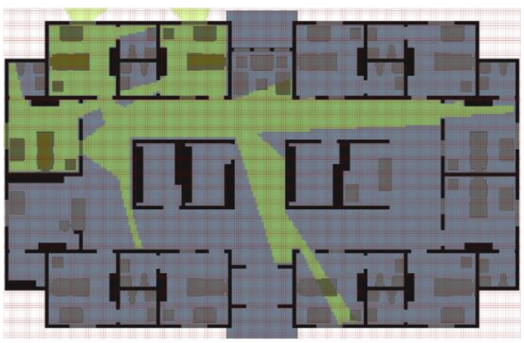

Figure 3-35-1- Visual targets.

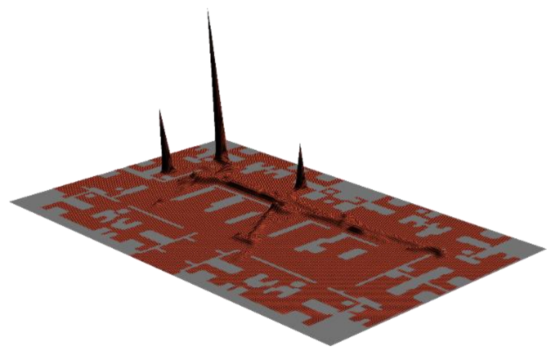

Figure 3-35-2: Evaluation event's PAP

Figure 3-35: An evaluation event that filters the scenario to find when, and where visual contact exists to patients 9, 10 and 11.

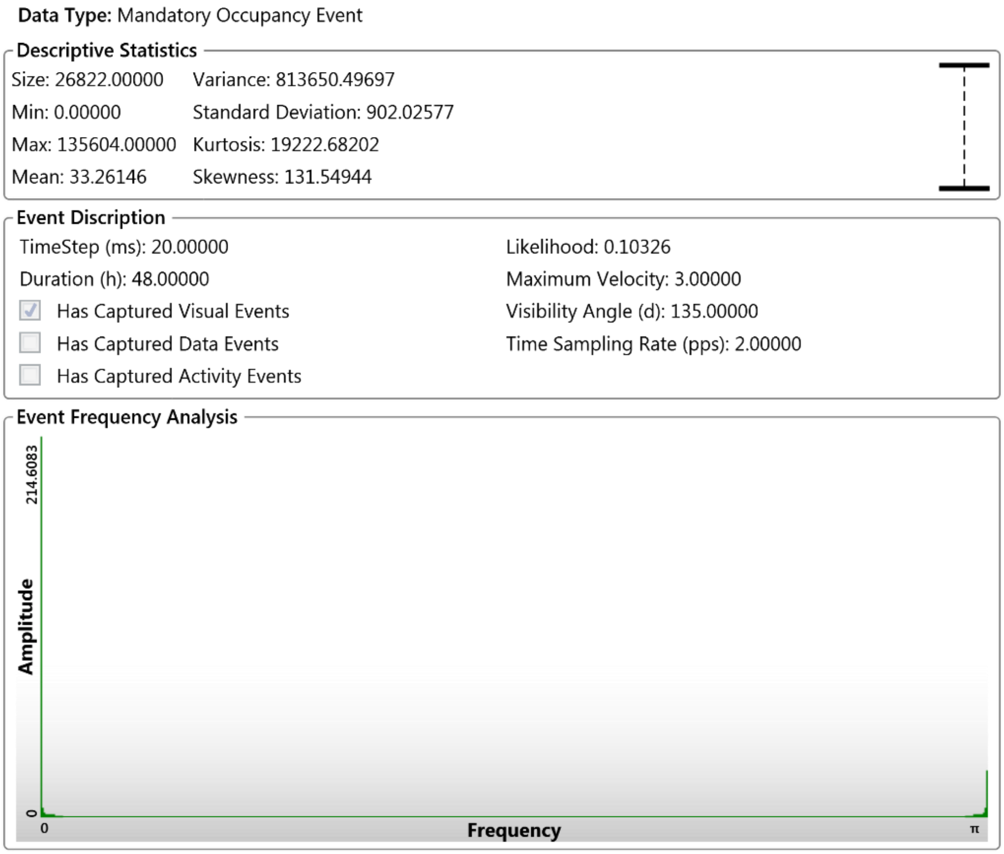

Figure 3-36: The transcript of the evaluation event shown in Figure 3-35.

As discussed in Chapter 1, previous works which used space syntax software to analyze visibility did not distinguish between being in visible area and having a line of sight within the cone of vision to the patients (Choi, 2011, Lu and Zimring, 2012). The evaluation event model allows us to accurately measure the difference between the two cases. To acknowledge the differences the probability of being in the visible area and not having a direct view to any of the patients can be calculated. To calculate this probability, the visibility area will be transformed to a layer of spatial data with values of one for green cells and zero for the rest of the cells. Now a combined event can be created to filter the states when spatial data value is one and visibility does not exist. Figure 3-37-1 shows the

PAP of this event and Figure 3-38 shows the how the interface of evaluation events allows for setting this Boolean logic. This even reports 6.98% chance for the nurse to be in the visible area and not having a direct view to any of the patients in rooms 9, 10 and 11. To capture the probability of being in the visibility area (i.e. the green area in Figure 3-35-1) we can set a new event which does not filter states based on visibility and only filters the states based on the visibility area (Figure 3-37-2). Defining a new event this probability will be reported as 16.98%. Simple rules of conditional probability can be used to calculate the probability of having a view to patients while being in the visibility area. In the following operations A stands for the visibility area and V refers to the existence of visibility. These simple operations show that there is 40% chance that when the agent is in the visibility are, it does not have a line of sight to any of the patients in rooms 9, 10, and 11.

$$P(A) = P(A \cap V) + P(A \cap \sim V) = 0.1032 + \ 0.0698 = 0.173$$
$$P(V|A) = \ P(V \cap A)/P(A) = 0.1032/0.173 = 0.5965$$
$$P(\sim V|A) = \ P(V \cap A)/P(A) = 0.0698/0.173 = 0.4034$$

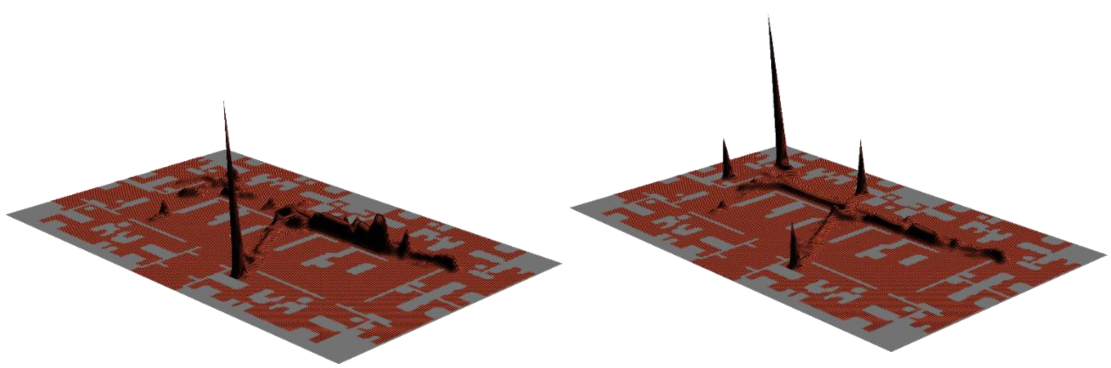

Figure 3-37-1: PAP when visibility does not exist

Figure 3-37-2: PAP of visibility area

Figure 3-37: The evaluation event on the right filters the scenario to find when the agent is in the area in which visual contact to patients 9, 10, and 11 can potentially

exist. The event on the left further filters the states to find when agent's orientation does not allow for a direct light of sight to these patients even though when the patient is in the potential visibility area.

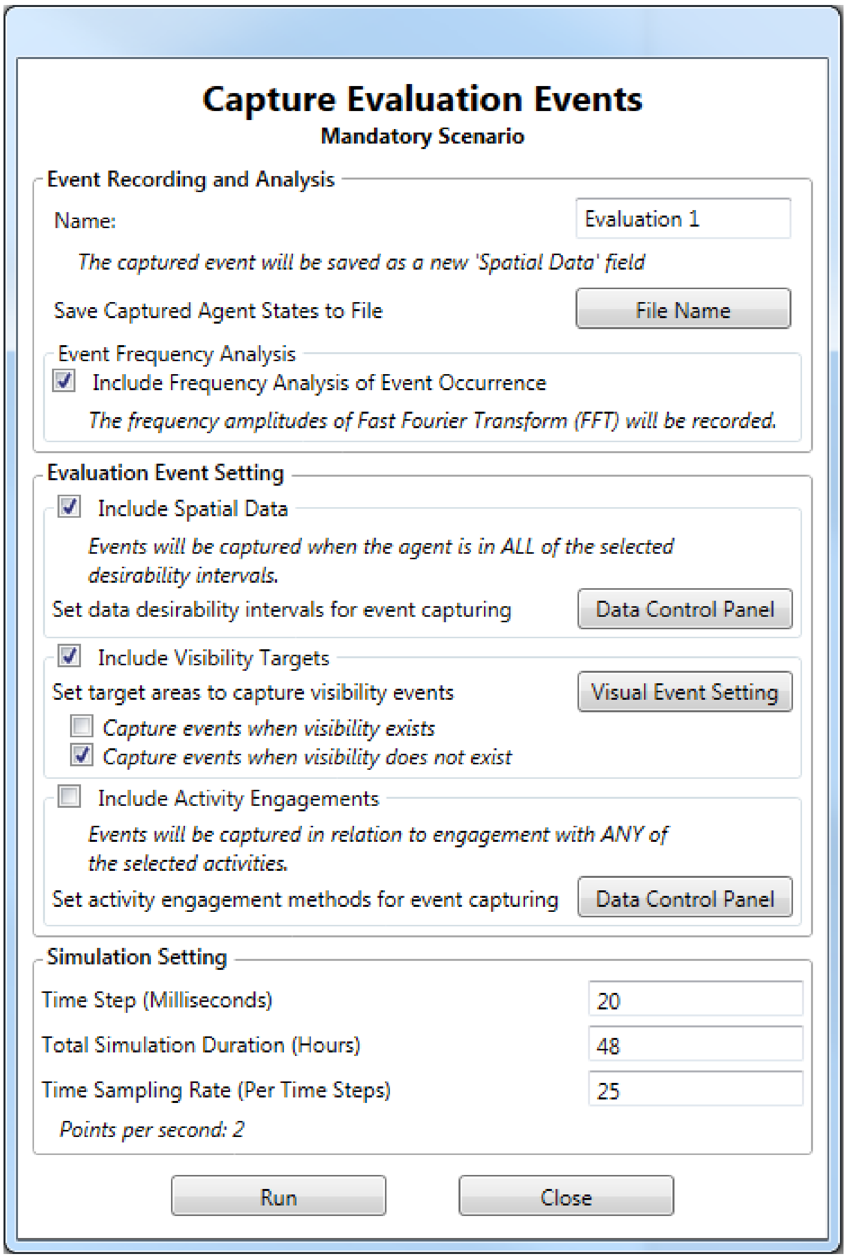

Figure 3-38: An example of setting filtering logic to capture evaluation events in OSM.

The selection of patients in rooms 9, 10 and 11 was an arbitrary choice to demonstrate the flexibility of the evaluation process to include multiple visibility targets and combine visibility filtering with spatial data filtering. An evaluation event which included all of the patients in this ward shows that there is 60.06% chance to have a view to at least one patient and 39.94% chance of having view to no patient during the performance of the scenario. This result does not reflect the chances for individual patients. Nonetheless, new events can be designed to focus on individual patients. While Lean instruction show a growing interest to patients visibility in hospital design (Grunden and Hagood, 2012), evaluation events can be applied to analyze visibility in many other ways as well. For instance, in the scenario which was visualized in Figure 3-30, a restorative scene exists in the northern side of the building. An evaluation event which focuses on the visibility to this scene reports 14.84% chance of having a view to this scene through the windows. Assuming that a view to this scene can alleviate the stress level of a nurse who delivers critical care to patients, this event can be combined with engagement with care delivery activity at the bedsides. The new event reports 4.79% chance. Figure 3-39 shows the PAPs of these two events.

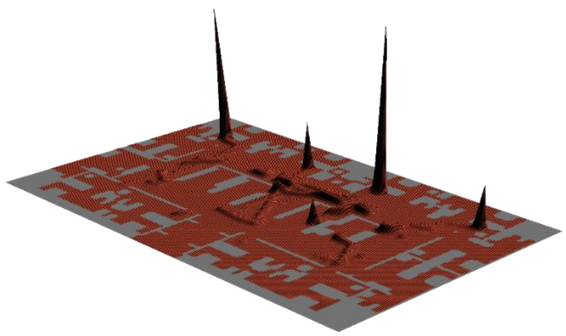

Figure 3-39-1: Visibility

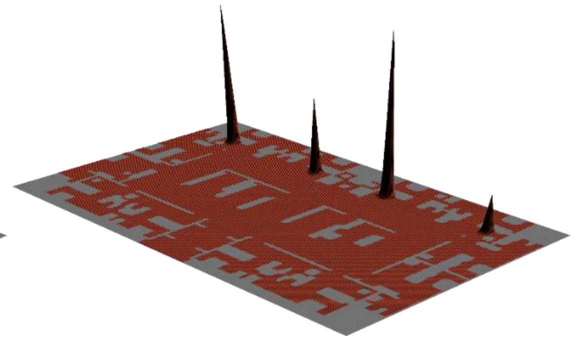

Figure 3-39-2: Visibility and delivering care at the bedside.

Figure 3-39: The PAPs of events which are designed in relation to visibility to the visual target shown in Figure 3-30.

Evaluation events can inform designers and facility managers about any change that are made in building layout, assigned tasks and environmental qualities. The PAPs in Figure 3-33 visually show that the chance for delivering care to patient 9 changes according to the presence or absence of the environmental data which was visualized in Figure 3-32. With evaluation events, these chances can be precisely measured and the two different cases can be compared with each other. The chance of engagement of care delivery to patient 9 before adding the environmental variable shown in Figure 3-33 is 0.55% and after adding it will be 0.69%. This shows that adding this quality will change the odds to the favor of patient 9 because the added environmental quality changes the navigation pattern in a way that the chance for visually detecting the need to deliver unpredicted care to this patient increases.

3.8 Conclusion

Throughout this chapter, a model for simulation of nursing scenario was developed and a software solution demonstrated the implementation and application of this model in a case-study. Nursing scenario is an example of a mandatory occupancy scenario and the Mandatory Occupancy Simulation Model (MOSM) which was discussed in this chapter can be used for the simulation of any other mandatory occupancy scenario. The main contribution of this model is the integration of the features which were determined in the summary of the literature review in Chapter 2.

This chapter showed that an Agent-based Model and a Discrete Event Simulation (DES) can be integrated to simulate the occupancy scenario and the occupant's behavior in the scenario. The scenario model includes activities and tasks which are developed based on an Object Oriented view. Different levels of priority of tasks were also integrated in the model. Another accomplishment in developing MOSM was to include visibility analysis. The agents that could visually detect environmental changes in their cone of vision, made it possible to create tasks that can only be visually detected.

The ABM component of MOSM allowed for the simulation of occupancy at micro-scale level. The dynamics of walking was also integrated at MOSM as a physically-based component that accounts for simulating an agent's physical state during the navigation and its possible collision with the barriers. Another novel contribution of MOSM is to account for an agent's preferences towards environmental qualities and path simplicity. Parameterizing the agents allowed for simulating the interactions between an agent's desires towards environmental qualities and path simplicity. Parameterization also allowed for using a metaheuristic algorithm to fine-tune the parameters to train an agent in a way that it could follow the footsteps of a human in a real building.

MOSM also includes several visualization features that include data visualization in 2D and 3D formats, real-time visualization of an occupancy scenario in 2D and 3D formats, visualization of activities and tasks as sequences of activities, and visualization of visibility events when they occur. The simulation was also designed to run in off-line mode without visualization in background threads to speed-up the process of capturing simulation results.

Finally, with MOSM it will be possible to record and filter an agent's states during the occupancy scenario. This allows designers at the design phase and facility managers who program activities in already-built buildings to query information from specific events and suggest informed changes. The evaluation events are reported in terms of their probability, frequency of occurrence, and locations where they occur. The above achievements in the form of a software solution demonstrate that software simulation can simulate, visualize and evaluate mandatory occupancy scenarios.

CHAPTER IV

SIMULATION, VISUALIZATION AND EVALUATION OF OPTIONAL OCCUPANCY SCENARIOS

4.1 Introduction

Within the scope of this study optional occupancy scenario describes how an occupant gets engaged in walking without planning for engagement in any activity. In this type of scenario the occupant does not have any predefined path or direction in mind and simply walks towards what attracts him/her. The original contribution of this chapter is to create an integrated model for simulation, visualization and evaluation of optional occupancy scenarios. The simulation component accounts for visibility of an occupant, and an occupant's unique desires in relation to path simplicity and environmental qualities when navigating space. While the techniques used in the simulation are different from mandatory occupancy scenarios, the visualization and evaluation components of this chapter are the same. The visualization component allows for 2D and 3D representation of the occupancy process and the evaluation component includes defining events and querying information about where, when, and their frequency of occurrence.

Space syntax theory is an example of this model of scenario that is also based on these assumptions. However, space syntax does not include an active walker model and is based on aggregate traffic patterns which are measured using graph-based approaches which were discussed in Chapter 2. In other words, predicting the aggregated traffic pattern in space syntax is not simulation-based. Additionally, the theory includes different ways of measuring the natural attraction of space which have contradictory implications. For instance, the difference between integration and angular simplicity was discussed by Turner in several of his works which were reviewed in Chapter 2 (Turner, 2000a, Turner, 2007). Space syntax also does not take any account for any environmental quality other than configuration of space (Penn and Turner, 2001). The methodology of using space syntax in research depends on examining the correlation of the observed phenomena with a large number of existing spatial indices which include, but is not limited to, connectivity, integration, angular steps, and numerous types of isovist properties. Within this approach any study finds its own unique index as the strongest factor that explains the observed phenomenon. A typical application of this approach can be found at the work of Peponis et al. (2004). As a result, the outcomes are always context-specific and there is not a theoretical framework to predict and find the best spatial index that explains the observed behavior. A list of other limitations of space syntax can also be found at Ratti (2004).

In spite of its limitations, space syntax theory is supported by numerous significant findings. This chapter is concerned with developing an active walker model and is heavily based on the visibility analysis which connects it to the area of space syntax research. As discussed in Chapter 2, the literature in space syntax includes a unique active walker model which is developed using an Agent-Based Model (ABM) (Penn and Turner, 2001). This model is merely based on visibility and still relies on the aggregate of the agents trails. Within this chapter we are concerned with integrating visibility, angular simplicity, and environmental qualities in a pedestrian dynamics model that simulates the behaviors of an active walker. The Optional Occupancy Scenario Model (OOSM) which is discussed in this chapter will add the new features to the existing ABM that was developed in space syntax.

In Section 2 of this chapter the details and algorithm for Optional Occupancy Scenario Model (OOSM) will be discussed. In Section 3 the validation method of this model will be discussed. Section 4 will put this model into practice in a case-study which is a shopping mall. Section 5 will discuss how the simulation framework can be used for querying information which may lead to insightful decisions. Finally, in the conclusion section the achievements of this study will be summarized and the fulfillment of the promises will be checked. This chapter heavily relies on some of the concepts which were discussed in Chapter 3. For the sake of brevity, these ideas will not be repeated and references to them will be provided when needed.

4.2 Optional Occupancy Scenario Model (OOSM)

Based on Gehl's (1987) definition the difference between optional occupancy scenario and mandatory occupancy scenario is the absence of activity plan in optional occupancy scenarios. Mandatory occupancy scenarios are task-based whereas optional occupancy scenarios are attraction based. Since there is no task-based necessity the scenario does not dictate walking and as a result the occupants do not walk when the environment does not offer enough attraction. In mandatory occupancy scenario the long term involvement of an occupant with tasks make it a reasonable assumption to believe that the occupant has developed accurate information about the environment. Nonetheless, in optional occupancy scenario a person might be walking in a shopping mall or the sidewalks of city center from where he or she has no previous knowledge. On the contrary, knowledge of the environment may also exist in this type of scenario. Within the scope of the simulation of optional occupancy scenario will be narrowed down to the cases in which no prior knowledge of the environment exists. Whether the environmental knowledge exists or not, this knowledge will be developed in the course of time when an occupants navigates in space. The scope of this study also does not include the learning process in which an occupant will become acquainted with an environment.

The Optional Occupancy Scenario Model (OOSM) which will be discussed in this chapter suggested an ABM in which an agent continuously finds the most attractive destination in its cone of vision and walks towards that destination. Since space syntax includes an agent-based simulation model which is based on visibility field of agents, it would be necessary to take a closer look at this model to highlight the differences between it and the suggested model in this chapter. The idea of combining space syntax models with pedestrian dynamics was envisioned by Batty (1997) and Helbing et al. (1997) in two different publications published at the same volume and issue of Nature (388). The literature shows some attempts to draw this connection. In a review of agent-based pedestrian modeling Batty (2003, Page 15) describes the results of an experiment to achieve this integration in a museum layout. In this experiment integrated attraction factors which were added to different areas of a gallery, social forces among visitors and repulsions from barriers. Sight was also added to the agents' features using pre-calculated isovists. Further details of this model and its implementation were neither reported in this study nor in other studies.

The other case of integrating ABM and space syntax is a much simpler model. The model relies on a grid of nodes on the walkable space in which the field of visibility (i.e. isovist) for each node is calculated. A node is selected randomly from all of the visible nodes within the view cone of an agent and the agent takes a few steps towards the selected node. When taking new steps is not possible, side steps will be taken. When the steps are completed or even taking side steps is not possible, the cycle starts again with a new search within the visibility area (Penn and Turner, 2001). A year later in another publication the same authors improved their suggested model and backed it with a theoretical discussion of natural movement. Gibson defines natural movement as process which includes looking around, walking towards something interesting, moving around it to see it from all sides, and repeating this process (Gibson, 1979, page 1). They hypothesize their model in this way: "When engaging in natural movement, a human will simply guide him or herself by moving towards further available walkable surface. The existence of walkable surface will be determined via the most easily accessed sense, typically his or her visual field" (Turner and Penn, 2002, page 480). In this algorithm the random choices of the agent from the visibility field is limited to a few directions.

The space syntax based agent simulation includes many shortcomings. It is not consistent with other theoretical claims that the space syntax theory poses. First, the decisions are completely made based on local conditions of the environment and the notion of local-to-global, which is the essence of the space syntax theory, has not impact on an agent's decision making process. Second, random selection of destinations from the field of visibility causes random changes in the direction of movement which does not even align with the theory that Turner (2000a) himself posed about angular simplicity. Third, agents in this approach are free to choose directions that will end up in collision with barriers.

Fourth, the dynamics of walking and interactions among the agents are not physically based. Finally, as discussed before, the model does not account for any of the environmental qualities. Of course, in the development of this model it was never claimed that the agent will demonstrate a natural walking behavior; it was rather suggested that the aggregate of the trail data represents the likelihood of agent's presence in space (Penn and Turner, 2001, Turner and Penn, 2002). Other than finding correlation these original papers do not describe how a realistic aggregate emerges out of unrealistic assumptions.

The choice of temporary destinations is more complex than choosing any visible point. The model that will be discussed in this section will also be completely based on local conditions. However, it includes a mechanism for selecting temporary destinations that do not result in collision with barriers, maintain the moving direction of the agents, and considers the desirability of environmental qualities. Each of these individual items will be discussed in the following sub-sections. Finally, a model that balances the desirability of all of these factors will be introduced.

As suggested by Gibson (1979), in the optional occupancy scenario the attractions (i.e. destinations) are temporarily selected. The destinations are updated in time intervals that follow an exponential Probability Density Function (PDF). A force-based model is used to push the agent towards the destinations that it chooses. The destination-seeking force will be added with the repulsion force from the closest barrier to make before being applied to the agent. The agent also orients itself towards the direction of the destination that it has chosen. The destination will be selected from the agent's cone of vision. The state of the agent will also be updated in short fixed time-steps which are 16.66 milliseconds and will result in 60 Hz frequencies of screen updates which suites real-time visualization.

OOSM includes a series of pre-calculations to find all possible destinations that an agent can select from each point in space and stores them in a look-up table that allows for rapidly retrieving data. These operations are time-consuming and if not pre-calculated will be repeated several times during the simulation. The selection of a destination from all possible destinations happens during the simulation and is concerned with the desirability and angular deviation from the occupants moving direction. In the next subsections the process of pre-calculating the destinations and the selecting one destination will be explained. Finally, OOSM will be summarized and its algorithm will be illustrated diagrammatically.

4.2.1 Pre-calculating Destinations

Isovist vs. Directly Accessible Area (DAA)

Figure 4-1 shows the layout of a restaurant. There are two types of barriers in this plan: the barriers filled with black color, which block both visual and physical access, and the barriers filled with gray color, which only block physical access but allow for the agent to look over them. An isovist by definition is bound to visible barriers (Benedikt, 1979). However, this definition can be expanded to find a field of visibility that is bound to the boundaries of physical barriers. In space syntax literature there is no distinction between physical and visual barriers. However, distinguishing the difference between them will be useful to differentiate between direct physical and visual accessibility. Figure 4-1 shows two different types of isovists which are defined in relation to these two different types of barriers. Both of these isovists are defined as a collection of cells.

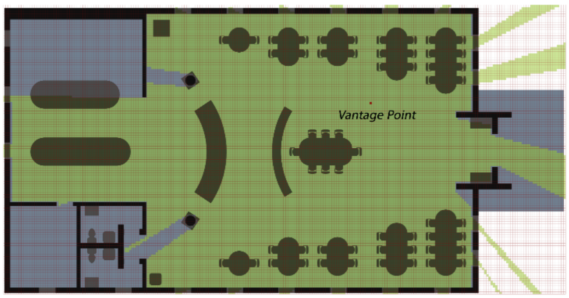

Figure 4-1-1: An isovist bound to the visible barriers

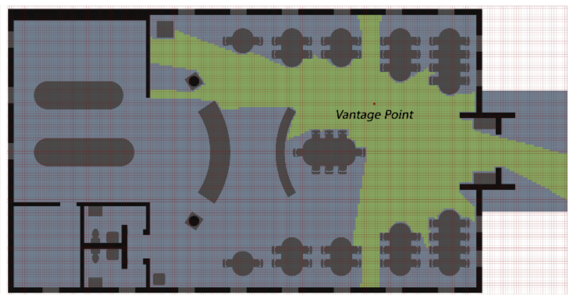

Figure 4-1-2: An isovist bound to physical barriers

Figure 4-1: All of the visible points are not necessarily accessible. Visible points can be on the top of physical barriers, or the physical access to them can demand detouring the barriers. However, the points that are physically accessible can be achieved with an isovist which is bound to the physical barriers.

Ideally, when there is not prior knowledge of the environment an occupant's choices of destination is limited to what he or she can see. The cells that are located in the visual isovist can be located on the physical barriers or even when they are located on the walkable field, they might not be directly accessible and accessing them may demand detouring. On the other hand, the cells that are located on the isovist which is defined in relation to physical barriers are directly accessible and do not demand several detours, although accessing them may require an occupant to change his or her direction of movement. Since the visual barriers are physical barriers too, the field of the physical isovist is included within the visual isovist but not the vice versa. This indicates that any path from the vantage point to a visible destination will inevitably pass through the Directly Accessible Area (DAA).

A detour demands a knowledge of the environment which, as discussed in Chapter 2, can be modeled by a type of roadmap. In the absence of this knowledge an occupant's decisions are limited to the areas that are both visually and physically accessible. The agent can also develop a partial roadmap within his or her visibility area and use it for planning paths. This approach was used in some of the previous studies to allow for detouring the barriers (Yan and Kalay, 2005). The choice of including roadmaps or partial roadmaps depends on the level of the knowledge of an occupant from the environment. In this study it will be assumed that this level of environmental knowledge does not exist. During the occupancy scenario as the level of knowledge of an occupant from the environment increases, partial roadmaps are formed and expanded to a level that they include the entire walkable space.

Spatially Desirable Destinations

An agent who does not have the intention of getting engaged in any activity and only wishes to walk will not choose destinations that are too close to it. In other words, the destinations will go out of scope if the agents get too close to them. The "decision scope" is a circle around the vantage point. Beyond this circle, any point within the DAA can be selected as a destination. However, the attraction of the destinations should be weighted in accordance to their distance from the agent. The destinations that are closer to the agent are more likely to be chosen compared to the destinations that are far away because they can be physically accessed more easily. The balance between distance and desirability can be achieved by applying a Gaussian filter that is clipped by the field of visibility (i.e. isovist) of each cell on different layers of spatial data. Figure 4-2 shows how the attraction of an area can be interpolated using this method. After applying this filter, the effect of distance will be included in the desirability value of a spatial data field and the destinations can be directly selected from the perimeter of the visibility scope circle.

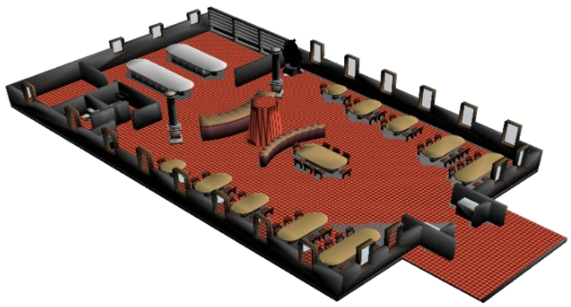

Figure 4-2-1: A layer of generic spatial data

Figure 4-2-2: Interpolated data using a Gaussian filter that clipped with the field of visibility.

Figure 4-2: There will not be any need to balance between distance and desirability of a quality after interpolating that quality within the field of visibility.

Collision-free Destinations

The choice to only include physically accessible cells on this circle limits the possible destinations or in some cases completely eliminates all of them. Figure 4-3 shows two different vantage points, P_1 and P_2, and their respective destination scope circles. While for P_1 the destination scope cycle overlaps with the DAA, for P_2 this overlap does not exist. The case of P_1 shows that the attraction of the destinations cannot be the only factor that influences the destination selection. The occupant in this case should choose a destination that simply allows for further navigation. The destinations that can let the occupant to further navigate into the space are at the edges of the DAA where the cells are not juxtaposed with the barriers. Figure 4-4 shows these destinations for vantage points P_1 and P_2. Since these destinations are not next to physical barriers they will be referred to by gap of DAA. Since the destinations which are located on the decision scope area are also located at the edge of DAA, the process of finding all possible destinations can be simplified to find the edges of DAA and filter out the cells that are immediately next to physical barriers.

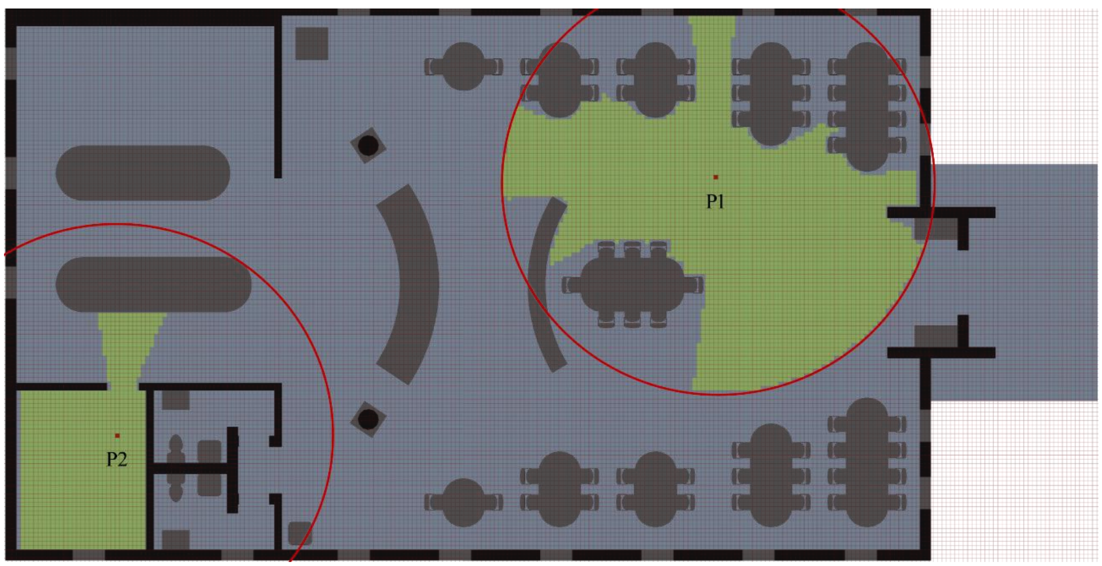

Figure 4-3: The edges of decision scope cycle for P_2 doe not include overlap with the DAA.

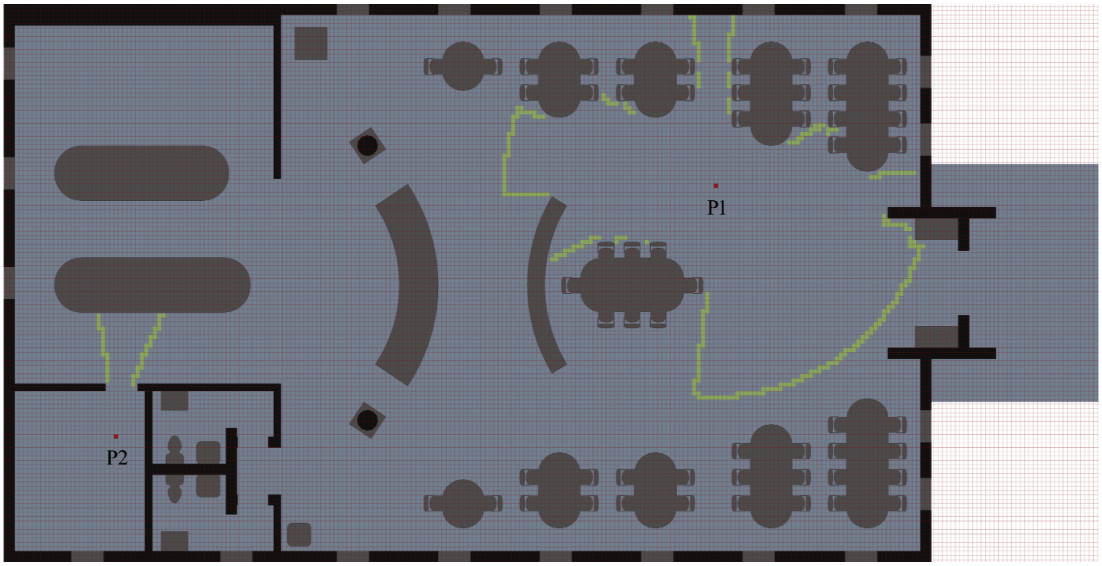

Figure 4-4: All possible destinations from vantage points P_1 and P_2.

Although all of the destinations can be captured in a generalized process now, some of these destinations are not directly accessible and will demand a detouring the barriers. Figure 4-5-1 shows how selecting a destination from the gap of DAA will be cause collision with the doorway. This problem can be solved by offsetting the edges of the physical barriers internally half of the size of the body of the agent. After this operation the destinations that re chosen are guaranteed to be conveniently accessible. Figure 4-5-2 shows the destinations after the offsetting operation.

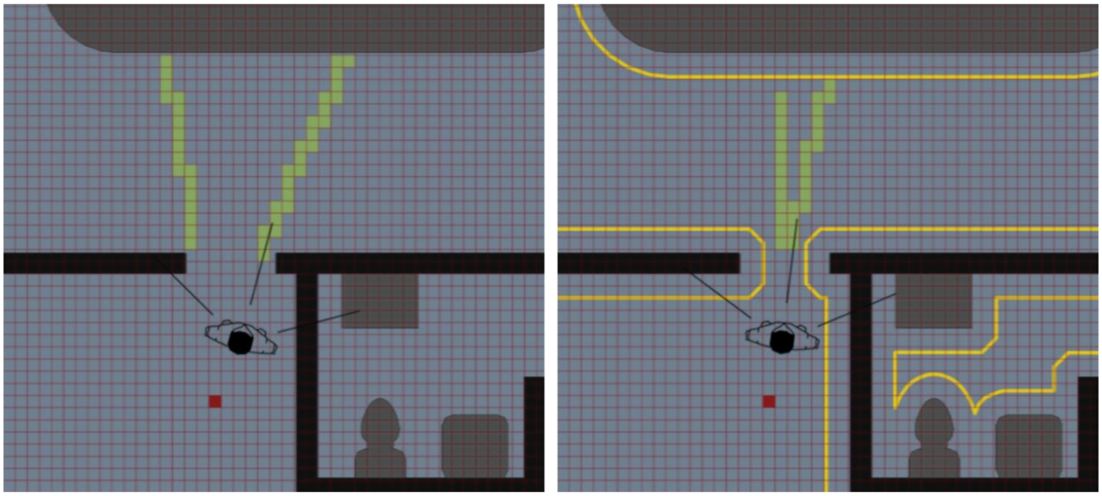

Figure 4-5-1: Destination found without the barrier buffer

Figure 4-5-2: Destination found with the barrier buffer

Figure 4-5: Applying boundary buffers will guarantee that the destinations within DAA will do not result in collision with barriers.

Simplification of the Destinations

As discussed earlier in the model the destinations are updated in each time-step and a force will be applied to the agent towards the destination that was temporarily selected. Therefore, the real location of the destinations do not matter, rather the direction that they define in relation to the agent are important. This provides a chance for removing the destinations create very similar directions in relation to the vantage point. In this process a maximum number of destinations around the vantage point, like N, will be required. The destinations will be sorted according to their angle with the vantage point and then classified in $360°/N$ categories. If a category includes more than one cell as a destination the cell with the highest attraction will be selected and the rest will be removed. N should be selected reasonably to minimize the discretization effect that it may impose. This process will also be helpful to manage the memory since the simplified destinations that are saved include much fewer references to the cell destinations. Figure 4-6-1 shows the destinations that are captured before simplification and Figure 4-6-2 shows the destinations after simplifying them according to their directions. In this case the maximum number of destinations is 180°and in each 1°degree angle category a destination with minimum distance to the barriers is removed. This process has filtered out 163 destinations out of 206 destinations which were initially captured.

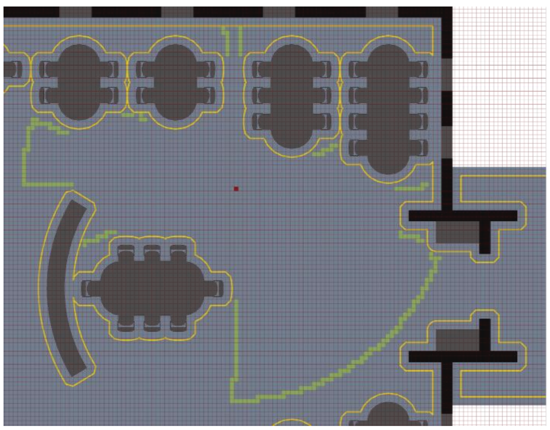

Figure 4-6-1: 206 captured destination

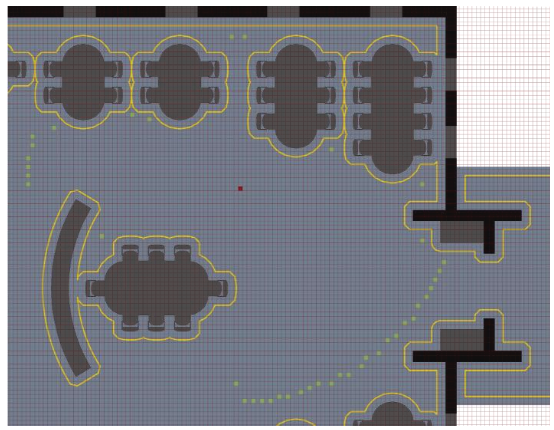

Figure 4-6-2: 43 simplified destinations

Figure 4-6: The simplification of the destinations of each cell according to the angle and desirability.

4.2.2 Selecting a Destination

So far a process was explained by which the destinations can be selected for any given cell in space. Now the process of selecting a single destination from the pre-calculated destinations will be explained. This process is probabilistic and accounts for both attraction and angular deviation of the destination cells. The first action is to exclude the destinations that are not located within an agent's cone of vision as possible candidates.

Figure 4-7 shows how this clipping process will eliminate some of the possible destinations which were shown in Figure 4-6-2. When the set of clipped destinations is empty the agent stops and looks around to find the best destination from all of the existing destinations. Therefore, when there is not destination in the cone of vision all of the possible destinations will be considered as potential candidates to choose from.

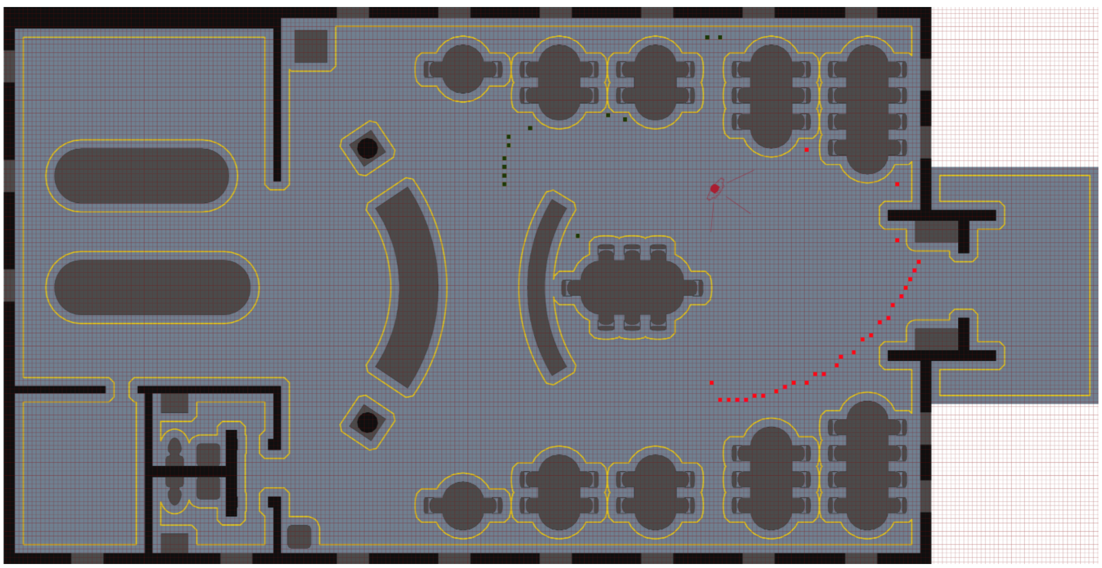

Figure 4-7: The destinations that the agent chooses are among those that are located inside its cone of vision.

As discussed in previous chapter to keep a path simple, the destinations that are aligned with the direction of the agent will be given priority. The destinations should also be given priority according to their attractions. Similar to Chapter 3, the attractions are modeled by parametric potential fields in which lower potentials correspond to the higher desirability (i.e. attraction). The selection process demands a "discrete choice model" that combines the effects of attraction and angular deviation. This type of model can be best explained by a logit regression (Ortúzar and Willumsen, 2011). The utility function which is used in this logit model is a linear regression of desirability and angular deviation factors. Within the parametric framework which was chosen for this model, the utility function introduces three parameters that can be subject to fine-tuning and training operations: a weighting factor for desirability, a weighting factor for angular deviation and a constant number. Using the logit model a weighting factor for the selection of each destination will be calculated and random destination will be selected according to the chance offered by its weighting factor. The introduction of randomness to OOSM indicates unlike MOSM that uses a potential field for path-planning, OOSM is not deterministic.

4.2.3 Summary of Model Description

Figure 4-8 summarizes the algorithm of the Optional Occupancy Scenario Model (OOSM) via a flowchart. The orange color shows that the only physical action that an agent can take is navigation. All of the green actions are directly or indirectly related to the process of making decisions. After starting the navigation the agent finds the pre-calculated destinations from the look-up table. The decisions for choosing destinations do not have to be updated in each time-step. If the average decision making time interval is known, an exponential distribution can be used to simulate the sequences of the decision making time interval. When the decision making time interval is updated a destination will be selected from the possible destinations which were retrieved from the look-up table. This process of selecting a destination starts with clipping the destinations using the cone of vision. If the cone of vision does not include any destination, all possible destinations will be considered as possible candidates. Using a logit model one of them will be stochastically chosen as the selected destination. The agent navigates towards the selected destination and the time-step updates. If the simulation continues and the decision making time interval is not passed the agent will continue walking towards the same destination. However, if for some reason navigation to the same destination is not possible or the decision making time interval is passed the choice of destination will be updated. This process continues until the simulation time finishes.

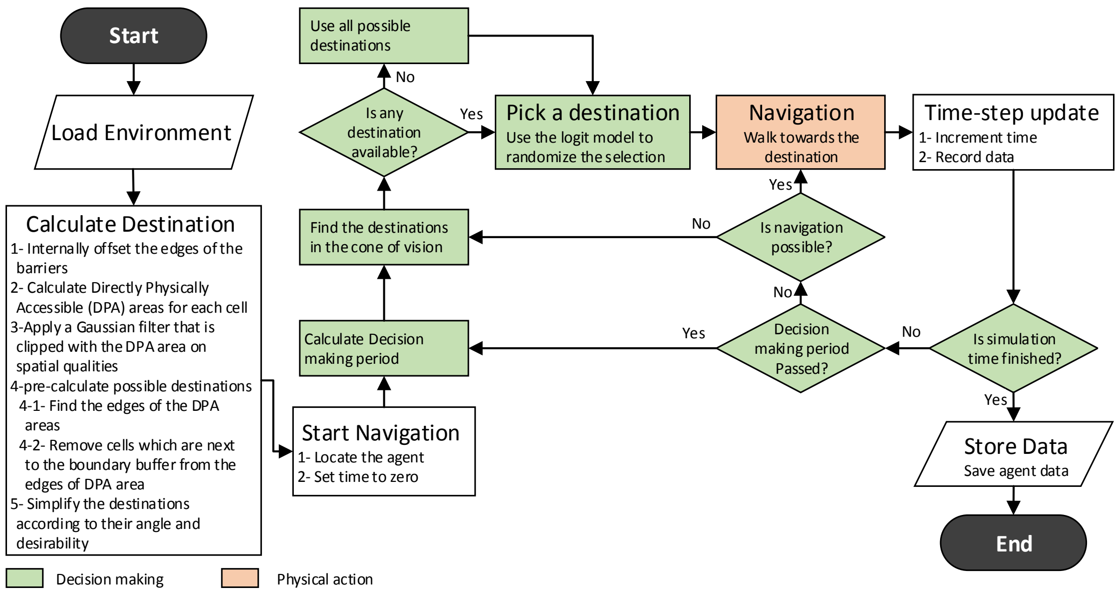

Figure 4-8: The flowchart of the OOSM process.

Similar to Chapter 3 the navigation system in OOSM is force-based. OOSM also includes features for simulating the physical body of the occupant, visualizing its walking dynamics, detecting collisions with barriers and calculating collision responses which are identical to MOSM features (see Chapter 3). There are basically two types of forces in the simulations: an attraction force towards the selected destination and a repulsion force from the barriers. The magnitude of the attraction force is always a constant number. Although the destinations are selected from the DAA, the occupant may not always be capable of avoiding collisions or getting too close to the barriers when the destination seeking forces are applied. Figure 4-9 visualizes a sequence of agent states in action. The green dotted lines show all of the destinations for each of the agent states. The barrier repulsion forces are only effective if the agent is capable of visually detecting the barriers and there is a possibility for collision with one of them. In this figure when barrier repulsion is effective the agent is color-coded in red. If the agent either has no view to the barrier or the agent knows that there is no chance for collision with any of the barriers the repulsion force will not be effective. In Figure 4-9 when the barrier repulsion forces are not effective the agent is color-coded in green.

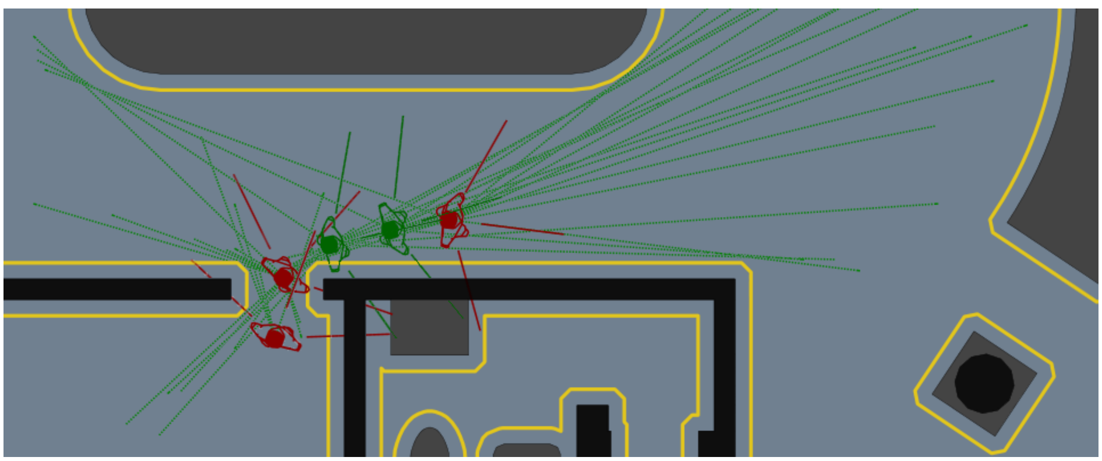

Figure 4-9: A sequence of an agent's states visualized in OOSM.

4.3 Validation

The purpose of validation process is to fine-tune the parameters in a way that an agent mimics the decisions that a human has represented in a real built environment. The decision that an agent makes is its choice of destination which accordingly influences its physical states such as acceleration, velocity, location, and direction. All of the factors related to the decision making are parameterized in the Occupancy Simulation Model (OSM). The validation process hypothesizes that a set of parameters can be found that reproduces the decisions of a human who is engaged with an optional occupancy scenario. From this perspective the idea for validation is simple. It includes a mechanism for measuring the difference between the observed and the simulated decisions and uses a meta-heuristic algorithm (Simulated Annealing) to evolve the parameters to minimize the measured difference.

The trail model which was used in Chapter 3 represents the results of the decisions that a human had made. As discussed in Chapter 3 this model allows for extracting the interpolated physical states of the agent at any time in-between observed states. Although the decision making processes are very different in OOSM and MOSM, the ideas of measuring the differences are identical. The trail will be divided into smaller sub-trails in equal time intervals, like T. The agent will be released with the state at the beginning of each sub-trail for the time length of T. With an ideal set of parameters the agent will be expected to adopt the state of the end of sub-trail from which it was released. The difference between an agent state after simulation and the state at the end of the sub-trail can be measured as the sum of the squared distances between distance, velocity, direction and acceleration 2D vectors. The objective of the Simulated Annealing (SA) algorithm will be set to minimize the sum of the differences that are captured all over the sub-trails. Figure 4-10 shows an example of evolving the parameters in which the values for acceleration magnitude, barrier repulsion rate, maximum repulsion, angle weighting factor, and desirability weighting factor were fine-tuned. The best solution found during running SA is represented by blue line segments which connect the agent location after simulation to the point of origin in the sub-trail from which it was released. The dashed line segments represent the current iteration which is being tested. The difference between the right hand-side and left hand-side visually represents how fitness has evolved at the end of the process after 10000 iterations.

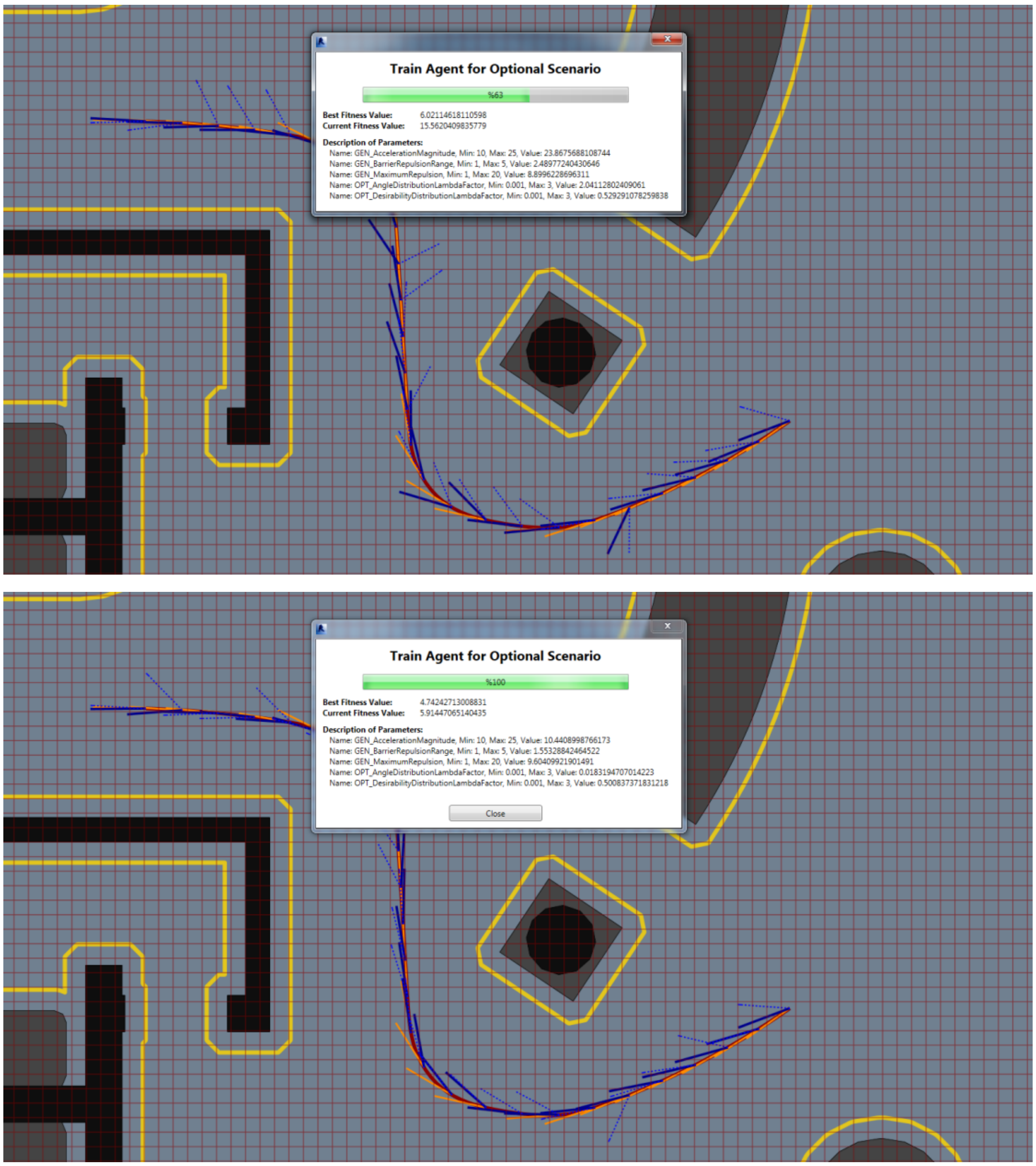

Figure 4-10: Two different snapshots of the progress of Simulated Annealing algorithm to fine-tune the parameter according to a trail model.

Since the decisions making process during the simulation includes randomness, the decisions that the agents make are not unique even in identical situations. Therefore, the observed trail is unlikely to be reproduced. However, similar decisions are very likely to be made. The existence of randomness in the model also indicates that when measuring the differences between the two states using one simulated state may create unreliable results. According to Central Limit Theorem the aggregate of a number of states is normally distributed and has a lower standard variation rate (Ross, 2014). Therefore, unlike MOSM, the validation in OOSM testes each parameter setting 30 times and uses the average difference which makes the validation process accordingly slower, but yields more reliable results. To speed-up the process OOSM includes parallel threads to simulate the agent's navigation in each sub-trail and measure the differences.

The fine-tuning process includes the limitations of all meta-heuristic algorithms, which is finding the best answer will never be guaranteed. As discussed in Chapter 3 the fine-tuning process is also exposed to over-fitting and under-fitting problems which will result in low predictability. Ideally a part of the trail model should be used to test the predictability of the suggested parameter values. The implementation of these features of machine learning is envisioned in future of this study.

4.4 Case Study

4.4.1 Case Study Description

Figure 4-11 shows the floor plan of a small shopping center that includes two shops in which groceries and furniture are sold, a real estate leasing office, a travel agency, a restaurant, and an ice-cream store. This shopping center can be a part of a larger mall or a plaza. Both the open and closed spaces are furnished with the furniture that serves different purposes. For example, the fast food is attached to a series of shaded tables in open space. This lay out follows a courtyard pattern that provides a pleasing view to vegetation and shaded tree canopies at the center. In these examples the agents will freely navigate in open spaces and publicly accessible indoor areas. The areas that are color-coded in light brown offer private services and will not be accessible to the navigating agent. In this section several scenarios in this layout will be tested in which different qualities will be introduced and their impacts will be examined. Practically the parameters that set the agent's navigation behavior should be determined in a fine-tuning process. OOSM has demonstrated the parameter tuning ability in the previous section. Since this study is not dealing with observed data from a field study, validation of parameters will be avoided in this section and the assumption will be made that the parameters and their values have already been validated using the methodology explained in previous section.

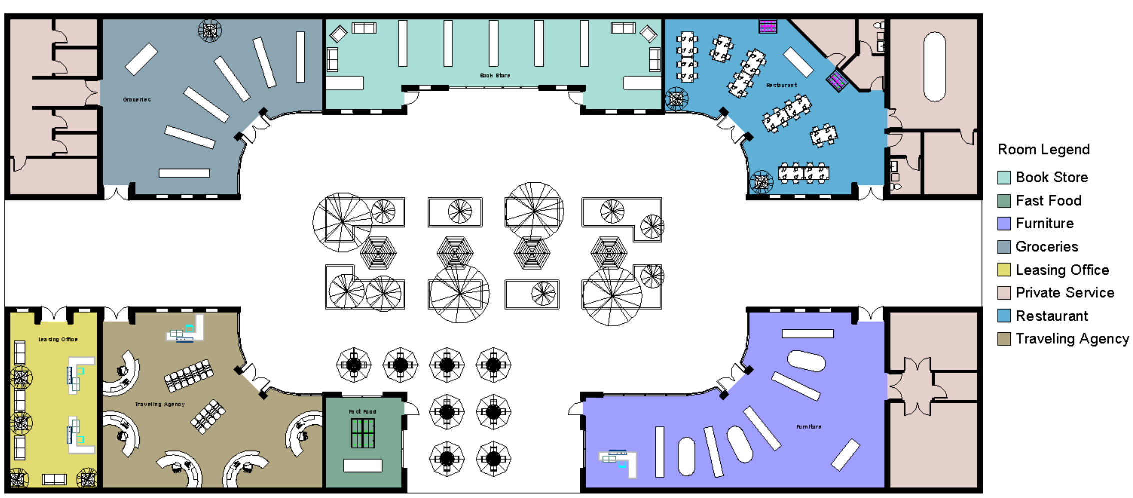

Figure 4-11: The layout of a shopping center and the functions that it offers.

4.4.2 *Simulation of Results*

In the first scenario keeping distance from the barriers is the only quality which the agent uses to choose its destinations. The potentials in this quality are determined by the formula $f(x) = B\left(1 - \sqrt{x/A}\right)^2$ for x values that are smaller than A and $f(x) = 0$ for x values that are greater than A. This function is a Bezier curve in which the maximum potential $B = 20$ is assigned to a point when its distance from the barriers is zero. The potential smoothly decreases to reach zero when the distance from the barriers equals to the size of the body of the agent (i.e. $A = 1.75\ Ft$ in this case). This cost function which is associated to the potential field has a very "limited range" of influence. Since the destinations that are more than an agent's body size away from the barriers have equal value of desirability the only factor that influences their selection will be their alignment with the direction to which the agent is headed. The results are captured in a fixed time step of 17 milliseconds. The destinations are captured from DAA depth of $100\,Ft$. The agent updates its destinations in time intervals that are exponentially distributed with the mean value of 1 second. Figure 4-12 shows the real-time performance of the scenario in OSM which includes 2D and 3D animations. In this scenario the trees are assumed as visual targets that provide pleasing scenery in the open area and if a line of sight to a visual target exists it will be visualized via a strong red line. All possible directions from the agent's location are also visualized via weaker green lines.

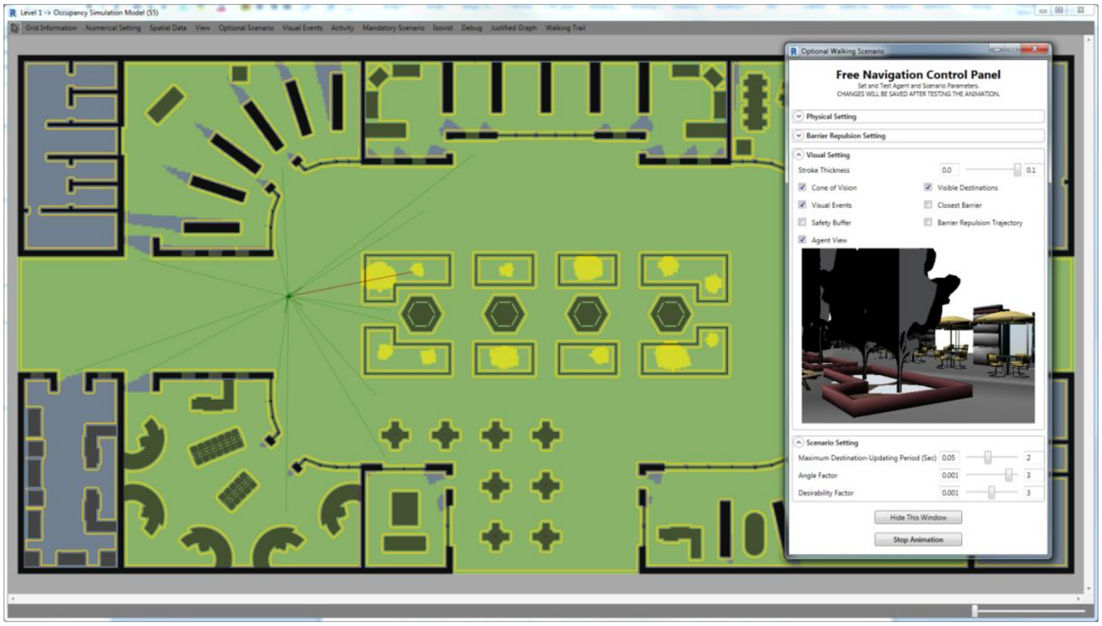

Figure 4-12: Visualizing the performance of the scenario in real-time.

Visualization does not have to be a part of the simulation of the optional occupancy scenarios. Without visualization the simulation can run faster and it can be sent to a background thread. The offline (vs. online) simulation will work with a fixed time-step and for a given duration of time. During the simulation the agent's locations will be recorded in a layer of spatial data to capture the PAP (Probability of Agent's Presence) in the shopping center. Figure 4-13 shows the PAP which was captured during the simulation shown in Figure 4-12. The hotter colors and the contour lines show areas where an agent with the defined characteristics is more likely to spend its time. This result was captured for a simulation time of 320 hours within 9 minutes. Each hour of occupancy was simulated in 1.70388 seconds (i.e. 124,348 time-step operations per second). The simulation used a single thread and did not involve GPU in computations. The results were obtained in a computer with the following details: CPU Intel(R) Xeon(R) CPU E5-1660 @3.30 GHz16.0 GB RAM, and 64-bit Windows 7 OS.

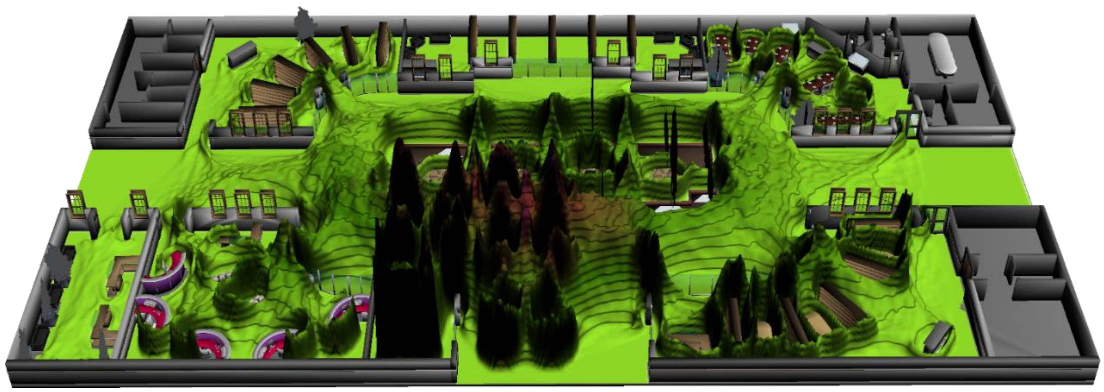

Figure 4-13: The Probability of Agent's Presence (PAP) given 100 *Ft* DAA depth, 170 degree vision angle, and low range cost of desirability from barriers.

4.4.3 Reliability of Results

Compared to mandatory occupancy scenario, the optional occupancy scenario which was descried includes numerous random variables to give the agents the freedom of choice. Randomness is an inherent property of agent-based models (Jennings, 2000). However, randomness is expected to be stabilized when aggregated. Table 4-1 shows the correlations between the PAP results that are obtained in different simulation durations. The results indicate that the correlations between the results increase along with the increasing of the simulation time. The correlation table can serve as a method for measuring the reliability of simulation results.

Table 4-1: Correlations between Probability of Agent's Presence (PAP) for different simulation durations.

Hours	***5***	***10***	***20***	***40***	***80***	***160***	***320***
5	1						
10	0.6539	1					
20	0.6929	0.7747	1				
40	0.7276	0.8365	0.8554	1			
80	0.7422	0.8410	0.8845	0.9346	1		
160	0.7524	0.8504	0.8995	0.9411	0.9692	1	
320	0.7572	0.8526	0.9014	0.9461	0.9750	0.9836	1

4.4.4 Analysis of Results

In this sub-section the effects of some of the parameters on the results will be discussed. These parameters represent the agent's unique preferences. A comparison between the DAAs of the points P_1 and P_1 in Figure 4-3 shows that increasing the depth will not change the shape of DAA if it is already limited to the boundaries of the physical barriers. The location of the agent and destinations which are available to it in Figure 4-12 also shows that 100 Ft depth of DAA captures the destinations which are mainly to avoid collisions with physical barriers. Since by increasing the depth of DAA eventually all of the DAAs will be limited to the barriers, it will not change the destinations for each point in the walkable field and the results will accordingly be the same. This is of course a property of this specific layout. The results of two simulations for the same duration length (i.e. 320 hours) and the same cost functions exhibit significant similarity between PAPs ($\rho = 0.86$) when the input parameter of DAA depth changes from 100 Ft to 50 Ft (See Table 4-2). However, when the DAA depth changes to 20 Ft, the resulted PAP correlates weakly with PAPs of 100 Ft and 50 Ft DAA depths ($\rho = 0.45$, $\rho = 0.60$). This indicates that the pattern of walking changes significantly according to the changes in the DAA depth. Figure 4-14 shows the distribution of PAP in the walkable field, which compared to Figure 4-13 represents the differences in the results. The significant difference that can be observed is that when DAA depth is set to 100 the agent turns prefers walking around the barriers which are surrounded by open space, whereas when the DAA depth is 20 the agent prefers open space.

Table 4-2: Correlations between Probability of Agent's Presence (PAP) distributions.

DAA Depth			***100 Ft***		***50 Ft***		***20 Ft***				***Space Syntax***	
	Cost Model		**Limited Range**	**Long Range**	**Limited Range**	**Long Range**	**Limited Range**	**Long Range**	**Limited Range**	**Limited Range**	**Standard**	**Line of Sight Length**
		Vision Angle	**170**	**170**	**170**	**170**	**170**	**170**	**100**	**50**	**170**	**170**
100 Ft	**Limited Range**	**170**	1.00									
	Long Range	**170**	0.90	1.00								
50 Ft	**Limited Range**	**170**	0.86	0.82	1.00							
	Long Range	**170**	0.77	0.84	0.93	1.00						
20 Ft	**Limited Range**	**170**	0.45	0.55	0.60	0.66	1.00					
	Long Range	**170**	0.39	0.47	0.52	0.60	0.86	1.00				
	Limited Range	**100**	0.45	0.54	0.60	0.65	0.99	0.87	1.00			
	Limited Range	**50**	0.44	0.54	0.60	0.65	0.99	0.85	1.00	1.00		
Space Syntax	**Standard**	**170**	0.30	0.45	0.52	0.57	0.81	0.61	0.81	0.81	1.0	
	Line of Sight Length	**170**	0.48	0.63	0.61	0.66	0.79	0.62	0.80	0.79	0.91	1.00

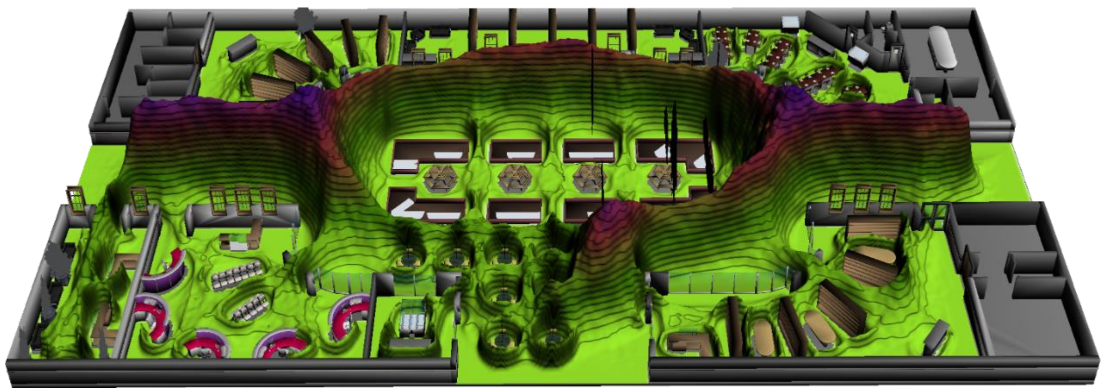

Figure 4-14: The Probability of Agent's Presence (PAP) given 20 Ft DAA depth, 170 degree vision angle, and low range cost of desirability from barriers.

For a similar reason the impact of the qualities will also be overridden by the DAA depth when the destinations are dictated by the boundaries of physical barriers. Trying a new model, $f(x) = -$x, for the cost of proximity to the barriers will prove this fact. Unlike the previous cost model which had a "limited range" of influence, the new cost model has a "long range" of influence and simply indicates that the agent prefers to choose destinations with maximum distance from the barriers. However, as Table 4-2 reports the PAP results for both DAA depths of 100 Ft and 50 Ft strongly when everything else is unchanged ($\rho =$ 0.90 for 100 Ft and $\rho = 0.93$ for 50 Ft DAA depths). When the depth of DAA is 20 Ft more directions are available to choose from and the change in the cost model yields a lower correlation value (i.e. $\rho = 0.86$).

The results that were so far obtained were not influenced by any environmental quality other that distance from barriers. Therefore, they can serve as the basis for comparison between OOSM and the model suggested in space syntax (Penn and Turner, 2001, Turner and Penn, 2002). Table 4-2 suggests significant correlations between the results of two different types of the space syntax agent-based models and the results which were captured by OOSM for DAA depth of 20 Ft and a limited range of cost which almost allows for selecting random destinations from the cone of vision (i.e. $\rho = 0.81$ for standard ABM and $\rho = 0.79$ for "line of sight length" ABM). Interestingly, when the cone of vision shrinks OOSM the correlations are almost the same and significant. Figure 4-15 visualized the results of standard ABM which strongly correlates with the PAP shown in Figure 4-14. The similarities between these results raises one question: do space syntax agent-based models and OOSM suggesting share inherent similarities?

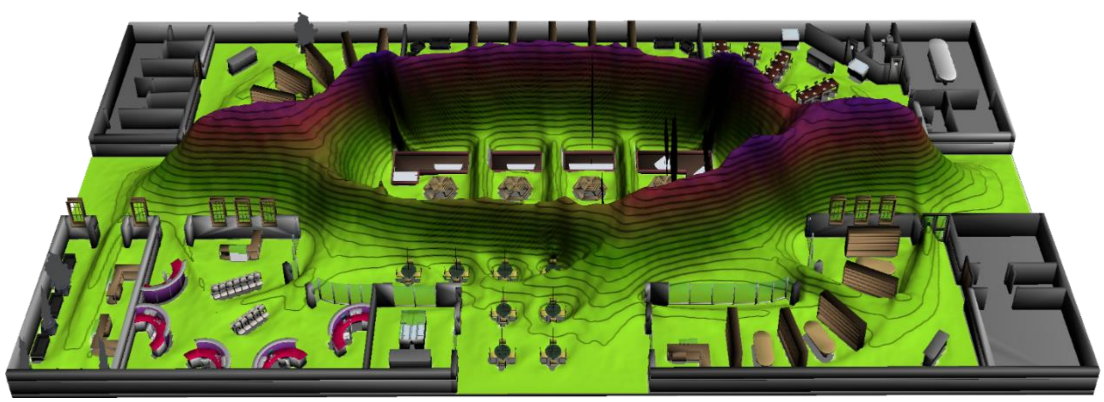

Figure 4-15: The results of standard ABM in space syntax calculated by Depthmap software with vision angle of 170 degrees visualized in OSM.

To understand the differences between the OOSM and Space Syntax a closer look at the choice of destination in space syntax AM will be necessary. Choosing any random node from the agent's cone of vision and taking some steps towards that seems like a very simple idea. However, even though the selection of the destinations from the cone of vision is uniformly random, the aggregate of choices of directions will be biased towards selecting destinations that align with the longest lines of sight. This model, therefore, reproduces the central idea of space syntax (Hillier and Hanson, 1984, Peponis et al., 1990). Figure 4-16 shows a typical isovist which has been radially divided to slices which form equal angles from its vantage points. When the probability of selecting points from a look-up table is uniformly random, the chance of selecting a point from each slice is proportionate to its area and since all of the slices have the same angle at the vantage point, their area is proportionate to the length of line of sight in them. When increasing the number of slices and making them thinner the probability of selecting each individual ray direction will become proportionate to its length within the isovist polygon. Therefore, technically the two different "standard" and "line of sight length" indices of ABM in space syntax should be the same, which is supported by the high correlation value in Table 4-2. Depthmap software (Turner, 2001) includes other models of space syntax-based ABMs for which there is not enough documentation to understand the mechanism of their operation (i.e. "occluded length" and "any occlusion").

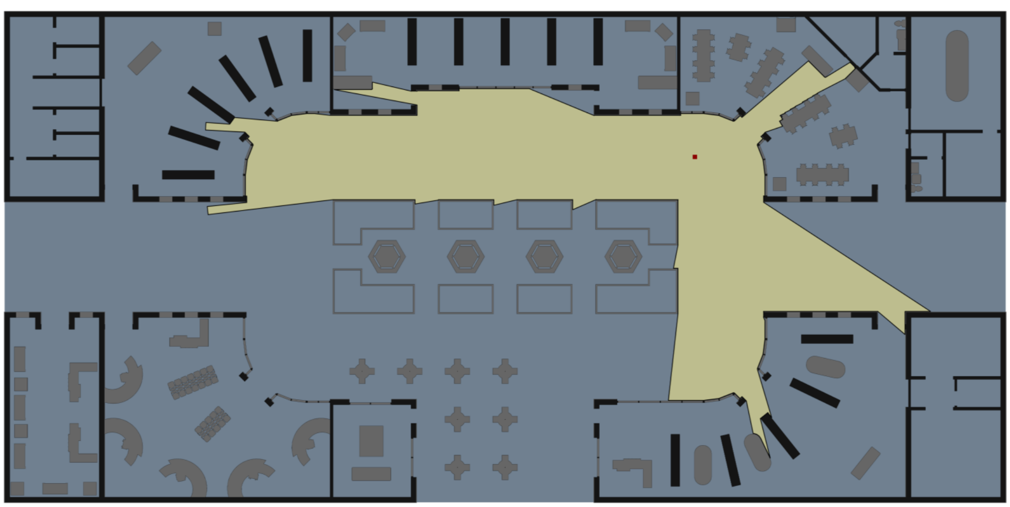

Figure 4-16: This shows how a uniform random choice of a point in the isovist will result in a choice of direction which is biased towards the length of the line of sight.

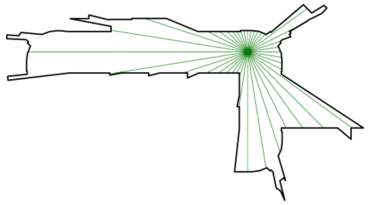

Figure 4-16-1: Creating equal angle radial slices inside the isovist polygon

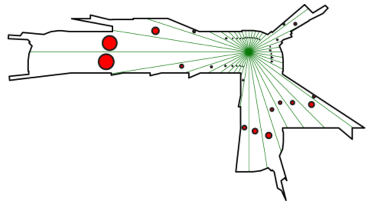

Figure 4-16-2: The area of the red disk is proportionate to the area of its slice

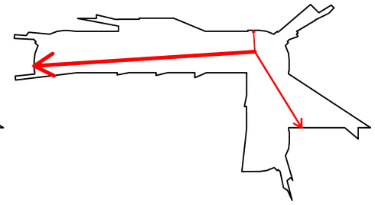

Figure 4-16-3: The probability of selecting each direction is proportionate to the length of its corresponding ray clipped by the isovist

Figure 4-16 Continued

Space syntax agent-based model is claimed to be an alternative to the traditional models of pedestrian dynamics which is based on traveling between origins and destinations (Turner and Penn, 2002). Analysis of the results of this model shows disproportionately favoring open spaces which are not obstructed. A new ABM was developed in space syntax to improve this limitation by bridging the gap between the mandatory models and the space syntax configurational model. The idea in this model is very simple. Each agent has a destination and in the field of visibility takes a random step that is close or closer to its destination. When space is not available increase the cone of vision angle from 170 to 360 degrees (Ferguson et al., 2007). The destinations (i.e. attractors) in this model were claimed to be land use pattern or other region-based attractions. This new model is essentially repeating the mandatory scenarios which uses a potential field, but does not allow for sharp changes in the direction of movement. This model can hardly be associated to configurational theory of space syntax and represents a primitive replication of the more accurate models which are already implemented in the domain of mandatory scenarios. For example, Yan and Kalay (2006) have developed this idea while also considering different means of spatial navigation, collision avoidance and attraction. The model suggested by Yan and Kalay is mandatory at short time durations when the agents travel to their destinations using an A* algorithm for path planning and optional when the agents choose their next destinations.

However, the problem of disproportionately favoring open spaces is still inherent in space syntax ABM. This model also by definition takes no account for any environmental quality and merely depends on the quality of the open space. A visual comparison between the results represented in Figure 4-14 and Figure 4-15 show that the agents in the OOSM become attracted to barriers and would walk around them while still preferring open spaces in general. OOSM still remains on the domain of optional occupancy scenarios and does not use the origin-destination mandatory scenarios. In the next sub-section, it will be shown that OOSM also accounts for environmental qualities, which define the element of attraction that is the essence of optional occupancy scenarios.

4.4.5 What-If Analysis

The results which were so far obtained and discussed did were only influenced by the desire of being away from the barriers. As discussed earlier the logit model in OOSM is designed to account for both static and dynamics costs. In this section a new layer of spatial quality will be introduced to show the behavioral changes that can occur accordingly. To demonstrate the changes the scenario simulated in Figure 4-14 will be used as a benchmark. The quality that will be added is the smell of the fast food which can spread over the walkable field. The simulation of how smell spreads in the walkable field is out of scope of this study. For the sake of demonstration it will be assumed that the food smell weakens linearly as the distance decreases and eventually fades out at the range of 75 feet. The interpolation formula is $F(x) = A\left(1 - \frac{x}{75}\right)$ if $x < 75$ otherwise $F(x) = 0$, where $A = 10$ is the initial value of the smell inside the fast food area and the shaded tables around it where the food is served. The cost function which is associated to this layer of spatial data is $G(x) = -Px$ where P $(0 \leq P \leq 1)$ is a parameter that determines the impact of the smell data and the negative sign switches the attraction to higher potentials (i.e. stronger smells). Figure 4-17 shows how the smell's attraction (i.e. $G(F(x))$ function) in the field.

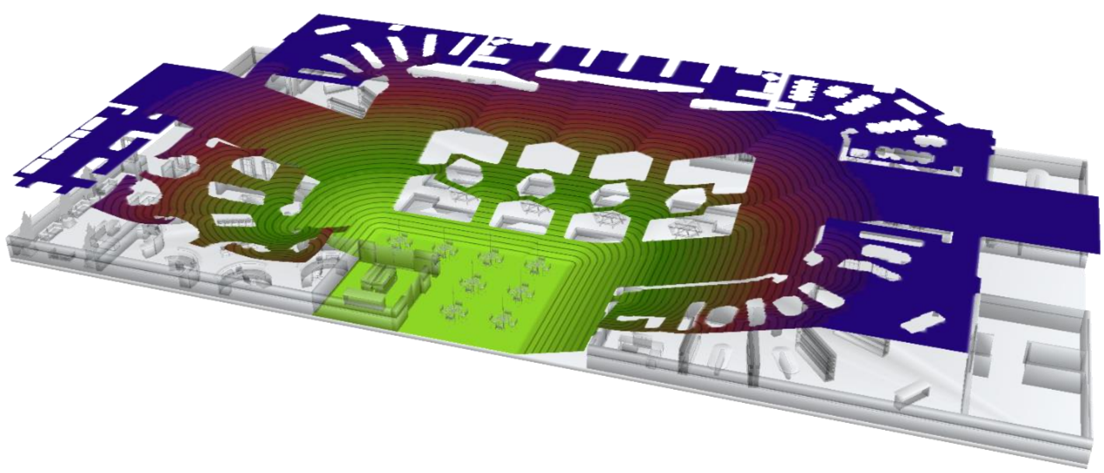

Figure 4-17: The attraction of the smell of the fast food in the shopping center.

Figure 4-18 shows the PAP of the agent who is sensitive to this smell for a series of different values of P. Increasing the value of P indicates higher attraction to the smell which accordingly changes the resulting PAP. A comparison between Figure 4-18 and the Figure 4-14 shows significant differences in the pattern of using space. While the attraction to this smell might still allow for exploring the entire space, the aggregate of the trail shows that the agents are more likely to spend their time in areas where the smell is stronger according to their sensitivity to the smell which is modeled with the parametric cost function. Within this trend of changes when the value of parameter P approaches zero the PAP shown in Figure 4-14 will be exactly reproduced. The value of the parameter P and even the attraction function itself should be determined in a fine-tuning process.

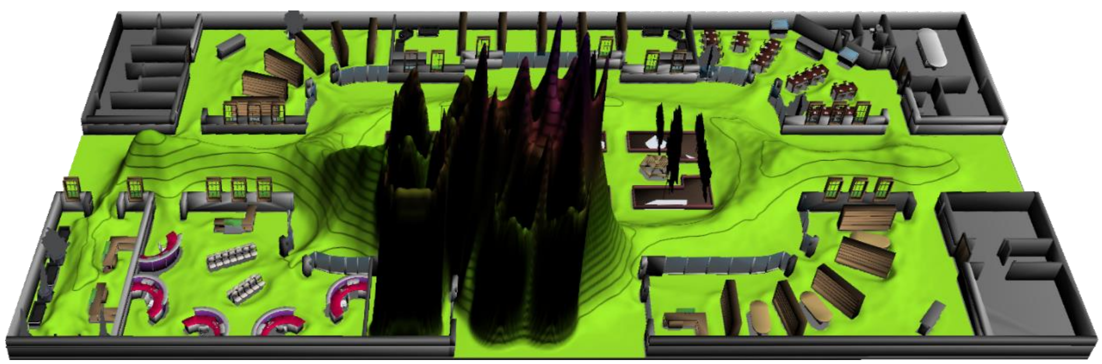

Figure 4-18-1: $P = 1$

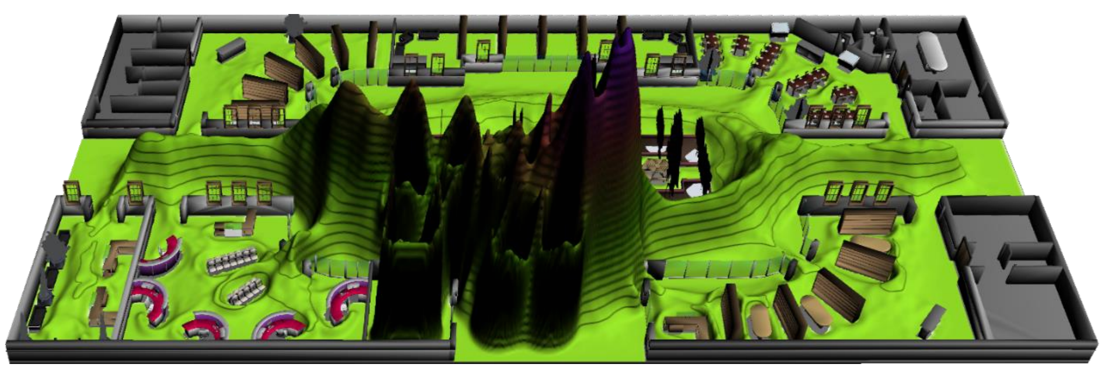

Figure 4-18-2: $P = 0.5$

Figure 4-18: Variations within PAP according to changes in attraction to the fast food smell which is represented by the value of parameter P.

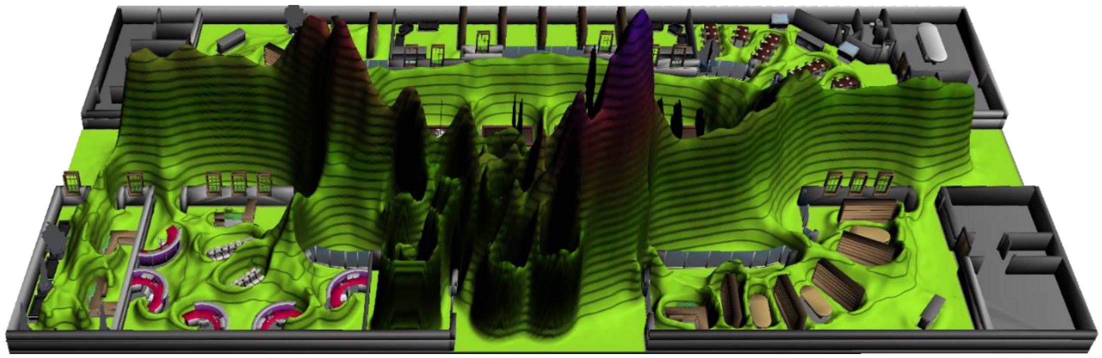

Figure 4-18-3: $P = 0.1$

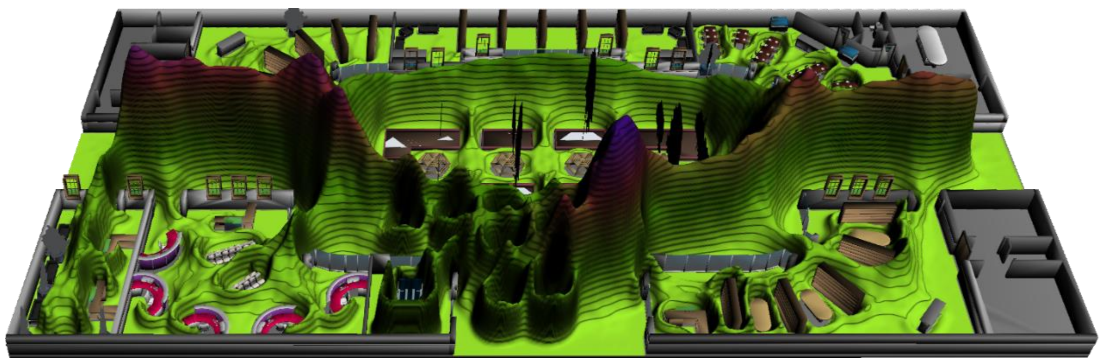

Figure 4-18-4: $P = 0.05$

Figure 4-18 Continued

This section focused on showing that a verity of different outcomes can be achieved according to the variations within the cost function. The transition from Figure 4-18-1 to Figure 4-18-4 shows that preferring a destination area can be considered as a desire for the agent that interacts with other desires of an occupant. This model allows the agents to choose other directions occasionally if they offer higher attractions. During the navigation the occupant may decide to reach a destination. Upon making this decision the occupancy model changes from optional to mandatory.

4.5 Evaluation

When an agent is engaged with an optional scenario it will experience different environmental qualities and visually connect to different targets. The satisfaction level of the agent, as discussed in Chapter 1, will also change accordingly. During the engagement with the optional scenario, the information about the agent's states in relation to all of the environmental variables can be collected. Querying this information can provide insight for designers and generally decision makers to extract more insightful information than a general spatial PAP (Probability of Agent's Presence). The data can be filtered in relation to all different fields of information that it contains. For example, the data query can answer the following questions.

1. *How often an agent will have a line of sight to a beautiful scene with a restorative effect?*
2. *Where the agent will be pushed out of its comfort zone in relation to one layer of environmental variable?*

Data query provides a performance transcript of occupancy scenario for the designer at the design phase and facility manager in after design phases to evaluate the outcomes of their decisions and suggest insightful changes.

4.5.1 Data Query Mechanism

The simulation model provides access to information from agent's states and the data query provides the logic for filtering them. Data query essentially is a Boolean logic that should be designed in accordance to the interests of the decision maker who wants to use the data. Agent states include two types of variables in relation to spatial data and visibility targets. An agent state can include multiple variables from both of these types. In Chapter 3 it was explained that evaluation in relation to environmental variables is defined based on a range of variation, such as temperature comfort zone, that includes or excludes a scalar value such as temperature at agent's location. Evaluation in relation to a visibility target can be based on the existence of a line of sight to a visual target. Figure 4-19 shows an example of the process of filtering states. The Boolean function applies an "AND" operation to the chosen spatial data and an "AND" operation to the selected activities. Finally, an "AND" operation is used to combine the results of the spatial query and visibility query. The Boolean equation which is encoded in this process is isolated in Equation 4-2. In the equation S is the agent state, $E(VT)$ is the evaluation of a visibility target, and $E(SD)$ is the evaluation of a spatial data layer (i.e. environmental variable). This function can change according to the interests of the designers or facility manages. This model is a simpler version of the query process which was discussed in Chapter 3 in a sense that an agent states in optional scenarios does not include information about activity engagement.

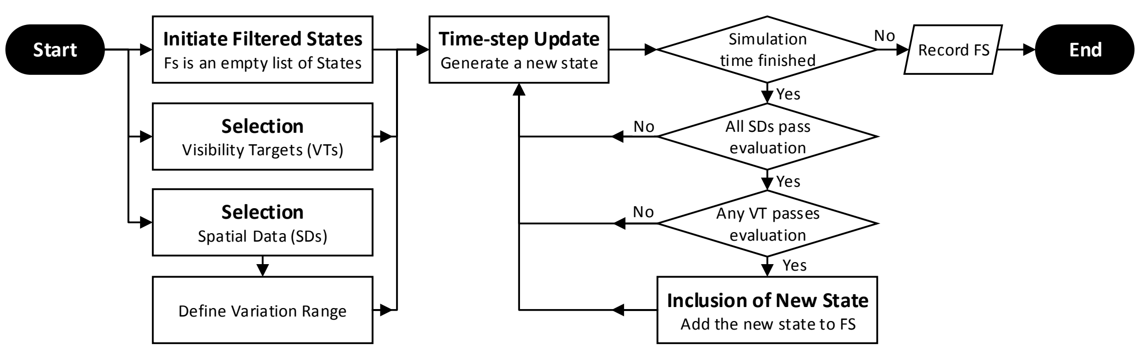

Figure 4-19: The process of data query in the simulation.

$$\exists\ E(VT \in S) \wedge \forall\ E(SD \in S)$$

Equation 4-2: An example of Boolean logic for data query.

4.5.2 Evaluation Results as Events

Similar to Chapter 3, to organize the filtered states the “evaluation event” data model will be created and used to report the query results. An evaluation event is a list of states that pass the Boolean function filter. During the simulation when the state of an agent starts to pass a given Boolean filter function an evaluation event in created. The created event continues as long as an agent’s state passes the filter, and terminates when the states no longer pass the states. Evaluation events also have a time length and an ordered list of states associated to them. Defining evaluation results as events that occur in the course of occupancy time makes it possible to analyze the frequency and likelihood of their occurrence in addition to the places where they have occurred. Therefore, evaluation events include portions of a scenario when the states pass a given query filter.

4.5.3 Informed Interventions

In previous section the simulation results and comparison between different scenarios were only possible visually. Evaluation events allow for narrowing down the scopes and looking for specific details. This section will show how the application of the evaluation events can be used to measure the differences between various scenarios numerically, which will result in insightful decisions. As the first example, let’s take a look at an event of spending time in the traveling agency. The settings that were used to produce Figure 4-18 will be used for this query in which the smell was effective ($P = 0.05$). For data query a layer of spatial data will be created in which the value of the cells inside the store is 1 and outside the store is zero. This layer can be used to filter the agent’s location.

The Boolean logic function can further filter the states to extract events when the agent has a line of sight to the trees in the center of the court yard. OSM reports 6.75% chance for the former and 3.79% for the latter event to occur. The PAP of these events are illustrated in Figure 4-20 and Figure 4-21 shows the transcript of the latter event in OSM. According to this transcript the pattern of re-occurrence of this event is highly regular ignoring the high frequencies in the Fourier series analysis.

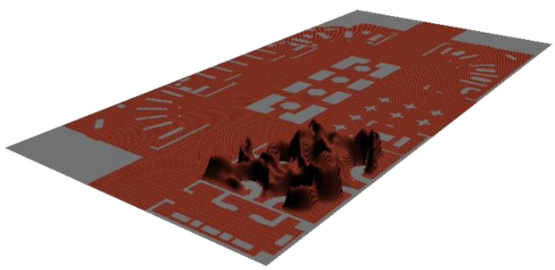

Figure 4-20-1: Presence in the traveling agency

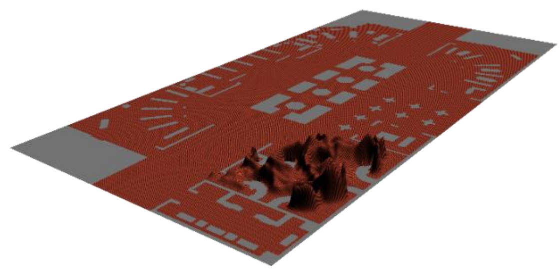

Figure 4-20-2: Presence in the traveling agency and having a view to the trees

Figure 4-20: The PAP of two different evaluation events that are filtered in relation to spatial data and visibility.

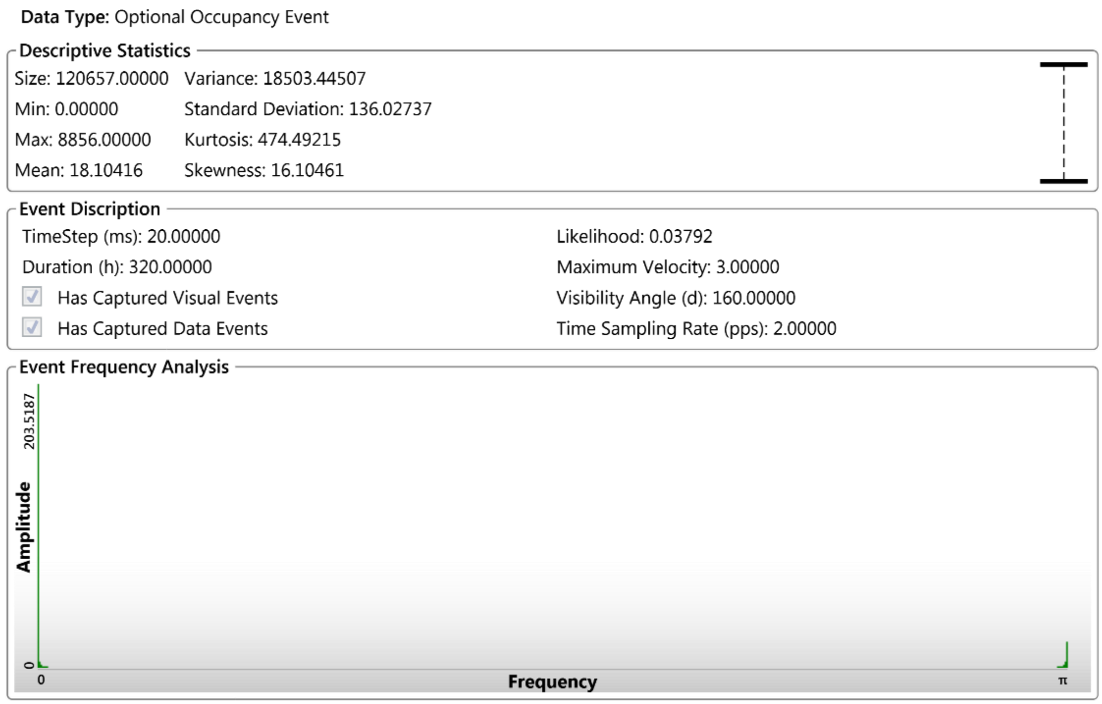

Figure 4-21: The transcript of the event shown in Figure 4-20-2.

The above example of capturing occupancy events can be useful for comparing the difference between scenarios. Imagine a business model which claims that the number of visitors to a store correlates with the sale rate of that store. Given this model, from Figure 4-18 it is obvious that agent's attraction to the fast food area changes the PAP throughout the layout to the favor of the fast food business. This impact on the next door stores is not very obvious though. Capturing events will allow us to numerically measure the differences between the scenarios by calculating their odd ratio. For example, the traveling agency which is next to the fast food has the PAP of 6.75% when the fast food smell attraction model is active. Without the attraction of the food smell this PAP is 6.72%. In this case the odd ratio is 1.0044 (i.e. 6.75/6.721) which indicates that there is not a substantial change in the pattern of visiting the traveling agency. In other words, while generally an agent with the given profile is attracted to the fast food area from the entire layout, the changes for traveling agency business is not very significant (see Figure 4-22). The odds ratio can help the decision makers to evaluate the outcome of their decisions by using the simulation model which was suggested in this chapter.

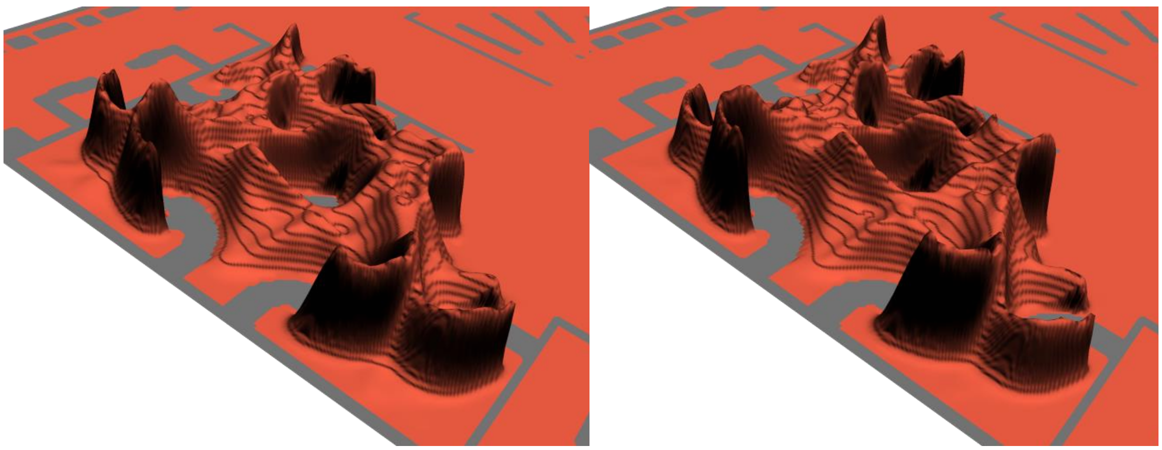

Figure 4-22-1: PAP distribution in the traveling agency without the attraction effect of the fast food smell.

Figure 4-22-1: PAP distribution in the traveling agency with the attraction effect of the fast food smell.

Figure 4-22: While there are some differences in the distribution of the agent's presence in space, the odds ratio for visiting the traveling agency does not represent a significant change.

4.6 Conclusion

Throughout this chapter an idea for simulation of optional occupancy scenario was developed and a software implementation of the idea demonstrated its feasibility. The occupancy scenario which was developed in this chapter simulates navigating space based on the attractions that an environment offers. The main contribution of this idea is the integration of the features which were discussed in the review of the literature in Chapter

2. The Optional Occupancy Simulation Model (OOSM) also accounts for the unique differences among the users and is capable of creating a unique agent profile by fine-tuning parameter in a way that the agent can reproduce the walking trail of a human in real environment. The desirability of the directions for the agent is based on the desirability of static environmental qualities and the desirability of keeping the paths simple. The dynamics of walking in the OOSM is physically-based and can be visualized in both 2D and 3D formats.

While the developed model is capable of effectively reproducing the results of agent-based model in space syntax, it offers a series of other advantages which are not present in space syntax agent-based model. These features include exhibiting a realistic walking behavior both in terms of being physically-based and reproducing observed walking trail, and accounting for any type of environmental variables and path simplicity. The development of the OOSM paves the way for creating a detailed transcript of the occupancy. This chapter showed that with this model designer at the design phase and facility managers in after design phases can anticipate the outcome of their decisions and make more informed decisions.

CHAPTER V

CONCLUDING REMARKS

5.1 Research Summary

Evaluation of design proposals is an integral part of design processes. Predicting people's behaviors in buildings and understanding desirability of environment from their perspectives is not possible without knowing their intentions in occupancy scenarios and their unique differences. People mainly have two reasons for getting engaged with occupancy scenarios: pleasure or obligations (Gehl, 1987). Each individual occupant may have a unique agenda for occupancy and idiosyncratic preferences as well. This study showed that the simulation models for visualization and evaluation of mandatory and optional occupancy scenarios can be developed and demonstrated the feasibility of this idea by developing software solutions for each of them which were used in different cases studies. The ingredients of the Occupancy Scenario Model (OSM) which was developed in this study belong to different disciplines including Computer Aided Design, architecture, computer science, and physics. The software solution was developed taking a post-positivism (Wang and Groat, 2013) and critical realism (Bhaskar, 1997, Bhaskar et al., 1998) research stances in a model-based strategy (Phillips et al., 2002).

The knowledge of people's locations in the environment and what they see is the critical factor for evaluation. With this knowledge the individual evaluation models (i.e. evidence) in the discipline of architecture can be used for evaluation. This knowledge, however, should be achieved through different techniques in mandatory and optional scenarios. Mandatory occupancy scenarios are task-based whereas optional occupancy scenarios are attraction-based. Due to the differences between them, two different models were developed for these scenarios in OSM: Mandatory Occupancy Scenario Model (MOSM) and Optional Occupancy Scenario Model (OOSM). The main difference between these two models is the mechanism for finding the destinations. Otherwise, these models utilize identical mechanisms for simulation, evaluation and visualization.

Destinations in mandatory occupancy scenarios were modeled using a task schedule using Discrete Event Simulation (DES). In this study the scenario of nursing was used as an example of mandatory occupancy scenarios and it was shown that tasks can be prioritized according to their expected time of activation and the risks that can be associated to them. In MOSM tasks were also detected visually. In optional occupancy scenarios, the destinations are chosen from the most desirable part of the environment which is visible to an occupant. In both mandatory and optional occupancy scenarios a mechanism for choosing destinations was suggested that maximizes pleasure and minimizes dissatisfaction as a principle of walking (Helbing et al., 1997). Therefore, evaluating the environment is not only the outcome of this study, but also was a part of the simulation model as well.

In both MOSM and OOSM desirability was measured against spatial data and simplicity of the paths. Spatial data, such as temperature, daylight, smell, are static and distributed over the walkable field. On the other hand, path simplicity is a dynamics factor to maintain an occupant's current movement trajectory. The desirability of the spatial data was models with a cost function which was associated to them. The overall desirability of each point is the sum of the static and dynamic costs that are associable to it. The aggregation of the costs imposed a challenge because the research evidence which were used for evaluation are often achieved in processes that isolate one factor from the rest of the world whereas the aggregation model adds them up with no regard for the interactions which have been removed at the research phase. To address this challenge the cost functions were parameterized to allow for making dependencies by sharing parameters and a fine-tuning process was suggested to find a set of parameters that best reproduced the trail of a human in a real building. While the computational algorithms can optimize fitness values, suggesting parametrized cost functions depends mainly on the tacit knowledge of the designers and is based on heuristics. Since the best parameters can be unique to the individual occupants, the Agent-Based Model (ABM) was also adopted to simulate the occupants.

MOSM was based on an activity model that includes a potential field to take an agent from any location on the walkable floor to the activity area. A mechanism for the creation of the potential field was suggested to guarantee that its steepest gradients will push the agent through a path which offers minimum overall cost (i.e. maximum overall desirability) in relation to distance, path simplicity and static costs. In OOSM a temporary destination was chosen from the area which is directly accessible to an agent and locates within its cone of vision. The destinations within this area were stochastically chosen in a mechanism that gave priority to both alignment of the destination with the agent's existing direction of movement and the static desirability that they offered.

MOSM and OOSM both are physically-based indicating that the barriers are simulated with rigid bodies and a force-based model is used to simulate the walking dynamics. The walking trail that is produced in this model can be compared with a human's trail in real environment as a fitness criterion. A simulated annealing algorithm was used to fine-tune the parameters to evolve the fitness of the produced trail of the agents and the observed trail or real humans. OSM allowed for 2D and 3D visualization of the occupancy scenarios. However, in none of these models visualization is not mandatory and hours of simulations can be achieved within minutes.

OSM reported the results of simulation as Probability of Agent's Presence (PAP) in the walkable field. A saturation model was suggested to suggest simulation time to make sure that the resulted PAPs are not changing and have reached a desired level of reliability. Evaluation of mandatory and optional occupancy scenarios in OSM were based on defining a Boolean logic which filtered some agent states in the course of occupancy to create evaluation events. The Boolean logic was defined in relation to an agent's engagement with activities, the range of spatial data which it experienced and existence of line of sights to visual targets. The results of the evaluation were reported based on probability, frequency, and locations of the occurrence of evaluation events.

5.2 Summary of Findings

This study includes several achievements which were discussed in previous chapters in detail and are itemized in Section 5.2.1. The greatest achievement of this study is yet the integration of all of these items in a single model. In previous chapters several publications were referenced which conceptualized the implementation of a system that includes some or all of the following features (Schaumann et al., 2016, Schaumann et al., 2015, Simeone and Kalay, 2012, Simeone et al., 2013a, Ekholm, 2001). Additionally, references to some works were provided that ideally required an agent-based model for simulations in healthcare, but used space syntax software in the absence of an idea model (Choi, 2011, Lu and Zimring, 2012).

5.2.1 Achievements of this study

1. *Most existing navigation models used in architecture and pedestrian dynamics are based on finding paths that are either shortest or fastest. A few studies included desirability in the path planning systems which were discussed before (Helbing et al., 1997, Hoogendoorn, 2003, Hartmann, 2010). This study suggested a new generalized model of navigation which is based on finding the most desirable paths in relation to length of the path, environmental qualities, and path simplicity. While most of the computational tools and theories of design have overlooked the impact of the environmental qualities, Jerke et al. (2008) claim that it is one of the bottom lines of creating value in environments.*
2. *OSM gains its validity from a training process which enables the agents to reproduce the observed trails of humans in real buildings.*
3. *The mechanism of simulating the effects of environmental qualities in OSM is effective and yet generalized. For example, day light, temperature and other qualities can be simulated in almost the same way. The training mechanism in OSM not only is useful for the simulation and evaluation mechanisms that OSM includes, but also can serve as the basis for understanding how different environmental factors interact to create the overall desirability when an observed trail is reproduced.*

4. OSM includes a mechanism for data interoperability to import and export spatial data and visualization of the data. The spatial data can be color-coded in 2D visualization mode. In 3D visualization mode the spatial data can be represented with topographic surfaces with different color-codes, topographic contours, or gridlines rendered on the top of them. This visualization technique will provide a strong sense of understanding of the spatial data which also represents the results of the simulation.

5. OSM is capable of animate the occupancy scenario in 3D mode from the eyes of the agents and in 2D mode from the top view plan. The visualization of the agent is supported by visualizing the visibility events and color-codes as well.

6. OSM uses a Building Information Model (BIM) as a building data repository. BIM is rapidly gaining popularity and replacing the traditional CAAD technology both at the design phase and in after design phases (Fitch, 2012).

7. MOSM includes agents which can detect changes in their field of visibility. Agents that can detect visual changes are not even present in space syntax model which is essentially a visibility analysis tool. Compared to space syntax model, MOSM also accounts for environmental qualities and the representation of occupants with their unique differences, preferences and task agendas.

8. While OOSM can effectively reproduce the results of space syntax agent-based model, it offers a tuning process and accounts for environmental qualities.

9. With several examples, this study showed that OSM can numerically measure the differences between various scenarios and provide insight for both designers and facility managers to make more informed decisions.

While this study showed the possibility of creating an integrated model for simulation, visualization and evaluation of occupancy scenarios, it will not claim that the implementation of this model is exclusive of other possible implementations or conclusive such that it closes the field of study. In the review of the literature, for example, several models of creating roadmaps were discussed that can replace the cellular grid model which was utilized in this study. Alternatively, the training algorithm, i.e. simulated annealing, can be replaced with any other meta-heuristic model or even more advanced machine learning algorithms. This study rather claims that creating an integrated model that simulates, visualizes, and evaluates the occupancy scenarios is possible and proved the realization of this idea.

5.3 Research Limitations and Future Directions

In spite of the achievements of this dissertation, it includes several limitations as well. These limitations were discussed in previous chapters in detail and are summarized in Section 5.3.1 for future improvements.

5.3.1 Limitations of this study

1. *The activity model in MOSM always associates areas to activities. This model cannot include activities that are mobile and are not associable to a particular area. For example, delivering care to a patient on a moving bed in emergency department of a hospital cannot be simulated with this activity model. Future studies could focus on modeling mobile activities as well.*
2. *Converting tasks to a sequence of activities in MOSM can include numerous possibilities. Ideally, the most convenient sequence should be extracted with respect*

to an agent's location. Future studies may try to find the best sequence in real-time during the performance of a scenario.

3. *Multi-tasking is a very important component of Mandatory Occupancy Scenarios which is not implemented and is open as a future research direction (Munyisia et al., 2011, Abbey et al., 2012).*
4. *The training process in both OSM should include mechanisms for avoiding over-fitting, maximizing the predictability and minimizing the degree of freedom of the model. These limitations are also expected to be addresses in future research directions.*
5. *An occupant in OSM responds to visibility and desirability, which are largely absent in almost all of the behavioral simulations, such as egress, ingress and even space syntax analysis. However, it currently includes only one agent. In future works it should be transformed to a multi-agent model that accounts for the interactions among the different occupants with unique profiles and scenarios.*
6. *OSM was developed based on a model-based approach and is not currently validated and calibrated against observed data. Adding empirical observations will add a new level of validity to the existing model.*
7. *As an evaluation engine, OSM can be integrated in optimization scenarios. This will require further enhancement of the computational performance of OSM which can be accomplished in future improvements. With this achievement, various machine learning algorithms can help designers to generate design alternatives and evaluate them.*

The future of this study can also envision increasing the number of agents and including their interactions. Using a multi-agent system after the achievements of this study seems like a more promising idea for future.

Occupancy scenarios are more diverse than what most of the existing literature or simulation tools suggest. This diversity can be appreciated when different dimensions of occupancy scenarios are scrutinized. For instance, an agent's knowledge of the environment is a factor which can be improved in the course of time when it lacks it initially. Even though the simulation time was set to 320 hours in Chapter 3, it was just to enhance the reliability of the results. It is plausible to believe that after a couple of hours the agent will build some level of knowledge from the environment and will not merely rely on its visibility field to make decisions. Alternatively, an optional occupancy scenario can turn into a mandatory scenario any time and then become optional again. For instance, the scenario of navigation for someone who is optionally navigating in a shopping mall, changes to mandatory as soon as he or she decides to purchase something from a specific shop.

Classifying occupancy scenarios to mandatory and optional will dismiss the level of richness of occupancy scenarios models in much the same way that ignoring the environmental qualities does. In reality, any hybrid combination of all aspects of occupancy scenarios is possible. Acknowledgement of the varieties of the dimensions of the problem also offers numerous opportunities for future studies.

REFERENCES

ROBERT WOOD JOHNSON FOUNDATION. 2007. *Active Living Research - Literature Database* [Online]. Robert Wood Johnson Foundation. Available: http://activelivingresearch.org/litdb [Accessed November 23 2013].

ABBEY, M., CHABOYER, W. & MITCHELL, M. 2012. Understanding the Work of Intensive Care Nurses: A Time and Motion Study. *Australian Critical Care,* 25**,** 13-22.

AIKEN, L. H., CLARKE, S. P., SLOANE, D. M., LAKE, E. T. & CHENEY, T. 2008. Effects of Hospital Care Environment on Patient Mortality and Nurse Outcomes. *The Journal of Nursing Administration,* 38**,** 223-229.

ALEXANDER, C. 1964. *Notes on the Synthesis of Form*, Cambridge : Harvard University Press.

ALEXANDER, C. 1979. *The Timeless Way of Building,* New York, Oxford University Press.

AMATO, N. M. & WU, Y. A Randomized Roadmap Method for Path and Manipulation Planning. Robotics and Automation, 1996. Proceedings., 1996 IEEE International Conference on, 22-28 Apr 1996 1996. 113-120 vol.1.

ANSI/ASHRAE 2013. Standard 55-2013. *Thermal Environmental Conditions for Human Occupancy.* Atlanta, United States.

ANTINAHO, T., KIVINEN, T., TURUNEN, H. & PARTANEN, P. 2015. Nurses' Working Time Use – How Value Adding It Is? *Journal of Nursing Management,* 23**,** 1094-1105.

APPLEGATE, D. L. 2006. *The Traveling Salesman Problem: A Computational Study,* Princeton, Princeton University Press.

ARCMAP. 2016. *An Overview of the Visibility Toolset* [Online]. Environmental Systems Research Institute, Inc. . Available: http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/an-overview-of-the-visibility-toolset.htm [Accessed 8,23 2016].

BATTY, M. 1997. Predicting Where We Walk. *Nature,* 388**,** 19-20.

BATTY, M. 2003. Agent-Based Pedestrian Modelling. *CASA Working Papers 61*. University College of London, London, UK. : Centre for Advanced Spatial Analysis

BATTY, M. 2005. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals,* Cambridge, Massachusetts, MIT Press.

BATTY, M. & LONGLEY, P. A. 2014. Modelling Spatial Morphologies: Fractal Patterns from Cellular Automata. *In:* ABRAHART, R. J. & SEE, L. M. (eds.) *Geocomputation, Second Edition.* CRC Press.

BAUER, H. & KNOBLICH, K. 1978. Recording of Walking Performance of Nurses Working in Hospital Departments. *Z Gesamte Hyg,* 24**,** 539-41.

BAYAZIT, O. B., LIEN, J.-M. & AMATO, N. 2004. Better Group Behaviors Using Rule-Based Roadmaps. *In:* BOISSONNAT, J.-D., BURDICK, J., GOLDBERG, K. & HUTCHINSON, S. (eds.) *Algorithmic Foundations of Robotics V.* Springer Berlin Heidelberg.

BAYAZIT, O. B., LIEN, J.-M. & AMATO, N. M. Simulating Flocking Behaviors in Complex Environments. Pacific Conference on Computer Graphics and Applications, 2002 Beijing, China. IEEE Computer Society, 104-115.

BENEDIKT, M. L. 1979. To Take Hold of Space: Isovists and Isovist Fields. *Environment and Planning B: Planning and Design,* 6**,** 47-65.

BERLYNE, D. E. 1963. Complexity and Incongruity Variables as Determinants of Exploratory Choice and Evaluative Ratings. *Canadian Journal of Psychology/Revue Canadienne De Psychologie,* 17**,** 274-290.

BHASKAR, R. 1997. *A Realist Theory of Science,* London Verso.

BHASKAR, R., ARCHER, M., COLLIER, A., LAWSON, T. & NORRIE, A. 1998. *Critical Realism: Essential Readings,* London Routledge.

BONABEAU, E. 2002. Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. *Proceedings of the National Academy of Sciences of the United States of America,* 99**,** 7280-7287.

BRAAKSMA, J. P. & COOK, W. J. 1980. Human Orientation in Transportation Terminals. *Transportation Engineering Journal,* 106**,** 189-203.

BRAILSFORD, C. S., HARPER, R. P., PATEL, B. & PITT, M. 2009. An Analysis of the Academic Literature on Simulation and Modelling in Health Care. *Journal of Simulation,* 3**,** 130-140.

BUILDINGSMART. 2014. *About Bim* [Online]. buildingSMART. Available: http://www.buildingsmart.org/openbim/bim/2/1/about-bim [Accessed 2014 2014].

BURGIO, L. D., ENGEL, B. T., HAWKINS, A., MCCORMICK, K. & SCHEVE, A. 1990. A Descriptive Analysis of Nursing Staff Behaviors in a Teaching Nursing Home: Differences among Nas, Lpns, and Rns. *Gerontologist,* 30**,** 107-12.

CAI, H. & ZIMRING, C. Out of Sight, out of Reach: Correlating Spatial Metrics of Nurse Station Typology with Nurses' Communication and Co-Awareness in an Intensive Care Unit. Eighth International Space Syntax Symposium, 2012 Santiago de Chile.

CANNY, J. 1988. *The Complexity of Robot Motion Planning,* MIT, MIT Press.

CHOI, Y.-S. 2011. *The Physical Environment and Patient Safety: An Investigation of Physical Environmental Factors Associated with Patient Falls.* 3535851 Ph.D., Georgia Institute of Technology.

CHRAIBI, M., FREIALDENHOVEN, M., SCHADSCHNEIDER, A. & SEYFRIED, A. 2013. Modeling the Desired Direction in a Force-Based Model for Pedestrian Dynamics. *In:* KOZLOV, V. V., BUSLAEV, P. A., BUGAEV, S. A., YASHINA, V. M., SCHADSCHNEIDER, A. & SCHRECKENBERG, M. (eds.) *Traffic and Granular Flow '11.* Berlin, Heidelberg: Springer Berlin Heidelberg.

CLAYTON, M. J., TEICHOLZ, P., FISCHER, M. & KUNZ, J. 1999. Virtual Components Consisting of Form, Function and Behavior. *Automation in Construction,* 8**,** 351-367.

CONSTRUCTION, M. H. 2013. The Business Value of Bim in North America: Multi-Year Trend Analysis and User Ratings (2007-12). McGraw Hill Construction: SmartMarket Report.

CORNELL, P., HERRIN-GRIFFITH, D., KEIM, C., PETSCHONEK, S., SANDERS, A. M., D'MELLO, S., GOLDEN, T. W. & SHEPHERD, G. 2010. Transforming Nursing Workflow, Part 1: The Chaotic Nature of Nurse Activities. *The Journal Of Nursing Administration,* 40**,** 366-373.

PROMODEL CORPORATION. 2015. Medmodel. Orem, UT: ProModel Corporation.

DALTON, R. C. 2003. The Secret Is to Follow Your Nose: Route Path Selection and Angularity. *Environment and Behavior,* 35**,** 107-131.

DAVIDSSON, P. 2002. Agent Based Social Simulation: A Computer Science View. *Journal of Artificial Societies and Social Simulation (JASSS),* 5.

DAWEN, X. & AMATO, N. M. A Kinematics-Based Probabilistic Roadmap Method for High Dof Closed Chain Systems. Robotics and Automation, 2004. Proceedings. ICRA '04. 2004 IEEE International Conference on, 26 April-1 May 2004 2004. 473-478 Vol.1.

DEARMON, V., ROUSSEL, L., BUCKNER, E. B., MULEKAR, M., POMRENKE, B., SALAS, S., MOSLEY, A., BROWN, S. & BROWN, A. 2013. Transforming Care at the Bedside (Tcab): Enhancing Direct Care and Value-Added Care. *Journal of Nursing Management,* 21**,** 668-678 11p.

DELLEFIELD, M. E., HARRINGTON, C. & KELLY, A. 2012. Observing How Rns Use Clinical Time in a Nursing Home: A Pilot Study. *Geriatric Nursing,* 33**,** 256-263.

DIJKSTRA, E. W. 1959. A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik,* 1**,** 269-271.

DOUCET, A., DE FREITAS, N. & GORDON, N. 2001. An Introduction to Sequential Monte Carlo Methods. *In:* DOUCET, A., DE FREITAS, N. & GORDON, N. (eds.) *Sequential Monte Carlo Methods in Practice.* New York, NY: Springer New York.

EASTMAN, C. M. 2008. *Bim Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors,* Hoboken, N.J., Wiley.

EKHOLM, A. Modelling of User Activities in Building Design. 19th eCAADe Conference Proceedings, 2001 Helsinki, Finland. 67-72.

EKHOLM, A. & FRIDQVIST, S. Modelling of User Organisations, Buildings and Spaces for the Design Process. *In:* TURK, Z., ed. CIB W78 Workshop, Construction on the Information Highway, 1996 Bled, Slovenia. 165-178.

ELBANHAWY, E., DALTON, R. & NASSAR, K. 2013. Integrating Space-Syntax and Discrete-Event Simulation for E-Mobility Analysis. *Aei 2013.* American Society of Civil Engineers.

FERGUSON, P., FRIEDRICH, E. & KARIMI, K. Origin-Destination Weighting in Agent Modelling for Pedestrian Movement Forecasting. *In:* GREENE, M., REYES, J. & CASTRO, A., eds. Eighth International Space Syntax Symposium, 2007 Santiago de Chile. PUC, 8153:1- 8153:13.

FITCH, E. 2012. The Business Value of Bim in North America: A Multi-Year Trend Analysis and User Ratings (2007-2012). Bedford, MA.

FOX, K. R. R. 1999. The Influence of Physical Activity on Mental Well-Being. *Public Health Nutrition,* 2**,** 411-8.

FREDMAN, M. L. & TARJAN, R. E. 1987. Fibonacci Heaps and Their Uses in Improved Network Optimization Algorithms. *J. ACM,* 34**,** 596-615.

FRIESEN, M. R. & MCLEOD, R. D. 2014. A Survey of Agent-Based Modeling of Hospital Environments. *IEEE Access,* 2**,** 227-233.

GANEM, J. 1998. A Behavioral Demonstration of Fermat's Principle. *The Physics Teacher,* 36**,** 76-78.

GEHL, J. 1987. *Life between Buildings: Using Public Space,* New York, USA, Van Nostrand Reinhold Company.

GERO, J. S. 1980. Computer-Aided Design by Optimization in Architecture. *Design Studies,* 1**,** 227-230.

GERO, J. S. 1990. Design Prototypes. A Knowledge Representation Schema for Design. *AI Magazine,* 11**,** 26-36.

GHOLIZADEH, M., JANATI, A., NADIMI, B., KABIRI, N. & ABRI, S. 2014. How Do Nurses Spend Their Time in the Hospital? *Journal of Clinical Research & Governance,* 3**,** 7.

GIBSON, J. J. 1979. *The Ecological Approach to Visual Perception,* Boston, MA, Psychology Press.

GOLLEDGE, R. G. 1995. Path Selection and Route Preference in Human Navigation: A Progress Report. *In:* FRANK, A. U. & KUHN, W. (eds.) *Spatial Information Theory a Theoretical Basis for Gis: International Conference Cosit '95 Semmering, Austria, September 21–23, 1995 Proceedings.* Berlin, Heidelberg: Springer Berlin Heidelberg.

GRUNDEN, N. & HAGOOD, C. 2012. *Lean-Led Hospital Design : Creating the Efficient Hospital of the Future,* Boca Raton Taylor & Francis/CRC Press.

HAMILTON, D. K. 2003. The Four Levels of Evidence-Based Practice. *Healthcare Design,* 3**,** 18-26.

HAMILTON, D. K. 2009. Is Evidence-Based Design a Field? *Health Environments Research & Design Journal (HERD) (Vendome Group LLC),* 3**,** 97-101 5p.

HAMILTON, D. K. & LEIFER, D. 2009. Evidence Based Design for Multiple Building Types. *Architectural Science Review,* 52**,** 239-240.

HAQ, S. & LUO, Y. 2012. Space Syntax in Healthcare Facilities Research: A Review. *HERD: Health Environments Research & Design Journal,* 5**,** 98-117.

HARTMANN, D. 2010. Adaptive Pedestrian Dynamics Based on Geodesics. *New Journal of Physics,* 12**,** 043032.

HELBING, D. 1991. A Mathematical Model for the Behavior of Pedestrians. *Behavioral Science,* 36**,** 298-310.

HELBING, D., BUZNA, L., JOHANSSON, A. & WERNER, T. 2005. Self-Organized Pedestrian Crowd Dynamics: Experiments, Simulations, and Design Solutions. *Transportation Science,* 39**,** 1-24.

HELBING, D., FARKAS, I. & VICSEK, T. 2000. Simulating Dynamical Features of Escape Panic. *Nature,* 407**,** 487-490.

HELBING, D., FARKAS, I. J., MOLNAR, P. & VICSEK, T. 2002. Simulation of Pedestrian Crowds in Normal and Evacuation Situations. *Pedestrian and Evacuation Dynamics*, 21**,** 21-58.

HELBING, D., KELTSCH, J. & MOLNAR, P. 1997. Modelling the Evolution of Human Trail Systems. *Nature,* 388**,** 47-50.

HELBING, D. & MOLNÁR, P. 1995. Social Force Model for Pedestrian Dynamics. *Physical Review E,* 51**,** 4282-4286.

HELBING, D., MOLNÁR, P. & SCHWEITZER, F. 1994. Computer Simulations of Pedestrian Dynamics and Trail Formation. *Evolution of Natural Structures***,** 229-234.

HENDRICH, A., CHOW, M. P., BAFNA, S., CHOUDHARY, R., HEO, Y. & SKIERCZYNSKI, B. A. 2009a. Unit-Related Factors That Affect Nursing Time with Patients: Spatial Analysis of the Time and Motion Study. *HERD: Health Environments Research & Design Journal,* 2**,** 5-20.

HENDRICH, A., CHOW, M. P., BAFNA, S., CHOUDHARY, R., YEONSOOK, H. & SKIERCZYNSKI, A. 2009b. Unit-Related Factors That Affect Nursing Time with Patients: Spatial Analysis of the Time and Motion Study. *Health Environments Research & Design Journal (HERD) (Vendome Group LLC),* 2**,** 5-20 16p.

HENDRICH, A., CHOW, M. P., SKIERCZYNSKI, B. A. & LU, Z. 2008. A 36-Hospital Time and Motion Study: How Do Medical-Surgical Nurses Spend Their Time? *The Permanente Journal,* 12**,** 25-34.

HILLIER, B. 1996. *Space Is the Machine: A Configurational Theory of Architecture,* New York, NY, USA Cambridge University Press.

HILLIER, B. 2007. *Space Is the Machine: A Configurational Theory of Architecture,* London, UK, Space Syntax.

HILLIER, B. & HANSON, J. 1984. *The Social Logic of Space,* Cambridge, Cambridge University Press.

HILLIER, B., PENN, A., HANSON, J., GRAJEWSKI, T. & XU, J. 1993. Natural Movement: Or, Configuration and Attraction in Urban Pedestrian Movement. *Environment and Planning B: Planning and Design,* 20**,** 29-66.

HOOGENDOORN, S. 2003. Walker Behaviour Modelling by Differential Games. *In:* EMMERICH, H., NESTLER, B. & SCHRECKENBERG, M. (eds.) *Interface and Transport Dynamics.* Springer Berlin Heidelberg.

HOOGENDOORN, S. & BOVY, P. H. L. 2003. Simulation of Pedestrian Flows by Optimal Control and Differential Games. *Optimal Control Applications and Methods,* 24**,** 153-172.

HOOGENDOORN, S. P. & BOVY, P. 2001. Nonlocal Continuous-Space Microscopic Simulation of Pedestrian Flows with Local Choice Behavior. *Transportation Research Record: Journal of the Transportation Research Board,* 1776**,** 201-210.

HOOGENDOORN, S. P. & BOVY, P. H. L. 2004. Pedestrian Route-Choice and Activity Scheduling Theory and Models. *Transportation Research Part B: Methodological,* 38**,** 169-190.

JACOBSON, S. H., HALL, S. N. & SWISHER, J. R. 2006. Discrete-Event Simulation of Health Care Systems. *In:* HALL, R. W. (ed.) *Patient Flow: Reducing Delay in Healthcare Delivery.* Boston, MA: Springer US.

JENNINGS, N. R. 2000. On Agent-Based Software Engineering. *Artificial Intelligence,* 117**,** 277-296.

JERKE, D., PORTER, D. R. & LASSAR, T. J. 2008. *Urban Design and the Bottom Line: Optimizing the Return on Perception,* ULI-Urban Land Institute.

JUNG, W. & LEE, G. 2015. The Status of Bim Adoption on Six Continents. *International Journal of Civil, Environmental, Structural, Construction and Architectural Engineering,* 9**,** 444-448.

KALAY, Y. E. 1992. Conclusion: Evaluating and Predicting Design Performance. *In:* KALAY, Y. E. (ed.) *Principles of Computer-Aided Design: Evaluating and Predicting Design Performance.* New York, N.Y. : Wiley-Interscience Publications.

KANE, R. L., SHAMLIYAN, T. A., MUELLER, C., DUVAL, S. & WILT, T. J. 2007. The Association of Registered Nurse Staffing Levels and Patient Outcomes: Systematic Review and Meta-Analysis. *Medical Care,* 45**,** 1195-1204.

KEATING, J. P. 1982. The Myth of Panic. *Fire Journal,* 76**,** 57-61.

KHAN, N. Analyzing Patient Flow: Reviewing Literature to Understand the Contribution of Space Syntax to Improve Operational Efficiency in Healthcare Settings. *In:* GREENE, M., REYES, I. & CASTRO, A., eds. Eighth International Space Syntax Symposium, 2012 Santiago de Chile, PUC. 8183:1-8183:11.

KULIGOWSKI, E. & GWYNNE, S. V. 2010. The Need for Behavioral Theory in Evacuation Modeling. *In:* KLINGSCH, W. W. F., ROGSCH, C., SCHADSCHNEIDER, A. & SCHRECKENBERG, M. (eds.) *Pedestrian and Evacuation Dynamics 2008.* Springer Berlin Heidelberg.

KULIGOWSKI, E. D. & PEACOCK, R. D. 2005. A Review of Building Evacuation Models. Gaithersburg: US Department of Commerce, National Institute of Standards and Technology.

LANG, J. T. 1987. *Creating Architectural Theory : The Role of the Behavioral Sciences in Environmental Design,* New York : Van Nostrand Reinhold Co.

LASKOWSKI, M., DEMIANYK, B. C. P., WITT, J., MUKHI, S. N., FRIESEN, M. R. & MCLEOD, R. D. 2011. Agent-Based Modeling of the Spread of Influenza-Like Illness in an Emergency Department: A Simulation Study. *IEEE Transactions on Information Technology in Biomedicine,* 15**,** 877-889.

LATOMBE, J. C. 1991. *Robot Motion Planning,* Springer US.

LAWSON, B. 1990. *How Designers Think : The Design Process Demystified,* Oxford ; Burlington, MA : Elsevier/Architectural Press.

LEE, C. & MOUDON, A. V. 2006. The 3ds+R: Quantifying Land Use and Urban Form Correlates of Walking. *Transportation research. Part D, Transport and environment,* 11**,** 204-215.

LEE, G., SACKS, R. & EASTMAN, C. M. 2006. Specifying Parametric Building Object Behavior (Bob) for a Building Information Modeling System. *Automation in Construction,* 15**,** 758-776.

LEWIN, K. 1951. *Field Theory in Social Science: Selected Theoretical Papers (Edited by Dorwin Cartwright.),* Oxford, England, Harpers.

LITMAN, T. A. 2003. Economic Value of Walkability. *Transportation Research Record***,** 1828, 3-11.

LU, Y. & ZIMRING, C. 2012. Can Intensive Care Staff See Their Patients? An Improved Visibility Analysis Methodology. *Environment and Behavior,* 44**,** 861-876.

MAGNANI, L., NERSESSIAN, N. J. & THAGARD, P. 1999. *Model-Based Reasoning in Scientific Discovery. Edited by Lorenzo Magnani, Nancy J. Nersessian, Paul Thagard,* Boston, MA : Springer US : Imprint : Springer, 1999.

MALLIDOU, A. A., CUMMINGS, G. G., SCHALM, C. & ESTABROOKS, C. A. 2013. Health Care Aides Use of Time in a Residential Long-Term Care Unit: A Time and Motion Study. *International Journal of Nursing Studies,* 50**,** 1229-1239.

MASEHIAN, E. & SEDIGHIZADEH, D. 2007. Classic and Heuristic Approaches in Robot Motion Planning-a Chronological Review. *World Academy of Science, Engineering and Technology,* 29**,** 101-106.

MORGAREIDGE, D., CAI, H. & JIA, J. 2014. Performance-Driven Design with the Support of Digital Tools: Applying Discrete Event Simulation and Space Syntax on the Design of the Emergency Department. *Frontiers of Architectural Research,* 3**,** 250-264.

MSDN. 2016. *Events (C# Programming Guide)* [Online]. msdn.microsoft.com. Available: https://msdn.microsoft.com/en-us/library/awbftdfh.aspx [Accessed 6,4 2016].

MSDN.MICROSOFT.COM. 2016. *Hashset<T>.Contains Method (T)* [Online]. msdn.microsoft.com. Available: https://msdn.microsoft.com/en-us/library/bb356440(v=vs.110).aspx [Accessed 8,19 2016].

MUNYISIA, E. N., YU, P. & HAILEY, D. 2011. How Nursing Staff Spend Their Time on Activities in a Nursing Home: An Observational Study. *Journal of Advanced Nursing,* 67**,** 1908-1917.

MUSTAFEE, N., KATSALIAKI, K. & TAYLOR, S. J. E. 2010. Profiling Literature in Healthcare Simulation. *Simulation,* 86**,** 543-558.

NAGEL, C., STADLER, A. & KOLBE, T. H. Conceptual Requirements for the Automatic Reconstruction of Building Information Models from Uninterpreted 3d Models. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 2009 2009.

NANDA, U., PATI, S. & NEJATI, A. 2015. Field Research and Parametric Analysis in a Medical–Surgical Unit. *HERD: Health Environments Research & Design Journal,* 8**,** 41-57.

NEGROPONTE, N. 1970. *The Architecture Machine: Toward a More Human Environment,* Cambridge, Massachusetts, MIT Press.

NISHINARI, K., KIRCHNER, A., NAMAZI, A. & SCHADSCHNEIDER, A. 2004. Extended Floor Field Ca Model for Evacuation Dynamics. *IEICE Transactions on Information and Systems,* 87**,** 726-732.

ROSSETER, R. 2014. *Nursing Shortage* [Online]. American Association of Colleges of Nursing Available: http://www.aacn.nche.edu/media-relations/fact-sheets/nursing-shortage [Accessed 7-4 2016].

OGILVIE, D., FOSTER, C. E., ROTHNIE, H., CAVILL, N., HAMILTON, V., FITZSIMONS, C. F. & MUTRIE, N. 2007. Interventions to Promote Walking: Systematic Review. *BMJ,* 334**,** 1204.

ONG, B. S., CHEN, M., LEE, V. & TAY, J. C. 2008. An Individual-Based Model of Influenza in Nosocomial Environments. *In:* BUBAK, M., VAN ALBADA, G. D., DONGARRA, J. & SLOOT, P. M. A. (eds.) *Computational Science – Iccs 2008: 8th International Conference, Kraków, Poland, June 23-25, 2008, Proceedings, Part I.* Berlin, Heidelberg: Springer Berlin Heidelberg.

ORTÚZAR, J. D. D. & WILLUMSEN, L. G. 2011. Discrete Choice Models. *Modelling Transport.* John Wiley & Sons, Ltd.

OWEN, N. 2004. Understanding Environmental Influences on Walking: Review and Research Agenda. *American Journal of Preventive Medicine,* 27**,** 67-76.

PALUSKA, S. A. L. 2000. Physical Activity and Mental Health: Current Concepts. *Sports Medicine,* 29**,** 167-80.

PATE, R. R., PRATT, M., BLAIR, S. N., HASKELL, W. L., MACERA, C. A., BOUCHARD, C., BUCHNER, D., ETTINGER, W., HEATH, G. W., KING, A. C. & ET AL. 1995. Physical Activity and Public Health. A Recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine. *JAMA,* 273**,** 402-7.

PATI, D. 2012. Estimating Design Impact on Waste Reduction: Examining Decentralized Nursing. *The Journal of Nursing Administration,* 42**,** 513-518.

PATI, D., HARVEY, T. E., REDDEN, P., SUMMERS, B. & PATI, S. 2015. An Empirical Examination of the Impacts of Decentralized Nursing Unit Design. *HERD: Health Environments Research & Design Journal,* 8**,** 56-70.

PENN, A. 2003. Space Syntax and Spatial Cognition: Or Why the Axial Line? *Environment and Behavior,* 35**,** 30-65.

PENN, A. & TURNER, A. Space Syntax Based Agent Simulation. 1st International Conference on Pedestrian and Evacuation Dynamics, 2001 2001. University of Duisburg, Germany.

PEPONIS, J., DALTON, R. C., WINEMAN, J. & DALTON, N. 2004. Measuring the Effects of Layout Upon Visitors' Spatial Behaviors in Open Plan Exhibition Settings. *Environment and Planning B: Planning and Design,* 31**,** 453-473.

PEPONIS, J., WINEMAN, J., RASHID, M., KIM, S. H. & BAFNA, S. 1997. On the Description of Shape and Spatial Configuration inside Buildings: Convex Partitions and Their Local Properties. *Environment and Planning B: Planning and Design,* 24**,** 761-781.

PEPONIS, J., ZIMRING, C. & CHOI, Y. K. 1990. Finding the Building in Wayfinding. *Environment and Behavior,* 22**,** 555-590.

PHILLIPS, J., LIVINGSTON, G. & BUCHANAN, B. 2002. Toward a Computational Model of Hypothesis Formation and Model Building in Science. *In:* MAGNANI, L. & NERSESSIAN, N. J. (eds.) *Model-Based Reasoning: Science, Technology, Values.* Boston, MA: Springer US.

RABL, A. & DE NAZELLE, A. 2012. Benefits of Shift from Car to Active Transport. *Transport Policy,* 19**,** 121-131.

RATTI, C. 2004. Space Syntax: Some Inconsistencies. *Environment and Planning B: Planning and Design*, 31**,** 487-499.

RENALDS, A., SMITH, T. & HALE, P. 2010. A Systematic Review of Built Environment and Health. *Family & Community Health,* 33**,** 68-68.

ROBERT WOOD JOHNSON FOUNDATION. 2016. *Active Living Research: Promoting Activity-Friendly Communities* [Online]. Robert Wood Johnson Foundation. Available: http://activelivingresearch.org/ [Accessed 08,22 2016].

REYNOLDS, C. W. 1987. Flocks, Herds and Schools: A Distributed Behavioral Model. *SIGGRAPH Computer Graphics,* 21**,** 25-34.

ROBINSON, S. 2004. *Simulation: The Practice of Model Development and Use,* Chichester, England, John Wiley and Sons, Inc.

RODRIGUEZ, S., GIESE, A., AMATO, N., ZARRINMEHR, S., AL-DOURI, F. & CLAYTON, M. 2012. Environmental Effect on Egress Simulation. *In:* KALLMANN, M. & BEKRIS, K. (eds.) *Motion in Games.* Springer Berlin Heidelberg.

RODRIGUEZ, S., LIEN, J.-M. & AMATO, N. M. A Framework for Planning Motion in Environments with Moving Obstacles. IEEE/RSJ International Conference on Intelligent Robots and Systems, 2007 San Diego, CA IEEE, 3309-3314.

ROGSCH, C., SCHRECKENBERG, M., TRIBBLE, E., KLINGSCH, W. & KRETZ, T. 2010. Was It Panic? An Overview About Mass-Emergencies and Their Origins All over the World for Recent Years. *In:* KLINGSCH, F. W. W., ROGSCH, C., SCHADSCHNEIDER, A. & SCHRECKENBERG, M. (eds.) *Pedestrian and Evacuation Dynamics 2008.* Berlin, Heidelberg: Springer Berlin Heidelberg.

ROSS, S. M. 2014. *Introduction to Probability and Statistics for Engineers and Scientists.* , San Diego, CA Academic Press.

RUOHONEN, T., NEITTAANMAKI, P. & TEITTINEN, J. Simulation Model for Improving the Operation of the Emergency Department of Special Health Care. Proceedings of the 2006 Winter Simulation Conference, 3-6 Dec. 2006 2006. 453-458.

RUSH, R. D. 1986. *The Building Systems Integration Handbook. Richard D. Rush,* Butterworth-Heinemann, Boston.

RUSSELL, S. J. & NORVIG, P. 2010. *Artificial Intelligence : A Modern Approach,* Upper Saddle River, N.J., Prentice Hall.

SADEK, A. H. & SHEPLEY, M. M. 2016. Space Syntax Analysis: Tools for Augmenting the Precision of Healthcare Facility Spatial Analysis. *HERD: Health Environments Research & Design Journal*.

SALINGAROS, N. A. 2006. *A Theory of Architecture,* Germany, Umbau-Verlag, Solingen.

SCHADSCHNEIDER, A., KLINGSCH, W., KLÜPFEL, H., KRETZ, T., ROGSCH, C. & SEYFRIED, A. 2011. Evacuation Dynamics: Empirical Results, Modeling and Applications. *In:* MEYERS, R. A. (ed.) *Extreme Environmental Events.* Springer New York.

SCHAUMANN, D., PILOSOF, N. P., DATE, K. & KALAY, Y. E. 2016. A Study of Human Behavior Simulation in Architectural Design for Healthcare Facilities. *Annali Dell'istituto Superiore Di Sanità,* 52**,** 24-32.

SCHAUMANN, D., WAN HONG, S., KALAY, Y. E. & SIMEONE, D. 2015. Simulating Human Behavior in Not-yet Built Environments by Means of Event-Based Narratives. *SimAUD.* Alexandria, VA, USA: Society for Modeling & Simulation International (SCS).

SHEPLEY, M. & DAVIES, K. 2003. Nursing Unit Configuration and Its Relationship to Noise and Nurse Walking Behavior: An Aids/Hiv Unit Case Study. *AIA Academy Journal,* 6**,** 12-14.

SHERWOOD, R. W. W. 2000. The Behavioral Determinants of Exercise: Implications for Physical Activity Interventions. *Annual Review of Nutrition,* 20**,** 21-44.

SIEBERS, O. P., MACAL, M. C., GARNETT, J., BUXTON, D. & PIDD, M. 2010. Discrete-Event Simulation Is Dead, Long Live Agent-Based Simulation! *Journal of Simulation,* 4**,** 204-210.

SIMEONE, D. & KALAY, Y. E. An Event-Based Model to Simulate Human Behaviour in Built Environments. The 30th International Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 12), 2012 Prague, Czech Republic. 525-532.

SIMEONE, D., KALAY, Y. E., SCHAUMANN, D. & HONG, S. W. Modelling and Simulating Use Processes in Buildings The 31st International Conference on Education and research in Computer Aided Architectural Design in Europe (eCAADe 13), 2013a Delft University of Technology, Delft, Netherlands. 59-67.

SIMEONE, D., KALAY, Y. E., SCHAUMANN, D. & HONG, S. W. Modelling and Simulating Use Processes in Buildings. eCAADe, 2013b Delft, Netherlands.

SIMEONE, D., TOLDO, I. & CURSI, S. 2014. Operational Scenarios Simulation to Support Building Design: A Hospital Design Case Study. *In:* HODICKY, J. (ed.) *Modelling and Simulation for Autonomous Systems: First International Workshop.* Rome, Italy: Springer International Publishing.

SIMON, H. A. 1969. *The Sciences of the Artificial,* Cambridge, Massachusetts, MIT Press.

SMITH, J. 2009. *Patterns - Wpf Apps with the Model-View-Viewmodel Design Pattern* [Online]. MSDN Magazine Blog: MSDN. Available: https://msdn.microsoft.com/en-us/magazine/dd419663.aspx#id0090051 [Accessed 10,8 2016].

STEADMAN, P. 1979. *The Evolution of Designs: Biological Analogy in Architecture and the Applied Arts,* Cambridge, Cambridge University Press.

STERMAN, J. D. 2001. System Dynamics Modeling: Tools for Learning in a Complex World. *California Management Review,* 43**,** 8-25.

SU, Z. & YAN, W. 2015. A Fast Genetic Algorithm for Solving Architectural Design Optimization Problems. *AI EDAM,* 29**,** 457-469.

TAMILSELVI, A. & REGUNATH, R. 2014. Work Sampling: A Quantitative Analysis of Nursing Activity in a Medical Ward. *Nitte University Journal of Health Science,* 3**,** 64-67.

TANEJA, S. 2013. *A Framework for Evaluation and Generation of Navigation Models for Map-Matching of Indoor Positioning Data.* 3573508 Ph.D., Carnegie Mellon University.

TEVINGTON, P. 2011. Mandatory Nurse-Patient Ratios. *Academy of Medical-Surgical Nurses,* 20**,** 265-268.

TURNER, A. 2000a. Angular Analysis: A Method for the Quantification of Space. London: Centre for Advanced Spatial Analysis, University College of London.

TURNER, A. Angular Analysis: A Method for the Quantification of Space. 3rd International Space Syntax Symposium 2000b Atlanta, GA.

TURNER, A. Depthmap: A Program to Perform Visibility Graph Analysis. 3rd International Space Syntax Symposium, 2001 Atlanta, GA. Space Syntax Limited, 31.1, 31.9.

TURNER, A. 2007. From Axial to Road-Centre Lines: A New Representation for Space Syntax and a New Model of Route Choice for Transport Network Analysis. *Environment and Planning B: Planning and Design,* 34**,** 539-555.

TURNER, A. & DALTON, N. 2005. A Simplified Route Choice Model Using the Shortest Angular Path Assumption. *8th International Conference on GeoComputation.* University of Michigan, USA.

TURNER, A. & PENN, A. 2002. Encoding Natural Movement as an Agent-Based System: An Investigation into Human Pedestrian Behaviour in the Built Environment. *Environment and Planning B: Planning and Design,* 29**,** 473-490.

ULRICH, R. S. 1984. View through a Window May Influence Recovery from Surgery. *Science,* 224**,** 420-421.

WAGNER, M. 2006. *The Geometries of Visual Space,* Mahwah, NJ Lawrence Erlbaum.

WAGNER, M., BAIRD, J. C. & BARBARESI, W. 1981. The Locus of Environmental Attention. *Journal of Environmental Psychology,* 1**,** 195-206.

WANG, D. & GROAT, L. N. 2013. *Architectural Research Methods.* , Hoboken : Wiley, 2013.

WILLIAMS, B. 1999. *Footcandles and Lux for Architectural Lighting: An Introduction to Illuminance* [Online]. Available: http://www.mts.net/~william5/library/illum.htm [Accessed 11, 19 2015].

WILLIAMS, H., HARRIS, R. & TURNER-STOKES, L. 2009. Work Sampling: A Quantitative Analysis of Nursing Activity in a Neuro-Rehabilitation Setting. *Journal of Advanced Nursing,* 65**,** 2097-2107 11p.

WONG, D. H., GALLEGOS, Y., WEINGER, M. B., CLACK, S., SLAGLE, J. & ANDERSON, C. T. 2003. Changes in Intensive Care Unit Nurse Task Activity after Installation of a Third-Generation Intensive Care Unit Information System. *Crit Care Med,* 31**,** 2488-94.

WOOLDRIDGE, M. 1997. Agent-Based Software Engineering. *IEE Proceedings - Software Engineering,* 144**,** 26-37.

YAN, W. & KALAY, Y. E. Simulating Human Behaviour in Built Environments. *In:* MARTENS, B. & BROWN, A., eds. Computer Aided Architectural Design Futures 2005, 2005/01/01 2005. Springer Netherlands, 301-310.

YAN, W. & KALAY, Y. E. Geometric, Cognitive and Behavioral Modeling of Environmental Users: Integrating an Agent-Based Model and a Statistical Model into a User Model. *In:* GERO, J. S., ed. Design Computing and Cognition '06, 2006/01/01 2006 Netherlands. Springer, 61-79.

ZARRINMEHR, S., RAHMANI ASL, M., YAN, W. & CLAYTON, M. J. Optimizing Building Layout to Minimize the Level of Danger in Panic Evacuation Using Genetic Algorithm and Agent-Based Crowd Simulation. 20th International Workshop: Intelligent Computing in Engineering 2013, 2013 Vienna, Austria.

ZHU, X., ARCH, B. & LEE, C. 2008. Personal, Social, and Environmental Correlates of Walking to School Behaviors: Case Study in Austin, Texas. *TheScientificWorldJOURNAL,* 8**,** 859-872.

APPENDIX A

OCCUPANCY SCENARIO MODEL (OSM) SOFTWARE

A.1 Introduction

This chapter will provide an overview of Occupancy Scenario Model (OSM) software and its implementation strategies. The detailed description of the software implementation at programming level will not be discussed in this chapter. However, this chapter includes some information about the top level data structures that are used in OSM. The design of OSM as a software was based on the main principles for Object-Oriented Programming paradigm to make its component reusable and not necessarily dependent on one scheme of building model. Specifically, OSM was designed to work with any Building Information Model (BIM) or Building Information Modeling authoring tools that supports external connections or provides methods for reading building data.

OSM was developed using C# programming language and it has a visualization engine which was developed using Windows Presentation Foundation (WPF). The User Interface (UI) of OSM uses XAML programming and C# codes that on the background control the UI. The UI and the simulation engine in OSM are completely separated and technically users with programming knowledge can use the engine and design a new UI system for OSM. OSM offers other functionalities which are not related to the scope of this study, and therefore will be excluded from this chapter. Examples of these features include calculation of polygonal isovists, and extracting and visualizing justified graphs in a semi-automatic process.

This chapter first discusses why BIM was preferred over other digital building models, namely Computer Aided Drawing (CAD), for OSM. Next, the strategic goals which are set for interoperability between OSM and BIM will be discussed and the top level data structures that make the interoperable framework possible will be explained. Previous chapters explained the simulation ideas algorithmically in a non-technical language as it relates to architecture. As an appendix to this study, this chapter will provides a deeper insight for modeling by discussing some of the related data structures and the functionalities that they provide in OMS. The topmost data models that will be discussed include spatial data, cellular isovists, agent model and scenario model.

A.1.1 What is BIM

A short overview of the differences and similarities between Computer Aided Drawing (CAD) and BIM can help us understand why BIM was preferred over CAD models. CAD files primarily consist of vectors, associated linetypes, and layer identifications. The advent of 3D modeling turned the focus from drawings and 3D images to the data itself (Eastman, 2008). BIM is an object-based data scheme and each of its object classes is a representation of one type of building component (Lee et al., 2006). BIM defines relations among objects so that when one object is modified, its dependent objects will automatically change. BIM allows the professionals to add their domain-specific data to the single shared model, reducing or eliminating inconsistencies among input files to various analytic and simulation tools (buildingSMART, 2014). According to other definitions, spatial modeling with quantity takeoff, construction scheduling and cost estimating are also features of BIM. In sum, BIM can be defined as shared digital repositories, rich 3D geometric and non-geometric models, design platforms, simulation environment, and collaborative and performance-based design processes.

Traditional CAD systems are being rapidly replaced with BIM authoring tools. A survey that analyzed BIM adoption reported that in North America the BIM adoption level increased from 28% to 71% from 2007 to 2012 and predicted that this rate should stabilize at 90%. This report also indicates that along with the increasing level of BIM adoption, the level of BIM implementation is also rapidly increasing (Construction, 2013). According to other surveys North America is the most advanced continent in terms of BIM adoption followed by Europe, Oceania, Asia, Middle East/Africa and South America (Jung and Lee, 2015).

A.1.2 Why BIM

Using BIM offers several advantages compared to traditional CAD systems that makes it useful for OSM. BIM is an object-based data scheme and each of its object classes is a representation of one type of building component (Lee et al., 2006). The object-based model of BIM creates rich semantics that can be very useful in data query. Understanding the functionalities of building objects is very important in OSM simulation. For example, curtain walls or windows in buildings should not be counted as visual obstacles; however, they will still serve as physical barriers. Understanding semantics from uninterpreted 3D models sets the bar very high for an automated interpretation process because it demands exploring numerous possibilities (Nagel et al., 2009). In general, semantics of BIM makes data query fast and guarantees reliable data retrieval.

In addition to the semantics of BIM, IFC as open source BIM data scheme and most of the commercial BIM authoring tools include Application Programming Interface (API) libraries that allow researchers to extend the functionalities of BIM. API libraries define the channels of communication among software components. API libraries control the accessibility to internal structure of a library and only expose the functionalities that the developers need.

A.2 OSM Development Strategies

OSM was designed as a library which satisfies the goals presented in Table 6-1. All of the items in this table intend to make OSM reusable and increase its life cycle. While using the data structures that are provided by the API library of a specific BIM format is necessary to access BIM data repository, relying on these data structures have several downsides as well. Merely relying on a specific API makes an extended application inseparable from it. Since the developers of the extended applications do not have control over the design of the API, their products may die out if not updated along with the updates of the API. There is also no guarantee that the API features which an extended application used will continue to exist when the API is updated. Over-reliance on the API of a specific BIM also make the extended application unable to be used with other BIM data schemes used in different BIM authoring tools. In other words, while an extended software application needs to connect to a BIM repository, it should ideally be separated from the specific BIM format as much as possible. The last item in Table 6-1 refers to the design of the extended application. While it is not related to BIM, it is based on a very similar idea to make the engine of the simulation reusable with different visualization platforms.

One of the well-established applications of this approach is in Windows Presentation Foundations (WPF) and is called Model-View-ViewModel (MVVM). In this approach the engine (i.e. Model) is completely independent from the View which the users see on the interface and the ViewModel implements the logic of transforming the model to the view. While some visualization platforms such as WPF offer data binding functionalities which makes the MVVM framework easy to implement, the idea of separating view form model is not limited to WPF (Smith, 2009).

Table 6-1: Achievements of this study.

1. *Maximizing independence from a specific BIM data scheme and BIM authoring tool*
2. *Using different BIM data schemes*
3. *Separating the simulation engine from the visualization platform*

A.2.1 Interoperability between OSM and BIM

OSM includes a two way pipelining mechanism for interoperability with BIM. The abstract class BIM_To_OSM_Base includes a list of public members that should be implemented to read BIM data according to its format. Table 6-2 shows the public members of this abstract base class. The exchange of information from OSM document to BIM is mainly for visualization and is accomplished by providing implementation for I_OSM_To_BIM interface. Table 6-3 shows the members of this interface that need to be implemented. OSM only requires these connections for instantiation.

Table 6-2: The public member of BIM_To_OSM_Base class that parses BIM data to OSM data structures.

	Name	Description
Methods		
UV	ConvertIntPointToUV (*IntPoint*)	*Converts the IntPoint to a UV.*
BarrierPolygons	ConvertINTPolygonToBarrierPolygon (*List<IntPoint>*)	*Converts the INTPolygon to BarrierPolygons.*
List<IntPoint>	ConvertUVListToINTPolygon (List<UV>)	*Converts a list of UV points to a list of IntPoints (i.e. an INTPolygon) which can be used for polygonal operations.*
IntPoint	ConvertUVToIntPoint (UV)	*Converts a UV to an IntPoint.*
BarrierPolygons	ExpandAllBarrierPolygons (double)	*Returns an array of polygons that is used for creating barrier buffers in optional occupancy scenarios.*
abstract List<GeometryModel3D>	GetSlicedMeshGeometries ()	*Gets the BIM Model as a list of meshes to which the materials are attached. The parsed model should be sliced with A plane at obstacle height. Implementation is required for this abstract method.*
BarrierPolygons	IsovistPolygon (UV, double, HashSet<UVLine>)	*Gets the polygonal Isovist.*
abstract List<GeometryModel3D>	ParseBIM ()	*Gets the BIM Model as a list of meshes to which the materials are attached. Implementation is required for this abstract method.*
List<IntPoint>	SimplifyINTPolygons (List<IntPoint>,value)	*Simplifies a list INTPolygons using expand and shrink technique.*
List<UV>	SimplifyPolygon (List<UV> , UInt16, double)	*Simplifies the polygon.*
Fields		
UV	FloorMaxBound	*The floor maximum bound.*
UV	FloorMinBound	*The floor minimum bound.*
double	MinimumLengthOfLine	*The minimum length of lines in the polygons.*
Properties		
double	CurveApproximationLength	*Gets or sets the length of line segments to approximate curves with polygons.*

Table 6-2 Continued

	Name	Description
BarrierPolygons[]	FieldBarriers	*Gets or sets the field barriers.*
BarrierPolygons[]	FieldWithoutHoles	*Gets or sets the field without holes.*
List<List<IntPoint>>	FootPrintOfAllBarriers	*Gets or sets the footprint INTPolygons of all barriers.*
List<List<IntPoint>>	FootPrintPolygonsOfFieldWithOutVoids	*Gets or sets the footprint INTPolygons of field without voids.*
List<List<IntPoint>>	FootPrintPolygonsOfFieldWithVoids	*Gets or sets the footprint INTPolygons of field with voids.*
List<List<IntPoint>>	FootPrintPolygonsOfPhysicalBarriers	*Gets or sets the footprint INTPolygons of physical barriers.*
List<List<IntPoint>>	FootPrintPolygonsOfVisualBarriers	*Gets or sets the footprint INTPolygons of visibility barriers.*
double	MinimumLineLengthSquared	*Gets or sets the minimum line length squared.*
BarrierPolygons[]	PhysicalBarriers	*Gets or sets the physical barriers.*
double	PlanElevation	*Gets or sets the elevation.*
string	PlanName	*Gets or sets the plan name of the BIM model.*
string	Report	*Gets or sets the report which are generated during the data format exchange.*
double	VisibilityObstacleHeight	*Gets or sets the minimum height of visual obstacle. Objects with higher heights will be considered visibility barriers and lower heights will be considered physical barriers.*
BarrierPolygons[]	VisualBarriers	*Gets or sets the visibility barriers.*

Table 6-3: The members of I_OSM_To_BIM interface which connect OSM to BIM.

	Name	Description
Methods		
UV	PickPoint()	*Picks the point from BIM environment.*

Table 6-3 Continued

	Name	Description
Methods		
void	VisualizeLine()	*Visualizes a line in BIM environment.*
void	VisualizeLines()	*Visualizes a collection of lines in BIM environment.*
void	VisualizePoint()	*Visualizes a point in BIM environment.*
void	VisualizePolygon()	*Visualizes a polygon in BIM environment.*

The case studies which were implemented in previous chapters were based on the implementations of Revit_To_OSM and OSM_To_Revit classes from BIM_To_OSM_Base and I_OSM_To_BIM and created an interoperable framework with Autodesk Revit. Other than the strategic goals that were discussed, creating an interoperable platform has several other advantages too. For example, since the API library of Autodesk Revit was released it was subject to numerous changes every year that even affected simple operations such as creating a line. Also, Revit as an example of commercial BIM authoring tools, does not allow for creating lines smaller than an absolute tolerance, or a polygon in which two line segments are slightly deviated. The API library of Autodesk Revit also does support multi-threading which is critical for enhancing the performance of an extended application. It is also too slow for some visualization operations and does not allow for creating animations. Many of these items which for OSM may be considered as limitations are in fact rather strategic decisions which were made in the design of Autodesk Revit to create robust geometric operations. However, they are not needed in operations that are included in OSM and only add to the computational overhead.

OSM also uses Windows Presentation Foundation (WPF) for visualization. WPF is a Microsoft rendering User Interface (UI) which uses DirectX, a Microsoft version of multimedia API libraries, for rendering windows applications. WPF UIs are designed in XAML code and are supported with all of .NET programming languages, including C#. WPF supports powerful 2D and 3D renderings and animations, and leverages Graphics Processing Unit (GPU) for rendering. Additionally, it allows for customizing its base classes to optimize the performance of drawing and rendering operations. While the User Interface is designed and included in the OSM library, this library completely separates the engine from the UI, and the UI design can change with no need to change the simulation engines. Figure 6-1 diagrammatically visualizes the strategies in development of OSM and the interoperability between BIM and OSM.

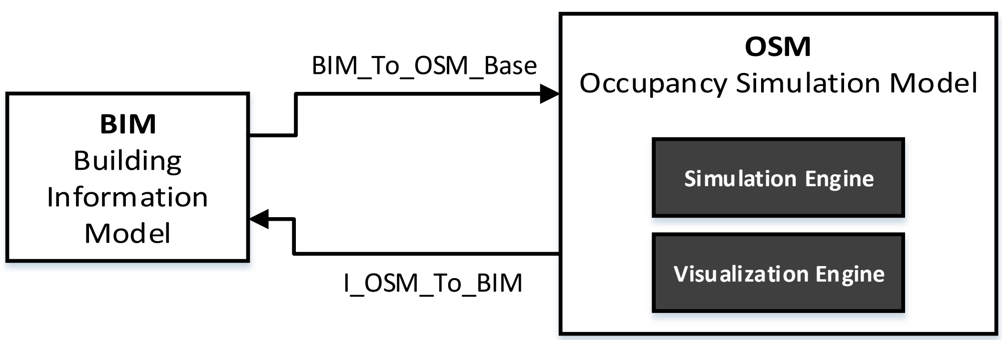

Figure 6-1: The framework of interoperability between Building Information Model (BIM) and Occupancy Simulation Model (OSM).

Explaining the details of implementation of Revit_To_OSM and OSM_To_Revit classes does not fit the scope of this study. However, a simple example will be used to demonstrate it. Figure 6-2 shows the start dialog window of OSM software in which the floor level, minimum height of visual obstacles and some information for approximation of splines are asked. In the background of this dialog window the BIM model is visualized. Figure 6-3 shows the 3D model of the same BIM in OSM. Figure 6-4 shows this model can be used for 3D visualization of spatial data. The visual obstacles in Figure 6-3 and Figure 6-4 are sliced with a plane at the visibility height of the agent which was determined in OSM UI in Figure 6-2. Based on this slicing operation a 2D model will also be produced that simplifies the complex 3D model to three layers of polygonal geometries: visibility barriers, physical barriers, and edges of walkable field. Figure 6-5 shows how selecting a different height for visual obstacles changes the 2D layout. In this 2D model a visual barrier both blocks visual and physical accessibility, a physical barrier only blocks physical accessibility, and field determines the boundaries of the walkable area. In its UI, OSM allows for hiding different layers of information to focus on one layer only.

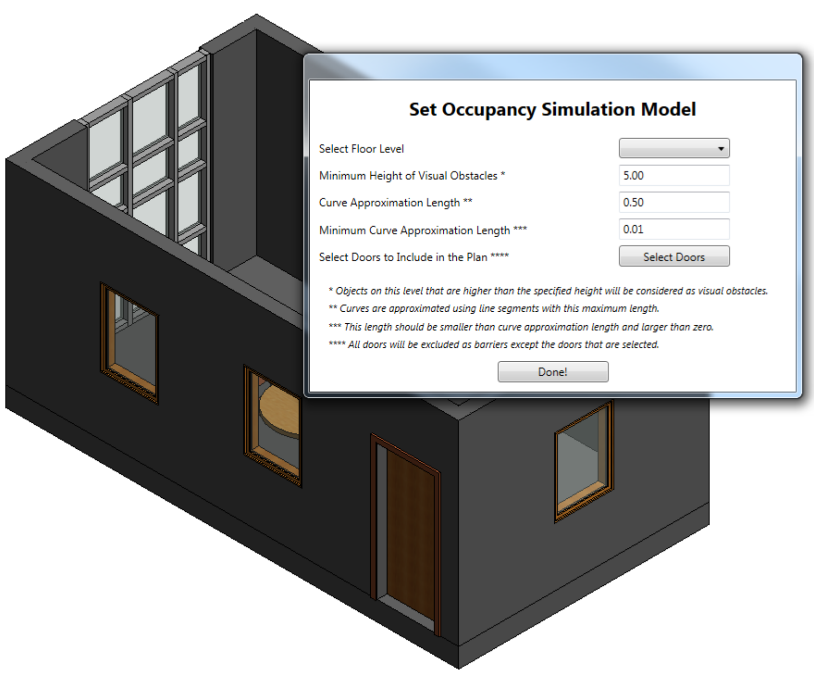

Figure 6-2: The Building Information Model (BIM) in Autodesk Revit with the Occupancy Simulation Model (OSM) dialog window.

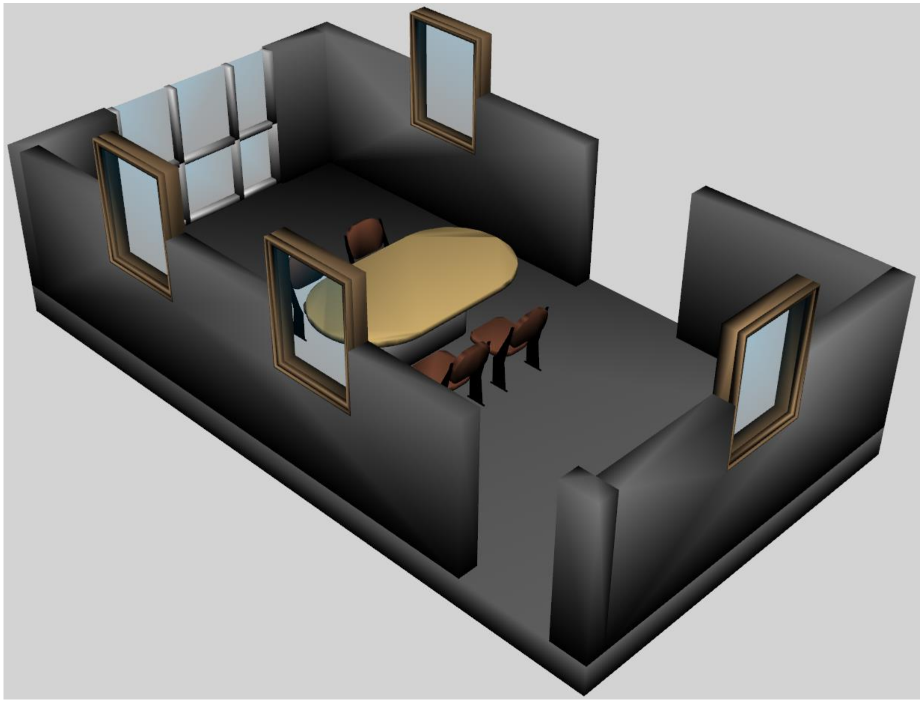

Figure 6-3: A building model at Occupancy Simulation Model (OSM) software.

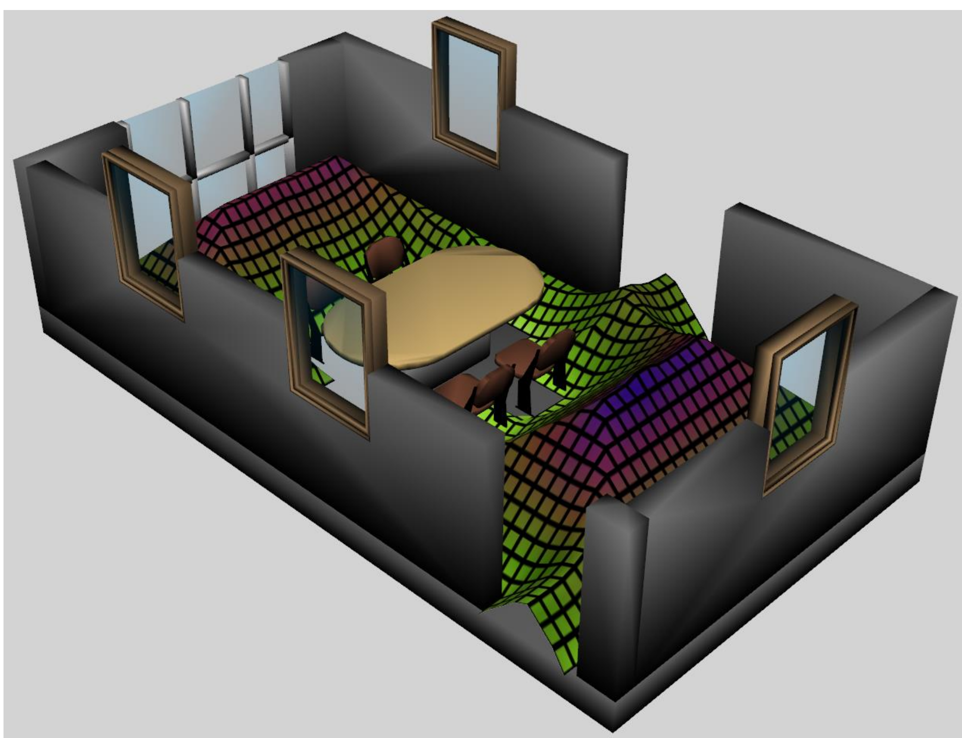

Figure 6-4: Visualization of spatial data in OSM.

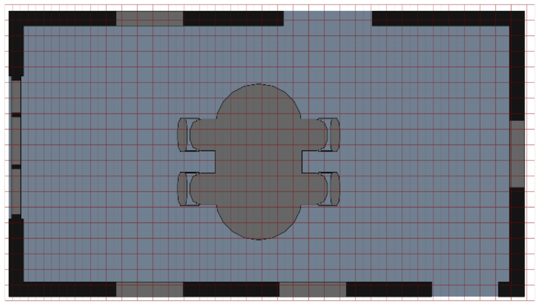
Figure 6-5-1- View Height equals to 5 Ft.

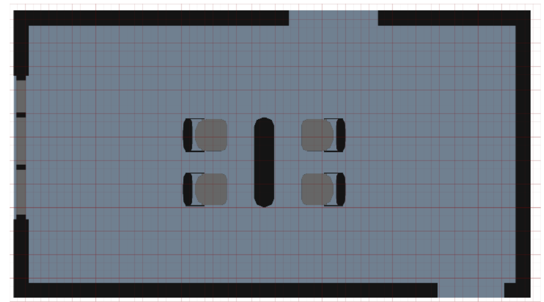
Figure 6-5-2- View height equals to 2 Ft.

Figure 6-5: A simplified 2D model of a building at OSM.

A.3 Spatial Data Models

OSM includes six different types of spatial data that associate numerical values to cells in the grid. Each layer of spatial data has a unique name, tow properties that return the maximum and minimum of the data, a type enumerator, and a dictionary that associates numerical values to cells. Using a dictionary was preferred over using a one or two dimensional array because in most of the cases large areas of the floor are not used for occupancy and there will not be any need to associate data to these areas. Therefore, often a dictionary data structure uses less memory while still allowing for efficiently retrieving data. These common aspects of all of these data structures are encapsulated in an interface which is named ISpatialData and includes the properties shown in Table 6-4. Using this interface generalizes the operations that only deal with the common aspects of the data such as filtering the data as an image, exporting it to Comma-Separated Values (CSV) format, visualizing the data, constructing a mesh geometry from the data, and exporting the data geometry in OBJ format.

Table 6-4: The ISpatialData model used in OSM to store spatial Data.

	Name	Description
Properties		
Dictionary<Cell, double>	Data	*Gets the data.*
double	Max	*Gets the maximum value of the data.*
double	Min	*Gets the minimum value of the data.*
String	Name	*Gets the name of the data.*
DataType	Type	*Gets the type of data.*

Figure 6-6 shows the inheritance structure of all spatial data types in OSM. This diagram shows that the SpatialDataField is inherited from the Function class and the Activity class is inherited from ActivityDestination class. The Function class includes a method that determines the cost (or potential vs. desirability) of a numeric value. The public properties of this class are available in Table 6-5. In this class the GetCost is a function pointer (i.e. delegate) that calculates the cost of data given a data value. This function pointer can be created form Lagrangian interpolation, a written formula, an identity function that returns the value of data, and a built-in method that uses a Bezier curve model for cost calculation. The written text formula allows for passing parameters to the function. Parameters are variables with values that change between an upper and lower bound and when changed will automatically update the functions that use them. The ActivityDestination class includes information about the destination of an activity and the focal point of the activity which were discussed in Chapter 3. The rest of the spatial data models in Figure 6-6 are mainly data containers. Dashed arrow lines in this figure represented inheritance from interfaces and solid arrow lines represent inheritance from another class.

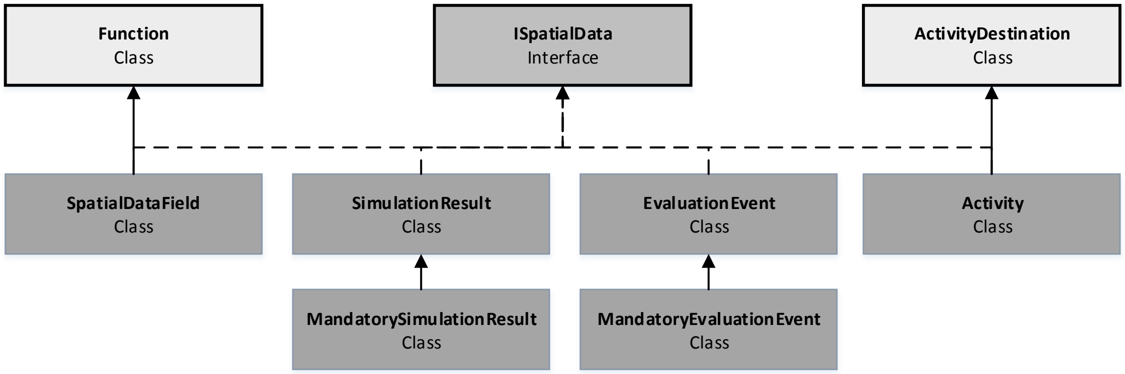

Figure 6-6: The structure of the inheritance of spatial data in OSM.

Table 6-5: The properties of the Function class.

	Name	Description
Constructors		
	Function(string)	*Initializes a new instance of the Function class.*
	Function(string, bool, bool)	*Initializes a new instance of the Function class.*
Methods		
void	SetBuiltInRepulsion()	*Sets the built in repulsion.*
void	SetInterpolation(IInterpolation)	*Sets the interpolation formula.*
void	SetInterpolation (IEnumerable<double>, IEnumerable<double>)	*Sets the interpolation formula.*
void	SetRawValue()	*Sets the identity function to GetCost method to return the data itself.*
void	SetStringFormula (CalculateCost)	*Sets the string formula.*
Properties		
enum	CostCalculationType	*Gets the type of the cost calculation.*
double	GetCost	*Gets the GetCost delegate.*
bool	HasBuiltInRepulsion	*Gets a value indicating whether this instance has built-in repulsion or not.*
bool	IncludeInActivityGeneration	*Indicates if this function should be included in the generation of the potential field of activities*
string	Name	*Gets the name.*
string	TextFormula	*Gets or sets the formula as a text.*

A.4 Isovist Calculation

The area of visibility which is used in occupancy simulation is a modeled as a collection of cells which uses a hash-table. The reason for using a hash-table instead of an array (i.e. an image that covers the floor) is that the number of visible cells are often much less than the number of cells in the floor and using a hash-table consumes less memory. Table 6-6 shows the public member of the Isovist class. The operations for calculation cellular isovists are included in the CellularIsovistCalculator class. Since this class is designed to work in parallel threads, its members are not exposed publicly to support thread safety. Instead, this class includes some static members that can be publicly accessed to calculate isovists. Table 6-7 shows the public members of CellularIsovistCalculator class.

Table 6-6: The public members of Isovist class.

	Name	Description
Constructors		
	Isovist (Cell, HashSet<Int32>)	*Initializes a new instance of the Isovist class.*
	Isovist (Cell)	*Initializes a new instance of the Isovist class which can be filled in a parallel thread.*
Methods		
void	Compute (double, BarrierType, CellularFloor, double)	*Computes the isovist at the specified depth of view. This method uses the GetIsovist method of CellularIsovistCalculator class to calculate the isovist.*
Double	GetArea (double)	*Returns the area of the field of visibility.*
List<BarrierPolygons>	GetBoundary (CellularFloor)	*Gets the boundary polygon of the visibility area.*
HashSet<int>	GetIsovistEdge (CellularFloor)	*Gets the cell IDs at the edges of the visibility area.*
Fields		
bool	IsEdgeLoaded	
Properties		

Table 6-6 Continued

	Name	Description
HashSet<UVLine>	EdgeLines	*Gets or sets the edges of the field of visibility.*
Cell	VantageCell	*Gets or sets the vantage cell of the isovist.*
HashSet<int>	VisibleCells	*Gets or sets the IDs of the visible cells.*

Table 6-7: The public and internal members of CellularIsovistCalculator class.

	Name	Description
Constructors		
	CellularIsovistCalculator(UV, BarrierType, CellularFloor, Double)	*Initializes a new instance of the CellularIsovistCalculator class. This constructor is designed to be called in parallel and access to it is only allowed internally.*
Methods		
List<Cell>	ExtractIsovistEscapeRoute(CellularFloor, bool[,], BarrierType, double)	*Extracts a list of cells that are visible and walking towards them will not result in collision with barriers.*
AgentEscapeRoutes	GetAgentEscapeRoutes(Cell, double, int, CellularFloor, Dictionary<Cell, double>, double)	*Returns an array of destinations for a cell where the agent is located.*
IsovistEscapeRoutes	GetAllEscapeRoute(UV, double, BarrierType, CellularFloor, double)	*Gets all escape routes from a vantage point. Represents the cells that are located at the boundaries of an isovist*
Isovist	GetIsovist(UV, double, BarrierType, CellularFloor, double)	*Gets the isovist.*
IsovistEscapeRoutes	GetWeightedSimplifiedEscapeRoute(UV, double, BarrierType, CellularFloor, Dictionary<Cell, double>,int, double)	*Gets a escape route which is simplified according to angle and the weighting factors that are assigned to them.*

A.4.1 Calculation of cellular Isovist

Similar to many other visibility tests, the isovist calculation includes ray tracing operations which are computationally expensive. While in most existing libraries such as Open Graphics Library (OpenGL) this process is leveraged by the computational power of GPU, an algorithm that minimizes the number of rays will still perform faster whether GPU or CPU is used for calculation. The algorithm that calculates the field of visibility attempts to minimize the number of rays using the idea of wave propagation from the vantage point of the isovist. Figure 6-7 shows a vantage point in a layout that include two visual obstacles. In the propagation process in each step the visibility edge expands one cell outwards and the edge gets updated. The expansion process will not include the cells that overlap with the edges of the visual obstacles. Once expanding the visibility edge if a cell intersects with the edge of a barrier the end points of that edge will be selected as potential origins for shooting rays that determine the edge between visible and not visible areas. In the state of expansion shown in Figure 6-7, two edges and three points are detected.

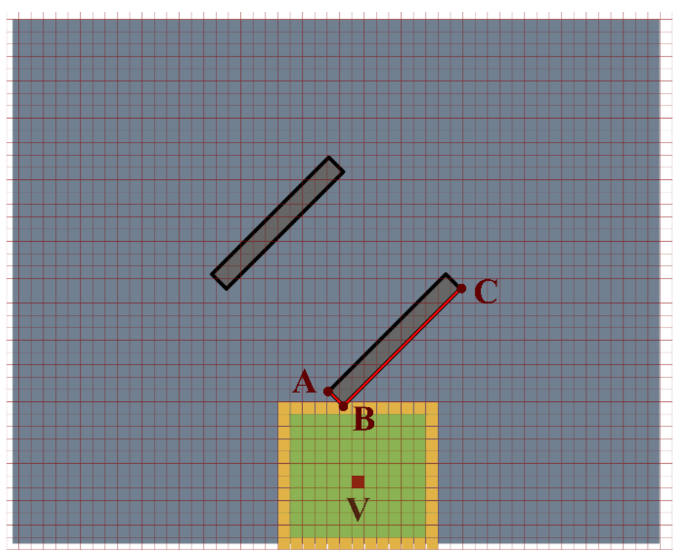

Figure 6-7: The edge of the field of visibility grows one cell in each step.

Some of the discovered points can be dismissed as candidates for shooting rays. Any ray that starts from Point B, for instance, will hit the barrier immediately. To understand if a candidate point should be the origin of a ray a simple and efficient test can be used. Let's say point M and N are the points before and after B on the same barrier polygon which includes B. In this example M and N are A and C. However, this cannot always be the case in more complex settings. Point B should be dismissed if the A and C are on two different sides of the VB line. This test only demands the calculation and comparisons of the magnitudes of two vector cross products: $\overrightarrow{VB} \times \overrightarrow{VC}$ and $\overrightarrow{VB} \times \overrightarrow{VA}$ (see Figure 6-8). If one of these numbers is positive and the other is negative then B and should be dismissed. The same test will prove that point A and C should be used as the origin of two rays.

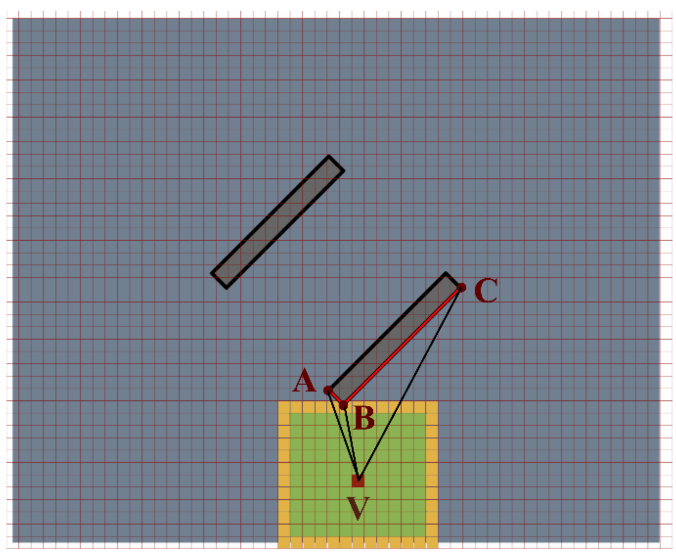

Figure 6-8: Point B should be dismissed from ray tracing because the points before and after it on the same polygon are on two sides of VB.

At this point it is known that two rays should be create from points A and C. However, these rays will only be created when the visibility edge reaches these points. The cells that a ray intersects with them on the floor will be marked as barriers from which the growing visibility edge cannot cross. Figure 6-9 shows this process. This process continues until the edge of visibility vanishes which means the number of cells on the edge reaches zero. During this process the origins of the rays will be stored in a lookup table to make sure that if an endpoint appears several times the same rays will not be generated again. Figure 6-10 shows that using this process the isovist can be calculated using as few as three rays. The efficiency of this process also depends on the design of the data structures which are used for representing cells and polygons.

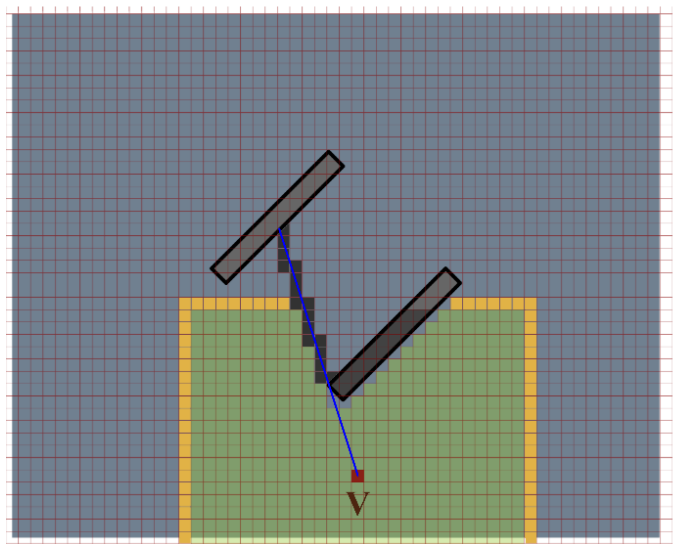

Figure 6-9: When the edge of visibility expands the cells marked by rays will serve as a barrier.

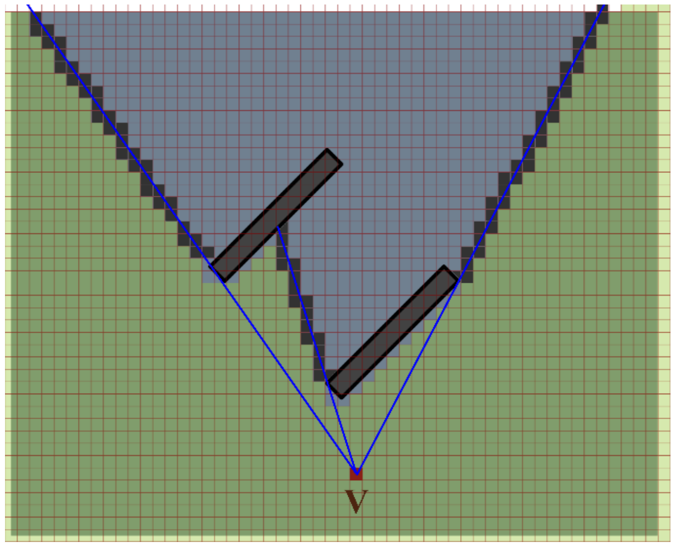

Figure 6-10: The isovist can be calculated with three rays in this example.

A.4.2 Pre-calculation of Cellular Isovist

In spite of the attempt to minimize the number of rays, depending on the resolution of the grid numerous ray tracing operations will be needed. On the other hand, calculating the isovists in real time is not a good idea because many of the isovists will be recalculated thousands of times during the simulation. Therefore, it is more reasonable to pre-calculate the entire isovists for simulations that need them. Pre-calculation also offers an alternative method for computing the isovists which is more efficient in some cases. Visibility is a mutual property indicating that for two isovists like I_1 and I_2 if I_1 includes the vantage point of I_2, then I_2 should also include the vantage point of I_1. Depending on this property we can calculate a small percentage of isovists and drive the rest of the isovists from them. Figure 6-11 shows the cells on the edges of the field and the edges of the visibility barriers. The number of these cells are much less than the number of cells on the floor. Imagine that during the calculation of the isovists of these points the isovist of cell V will also be filled if V is included in any of these isovists. This process can be done in parallel operation with strategies that guarantee thread safety. Figure 6-12 shows that after this process the cells on the edges of the isovist of V are almost completely calculated automatically. Optional occupancy scenarios in OSM include operations for finding the edges of visibility field and sorting the cells on the edge based on their angles with the vantage point. In this process the edge is automatically calculated and after sorting the cells based on their angles it is easier to find the missing parts of the edge which is highlighted in green. Overall, using the pre-calculation technique it would be possible to decrease some computational cost.

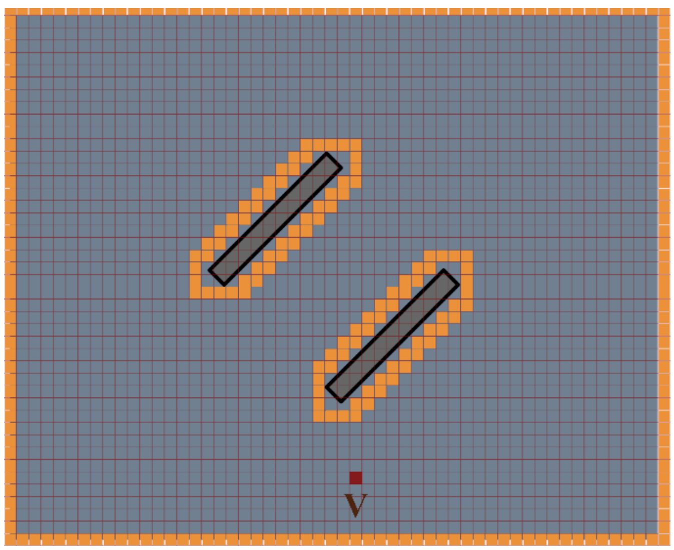

Figure 6-11: The isovist of the cells on the edges of field will be calculated.

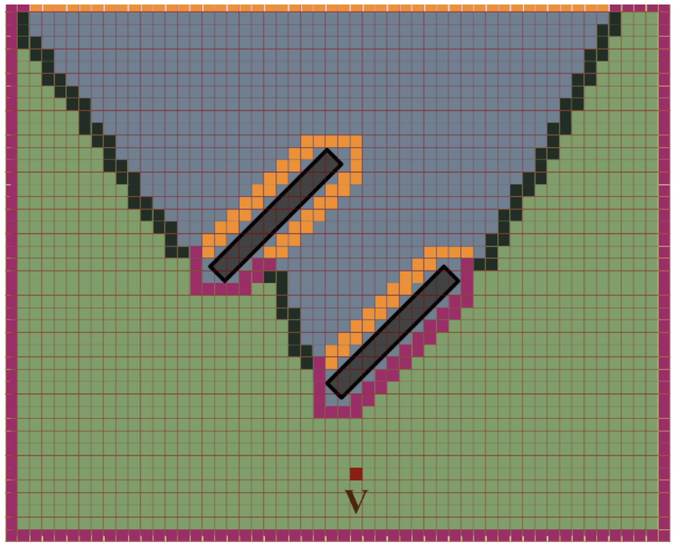

Figure 6-12: When the isovist of the cells shown in Figure 6-11 are calculated the edges of the isovists of V and the rest of the cells are almost calculated.

A.5 Agent Model

This section provides a brief overview of the agent models as software components in OSM. Similar to spatial data, agent models that are used for simulation, training, and visualization in both mandatory and optional scenarios include common characters which are encapsulated in a several interfaces. IAgent interface locates at the topmost level all of these interfaces. Table 6-8 shows the common properties of all of the agents. From this interface the ISimulateAgent interface is inherited which adds the "simulate()" function to IAgent. The IVisualAgent is also inherited from IAgent and adds the properties shown in Table 6-9 that serve animation and visualization purposes. All of the agent models in OSM that are used for simulation, visualization or training are inherited from these three interfaces. Figure 6-13 visualizes the relationships between the agent models in OSM. Dashed arrow lines in this figure represented inheritance from interfaces.

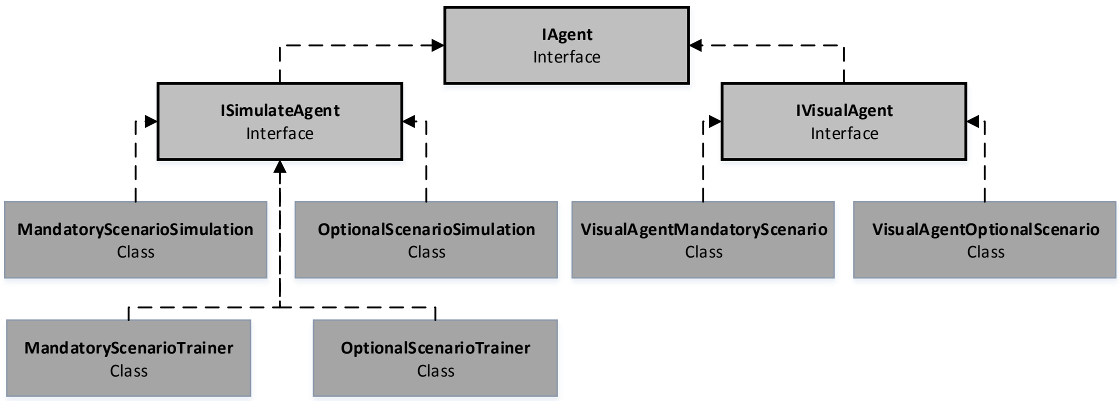

Figure 6-13: The structure of the inheritance of agent models in OSM.

Table 6-8: The IAgent interface that encapsulates the common properties of all of the agents.

	Name	Description
Methods		
void	LoadRepulsionMagnitude()	*Loads the repulsion vector's magnitude.*
void	TimeStepUpdate()	*Updates the time-step.*
Properties		
double	AccelerationMagnitude	*Gets or sets the acceleration magnitude.*
double	AngularVelocity	*Gets or sets the angular velocity.*
double	BarrierFriction	*Gets or sets the barrier friction.*
double	BarrierRepulsionRange	*Gets or sets the barrier repulsion range.*
double	BodyElasticity	*Gets or sets the body elasticity.*
double	BodySize	*Gets or sets the size of the body.*
StateBase	CurrentState	*Gets or sets the current state of the agent.*
CollisionAnalyzer	EdgeCollisionState	*Gets or sets the state of the edge collision.*
double	RepulsionChangeRate	*Gets or sets the repulsion change rate.*
double	TimeStep	*Gets or sets the time-step.*
double	TotalWalkedLength	*Gets or sets the walked total length.*
double	TotalWalkTime	*Gets or sets the total walk time.*
double	VelocityMagnitude	*Gets or sets the velocity magnitude.*

Table 6-8 Continued

	Name	Description
double	VisibilityAngle	*Gets or sets the visibility angle.*
double	VisibilityCosineFactor	*Gets or sets the visibility cosine factor.*

Table 6-9: The IVisualAgent interface adds visualization features to the IAgent interface.

	Name	Description
Methods		
void	SetGeometry	*Sets the geometry of the animated agent.*
void	StopAnimation	*Stops the animation.*
void	WalkInit(CellularFloor, Dictionary<Cell, AgentEscapeRoutes>)	*Initializes the animation.*
Properties		
double	AnimationTimer	*Gets the animation timer.*
bool	ShowSafetyBuffer	*Gets or sets a value indicating whether to show the safety buffer around the agent.*
bool	ShowVisibilityCone	*Gets or sets a value indicating whether to show visibility cone.*
Storyboard	TimeStoryboard	*Gets the time storyboard used for animation.*

A.6 Scenario Model

In Chapter 3 and Chapter 4 the scenario models in the simulation were discussed using detailed flowcharts. This section provides a general overview of the data models for scenario and sequences which combined Agent-Based Model (ABM) with Discrete Event Simulation (DES). OSM includes a repository of activities from which task models will be created as a sequence of activities. The scenario model which is at the topmost level includes a repository of sequences. Figure 6-13 visualized the relationships between activities, sequences and scenario in OSM for simulation of mandatory scenarios. This figure visualizes two scenarios for the sake of demonstration. In Chapter 3 it was shown that the number of sequences can be much more. The data model of activity was discussed previously in this chapter as spatial data. Table 6-10 and Table 6-11 which follow Figure 6-14 provide more insight into the data structures of Scenario and Sequence classes.

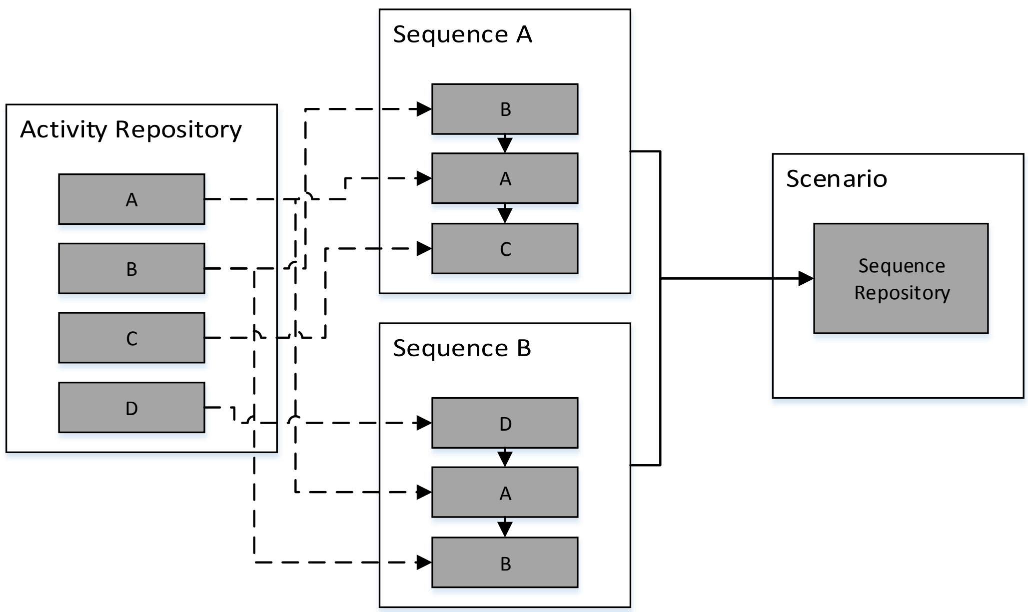

Figure 6-14: The relation between activity, sequence and scenario in OSM.

Table 6-10: The public members of Sequence class in OSM.

	Name	Description
Constructors		
	Sequence (IEnumerable< string >, string, double)	*Initializes a new instance of the Sequence class.*
Methods		
void	AssignVisualEvent (VisibilityTarget)	*Assigns the visual event to this task to get it visually detectable.*
Sequence	FromStringRepresentation (string)	*Creates an instance of Sequence from its string representation.*

Table 6-10 Continued

	Name	Description
string	GetStringRepresentation ()	*Gets the string representation of this task.*
Properties		
double	ActivationLambdaFactor	*Gets or sets the activation lambda factor of the exponential distribution.*
int	ActivityCount	*Gets the number of activities that this task includes.*
List<string>	ActivityNames	*Gets or sets the activity names.*
bool	HasVisualAwarenessField	*Gets a value indicating whether this instance has visual awareness field.*
string	Name	*Gets the name.*
double	TimeToGetVisuallyDetected	*Gets or sets the time to get visually detected for this task after its activation. This value is valid only if the Sequence has a visual awareness field*
VisibilityTarget	VisualAwarenessField	*Gets or sets the visual awareness field from which this task can be visually detected. This property is set to null when the task does not require visual detection.*

Table 6-11: The public members of Scenario class in OSM.

	Name	Description
Constructors		
	Scenario()	Initializes a new instance of the Scenario class.
Methods		
bool	IsReadyForPerformance()	Determines whether this scenario is ready for performance.
void	LoadQueues (Dictionary<string, Activity>, double, double)	Loads the task queue and makes the scenario ready for performance.
void	ReActivate (Sequence, double)	This method is called right after the termination of a sequence to put it in use again.
bool	RemoveSequence (Sequence)	Removes the sequence. If the operation succeeds return true otherwise returns false.
Properties		
SortedDictionary<double, Sequence>	ExpectedTasks	Gets or sets the expected tasks.
HashSet<string>	MainStations	Gets or sets the names of the main stations.

Table 6-11 Continued

	Name	Description
string	Message	Gets the user interface message.
HashSet<Sequence>	Sequences	Gets or sets the sequences.
Dictionary<double, Sequence>	UnexpectedTasks	Gets or sets the unexpected tasks.