Occupants Behavior-Based Design Study Using BIM-GIS Integration: An Alternative Design Approach for Architects

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Abstract

Occupant behavior is considered as one of the important factors that can influence the energy consumption of a building, therefore knowing occupant behavior as supporting data can help architects to design more resilient, and sustainable architecture. Employing this data in the design and construction can help with creating more efficient buildings. Simulation can help us to experiment and understand the behavior of the system using these data by creating logical, justifiable, and valid models. Recently, occupancy behavior data has been used in different simulation tools. However, most of the research focusing on indoor navigation does not consider Building Information Modeling (BIM) and its properties while making the occupancy behavior simulation. When it comes to the energy performance of the building, building model should be taken into account as it would help the design team to with a better understanding of the project. In this paper, we used a BIM-GIS platform, to demonstrate how the occupant tracking and behavior pattern extracted from a simulation model using stochastic data can be used as a facilitating information for the design process.

Keywords

BIM-GIS • Occupant behavior • Modeling simulation

92.1 Introduction

As city population and density grow, the environmental impact of buildings becomes more important as how we build our community directly affects the behavior of people [1]. Designers have a decisive role and can make a huge impact on the society by their approach to design. According to the International Energy Agency (IEA), different variables such as climate, building envelope, indoor design criteria and the occupant behavior are considered as factors that affects the energy usage of buildings [2, 3]. As stated by Clevenger and Haymaker [4], unlike other factors, occupant behavior and how people behave and move in the building is highly subjective, which can bring an uncertainty and a significant amount of margin of error to the energy modeling behavior. The type of human-building interactions such as using air conditioner and turning light switches on and off result in consuming a significant amount of energy in buildings [5]. During operational stages, significant energy consumptions and environmental impacts are registered. According to Bottaccioli et al. [6], users behavior leads to 30% energy waste 30% inside the buildings. Moreover, during the occupancy phase, not all the building space is in use and occupied at the same time, this factor leads to a waste of great amount of energy. Therefore, it is important to consider this factor as a benchmark for reaching a passive design as an approach with the goal of reducing the energy consumption by employing natural resources [7].

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The stochastic occupancy pattern can be detected by occupancy sensors, which are commonly installed in today's smart buildings. Therefore, it is a rational idea to utilize the occupancy information in order to reduce the energy consumption caused by human-building interaction while maintaining occupants' comfort. The occupant variable and the behavior tracking are crucial for defining operational and rational services based on the real needs of users, which leads to avoiding energy waste [6, 8]. Many diverse techniques for indoor location and human tracking related to the problem can be found in the literature. The expense and time required to install, configure, and maintain these systems have prohibited general deployment to date. One solution to this problem is to employ occupancy simulation modeling to simulate the behavior and movement of people inside the building using probability distribution and stochastic models [9, 10].

This paper discusses the possible methodologies and techniques for collecting occupancy behavior data, when many inefficiencies of the building process arise and when it is crucial to tailor the services to the occupancy variable patterns. For this reason, a literature review was completed to explain the different methods used by scholars regarding the collection of the users' data in the indoor environment. In the next step, we integrated a BIM-GIS platform with the occupancy behavior information to facilitate the designers into designing a more sustainable, efficient structure.

92.2 Background

In the rising age of technology and smartphones, almost everyone uses Geographical Positioning System (GPS) for navigating between different places. While this satellite-based system is widely used for outside positioning, it is considered inaccurate for indoor tracking and locating applications, therefore, it is not considered as a valid tool in this scenario [11]. While considerable research practices have focused on precise indoor tracking methods, there is still a major scarcity of using indoor tracking in practice [12, 13].

Gathering and analyzing data driven from the occupant movement inside the building can be used for numerous applications. Berbakov et al. [14] used indoor tracking systems in emergent situations, where this system can facilitate occupants' evacuation process, as it can help firefighters to locate and access different parts of the building easily. Grönroos et al. [15] studied the application of using indoor navigation in healthcare settings and how it can be useful by coordinating the movements of the professional personnel. The construction industry also benefits from this system. Using Spot-R, which is a non-GPS system, contractors are able to track the workers and the equipment location in order to maintain the safety of their personnel during the construction process [16]. In addition, many researchers have used the occupant tracking information to achieve a passive design as occupant behavior is considered one of the major factors in building energy consumption [2, 3, 17]. While some of the effects of occupant behavior on the energy consumption, such as adjusting the thermostat and, opening and closing windows are obvious, latent effects of occupants on the comfort zone also exist. These latent effects include the internal heat gain in the space due to the human body temperature's emission into space through radiation, which in turn affects the room temperature [18]. Using an accurate occupant tracking method, the researchers are not only able to track and record the occupant's path and walking pattern inside the building but can also record the number of people in any space at any time. Therefore, using this system as an auxiliary tool can greatly help designers achieve a structure in accordance with the occupant's need, leading to reducing the energy consumption of the buildings. In this regard, Zhang et al. [12] designed and developed "Montage", a framework which facilitates recording real-time multi-user formation tracking and localization using smartphones.

92.2.1 Tracking Devices

Radio frequency-based technologies, Wi-Fi, and Bluetooth are considered as the main methods for occupancy detection [17, 19, 20]. In radio frequency-based technologies such as Radio Frequency Identification (RFID), a particular object, known as Tag, transmit radio waves to the receiver and the receiver then sends the data to the computer [19]. RFID technology makes the building up of indoor localization system with low cost possible [21]. They are accurate but not applicable to phones [13, 22]. Also, the main disadvantage of this system is that it does not rely on the existing infrastructure, meaning that for occupancy tracking, many tags and receivers, depending on the area of the study, must be purchased and installed into the building [19]. Some of the existing methods rely on fingerprints are considered as user intensive and environment restrictive in data collection stage [13].

On the other hand, systems such as WiFi and Bluetooth positioning do not require any addition to the existing infrastructure as almost all of the public spaces nowadays are equipped with WiFi internet system. In addition, WiFi and Bluetooth are the two preferred methods by the Inlocation alliance (ILA), a foundation which focuses on facilitating a high accurate indoor positioning system [23]. WiFi tracking system uses every router as a spotter, getting signals from the smartphone device of the subject that is tracking, this signal is sent to the main server, showing the user location [24]. Çiftler et al. [25] proposed a zone-based occupancy monitoring system in order to broaden the coverage area of the WiFi tacking system. Shin and Cha [26] introduced an indoor user tracking system. The system constructs a topological map with Wi-Fi signal calibrations, assigns semantically meaningful labels into the map, and estimates the semantic location of the user based on the current Wi-Fi observation. Bottaccioli et al. [6] correlated different information by integrating Internet of Things (IoT) devices with BIM and GIS technologies. They used BIM models for monitoring and modeling the energy performance of the building and GIS for providing geo-referenced information about building, distribution systems and deployed IoT devices. Spot-R, which was mentioned previously, is another system which integrates with the BIM model in order to help and accelerate the process of locating and helping construction workers when an accident happens on the jobsite [16].

92.2.2 Simulation Modeling

While employing tracking devices and performing experimental studies can be considered time consuming and costly, model simulation is considered as a tool for developing and experimenting the behavior [27]. Computer simulations can create a model that represents the overall logic of various activities and resources of a project. Feng et al. [28] have used Discrete Event Simulation (DES) process—a process that codifies the behavior of a complex system as an ordered sequence of well-defined events—to model the occupant behavior inside the building. Using this approach, the researcher is able to study the occupant movement inside of the simulated building layout, which will result in more accurate results [9]. In order to employ the data from tracking devices such as WiFi, real time data is needed which due to security and privacy concerns, are not shared by many buildings. In addition, based on the discussed literature, another important criterion than leverages using simulation process instead of tracking devices is the fact that for using devices such as Wi-Fi tracking or Bluetooth, we need an actual, built model. This would limit our degree of freedom in altering the design. On the other hand, simulation can be used as early as the schematic design phase, giving the designers the ability to change their model according to the simulation result in the earlier phase of design and construction process.

92.2.3 BIM-GIS

Unlike the traditional approach to design and construction, the construction industry is now leaning towards integrating data, driven from different resources into the design [29]. Employing dynamic and static data has numerous benefits and advantages such as cost optimization, jobsite and worker safety, accurate estimating, coordination, and communication [30]. BIM is considered the ideal platform for this approach as it contains data and information, using BIM models these factors can be checked and processed automatically which saves time, minimizes the possibility of errors, and leads to a better quality design for the users [29, 31, 32]. Therefore, BIM is currently used in most of the studies which focus on energy analysis, however there is a lack of research which studies the occupant behavior in a building using a BIM-GIS platform.

Geospatial Information System (GIS) data help us to visualize, record, and analyze the geographical information of every data. Building Information Modeling (BIM) as an intelligent technology helps the design-build team to form, manage, and perform more efficient buildings [33]. Many researchers [34, 35] have applied BIM-GIS systems in order to make the construction procedure more efficient. However, in this research, we tend to use BIM-GIS integration to simulate the occupant behavior in confined spaces. It enables the researcher to model any spatial and geographical data in the building while considering all aspects of the building. Using BIM-GIS technology, architects are able to better project and more intuitively describe the occupant behavior in a design scheme, and conduct the analysis based on relevant building technologies and simulation results, to provide a strong basis for evaluation and performance quantification.

92.3 Methodology

The aim of this study was to investigate the application of using occupant behavior and its effect on facilitating the designers and architects toward a more sustainable, resilient design. In order to achieve this goal, a mixed methods approach, including qualitative and experimental studies, was used. First, the study reviewed different methodologies and approaches available

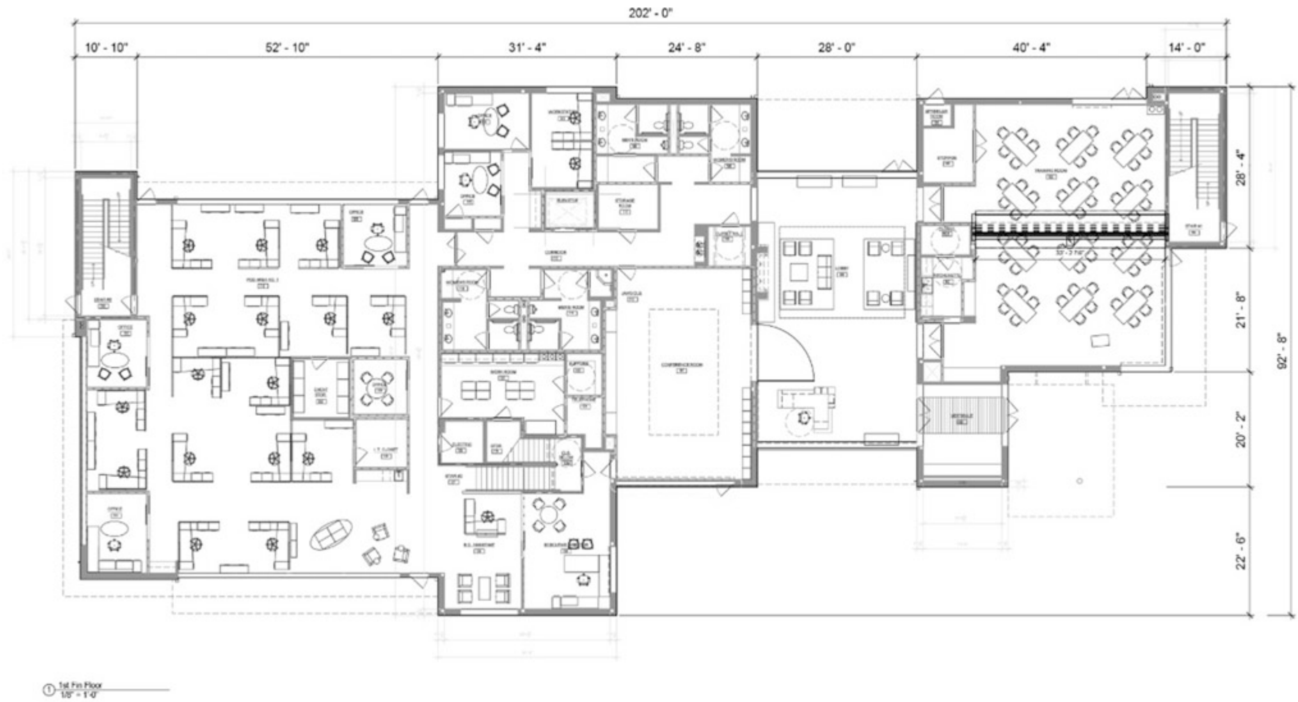

Fig. 92.1 First floor plan

for tracking occupant behavior and discussed their features based on the existing literature. In the next step, in order to show how the data from modeling the human behavior can interact with a BIM-GIS system, we modeled the first floor of an office building located in Dallas, Texas with a total floor area of 13,000 square feet (SF) using Autodesk Revit® and then imported the model into ArcGIS® desktop. The required layers included in the model are polylines as the representation for walls, stairs and doors, and the polygons for spaces. The spaces are important to show the location of occupants and time spent in the space. As shown in Fig. 92.1, this office building contains a large Lobby, a bullpen area with open offices, a conference room, 15 private offices, and restrooms. Occupancy Simulator app version 1.3.2, developed by Lawrence Berkeley National Laboratory, was used to calculate the number of people working and using the building floor at any given [28].

The Markov chain model, a probability distribution simulator tool was used to model occupant behavior inside the building [28]. Each space was defined manually in the simulator system, based on the size and the functionality of the space (e.g. private office, 250 SF). By inputting the space type and the area to the simulator, the number of occupants in each space was calculated by the program based on space density suggested by the Database for Energy Efficiency Resources (DEER) building prototypes. In the next step, the occupancy type was defined based on the pattern of people entering the building. In this scenario, the days of operation for the building was set on weekdays (Monday through Fridays) from 8:30 in the morning to 5:30 in the evening, with the variation of ±30 min. The date and time set for the simulation was April 12 from 8:00 am to 6:00 pm. The result from the whole building simulation is shown in Fig. 92.2.

The results from the simulation were extracted to an Excel® spreadsheet and include the number of individuals in every space through a discrete time of every 10 min, helping the researchers to model the occupant presence and movement inside the building by room. Table 92.1 shows the attribute table for each space. Using the spreadsheet, the researchers selected two peak times during the day which represent the times at which the building is occupied more than the other times during the day. We considered 9:40 and 12:20 pm as two indicators for our model where the total number of occupants in the building is 200 and 240 which are highlighted in Table 92.1.

According to the data shown in Table 92.1, a set of random points was placed into each space using the point feature in ArcGIS®. Each point represents individual occupants and visitors in the building on a weekday during the specified hours. A shapefile was then created as the occupant behavior layer and saved to the office building dataset. The next step involved the aggregation of occupants in each space with the whole building to find what spaces could be considered energy usage hot spots. In order to achieve this goal, the occupant behavior layer dispense was modeled to find the hot spots through the kernel density tool in ArcGIS®. The workflow is shown is Figs. 92.3 and 92.4. The kernel density shapes show the

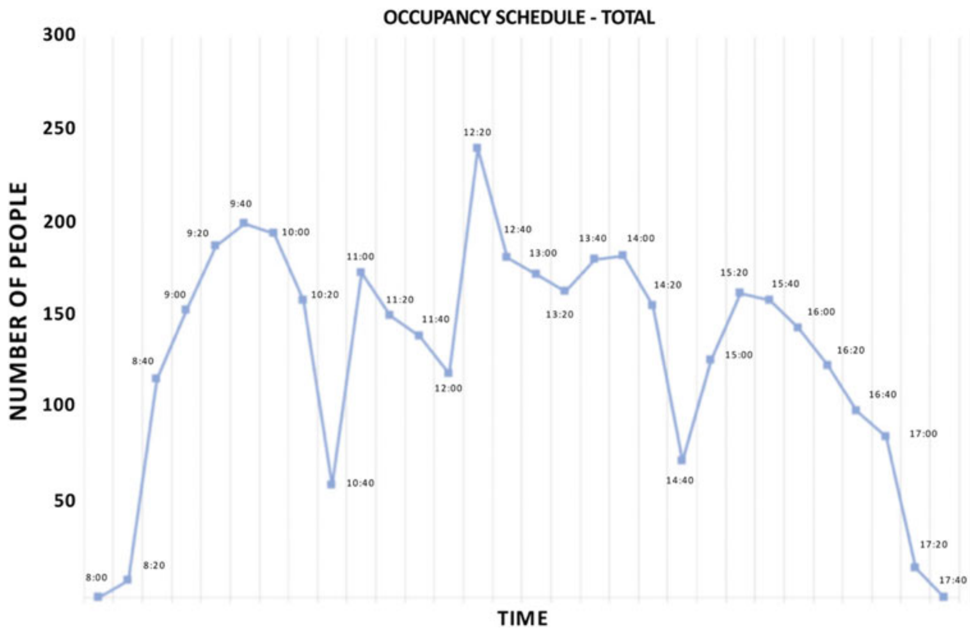

Fig. 92.2 Simulation result

Table 92.1 Simulation result table

Time	Office-Open1	Office-Open2	Office-Open3	Office-Open4	Office-Open5	Office-Open6	Office-Open7	Office-Open8	Office-Open9	Office-Open10	Office-Private1	Office-Private2	Office-Private3	Office-Private4	Office-Private5
8:00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8:20	1	0	0	1	0	1	0	0	0	0	0	0	0	0	1
8:40	1	1	1	16	0	4	1	1	0	16	1	1	1	0	16
9:00	0	1	1	16	1	3	1	5	0	16	11	1	11	1	16
9:20	11	1	12	16	1	1	1	1	6	16	1	1	11	2	16
9:40	1	1	12	16	3	17	1	1	17	16	1	5	1	1	16
10:00	1	1	12	16	3	17	1	1	17	16	1	5	2	2	16
10:20	1	1	12	1	7	17	1	1	17	1	7	20	1	1	1
10:40	1	1	1	4	1	1	1	1	1	14	7	1	1	1	0
11:00	1	1	1	9	16	1	1	14	1	1	16	1	16	1	16
11:20	1	1	1	1	16	0	1	0	1	1	16	1	16	1	16
11:40	11	0	0	0	16	0	1	0	1	0	16	0	16	1	16
12:00	1	1	1	1	16	1	0	0	0	0	16	0	16	0	16
12:20	0	16	1	16	1	16	16	17	0	19	18	1	0	17	12
12:40	0	16	0	16	1	16	16	17	1	1	0	7	0	17	0
13:00	1	16	0	16	0	16	16	17	1	1	0	0	1	17	0
13:20	1	17	17	1	0	1	17	1	1	17	1	14	1	1	1
13:40	16	17	17	1	1	1	17	1	14	17	1	1	1	1	1
14:00	16	17	17	1	1	15	17	1	1	17	1	1	19	1	1
14:20	16	17	17	1	1	1	17	1	1	17	1	1	1	6	1
14:40	16	1	1	1	1	1	1	1	1	1	1	1	1	4	9
15:00	16	1	1	1	0	1	1	1	14	1	1	1	1	8	15
15:20	16	17	6	17	17	1	5	1	1	1	1	1	1	9	11
15:40	16	1	20	1	1	1	1	1	1	17	1	1	1	19	1
16:00	16	6	1	7	1	1	1	1	1	17	10	15	1	1	1
16:20	16	10	1	1	1	10	1	1	1	17	1	0	1	1	1
16:40	1	2	1	1	1	1	1	1	1	17	1	1	1	5	0
17:00	0	3	1	0	0	1	1	1	0	17	1	1	0	0	0
17:20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17:40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Time	Office-Private6	Office-Private7	Office-Private8	Office-Private9	Office-Private10	Office-Private11	Office-Private12	Office-Private13	Office-Private14	Office-Private15	Conference Room	Restroom	Lobby	Whole
8:00	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8:20	1	0	0	0	0	0	0	0	0	3	0	1	0	9
8:40	1	0	0	16	1	1	16	16	2	3	0	1	0	117
9:00	1	1	0	16	1	1	16	16	12	3	0	2	1	154
9:20	1	1	0	16	1	1	16	16	12	3	2	5	17	188
9:40	1	6	1	16	1	1	16	16	2	3	10	1	17	200
10:00	1	6	1	16	1	2	12	12	2	3	10	1	17	195
10:20	1	8	1	5	19	1	1	1	2	3	10	1	17	159
10:40	1	1	1	1	1	1	1	1	2	3	9	1	1	60
11:00	1	1	16	1	1	16	1	1	0	16	9	1	14	174
11:20	1	1	16	1	1	16	1	0	15	16	9	0	1	151
11:40	1	11	16	1	0	16	1	0	0	16	0	0	0	140
12:00	0	1	16	0	1	16	0	0	0	16	0	1	0	120
12:20	1	17	1	0	17	18	0	0	16	0	0	4	16	240
12:40	1	17	0	1	17	0	1	1	16	0	0	4	16	182
13:00	1	17	0	3	17	0	1	1	2	0	9	4	16	173
13:20	17	1	1	0	17	0	1	4	2	15	9	5	1	164
13:40	17	6	1	1	17	1	1	1	2	3	9	1	14	181
14:00	17	1	1	1	17	1	1	1	2	3	10	1	1	183
14:20	17	1	1	1	17	1	1	1	2	3	10	1	1	156
14:40	1	1	0	1	1	1	1	1	2	12	9	1	1	73
15:00	11	1	0	14	1	1	12	1	2	3	9	8	1	127
15:20	12	1	0	1	11	1	1	1	2	17	9	1	1	163
15:40	13	17	1	3	3	1	5	1	2	3	9	1	17	159
16:00	3	17	1	1	1	1	16	1	2	3	0	1	17	144
16:20	1	17	0	1	1	1	16	1	2	3	0	1	17	124
16:40	1	17	0	1	1	1	1	19	2	3	0	2	17	100
17:00	1	17	0	1	1	1	1	15	0	3	0	3	17	86
17:20	0	0	0	1	3	1	0	11	0	0	0	0	0	16
17:40	0	0	0	0	0	0	0	0	0	0	0	0	0	0

probability distribution of people in the space, with the center having the most probability of people being there, and the possibility decreases as it gets to the margins of the shape.

92.4 Results

In this paper, we integrated the occupancy behavior data from a simulation app with a BIM-GIS system to create a visual tool to help architects design spaces and buildings based on the anticipated behavior of occupants. Using the proposed method, we were able to zone this office building based on the number of occupants using the space through the day. As shown in Figs. 92.3 and 92.4, the building could be separated into four different zones, where each zone had its own energy usage pattern and strategy. For example, in Fig. 92.3 there is a high concentration of occupants in regions A, B, and C at 12:20 pm. Knowing this information, designers can amend their drawings with the focus on these regions. For example,

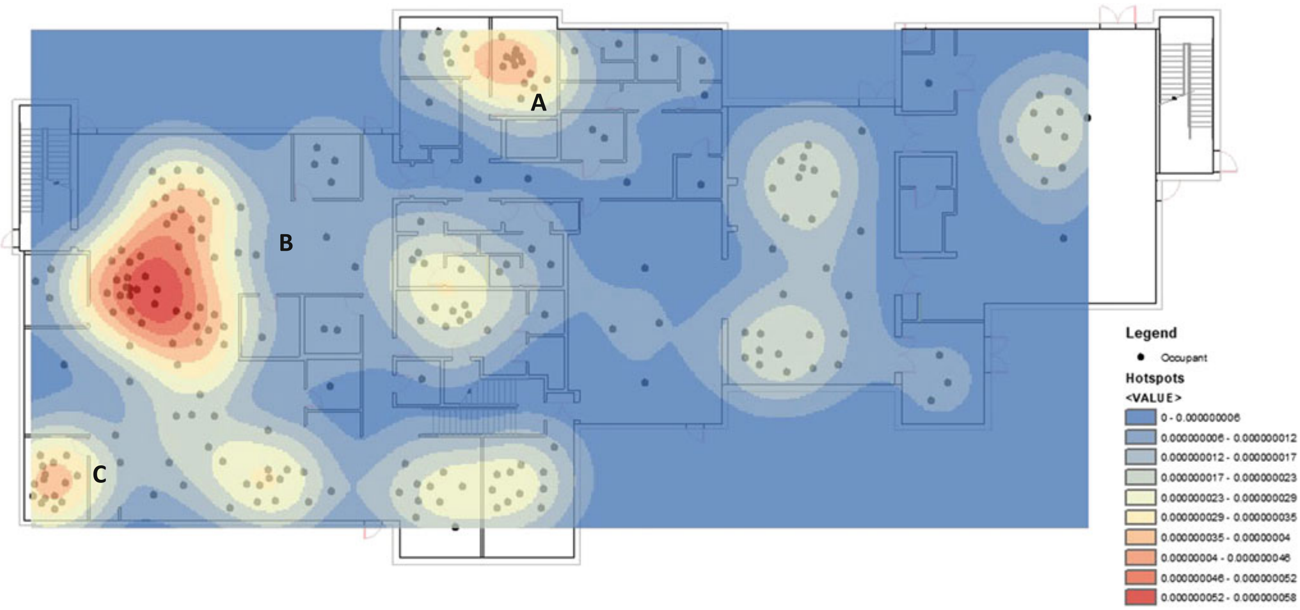

Fig. 92.3 Occupants' probability distribution at 9:40

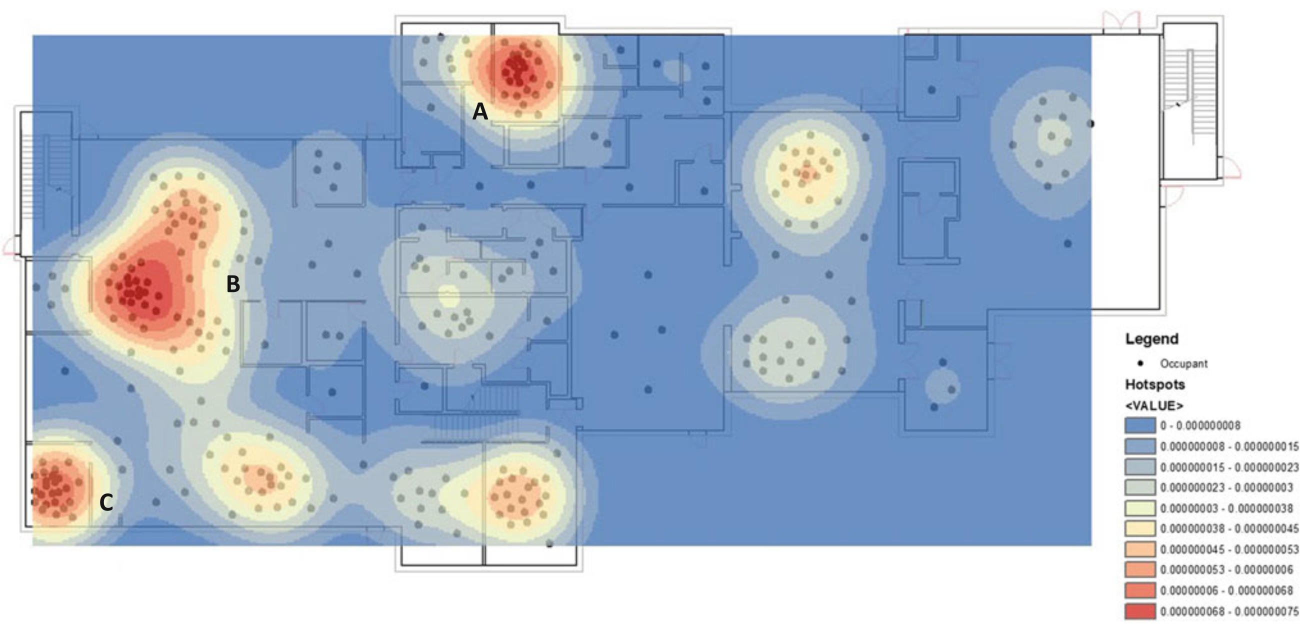

Fig. 92.4 Occupants' probability distribution at 12:20 pm

providing more natural ventilation for these regions or designing in a way that these regions could benefit from natural daylighting could be the result of this simulation.

92.5 Conclusion

This paper presents one way in which a BIM-GIS system could be employed as a platform for the architecture and construction industry to study the occupancy movement and develop more specific, occupant-based design. Integrating the BIM model with the data driven from the simulation using GIS can help to divide the building into different zones based on the occupancy rate and percentage. This visualization and modeling technique serves as a visual tool, helping the architect to design not only according to the building usage, but also according to the occupants of the building and their needs. This zoning would help architects to consider the number of occupants and occupancy peak in different areas a variable in their design, leading to a more optimized design, where different design strategies such as natural ventilation are targeted, located, and created based on the occupant need. Instead of considering the whole building as one static model, the engineers could look at each building individually as a dynamic model.

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