Understanding Occupant Behaviors in Dynamic Environments using OBiDE Framework

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***Abstract*—Occupants` movements and presence are fundamental and the pre-requisite for any type of occupant behaviors` understanding which tells whether a building location is occupied, the number of occupants or an occupant with a specific profile in a certain location. Numerous studies have been conducted over the past few decades to model occupant behaviors stochastically for an improved understanding of their activities for different facility management applications. Despite many research efforts to model dynamic behaviors of building occupants, there is still a gap exists in understanding their behaviors in the context of dynamic building environments. The contextual data linked to locations in dynamic environments evolve often over time in terms of position, size, properties and relationships with the environment. This changing building environment effects the occupants` movements and presence inside the facility which ultimately degrades the process of inferring their accurate activities based on the location context. Henceforth, the evolving building information is required to be mapped with occupant movements for an improved understanding of their changing behaviors. To fill this research gap, a framework named 'Occupant Behaviors in Dynamic Environments' (OBiDE) is designed for providing a 'blueprint map' to integrate existing DNAS (Drivers, Needs, Systems, Actions) model (i.e. a scheme to model occupant behaviors) with our STriDE (Semantic Trajectories in Dynamic Environments) data model to include the dynamicity of building locations for an improved understanding of occupant behaviors. The proposed framework extends the usability of DNAS by providing a centralized knowledge base that holds the movements of occupants with relevant historicized contextual information of the building environment to study occupant behaviors for different facility management applications.**

Keywords—Behavior; Buildings; Dynamic environments; Spatio-Temporal; Safety Management

I. Introduction

Occupants are the important factor for building monitoring and management operations as they impact the building environments actively (i.e. production of heat because of their presence) and passively (i.e. operating building appliances) [1]. For ensuring an appropriate level of quality of services to the building occupants, the most crucial challenge faced by the facility managers is to understand the occupant behaviors and their interactions with buildings [1, 2]. Although, this is a complex activity because the occupant behaviors and the buildings are dynamic in nature and context-dependent. Here, a context refers to any information based on the contextual factors such as space, time and environment utilized for categorizing the situation of occupants [2, 3]. Failure in understanding occupant behaviors because of inadequate integration of all relevant contextual factors associated with the occupants and the building environments can result into serious financial and management crises such as under-utilization of the building spaces, decreased productivity due to poor environmental conditions, increased energy usage, and safety hazards [1 - 4]. On the contrary, if the occupant behaviors are modeled and predicted effectively by incorporating all the possible contextual factors (social-personal, economic, etc.) which may influence occupant behaviors will lead to an increased physical comfort, enhanced safety at work and improved work performance of the occupants while keeping the level of building resources to the optimum [1, 5]. Existing literature [4 – 9] encompasses many studies for constructing occupant behavior extraction systems which help facility managers in decision making for building operations by stochastically modeling the dynamic behaviors of occupants by incorporating the random variations in their behaviors over time. Despite such numerous existing studies, there is still a gap exists in the development and application of such systems which have the ability to track the changes occur in building environments and can be used to study occupant behaviors (movements and their interactions with the building) using the evolving building environment context. To fill this research gap, initially existing occupant behavior frameworks were reviewed from the literature which resulted in choosing the DNAS framework [4] based on its relevance to our case-study and usability as well as popularity that is perceived from its citations. A DNAS framework has four components which are; 1. the 'drivers', 2. the 'needs', 3. the 'actions' which building occupants perform to fulfill their needs and 4. the 'systems' with which the occupants interact to perform actions. Although, the application of DNAS framework [4] is primarily explored for energy-related occupant behavior modeling in the existing literature. However, this framework can be treated as a foundation to represent other types of occupant behaviors as it provides a basic ontology to represent occupant behaviors with the help of four core components as discussed above. For instance, in our case study, we have used DNAS to model safety-related occupant behaviors. To understand occupant behaviors with evolving building environment, the dynamicity of the building environment in terms of geometry and contextual information is achieved using our STriDE model [10]. The STriDE model aims to provide a centralized knowledge base which holds the movements of occupants with relevant historicized contextual information of the building environment. The stored occupant movements are later inputted to a probabilistic model (i.e. Hidden Markov Model) to infer the movement states of occupants by enriching the DNAS ontology for understanding categorized movements for our safety management application. The case-study mentioned for safety-based application is just to show a proof-of-concept application of the OBiDE framework. However, the proposed framework can also be used for different facility management applications where the buildings evolve over time.

The rest of the paper is organized as follows: Section 2 describes the background of the study. First, it defines the occupant behaviors. Second, it describes the main steps involved in occupant behavior modeling. Third, the importance of incorporating the dynamicity of building environments is stated. Section 3 is based on the proposed integrated framework. Section 4 presents a brief case study using the proposed framework. Section 5 presents a discussion and a conclusion.

II. BACKGROUND

A. What are occupant behaviors?

Behaviors are observable actions or reactions of a user in response to external or internal stimuli. These actions or reactions can be categorized into four main types which are; physiological adjustments (e.g. sweating, shivering, etc.), individual adjustments (e.g. selection of clothes, using earplugs, etc.), environmental adjustments (HVAC adjustment, window opening/closing, etc.) and spatial adjustments (moving from one building facility to another, etc.) [1]. In other words, behaviors are the interactions (leaving or entering a room, visual and thermal indoor conditions adjusting using windows or blinds, doors, etc.) of building occupants which can be categorized into different movements, simple presence or actions with their environment (building, its systems and appliances) that impact on the building performance (heating/cooling, indoor air quality, energy, comfort, etc.) during a building lifecycle [2]. Thereby, an occupant interaction which results in changing a building state (presence or absence in case of occupancy monitoring) or no interaction leaving the present state of a building unchanged are both facets of occupant behaviors [1]. Existing literature contains numerous systems to model occupant behaviors shown in Table 1. For modelling the occupant behaviors and their interactions with the building, the occupants` movements and presence is the precondition for any kind of behavior understanding as building occupants can only interact with the building environment only if they are present inside the building [5].

B. Occupant behavior modeling

In the literature [1, 2, 4, 5], there exists four major types of approaches to model occupant behaviors which are: static-deterministic, static-stochastic, dynamic-deterministic and dynamic-stochastic. The static models do not have the ability to capture the influences that a building and its occupants can have on one another. These models are designed for understanding non-adaptive behaviors e.g. turning off the lights when occupants are going for a holiday, etc. Conversely, dynamic models deal with two-way interactions between a building and its occupants and are suitable for adaptive nature of occupants' behaviors e.g. turning on the lights, changing the heating or cooling of the building, etc. Deterministic models output the same outcomes every time when a simulation is run and give the homogeneous and deterministic results. Whereas, stochastic models produce different output every time when a simulation is run because the modelling parameters are selected randomly. According to the existing literature, the most commonly used modelling approach used in the industry is static-deterministic modelling. However, this modelling approach is not suitable for constructing a robust building design as the uncertainty of occupants` behaviors is not considered. To include the uncertainty of the building occupants` behaviors, stochastic models are recommended [5].

The three types of most commonly used stochastic models are; (1) Markov chain models, (2) Bernoulli models and (3) survival models [5]. Discrete-time and discrete-event are the two main types of Markov chain models which take into an account the environmental conditions for predicting occupants` actions in the recent most timestep or an event [5]. The major limitation of Markov chain models is that they are not feasible to apply to the entire population of occupants as the computation and modelling effort increases linearly as the number of occupants increases. In contrast of Markov chain models, Bernoulli models are the most simplified memoryless stochastic models in which the probabilities of events are independent on the previous events [5]. Hence, Bernoulli processes do not require much information for modelling occupants` behaviors. Bernoulli modelling is used for energy modelling at the large scale as its scope can be efficiently applied to the entire building. However, Bernoulli processes do not output individual occupant behavior and are not capable of predicting the timings of individual occupant`s behaviors. The third type of modelling approach i.e. survival modelling is used for estimating the time duration until an event occurs. For example, these models are used for estimating for how long a building probably remains unchanged by its occupants [5]. In addition to three basic types of modelling approaches as discussed above, there exists an extension of the Markov chain models which use agent-based modelling. Agent-based models predict the influence of occupants by modelling individuals, their mutual interactions and how they interact with their building environment [5]. In agent-based modelling, a huge amount of information (defining role and relationships between the agents) is typically required and thus increase the modelling complexity. The term complexity is defined as the amount of details required for modelling which is dependent on size (number of model components) and a resolution (number of model variables). An agent`s description generally consists of their attributes, resources, behavioral rules, etc. An extensive range of human agents present in the literature which include agents subject to reinforcement or belief-based learning, non-adaptive agents, and agents with capabilities of evolving new behaviors [5].

For understanding the occupant interactions, the modelling process of their behaviors conventionally initiates from the data acquisition of occupants [11] along with the building environmental parameters. The methods for collecting occupant behaviors can be divided into three main categories, which are; 1) physical acquisition which can be a) on-site data collection or laboratory studies in controlled environments, 2) surveys, interviews and focus groups, 3) virtual reality experiments [5]. Physical acquisition studies involve monitoring building occupants in their physical environment. This environment can be an actual site where the occupants are present or a pre-fabricated environment in a laboratory setting that is controlled for a specific time to investigate the occupant behaviors. However, laboratory studies are expensive to build and may infer the behaviors differently as in real buildings the stress level of the occupants is higher [5]. Moreover, the visibility of monitoring sensors installed in laboratories makes occupants conscious that they are been monitored which ultimately constrains their behaviors [5]. Surveys and focus groups depend on the self-reporting of

Table 1: Existing Occupant Behavior Models

Use case	Year	Type of behavior	Approach used	Environment (Simulation/ actual site)	Sensor data /technologies/methods used
Behavioral modelling for building performance simulation [13]	2017	Occupancy	Probabilistic	University	Air temperature, global horizontal solar radiation and occupancy data.
Modelling window control behavior [14]	2017	Window control	Probabilistic	Residential apartment	Temperature, humidity, illuminance, CO2 concentration, and wind speed
Modelling building emergency evacuation plans [15]	2019	Movements	Agent-based	University	n/a
Understanding the effect of worker-management interactions [16]	2019	Worker's shortcut-taking behaviors	Agent-based	Simulation	AnyLogic platform
A proactive workers' safety risk evaluation framework [17]	2019	Position and posture	-	Building (Indoor)	Inertial measurement unit (IMU), 3D skeleton data recording
A supervised learning approach for determining factors for unsafe behaviors [18]	2018	Working at heights	Machine learning-based	Tunnel construction project	Data collected based on the theory of reasoned action (TRA)
Safety harness detection [19]	2018	Falls from heights	Machine learning-based	Construction site	Convolutional neural networks, images and video recordings
Extracting and classifying unsafe behaviors linked with climbing a ladder [20]	2018	Falls from heights	Deep hybrid learning-based	Building (Indoor)	Convolution neural networks and long short-term memory, images and video recordings
Monitoring construction workers' vigilance [21]	2019	Obstacle avoidance while performing the tasks	Structured surveys	Construction site	Wavelet packet decomposition, hybrid kinematic-EEG data
Detecting workers under varying poses against changing backgrounds [22]	2019	Worker postures	Machine learning-based	Construction site	Convolutional neural networks, images from a movable digital camera
Tracking workers' gaze positions [23]	2018	Eye movements of workers	Computer vision-based	Construction site	Eye-tracking glasses, images and video recordings
Skeleton-based approach for identifying unsafe behaviors [24]	2018	Worker body postures	-	Laboratory	Kinect 2.0 camera, video recordings
Measuring workers affinity for or aversion to risky behaviors near hazardous zones [25]	2018	Risk taking behaviors	Machine learning-based	Open field	Smartphone GPS, random walks data
Identifying workers’ near-miss falls [26]	2019	Falls from heights	Artificial neural network (ANN)	Open field (test platform)	Smartphones with triaxial accelerometers, gyroscopes, three-axis acceleration and angle data
A robotic wearable exoskeleton for worker safety [27]	2018	Worker body postures	-	Building (Indoor)	Inertial measurement unit (IMU) system, motion data
Real-time locating for non-hard-hat workers [28]	2019	Workers without safety hats	Internet of Things (IoT)-based	Laboratory and a real construction site	RFID triggers, thermal infrared sensor data
Monitoring harness use in construction [29]	2019	Working at heights	Internet of Things (IoT)-based	Construction site	Extended Kalman filter and Bluetooth Low Energy (BLE) beacon, LIDAR sensor data
Planning labor evacuation for construction sites [30]	2018	Movements	Agent-based	Residential Building	Building Information Modelling (BIM)
Simulating the motions of heterogeneous human agents in case of emergency [31]	2018	Movements	Agent-based	School building	Digital video cameras
Graph-based building simulation and data assimilation [32]	2018	Occupancy	Agent-based	Airport terminal	Video cameras
Predicting people’s presence in buildings [33]	2015	Occupancy	Non-Probabilistic	University	Motion detectors
Predictability of occupant presence using random walk modelling [34]	2017	Occupancy	Probabilistic	Laboratory	Webcams
Predicting occupancy diversity factors [35]	2010	Occupancy	Non-Probabilistic	University	Security cameras and doorway counting sensors
Estimating the occupant activity level [36]	2018	Activity	Probabilistic	Summerhouse and school	CO_2 sensors
Window opening model using deep learning methods [37]	2018	Window control	Probabilistic	Office building	Indoor climate and air quality monitoring sensors

individual behaviors by filling out the questionnaires or through interviews. This method is cost-effective and enables to acquire behaviors which are not possible to measure using sensors (for instance; perception, attitudes, etc.). However, existing studies [5] show that reported behaviors of building occupants may not always correlate with their actual behaviors. In addition, misunderstanding of the questions in the surveys may also lead to incorrect reporting the information about the occupants [5]. Apart from these two traditional approaches, the most emerging approach for occupant behavior modelling is virtual reality-based environments. This approach provides greater control of the environment in terms of environmental conditions (e.g. building layouts). However, there is limited support for visual and air quality configurations [1].

In the existing literature [1, 5], an extensive range of different types of sensors (wired and wireless) for monitoring occupants and the environment are present to acquire rich information for modelling occupant behaviors and their interactions (energy consumption, etc.) with the buildings. Some of them are mentioned below.

- Mechanical sensing such as door badges, piezoelectric mats, etc.
- Image-based sensing using visual information captured from the cameras.
- Motion-based sensing such as passive infrared (PIR), ultrasonic Doppler and ultrasonic ranging sensors for detecting the presence or absence of occupants through the occupants' movements.
- Manual observations need humans for collecting datasets.
- Wireless RF sensing using ambient sensors for temperature, humidity, light, etc.
- Consumption sensing for measuring water, electricity and gas usage in buildings.

For selecting the sensing technologies for data acquisition, there exists nine factors [1, 5] which needs to be considered which are; 1. cost (including acquiring, installing and operating cost of the sensors), 2. power type (battery or main power), 3. accuracy (difference between sensed data values and ground truth), 4. sensor coverage range (distance and a view angle the sensors cover), 5. data collection type (event-based or periodic), 6. data storage (on-board storage of sensors), 7. deployment region (building inside or outside), 8. deployment level and 9. data sensed (binary data or value-based sensing). The quality of data captured from various types of sensor-based systems differs greatly in terms of the resolution of the sensors deployed (see Fig. 2). Spatial, temporal and occupant resolutions are combined for determining the overall resolution of the system for capturing the occupant behaviors. Spatial resolution is defined in terms of building infrastructure (i.e. floor, rooms). Whereas, occupant resolution can have 4 different levels of information which are; 1) simple detection based on the occupant presence in 0 or 1 values, 2) counting the number of occupants, 3) identifying the occupants, and 4) recognizing the occupants` activities. Along with spatial and occupant resolution, temporal resolution defines the smallest time period in which variations in spatial and occupant resolutions can be informed by a deployed sensor. As the resolution of the captured sensor data increases, the building space gets smaller, the occupants become more distinct based on their identities and the information from the sensor data will be accessible faster. For example, a low-resolution system will only capture the binary information (presence/absence) of the occupants in a specific time where the identities of the occupants are not recognized. Whereas, a high-resolution system will be able to detect the number of occupants, their identifications, as well as their activities.

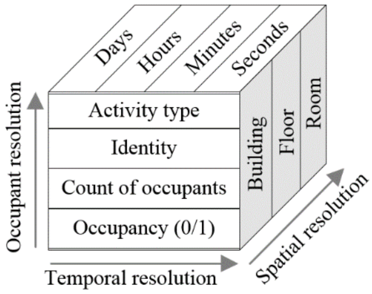

Fig. 1. Occupancy resolution [5, 11]

C. *Need for incorporating the dynamicity of building environments*

After an extensive review of occupant behavior modeling [13-37], it is observed that numerous models are developed to understand occupant behaviors. Each model is developed after conducting different types of measurements and surveys that focus on incorporating different model variables (e.g. physical, biological and environmental) and human factors for representing different behaviors (e.g. movements, occupancy, body postures, etc.) for different applications of facility management with respect to different types of buildings (residential, commercial, etc.). As a result, the existing models for understanding occupant behaviors cannot be compared to one another. However, Hong et al. [4] provided a DNAS model, which acts as a technical framework to standardize the major components (Drivers, Needs, Actions, and Systems) required to model occupant behaviors. A DNAS framework aims to model energy-related occupant behaviors. However, a feature that is observed fundamental in DNAS and most of other developed occupant modeling frameworks is occupants` movements and presence. In fact, the occupants` presence is considered as the prerequisite for any kind of behavior understanding as building occupants can only interact with the building environment if they are present inside the building [5]. Existing systems in the literature are built by capturing the stochastic and reactive nature of occupant behaviors to model their movements and presence in buildings. Ultimately, these systems contribute to improve understanding of occupant behaviors by increasing the occupancy resolution (i.e. inferring different occupant activities using their movements and presence) for different building monitoring and management applications. However, the existing systems for occupant behavior modeling do not incorporate the information of complex dynamic environments where the building objects evolve over time. With the passage of time, the functionalities of the building locations often change (i.e. change in semantics/context). For example, a room named 'inventory' in a building is now an 'office' having different functionality. Likewise, due to the placement of certain inventory on a specific area of a building, the floor area of a building (a set of rooms) became a ‘restricted area. In addition, new walls or infrastructure support may be added in a building. This will result in a change in the dimensions (i.e. geometry) of building locations (called as spatial changes). Change in the semantics of building locations occur often in constructed buildings whereas, the spatial changes take place rarely. Such changes need to be incorporated in occupant behavior modeling as a change in the purpose or a position of building locations will result in different behaviors of occupants which ultimately represent different occupant activities [12]. The updated spatial and semantic information about the building locations along with the previous information will contribute to improved understanding of occupant behaviors with respect to the changes occurred in the building environment. Resulted occupant behaviors after modeling the dynamicity of the building environment can be used for different construction and built environment applications such as; construction resource monitoring for improved safety, managing building spaces based on their utilization, implementing occupant access control system, etc. To address these requirements of the dynamic building environments which contain evolving building objects, we have used our ontology graph-based STriDE model.

III. OBIDE FRAMEWORK

The proposed integrated framework as shown in Fig. 2 describes occupant behaviors using a DNAS model [4] having four major components which are drivers, needs, actions and systems. Drivers represent the factors which stimulate an action to be performed by the occupant in a building environment. Needs are the requirements (physical, non-physical) which should be met in a building to acquire the desired satisfaction. Actions are the interactions or movements of the occupants in a building to achieve a certain level of comfort. Systems represent a building and its equipment with which the occupants interact. More information on DNAS model can be found here [4]. After describing the occupant behaviors which need to be modeled, a process of data acquisition takes place to enrich the DNAS ontology with more information required for modeling the occupant behaviors. The additional information is linked with the actions of the occupants which is conventionally collected using different sensors. The type of sensor data and the method using which the data is acquired for modeling the behaviors after enriching the DNAS ontology is completely dependent on the type of application. However, for every application scenario, occupants` movements and presence is the pre-requisite for any kind of actions which will lead to behavior understanding of occupants as occupants can only interact with the building environment if they are physically present inside the building [5]. If the occupants` movements and presence are modeled correctly, this will increase the occupancy resolution of the model which ultimately helps to infer occupant activities with higher accuracy [3]. Keeping this minimum level of modeling as a foundation, the STriDE model is used to incorporate the dynamicity of building environment to better understand the occupants` movements (actions) which can later help to infer occupant activities. The STriDE models the building environment as a collection of different building objects (entities). In our case, we have three building entities which are trajectory (corresponds to occupant location i.e. spatio-temporal point), location (a physical building location evolves over time) and occupant. Each building entity evolves over time under the action of different processes. The life cycle of each entity is summed up into a series of states. Each state represents a change in the entity. As shown in Fig. 3, a change can occur in the location, geometry or the semantic (thematic) attributes of an entity.

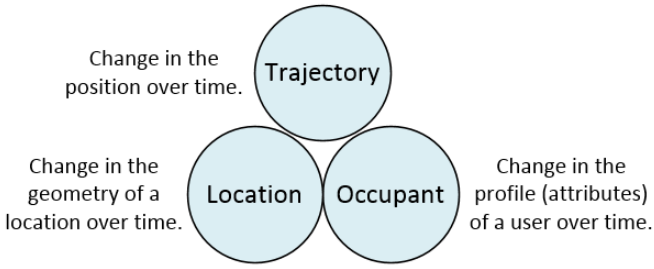

Fig. 3. Entities of a dynamic building environment

These different changes can happen independently or concurrently. In STriDE, the ‘concepts’ are defined to tag building locations with spatio-temporal trajectories of occupants. The STriDE model uses a set of classes and properties from the existing vocabularies for defining the concepts and their relationships which are; 1. Simple Knowledge Organization System (SKOS), 2. Dublin Core Terms (DCT) and 3. GeoSPARQL (GEO). Using these vocabularies, the concepts are defined and stored in the ‘concept scheme’. A concept scheme is a collection of different concepts defined as a hierarchy which correspond to different building locations. The purpose of defining as a hierarchy is to be more precise about the tagging of building location to spatio-temporal trajectoties of occupants. Using a set of different concepts, occupant profiles are created to define the access level of the occupants. For identifying the occupants, the tagged concepts with the occupant trajectory`s timeslices (TSs) are compared with the allocated concepts as per their profiles.

To model the building environment, the STriDE keeps track the building entities (see Fig. 3) as well as different relations among them which are;

- the spatial relation; specifies how an entity is in building in relation to some reference entity (a room). For example, an entity A (i.e. an object) passes through entity B (i.e. a location) or the geometries of entities A and B overlap each other or touch at a specific point in a building.
- the spatio-temporal relation specifies how building entities (two rooms, or a room and an occupant) are related with each other at the same time.
- the filiation relation specifies how building entities are related by ancestry or successor [2]. It defines the succession links which exist between several representations of the same entity at different time instants.

The STriDE model deals with two types of filiation relationships [10]; a continuation (an identity of a building entity remains the same while an entity undergoes a change)

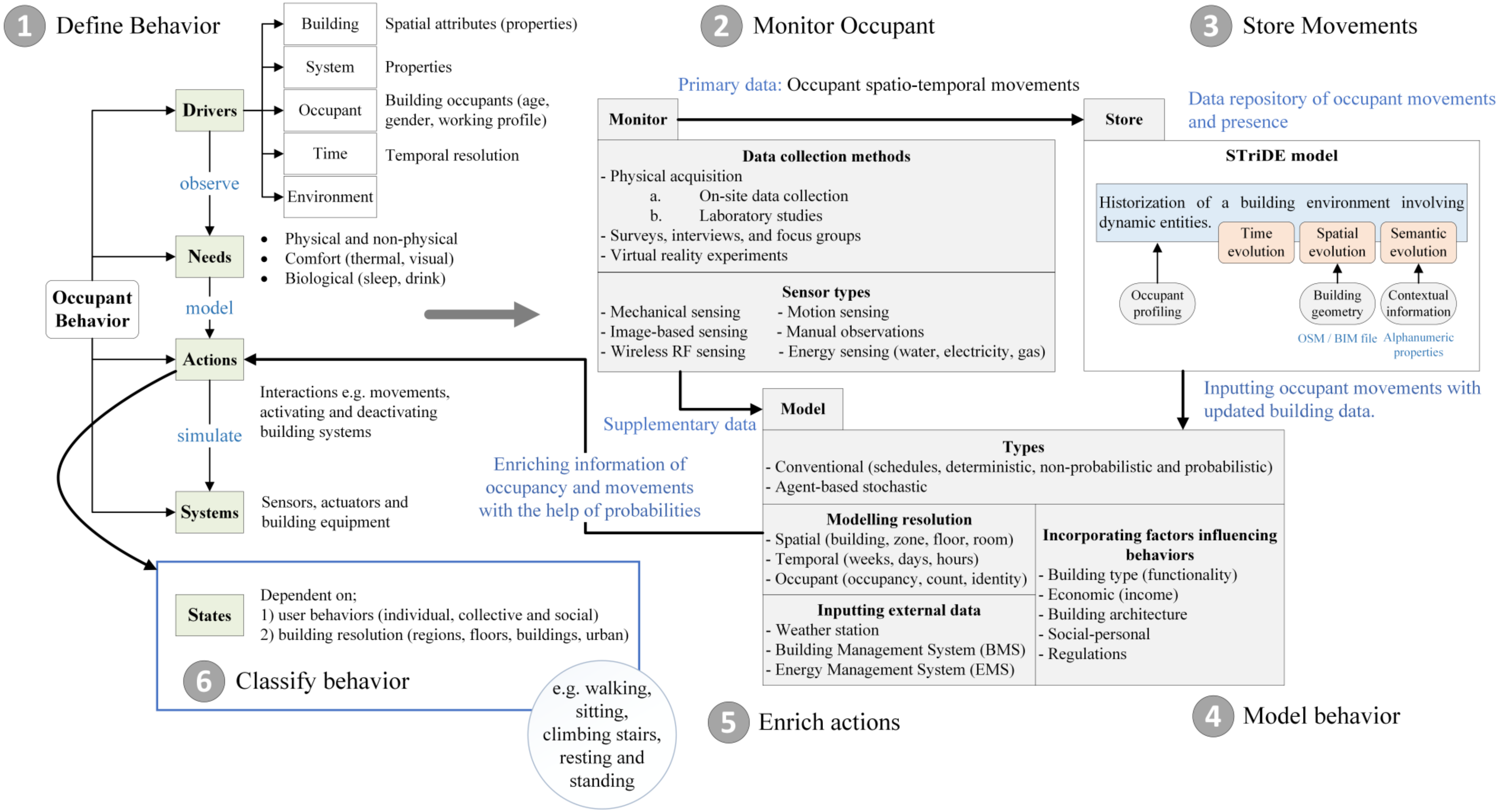

Fig. 2. Generalized OBiDE framework

and a derivation (after a change a new building entity is created from the parent entity). For tracking the evolution of building entities (occupants, trajectories and rooms) and their relations with one another, the STriDE model uses the concept of (TSs). A TS includes four components which are; an identity, alphanumeric properties (semantic component), a geographical (spatial) and a time component. At the occurrence of a change in any component of a TS excluding the identity, a new TS is generated inheriting the components of the last known TS. To show how the STriDE model keeps track the evolution of dynamic building entities (location, trajectory and occupant) using TSs, three possible scenarios are described which are;

1. *The functionality of a location is changed* (geographical component): A building room named: Office having a size of $24m^2$ as shown in Fig. 4. The room is tagged as an Office in a model having a defined geometry. After a while, a building room named: Office is now a simple Room having a same geometry of $24m^2$ and tagged as Room with a help of a new TS Room1_1 in a model having the same geometry as of Office. The transition between an Office to a Room is stored using a filiation link as shown in Fig. 5.
2. *The geometry of a building room is changed*: A building room named: Room has now a size (geometry) of 28m2. A new TS is created with a name of Room11 to hold this change in geometry. The change in the geometry between an Office to a Room is stored using a filiation link as shown in Fig. 6.

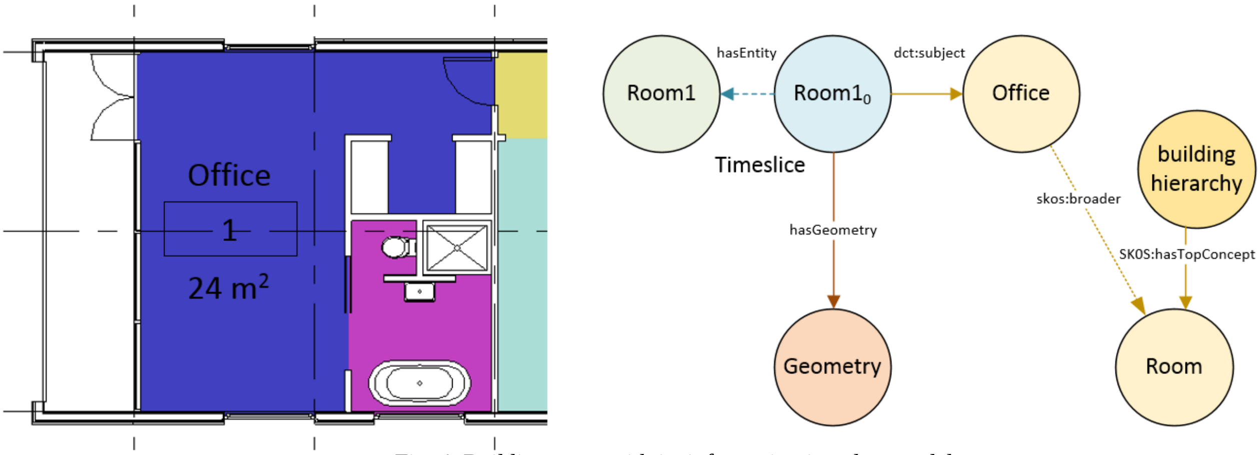

Fig. 4. Building room with its information in a data model.

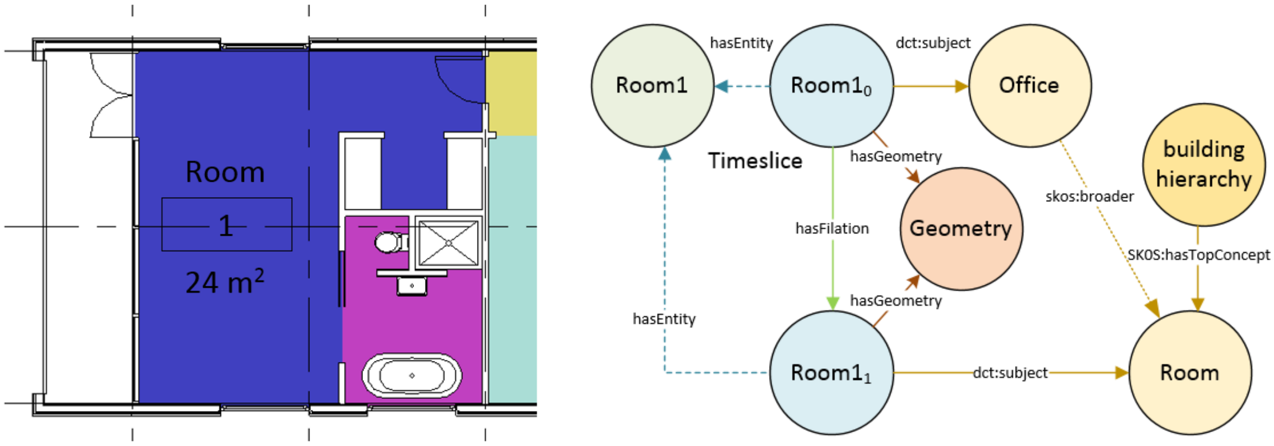

Fig. 5. The functionality of a building room is changed.

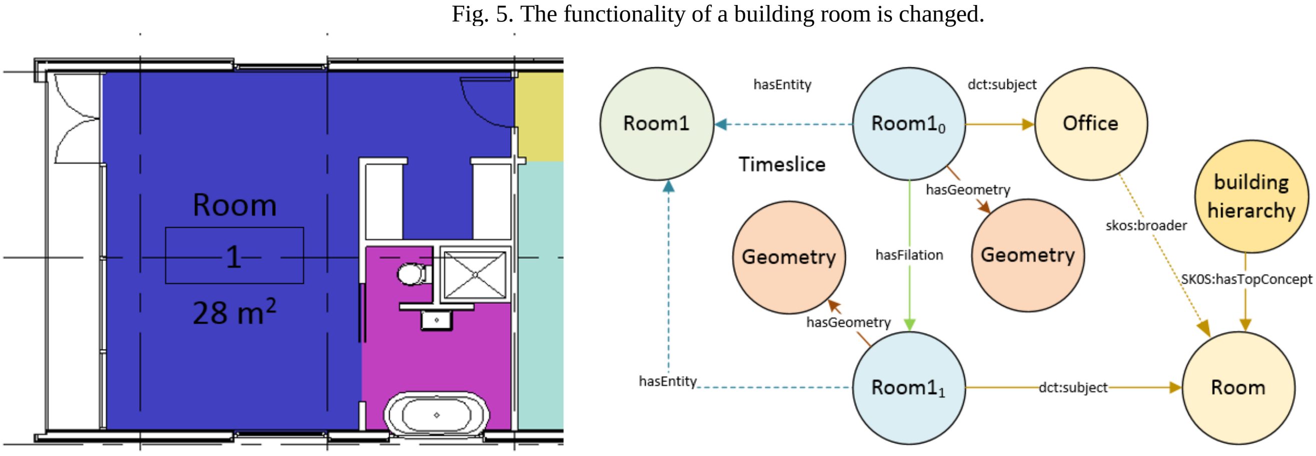

Fig. 6. The geometry of a building room is changed.

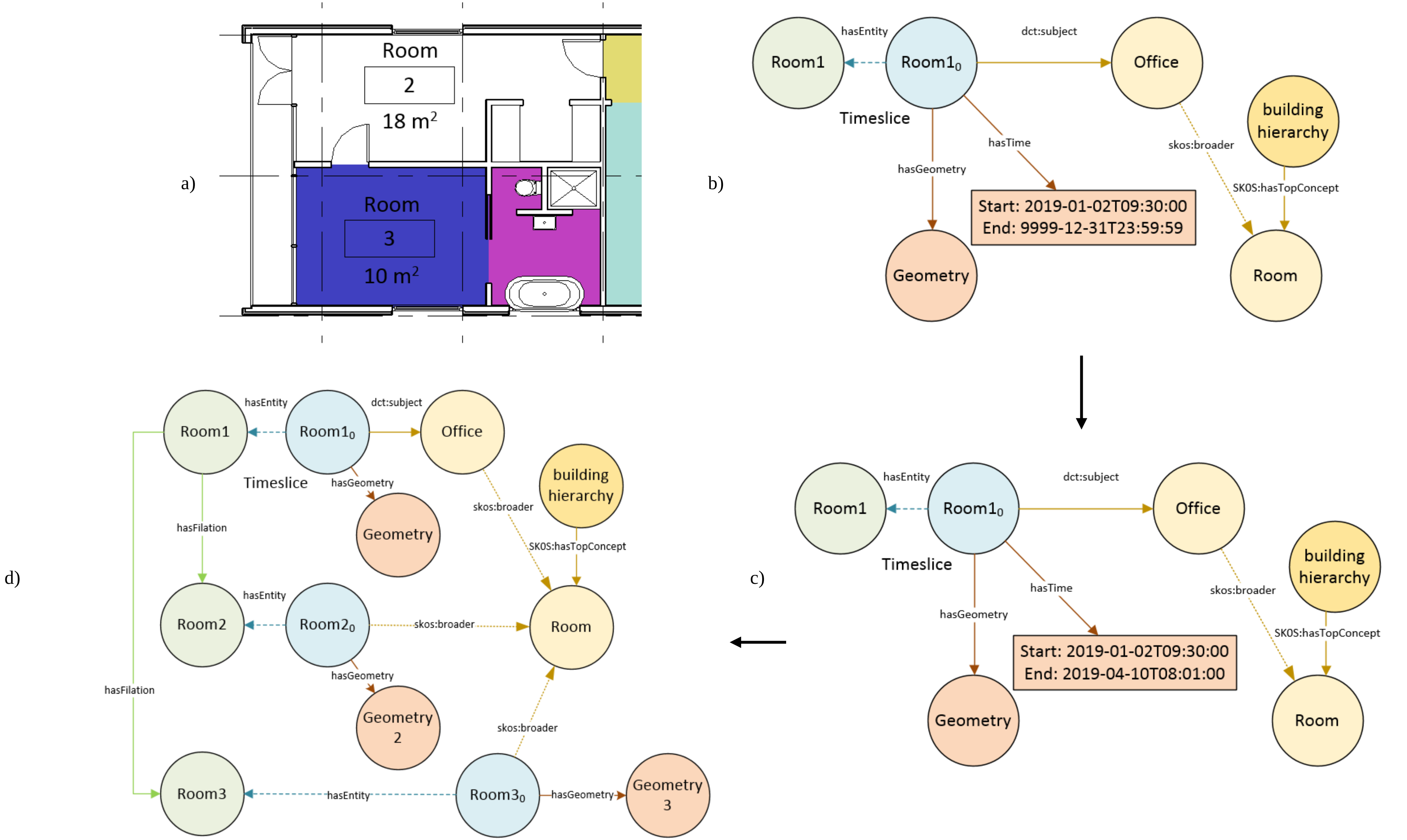

Fig. 7. The creation of new building rooms

3. The creation of new building room: A building room named: Office is destroyed (see Fig. 7a and b). Initially, its TS $Room1_0$ is updated by changing its End date-timestamp to show that a room is no longer exists (see Fig. 7c). In addition, two new TSs are constructed which are $Room2_0$ and $Room3_0$ to show the construction of the two rooms having different geometries (see Fig. 7d). For this case, new rooms are created which are linked to the previous room. Therefore, filiation links are used.

The OBiDE framework aims to add the dynamic context to occupant behaviors` modeling process as context (details about building space, time and environment) should be closely connected with the occupant movements for an enhanced understanding of their actions. After creating a knowledge base of historized movements of occupants using the STriDE model by tracking the evolutions in the building environment, an appropriate modeling technique as per application requirements (agent-based or conventional) can be applied to the movements for calculating the probabilities of different actions of occupants in different building locations. A critical question here is the degree of detail about occupants and the environment which should be included in the modeling stage to attain the targeted understanding of occupant behaviors. This additional information encompasses occupant profiles, the type and the number of buildings, and the required temporal (e.g. hours, minutes, seconds) and spatial resolutions (e.g. floors, rooms). Our STriDE model has the ability to implement an access control system after creating different occupant profiles with the help of concepts as described above. In addition, the STriDE model can manage data of multiple buildings with the help of OpenStreetMap (OSM) files for tagging updated building locations to spatio-temporal movements of occupants. Moreover, the temporal resolution is kept maximum i.e. seconds, whereas the spatial resolution is kept to rooms.

Understanding occupant behaviors is a complex phenomenon. It not only involves the process of tracking movements with their dynamic context and computing the probabilities of their different actions inside the building that is one of the pre-requisites of any kind of behavioral analysis but also needs to incorporate several external factors (e.g. weather information, data from building management and monitoring systems, etc.) to study occupant behaviors in more detail by extracting insights about occupant activities from their actions. However, the scope of the proposed framework is kept limited to include dynamicity of the building environment into occupant movements and presence by enriching the DNAS ontology (specifically actions) which can help to infer occupant activities for different facility management applications.

IV. Application of Proposed Framework

The proposed framework (see Fig. 2) requires sensory data to include context to occupant movements and presence for performing behavioral analysis. The acquisition of relevant sensor data is based on the application requirement. For example, the safety manager of a building requires to monitor the movements of the occupants in a building. In this case, using our OBiDE framework, 'driver' is monitoring movements of occupants, 'need' is achieving safety management in a building by identifying unsafe movements, 'action' is tracking movements of occupants using their spatio-temporal trajectories, 'system' corresponds to Bluetooth Low Energy (BLE) beacons for sensor data acquisition deployed in a building and 'states' are 1) static (no movement), 2) normal movement ($0 <$ steps ≤ 84 and $\pi/2 \leq$ angle $< \pi$) and 3) risky/unsafe (steps > 84 angle $\geq \pi$). Existing literature [38-40] suggests that the movement behavior of an occupant is defined using step length and turning angle. The average walking speed of a person range from 1.0 to 1.6 meters per second (m/s). Keeping an indoor environment into account, a value of 1.4 m/s as a safe walking speed limit that will give us 84 steps per minute i.e. the sum of step lengths for a minute.

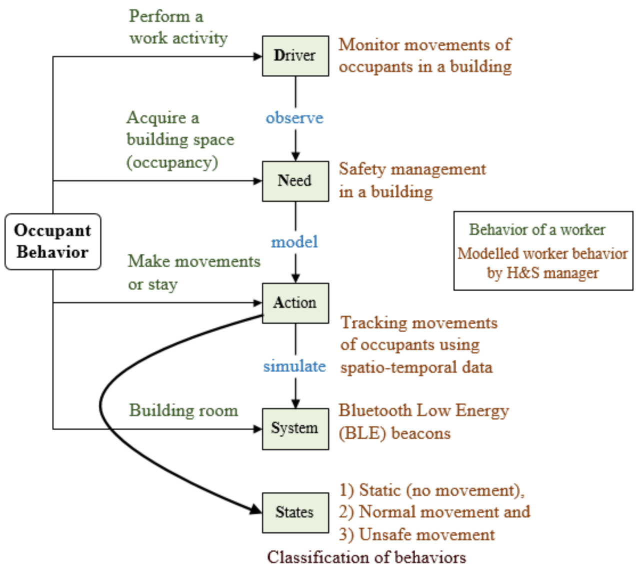

Fig. 8. Application of a proposed framework

For understanding movement-based behaviors for a safety management application, around 200 BLE beacons are installed on different building locations. Approximately 13,223 location coordinates are collected across different locations using deployed beacons. After sensor data acquisition, the acquired location data is transformed into trajectories after preprocessing (i.e. filtering). More information on trajectories and their preprocessing can be found in [12]. After preprocessing the trajectories, the STriDE model is used to add contextual information of a building environment in collected trajectories for mapping actual building locations with each trajectory point. For modeling the behaviors to recognize and categorize the movements into different states, many types of non-probabilistic and probabilistic approaches exist in the literature such as Bayesian dynamic models and clustering techniques, state-based models such as simple Markov chains and HMMs, patterns matching algorithms and deep learning-based techniques [41]. Though, HMMs-based method is selected for our application as statistical HMMs describe occupant movements as a series of Markovian stochastic processes where the probability distribution of a future state (i.e. safe or unsafe behavior or a next location) of a stochastic (i.e. a random) process (a trajectory in our case) is only dependent on its current state or a current location which disregards the requirements of including the preceding states and ultimately minimal training data is required [42].

Fig. 9. Deployment of BLE beacons in a building

SPARQL Results (returned in 55 ms)

traj	userName	location
stride:TrajOfMaintenance1-1	Maintenance 1	Outdoor pathway
stride:TrajOfMaintenance1-2	Maintenance 1	Storage room
stride:TrajOfUser1-1	User 1	Outdoor pathway
stride:TrajOfUser1-2	User 1	Corridor of floor 0
stride:TrajOfUser1-3	User 1	Office 1

Fig. 10. Occupant movements transformed into a trajectory using STriDE model

For inputting the movement states into HMMs, Gamma distribution [43] for step lengths and Von Mises distribution [44] (also known as the circular normal distribution) for turning angles are used. After describing the states, a Baum-Welch algorithm with Viterbi algorithm [42] is used to extract most probable movement states across each building location. For visualizing the states resulted from HMMs, BIM-based software i.e. Revit Architecture is used (see Fig. 11 at *T=1*). No movements but presence is shown in Green, normal movements are in Orange and risky movements in Red color in different building locations. The BIM approach is selected because existing literature recognizes it as a 'future IT solution' and favored over traditional 3D CAD approaches as it is an efficient way of information management during the building lifecycle [45]. For tracking the evolution of building objects (occupants, trajectories and locations), the STriDE model uses the concept of timeslices (TSs). To show a proof-of-concept application of our framework to hold the building evolution with the semantically-enriched trajectories to study movement behaviors for safety management, let's suppose we have a building from where the spatio-temporal data is collected (as discussed above) and the purpose of one of the building locations is changed (see Fig. 11 at *T=2*). The location 'office' is now a 'storage room'. The STriDE model uses 'concepts' for describing the building locations. In Fig. 2, there is a hierarchy of SKOS concepts. It has a skos:hasTopConcept connects skos:Concept room. Two skos:Concept (office and room) are defined. All these concepts form a hierarchy. In addition, there is a profile named employeeProfile which gives access to all the concepts (locations). As soon as the functionality of a room (i.e. a context) is changed, a new TS is created. For instance, a user Jane is an entity of a TS ts-jane$_0$ and her position is tracked by a trajectory tr-jane. We can observe by a link between tr-jane$_0$ and room1 that Jane is in room1. The entity room1 was initially an office as suggested by the dct:subject link of tr-room1$_0$ towards the concept office. Later, this room is changed as a storage room having the same geometry as of the office represented as ts-room1$_1$.

V. Discussion with Conclusion

While numerous studies have been conducted in the literature to model dynamic nature of occupant behaviors in different building environments (see Table 1). However, the dynamicity of the building environments did not appear to be achieved before to understand occupant behaviors. The incorporation of different types of transitions resulting from spatial, spatio-temporal and filiation evolution in building entities should be catered in a single model to understand occupant behaviors in terms of changing environments [10, 11]. To address this objective, OBiDE integrated framework is proposed (see Fig. 11) which offers; 1) a centralized knowledge base for mining movement-related behavioral interactions of the occupants with the building environment, 2) a process of data enrichment of DNAS ontology using the results of a state-of-the-art machine learning model (Hidden Markov Model (HMM) in our case) in the form of 'hidden states' which are used to find the correlations and patterns in the acquired sensor data for studying the occupant behaviors. 3) Moreover, incorporation of the dynamicity of the building locations in data modeling stage in terms of the evolving spatial and contextual information over time. Our OBiDE integrated model provides a knowledge model to study occupant behaviors using a building context with the help of

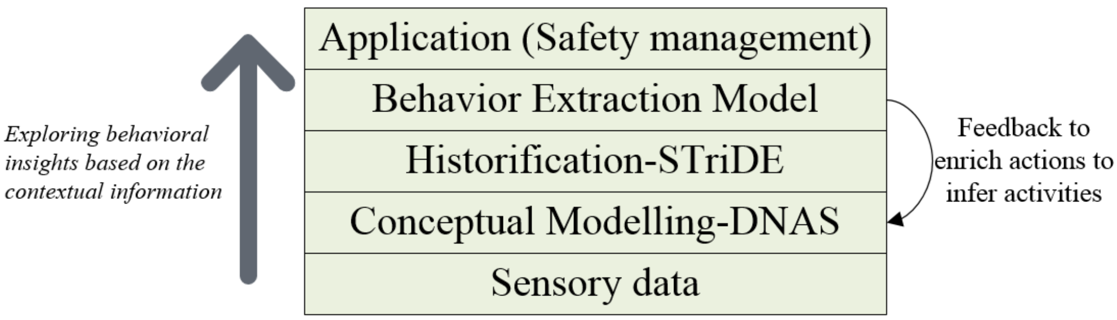

Fig. 11. Different stages in OBiDE framwork

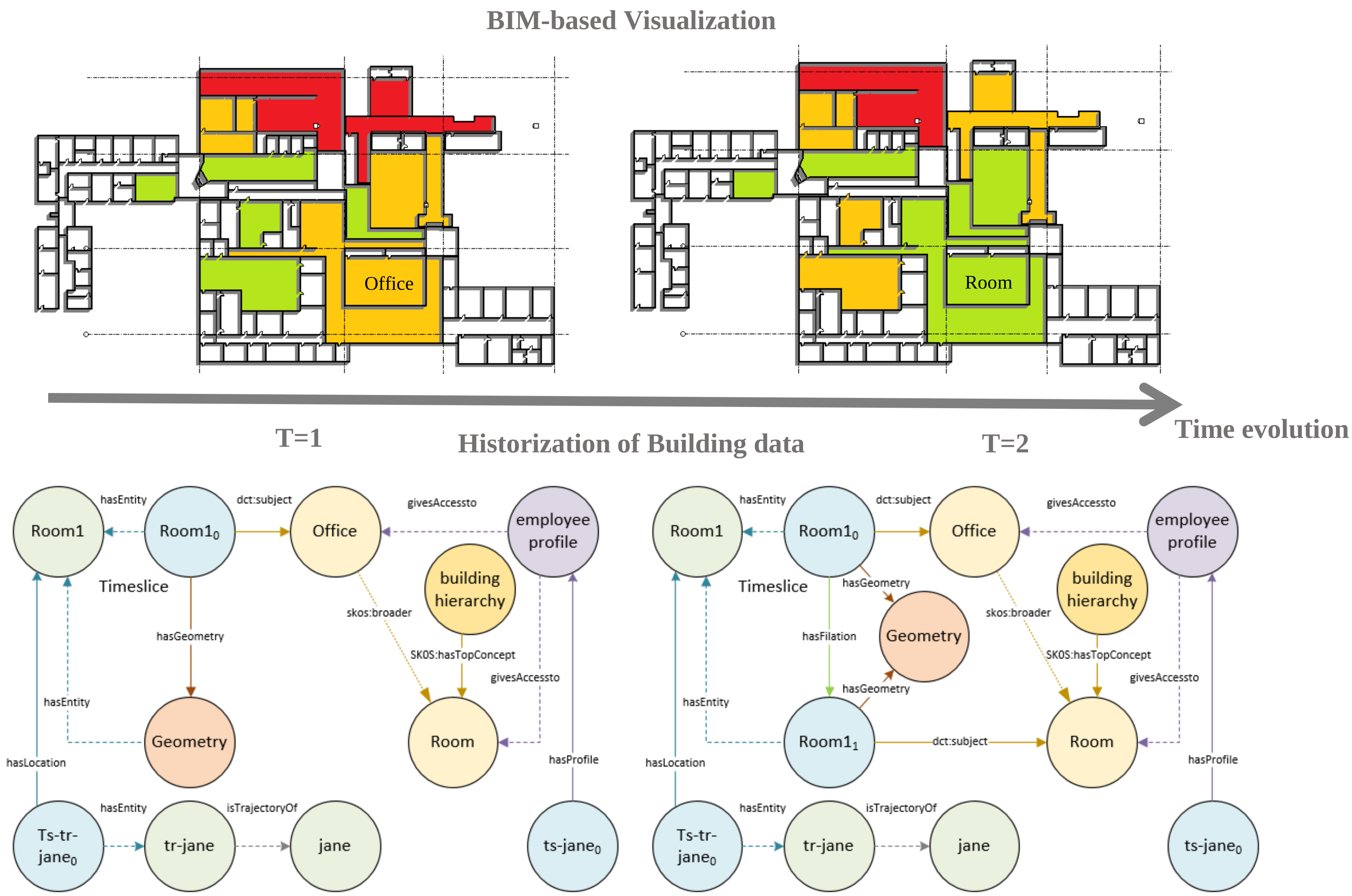

Fig. 11. OBiDE historization of building evolution (Timeslices are in Blue, entities are in Green, SKOS concepts are in Yellow, profile is in Purple and geometry is in Red color).

stored trajectories. Later, probabilistic model based on the application requirements is applied for categorizing different types of movements using the stored trajectories. Occupant behaviors are modeled stochastically because, occupant movements and presence evolve over time due to the change in the building environment. For our application scenario of safety management in a building, HMMs are used for categorizing the occupant movements. To categorize movements into three states which are static (stay location), normal and risky, the values of step lengths and turning angles are used for defining the hidden states. In Fig. 11, at a time instance, the most probable stay locations of occupants are shown in Green in color using the universal Architecture, Engineering & Construction (AEC) industry standard i.e. Building Information Model (BIM). Whereas, the most probable building locations at a time instance where there are the normal and risky movements of occupants are shown in Yellow and Red in color. Generated BIM-based visualizations provide insights about building occupants` movements in real-time using a building context. As a result, locations with risky movements can be easily identified, and necessary actions can be taken accordingly by the safety managers. Managing the safety in a building by acquiring spatio-temporal data, transforming them into semantic trajectories and exploring the states of the occupants to represent their movement behaviors using four components which are ‘driver’, ‘need’, ‘action’, and ‘system’ to extract the ‘states’ of movements is one of the use-cases of the proposed framework. However, the proposed framework which enriches the details of actions in the original DNAS ontology to study occupant behaviors can be used in different types of other applications for managing the information of occupants and evolving building environment and infrastructure during a building lifecycle starting from a construction phase to a facility management phase.

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