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Comparing different approaches of Agent-Based Occupancy Modelling for predicting realistic Electricity Consumption in Office Buildings

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Abstract: Having a good grasp on modelling the dynamics of occupants for estimating electricity consumption in office buildings is a vital asset for realistic predictions. Nowadays, agent-based models are widely used for this purpose. Previous approaches to modelling dynamics of occupants in multi-floor office buildings simplified the models by teleporting agents between zones during transitions without considering the routes used to reach their final destination such as going through corridors, stairways and hallways, thus, underestimating the potential energy usage during those transition period. This paper proposes a more realistic approach by incorporating detailed routes of agent movement when transiting from one zone to another. To demonstrate the case, detailed routes and route choice preferences are used as inputs within the model for the agents to make independent decisions when transiting from one place to another within the simulated office building. The route choice preferences are computed from data gained from an earlier extensive real world occupancy detection trial conducted within the model office building using state of the art indoor positioning system. The simulation experiments compare the previous approach against the proposed approach and based on the evaluation it is found that there is approximately 19% underestimation of electricity consumption per day when detailed routes are not considered. The research demonstrates, the proposed approach is applicable to any office buildings and will produce predictions which will be much more realistic and closer to the real world electricity consumption level.

Keywords: Building Occupancy; Building Performance; Indoor Positioning; Agent Based Modelling, Electricity Consumption

1 Introduction

Building Performance Simulation (BPS) is a widely accepted and established method for predicting energy consumption in the design phase of commercial buildings. As discussed in [1], [2] the energy-use behaviour in commercial buildings depends on factors such as occupancy pattern, occupant activity and interactions with building infrastructures and appliances. Occupancy monitoring can help to identify occupancy numbers and patterns which acts as a key input for advanced building simulation tools such as Energy Plus, ESPR, DeST and TRNSYS, producing energy consumption forecast for heating, cooling and lighting and guiding design choices. Nevertheless, their advanced abilities to model complex building systems fall short of considering different and changing energy use characteristics of building occupants, contributing to important prediction errors. In parallel, Agent-Based Modeling (ABM) has emerged in recent years as a technique capable of capturing occupants' dynamic energy consumption behaviours and actions. ABM is a simulation technique where agents can behave independently and stochastically such that the general behaviour of a complex system emerges from the interactions of its agents [3]. Agent based simulation technique is capable of producing complex stochastic occupant models exhibiting real world characteristics and features of occupant behaviours and interactions important for realistic predictions of energy consumption in both commercial and residential buildings.

Related work

According to the United Nations report in [4], the populations of cities worldwide will be increasing at a rate of 2 million per week and due to improved living conditions, jobs and basic amenities, more and more people are relocating to cities. This requires careful planning and maintenance of the city infrastructure and optimised allocation of energy resources such as water and electricity to avoid wastage. To ensure this, it is critical to understand and predict the energy requirements at the design stages of infrastructure to evaluate its post-operation performance. In recent years lot of focus has been given to understanding energy consumption in commercial and academic buildings since they consume and waste the most [5]. Especially in academic buildings, since government grant allocation is directly related to energy efficiency it is increasingly becoming important to reduce energy consumption but maintain the same level of facilities and services [6]. According to one study, 19% of the UK, CO_2 is contributed by non-commercial buildings with current statistics providing evidence to suggest that building energy performance is not up to the mark. [7] One of the earliest research projects related to Post Occupancy Evaluation (POE) and Post-occupancy Review of Buildings and their Engineering (PROBE) aiming to illustrate the extent of this so-called "performance gap" can be seen in [8]. Most recent papers [9]–[12] covering the last 10 years show there is a significant difference between predicted performances during the design stage and with actual occupied stage. The reason for this performance gap is due to various discrepancies related to design and model assumptions, management of power sources, occupancy behaviour and quality of building materials. Results from the PROBE study suggested the measured electricity demands are approximately 60–70% higher than predicted in schools and offices, and over 85% higher than predicted in university campuses [9]. Thus, realistic models would likely help to better estimate and understand their consumption behaviour. This could also help to raise awareness for energy conservation and identify energy saving potential from occupant behavioural measures as seen in [13], [14]. Simulation results showed appropriate measures and changes in behaviour can achieve 41% energy savings and schedules of occupancy play a major role in the savings measure.

A lot of prior research looked into development of agent based model to predict building energy consumption and investigated agent activities, behaviours and interaction with building infrastructure as simulation input. As seen in [13] the author developed a single floor agent based model and incorporated electrical appliances, building lighting and diverse occupant behavioural stereotypes to simulate electricity usage and also investigated different strategies that can influence energy management policies towards a more energy saving occupancy behaviour. One of the major simplifications of the model was teleporting agents to their destination when moving from one zone to another. Similar work focusing on influencing occupant behavioural changes towards more economical energy consumption can be seen in [15] which implements an agent based model to simulate the occupancy of student residences on the university campus in Shenzhen, China. In [16], [17] the authors introduced hourly modelling of electricity consumption and tiered pricing mechanism-based electricity consumption to see if occupant electricity usage behaviour can be impacted. Similar work can be seen in [18] where agent behaviour is observed as a major factor in predicting energy usage trends and reducing consumption. Predefined occupancy activity profiles and scenarios are used as input within the model. Similarly, in [19] occupancy behaviour has been highlighted as the major factor that influences realistic energy consumption prediction and [20] demonstrated human building interaction by incorporating characteristics and environmental context of real offices as occupant profiles and studied how thermal comfort and HVAC are impacted. The use of machine learning models to generate synthetic occupancy profiles of academic building can be seen in [21] taking into consideration several students as occupants, use of computers and lighting, as well as weather data as input in the model. Interactions with lights were either PIR controlled or manually controlled, and all rooms had desktop PCs as input. Interestingly occupant behaviour was also simplified when it comes to agent movements such as entering the building and transporting the agents to their destination such as meeting rooms or public places of learning based on the shortest distance using a concept known as the social force model (SFM). The use of detailed occupancy patterns and information may also contribute to optimal workplace design and spatial layout of the floor plan as seen in [22] and [23] proposes a framework where the level of detail (LoD) related to occupant presence and actions, occupant type and spatial location and the modeling approach necessary to develop a realistic agent based model. The importance of occupancy behaviour and its relation to better prediction of energy usage in office buildings can be seen again in [24] where the author proposes a scalable model to predict occupancy schedule, based on occupant presence, location, and interaction with the model building. Although occupant movement detail is again limited to zone level transition. A recent work on HVAC energy demand prediction in airport terminals [25] shows the incorporation of corridors and hallways for computing demand prediction during the transition from one zone to another during checkout and boarding in the terminal but it is likely that that hallways and corridors in airports are big enough to form individual zones. Regardless there has been a major simplification when modelling agent movements between zones such as corridors and stairways in commercial and academic office spaces. Contemporary work on mathematical or graphical multi-state and single state occupancy models such as using Markov chain [26]–[30] also investigated zone level occupancy by simply teleporting agents to their designated zone during state transition when performing activities in the simulation environment.

Contribution

In agent based model agents are free to move and make independent choices in the simulation environment with their unique characteristics. Although they are quite good at predicting consumption patterns a lot of calibration is required due to oversimplification. This is a major drawback, especially for predicting building energy performance during the design stage due to the lack of actual consumption data likely to be seen in post design occupancy. As discussed, previous papers mention different approaches, metrics, and input parameters but none of them discussed agent movement behaviour incorporating possible routes between state transitions, taken during the movement between zones.

In this paper, a novel methodology for agent based model development is proposed that looks into a specific case study to analyse the potential impact on the predicted electricity consumption by incorporating transition routes for agents when they are travelling between zones within the simulation environment. The conceptual model is implemented based on a standardized framework developed by [31] known as Engineering Agent-Based Social Simulation (EABSS) following software engineering principles and techniques for developing agent based models. The insights gained from this case study are a major contribution of this paper and the potential impact on the prediction capability is discussed quantitatively and validated against real world electricity consumption data. The next section will discuss the methodology adopted followed by the model development and simulation results then a discussion and conclusion.

2 Methodology

2.1 Occupancy Trial and Simulation

One of the core aspects of built environment research is the efficient management of building energy demand leading to sustainable and optimal energy usage. This leads to modelling energy usage in the design stage of buildings with credible and realistic input parameters related to building layouts, expected occupancy and agent behaviours within the simulation settings. Current study focuses on the implementation of a building occupancy model by incorporating realistic transition routes as parameters within the simulation environment and demonstrate the difference in energy usage prediction when not included. Thus, highlighting the limitations of existing methodologies where agents are simply teleported to their destinations.

The methodology adopted in the occupancy model development can be seen in the simplified block diagram of Figure 1. It could be divided into three stages. The first stage is to identify route preference patterns in the test bed building such as the use of stairs, hallways and corridors through a real-world occupancy trial leading to occupancy data collection. In the second stage, the data is post processed to obtain the transition probabilities of route choice preferences. The third stage implements the agent based occupant model and uses the transition probabilities as inputs within the simulation environment to predict electricity consumption from lighting and compare and contrast when not using them.

The occupant model implements a simplified version of the Nottingham Geospatial Building (NGB)'s first two floors and its population as a case study following the EABSS principle [31]. To identify route choice preferences within the building, the occupancy of individuals was observed by tracking participants using state-of-the-art indoor positioning system while performing spatially distributed Lego building tasks. It required participants to start from various locations, move around the building and perform a series of tasks mimicking day to day activities within a specified time.

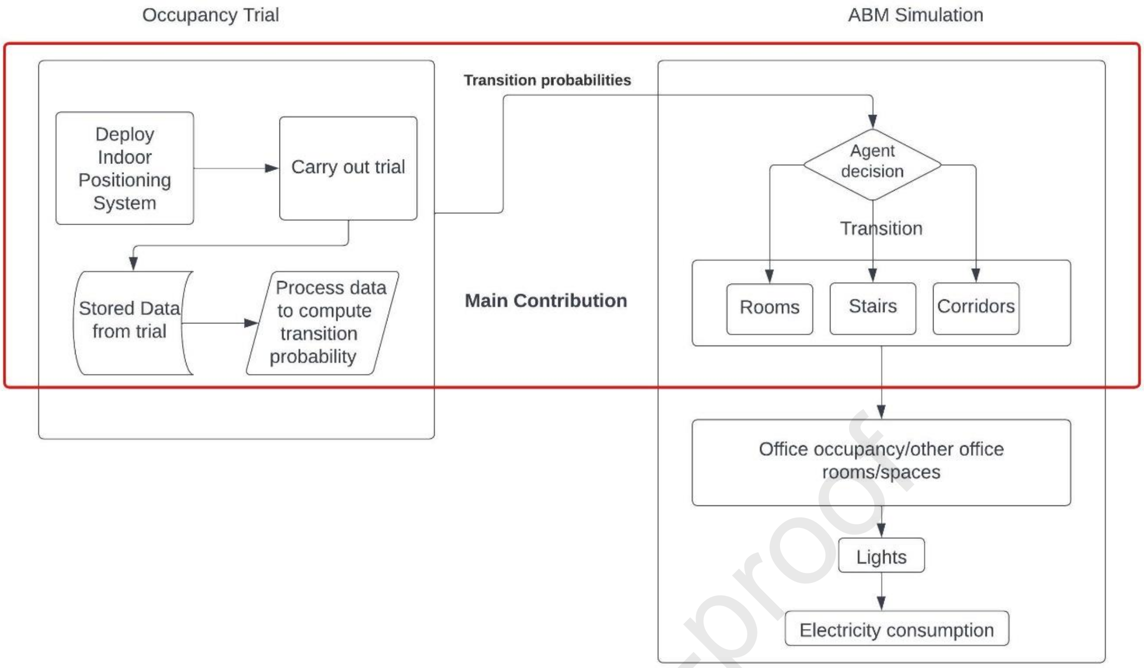


Fig 1: Block diagram of the overall framework.

For simplification, the movement was limited to travelling between major rooms when performing tasks to cover all possible transitions through corridors and stairs to identify zones and floors. As seen from Figure 2, the NGB floor plan is partitioned into multiple zones, and the major rooms such as A20, A19, B05, Store and kitchen, corridors and stairways are marked for agent destination. Floor A is divided into four zones and Floor B into three zones. It is expected that when participants travel from one zone to another, they will have their preferences of route choice. The partition of the floor maps and designation of zones were completely arbitrary and done to simplify the Lego trial task and route preference identification. The same principle is used in the agent-based model allowing agents to move from one place to another based on their route choice preferences. Route choices may include going through other rooms, corridors, and stairs when travelling between zones and within zones and could exhibit different patterns depending on their location at any given point in time.

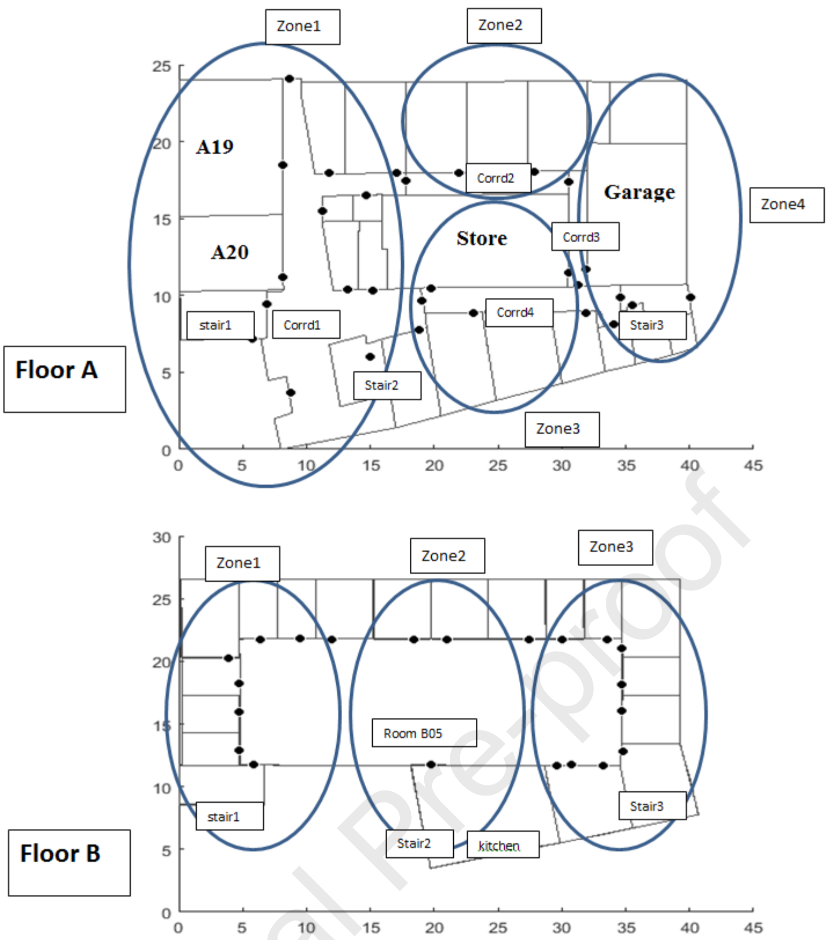


Fig 2: The floors A and B respectively of NGB and its partition into zones and rooms.

The indoor positioning system was developed using Wifi and Bluetooth sensors and was deployed across the two floors of the NGB. In total, 22 volunteers agreed to participate in 50 trials Each of the participants was provided with a smartphone with a data logger running, copies of floor maps and an instruction sheet and had 20 minutes to complete the task. The recorded data is post-processed for each trial and used to compute the participant's transition routes taken when performing the tasks using appropriate tools and techniques, details of which can be found in our previous study [32] and [33]. The trials helped to recreate a realistic day to day occupancy of the building and identify how different rooms, stairs and corridors are used and their preferences. Below is a sample instruction to understand what a typical trial looked like.

Sample instructions for a Trial.

1. *You will start from a Zone in room B05, floor B (to be shown by the researcher). Keep the phone in your trouser pocket and wait for approximately 20 seconds for initialisation after the data logger is started by the researcher.*
2. *Go to Corridor 4 and Corridor 2 (marked on the floor map) and find the Lego model pictures on the floor. There will be a total of eight pictures.*
3. *Keep the Lego pictures with you as well as all other sheets.*

4. *Take the Lego pictures in room A20, floor A. The Lego bricks are also kept in room A20, marked on the map. You can check the Lego pictures decide which model you want to build and gather the Lego bag. You can then go and build Lego models in room A19, Floor A. You can only take one Lego picture for building at a time. If you finish or decide to change your mind and build another one, you can check the remaining Lego model pictures in room A20 and collect appropriate Lego structures as many times as you want, but you can build the models only in room A19.*
5. *You will have to complete as many models as you can within 20 minutes.*
6. *When finished, the researcher will ask you to stop, and he will stop the data logger app for you.*

2.2 Route choice probability

One of the main objectives of the trials was to ensure all possible transitions were covered that involved going through stairs and corridors since their preference would act as input in the model. Table 1 below provides the possible transition between zones covered by the trials and implemented in the model and Table 2 provides some examples of transition route choices a person can have when moving between zones in the model. For each zone transition, there can be several possible routes via corridors, stairs and rooms as seen in Figure 2. Transition probabilities of route choices were derived simply by calculating how many times each possible route was chosen during transition based on their start and end locations and the zones they passed through. The complete lookup list of route choice probability derived can be found coded in the simulation environment which can be accessed through the shared GitHub repository.

Table 1: Zone transition covered.

Start Zone	Target Zones to cover			
Zone 1 Floor B ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 2 Floor B ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 3 Floor B ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 1 Floor A ----->	Zone 1 Floor B	Zone 2 Floor B	Zone 3 Floor B	
Zone 2 Floor A ----->	Zone 1 Floor B	Zone 2 Floor B	Zone 3 Floor B	
Zone 3 Floor A ----->	Zone 1 Floor B	Zone 2 Floor B	Zone 3 Floor B	
Zone 4 Floor A ----->	Zone 1 Floor B	Zone 2 Floor B	Zone 3 Floor B	
Zone 1 Floor A ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 2 Floor A ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 3 Floor A ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A
Zone 4 Floor A ----->	Zone 1 Floor A	Zone 2 Floor A	Zone 3 Floor A	Zone 4 Floor A

Table 2: Agent route choice example.

Start zone	End zone	Transition Routes & Probabilities
Zone 1, Floor A	Zone 3, Floor A	Corr1, Corr4 = 0.99 Corr1, Corr2, Corr3 = 0.01
Zone 4, Floor A	Zone 1, Floor B	Corr1, Corr2, Corr3, kitchen, Stair2 = 0 Corr1, Corr2, Corr3, kitchen, B05, Stair1 = 0 Corr1, Corr3, Corr4, kitchen, B05, Stair1 = 0.4 Corr1, Corr3, Corr4, Stair2, kitchen = 0 Corr3, Corr4, Stair3, kitchen = 0.6

Zone 2, Floor A	Zone 3, Floor B	Corr1, Corr2, Kitchen, Stair2= 0 Corr1, Corr2, Corr3, Corr4, Kitchen, B05, Stair1= 0 Corr1, Corr2, Kitchen, B05, Stair1= 0.3 Corr1, Corr2, Corr3, Corr4, B05, Stair2= 0 Corr1, Corr2, Corr4, Kitchen, Stair3= 0 Corr2, Corr3, Corr4, B05, Stair3= 0.7

During the trials, the participants had complete control over route choices to reach their destination and were not advised or distracted during the task. The instructions like the one above were changed for different participants by changing the location of the resources to be collected and their starting point so that occupancy across a variety of locations and routes can be observed within the building as seen in Table 1. Thus, a credible source of transition data is gathered covering all the zones and various combinations of routes and their probabilities for the agents to choose from during movement between zones in the simulation environment.

3 Model Development

3.1 Creating a conceptual model

In this section, the conceptual model is developed using the EABSS framework [31] which provides a step-by-step approach to conceptualise and develop agent-based models as seen in Figure 3.

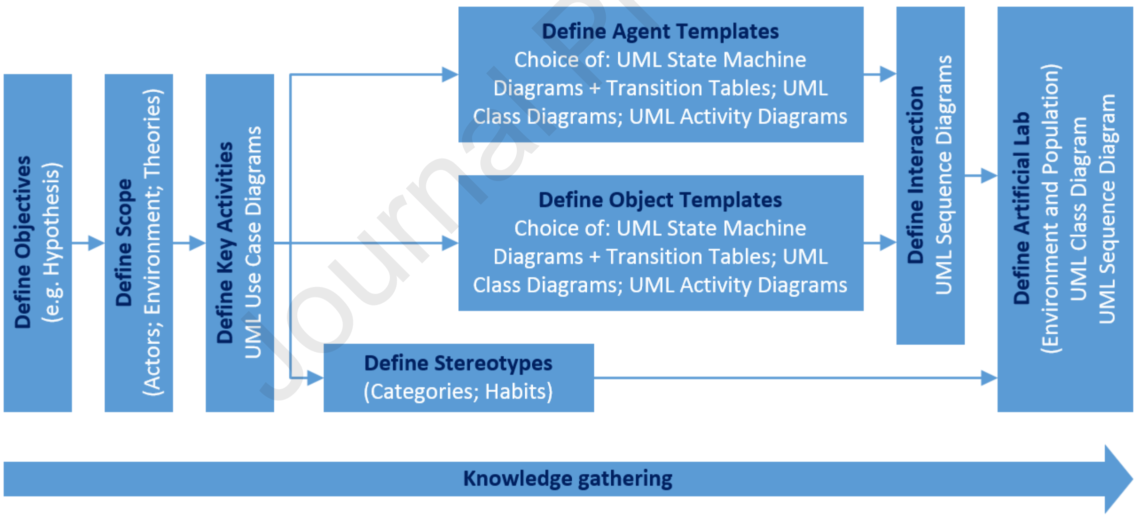


Fig 3: Structure of the EABSS framework as depicted in [31]

DEFINE OBJECTIVES

Aim: Develop a building occupation model to analyse the local dynamics of electricity consumption over time by introducing intra-state transition between rooms, stairs, and corridors in multi-floor offices such as academic buildings.

Hypothesis: Using trajectory information during the agent's transition between rooms and floors helps to predict a more realistic electricity usage, compared to other commonly used agent transition representations.

Experimental factors: These are the parameters needed to set up before a simulation run to define the individual experiments which is to test if the hypothesis holds for different scenarios of agent occupancy modelling:

1. Type of agent occupancy modelling

Responses: These are simulation outputs required to test the hypothesis and to improve the credibility of the model by increasing transparency and understanding of the processes modelled. In this case, the following is required:

1. Aggregate electricity consumption of the agent population (per half hour)
2. Aggregate building occupancy (per half hour).

DEFINE SCOPE

The scope table template defined in the EABSS framework is used for defining relevant elements and phenomena that need to be represented in the model, considering the hypothesis tested. The result can be seen in Table 3.

Table 3: Scope table of our conceptual model.

Start	End	Transition Routes	Decision	Justification
Actor		Faculty	Include as a group: Users	Occupies everyday
		Research Fellow		
		PhD Students		
		Visitors	Exclude	Does not have regular presence, so no control
		MSc Students		
Physical Environment	Appliances	HVAC	Exclude	Does not impact the consumption of electricity due to the movement of occupants in the building, also not every element usage by occupants can be controlled
		Computer		
		Microwave		
		Fridge		
		Personal Appliances		
		Light	Include	Can be controlled by the user and has a direct impact according to occupants' presence in the area
	Weather	Temperature	Exclude	Not required to prove hypothesis
		Day/Night		
	Room	Kitchen	Include as other rooms	Common areas used for different reasons and impact electricity usage from lights
		Toilet		
		Corridors		
		Activity rooms		
		Stairways	Include	Used for the transition between floors and also impacts electricity usage from lights
		Own Office	Include	Required for every occupant
		Out of building	Include	Required to include out of office breaks impacting possible electricity usage from light switch off/on
Social/Psychological Aspect		Communication between occupants. General shout out during a seminar or lunch breaks	Include	Word of mouth communication to join seminar, presentation or joining colleagues during lunch, out of office breaks. Many impact electricity usage from the light source depending on occupancy
		Comparative feedback	Exclude	Not required to prove hypothesis
		Informative feedback		
		Apportionment level		
		Free – riding		
		Sanction		
		Anonymity		

DEFINE ACTIVITIES

In Figure 4 the possible interactions between the actors and the interactions between the actors and the physical environment can be seen. The bubbles represent so called "use cases” [34]. Agents have their own office space, they can use other rooms such as toilets, kitchen and printing, and they can communicate to go to seminars in groups and go out of office buildings.

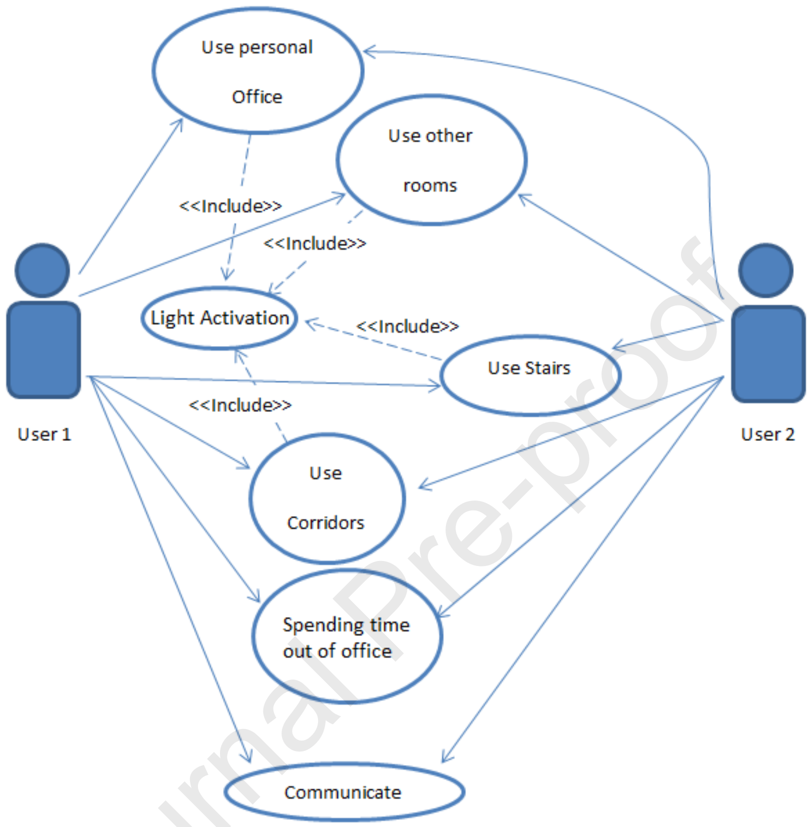
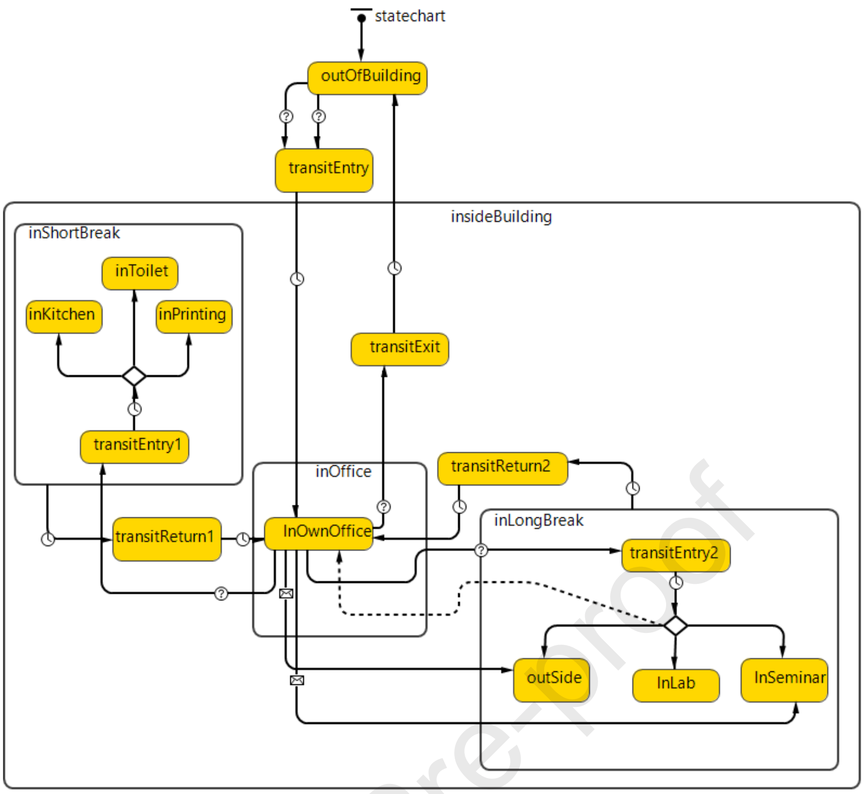


Fig 4: Use case diagram of our conceptual model.

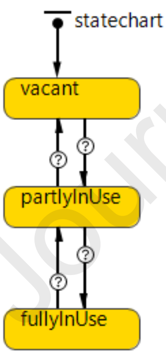
DEFINE AGENT/OBJECT TEMPLATES

State charts are used to define the states' actors (also called agents) and objects can be in and how they transition from one state to another. Then the trigger mechanisms are defined for these transitions in a table.

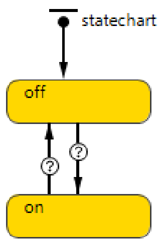
User agents: Initially these user agents are out of the building; at a certain time (depending on their stereotype) they will enter the building and go directly to their office. Only from there, they can reach other facilities. Their office arrival and departure time is computed based on which they enter and exit the building. When the agent moves into and between different parts of the building, they need to pass through some transit state (e.g.: transitEntry1, transitReturn1) as seen in Figure 5 below. Details of agent occupancy are explained later in section 3.2.2. The probabilities of route choices are coded within each transit state which helps to compute the route covering stairways, corridors, and other rooms to their destination. The destination can be other rooms within the same floor or another or places inside the compound state of "inShortbreak", "inLongBreak" and "inOffice" or entering and exiting the "insideBuilding" state altogether.



State chart for user agents.



State chart for office object



Sate chart for light object

Fig 5: State chart in the conceptual model

A list of all the transitions between states within the user agent, what triggers them, and when they are triggered, can be found in Table 4.

Table 4: Transition table for user agents in our conceptual model.

From State	To State	Triggered by	When ?
outOfBuilding	transitEntry	Conditions	When agent arrival time matches with the simulation time during weekdays or agent arrival time matches and the day is a weekend with a given probability
transitEntry	inOwnOffice	Timeout	Average travelling time of 5 min from entrance to own office inside the building and identifying the possible trajectory route in the Entry State

inOwnOffice	transitEntry1	Condition	When current simulation time matches with a uniform distribution pick within agent arrival and leave time
transitEntry1	inShortBreak	Timeout	Identification of possible route to destination with an average travelling time of 5 min
inShortBreak	transitReturn1	Timeout	Leave after between 5 to 10 min
transitReturn1	inOwnOffice	Timeout	Identification of possible route to own office with an average travelling time of 5 min
inOwnOffice	transitEntry2	Condition	When current simulation time matches with a uniform distribution pick within agent arrival and leave time
transitEntry2	inLongBreak	Timeout	Identification of possible route to destination with an average travelling time of 5 min
inLongBreak	TransitReturn2	Timeout	Leave after between 20 to 40 min
transitReturn2	inOwnOffice	Timeout	Identification of possible route to own office with an average travelling time of 5 min
inLongBreak	inOwnOffice	Condition	If room attendance is above threshold/full
inOwnOffice	inLongBreak (Outside)	Message + guard	When message is received by an agent and probability of response (*groupProb*) satisfies
inOwnOffice	inOtherRooms (Seminar Rooms)	Message + guard	When message is received by an agent and probability of response (*groupProb*) satisfies during Wednesday or Tuesday only
inOwnOffice	Exit	Condition	When leave time is reached
transitExit	outOfBuilding	timeout	Identification of route to out of building with an average travel time of 5 min

Office object: The state chart for the office object is shown in Figure 5. It simply shows the three occupancy states, “vacant”, “partlyInUse” and “fullyInUse”. The “partlyInUse” is just a transition between the office being “vacant” and “fullyInUse” depending on if all lights in the room are switched on.

The transition table (Table 5) provides details about the potential transitions between the three states of the office object. When an agent enters or leaves any office room, the lights are switched on or off causing the “energyConsumption” variable to satisfy either of the conditions and trigger a state change. The individual power capacity of the lights in the model is kept constant at 60W for simplicity.

Table 5: State chart transition table of office shown in Figure 5.

From State	To State	Triggered by	When ?
vacant	partlyInUse	energyConsumption > 0	Agent moves in the office
partlyInUse	fullyInUse	energyConsumption >= numberOfLights*60	When all lights are switched on
fullyInUse	partlyInUse	energyConsumption <= 2*(numberOfLights*60)/3	When agent leaving office

Light object: The state chart for a light object is shown in Figure 5. It's quite simple. There are two states "on" and "off", and an entry point leading into the "off" state.

The transition table (Table 6) provides details about the potential transitions between the two states of the light object. The condition that is used for triggering the transition depends on the room occupancy.

Table 6: State chart transition table of light shown in Figure 5.

From State	To State	Triggered by	When ?
Off	On	condition	When agent enters room
On	Off	condition	When agent leaves room

DEFINE INTERACTION

The sequence diagram in Figure 6 captures the interaction between actors and between actors and the physical world in more detail. It also shows the order of interaction and other methods of interaction such as message passing between entities and the lifeline of each interaction using vertical lines and solid line arrows.

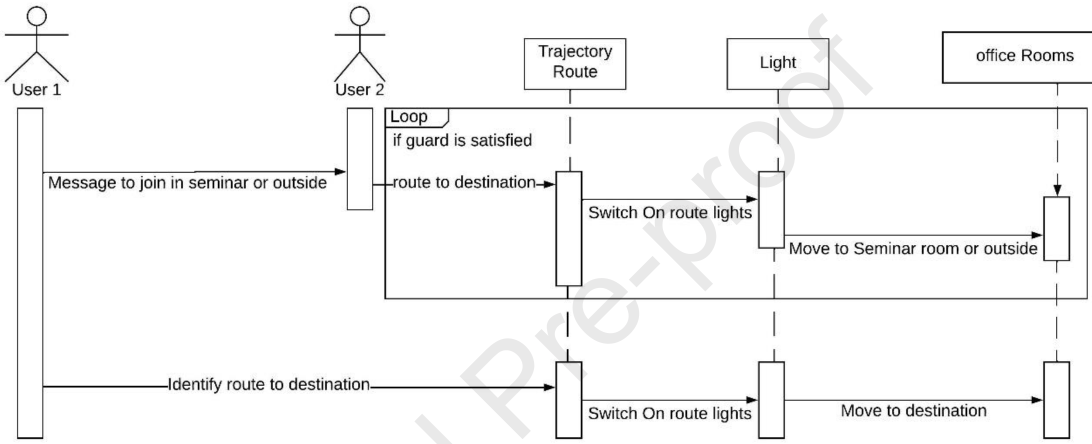


Fig 6: Sequence diagram for our conceptual model.

DEFINE ARTIFICIAL LAB

The artificial lab is the primary environment where all the entities defined above are embedded. It also provides some global functionalities. A class visualisation of the artificial lab is shown in Figure 7. Class visualisations are composed of three compartments: name, attributes, and operations. Her, the attributes represent parameters (experimental factors) and variables (including container variables that contain our agents/objects, identifiable by their [] ending). The operations represent activities performed by the environment (e.g. statistics; read/write files) to generate and store the required responses.

Fig 7: The artificial Lab class of the simulation model environment.

3.2 Implementing the Conceptual Model

Energy Calculation Engine

For the implementation of the conceptual model, a multi-paradigm simulation package; AnyLogic [35] is used, which supports agent-based, discrete event and system dynamics simulation as well as optimisations. The NGB lighting infrastructure is carefully observed physically, and the original floor plan design is studied to identify the number of lights in each room and their associated power, Φ_i. The building has a variety of light models and designs having different power capacities. So, for simplification, the power capacity for each light in the model is kept constant at 60w, and the number of lights λ in each room in the model is allocated according to equation 1 below.

$$\lambda = \frac{\sum_1^i \Phi}{60} \quad (1)$$

Here Φ is the power associated with each light in the actual room. The number of lights λ is calculated for each model room and assigned during model implementation. Also, occupants in each room were observed before allocation, which also includes office sharing between multiple occupants and an open plan office space as well. During the simulation the engine computes the electricity power consumption (W) based on the agents' occupancy and a recurring check is done every minute for rooms, corridors and stairs' occupancy and the lights are switched on or off accordingly. Since the individual capacity of the lights is kept constant at 60W the total number of lights in the rooms, corridors and stairs is checked to calculate the total power (W) consumption every minute for the entire office space.

Stereotypes

The agent population is divided into four stereotypes based on their work pattern and their arrival and departure time in the NGB office as seen in Table 7.

Table 7: Agent population's behaviour stereotype in the simulation environment.

Stereotypes	Workday	Arrival	Departure
Early Bird	Mon - Fri	6am – 8am	60% probability 4pm – 7pm 40% probability 1pm – 9pm
Timetable complier	Mon - Fri	9am – 10am	
Flexible	Mon - Fri	10am – 1pm	
Hardworking	Mon – Fri + Sat/Sun	30% probability 9am – 10am	

Population Dynamics

The agents communicate with the agent population, in general, to invite colleagues for seminars and take out-of-office breaks. To avoid complexity, networks among agents representing close circles and friendships were not created, which might be common among colleagues. It was observed that occupants in g NGB were showing almost negligible probability of forming large social circles or herding behaviour in this building and as such general mass communication was assigned a low probability of response.

For model simplification, some key rooms were selected for agent transition to and from their respective offices, which were always accessed by the building occupiers of the two floors irrespective of their office desk locations. For the transition to other rooms, route choices are implemented incorporating detailed trajectories between rooms and corridors, which also involved stairways depending on the model scenario. The destinations are separated into two blocks, 'inShortBreak' for a 5 to 10 minute break and 'inLongBreak' for a 20 to 40 minute break, as shown earlier in the state chart diagram in Figure 5.

Occupant Movement Strategies

Each agent is assigned an office and the stereotype they belong. The agent follows the arrival and departure time depending on the stereotype they are assigned when entering and leaving the office and then goes through the transit states defined in Figure 5 before moving into any rooms or out of the building. The transit states define what kind of transition strategy to follow eg: probability-based route choice, random route choice or direct teleporting to their destination. The probability-based route choice is derived from the trial data already discussed in Section 2 and the route choice computation for the transition is coded within the transit states. Details of possible transition states an agent can go through can be found in Table 4 as well.

Lighting Policies

For the simulation, two lighting policies are used. For the base model, the NGB lighting policy was implemented which was a mixture of PIR sensor controlled and Estates controlled i.e. switched on for 24 hours. For the later models, all lights were changed into PIR controlled smart lighting, meaning the lights turned on/off based on occupancy. More details can be found in section 4 below.

Simulation Model

A screenshot of the main screen of the implemented simulation model (the implementation of the artificial lab from the conceptual model) is shown in Figure 8. The model shows the floor plan of the NGB on the left and some informative stats about electricity consumption on the right.

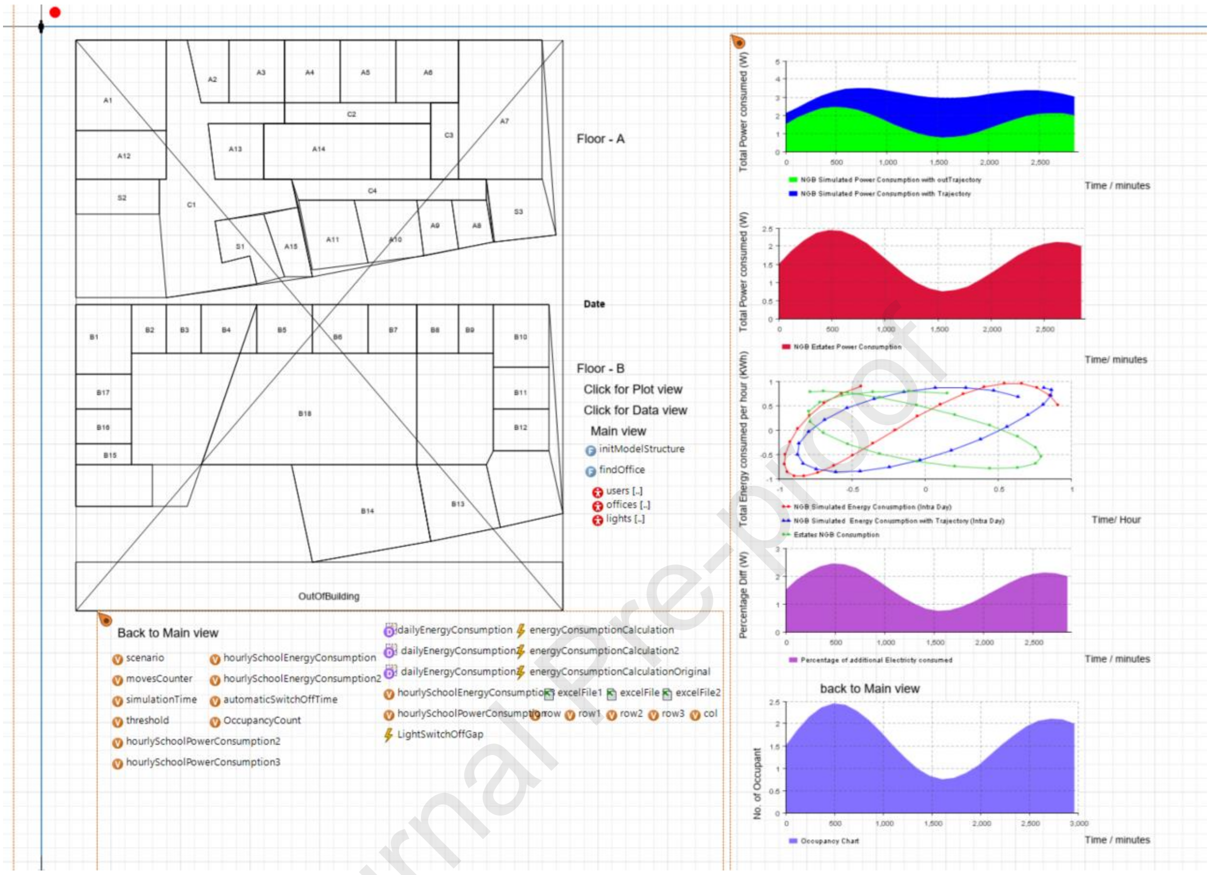


Fig 8: Main screen of final simulation model.

The agents/objects have been implemented as described in the conceptual model. When running the simulation, access to the main screen and each agent/object is provided via the simulation environment. The implemented model is available for download from the following source, https://github.com/shadab1418/NGB-Occupancy-Model.git.

4 Experimentation

In this section, two case studies are conducted by running computer simulation experiments with the model developed. The experiments are described in more detail followed by the analysis and discussion of the simulation outputs for each of the experiments.

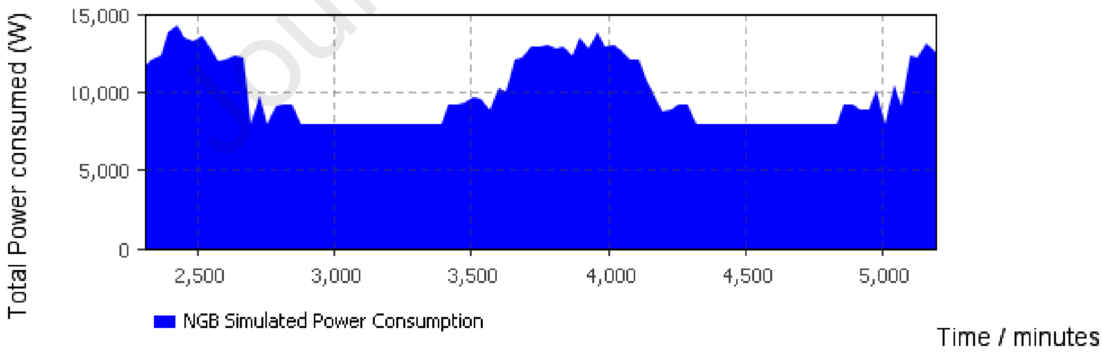
- **Case study 1**: At first, the lighting electricity usage of NGB with existing lighting policy as a base case is simulated and compared against actual lighting electricity consumption data collected from Estates for validation and calibration of the model.
- **Case study 2**: The base case model always had lights switched on, especially in corridors, stairs, kitchen etc. So, to ensure clear distinction the base model is modified to simulate lighting electricity usage but using smart lighting policy (e.g., using PIR sensors) for each of the following cases.

- Simulate the agent's movement without incorporating individual trajectories during the transition between rooms and corridors; teleporting agents to their destinations during simulation, as done by [13].
- Simulate the agent's movement incorporating individual trajectories during the transition between rooms and corridors.
- Compare and contrast the energy usage with and without trajectories.

4.1 Case Study 1: Model validation using existing Lighting Policy against Estates' Data

To understand the efficacy of the model, it is important to compare and validate the model against real-world data. In this case, the base model was designed to mimic the NGB lighting policy currently being implemented. Based on observation of the building, it was found to be a mixture of PIR sensor controlled and centrally controlled. Some sections of the building lights are active 24 hours such as the reception area, corridors on floor A, open plan space on floor B, stairways, kitchen etc. To verify this, electricity consumption data of NGB for lights were collected from the University of Nottingham Estates department for February.

For the first experiment, the base model is used for simulation. For the simplicity of the model, only weekday energy data is simulated and compared. This is because the occupancy behaviour of NGB during weekends could not be observed reliably. Figure 9 shows the simulated lighting electricity consumption data (W) updated every 30 minutes and the actual electricity consumption data (W) of Estates from sample weekdays. Both the plots show some similarity in their pattern and electricity consumption. Figure 10 shows the lighting electricity consumption in (KWh) for both the simulated and Estates' data over a 24 hour period which is also similar in pattern.



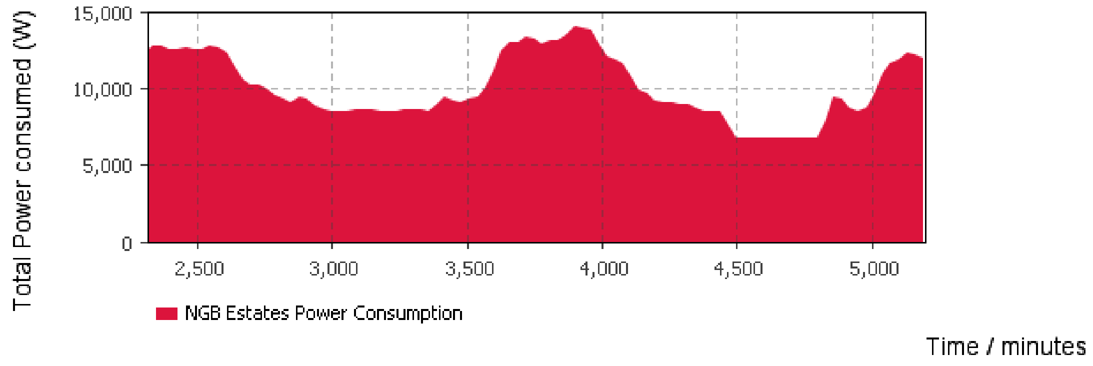


Fig 9: NGB simulated and Estates actual power consumption during weekdays only.

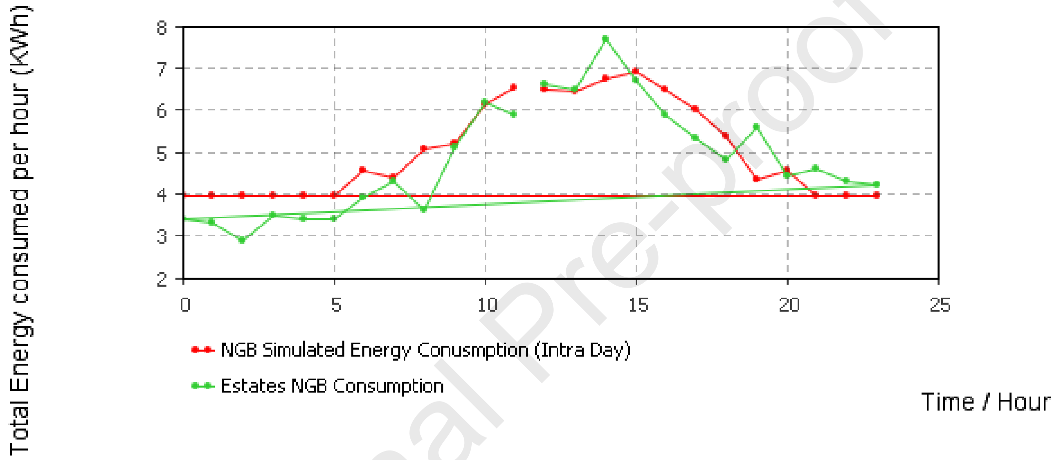


Fig 10: Simulation energy data vs Estate's energy data consumption over 24 hours.

It is important to note that a simple discrete uniform distribution is followed to determine the agent's occupancy behaviour representing entry and exit time, their likelihood of coming to the office and transition between rooms and facilities.

To ensure the statistical significance of the result, the simulation was replicated 100 times with a random seed for each run of 24 hours and then compared with Estates' data. The plot in Figure 11 illustrates the lighting electricity consumption predicted every 30 minutes over 24 hours.

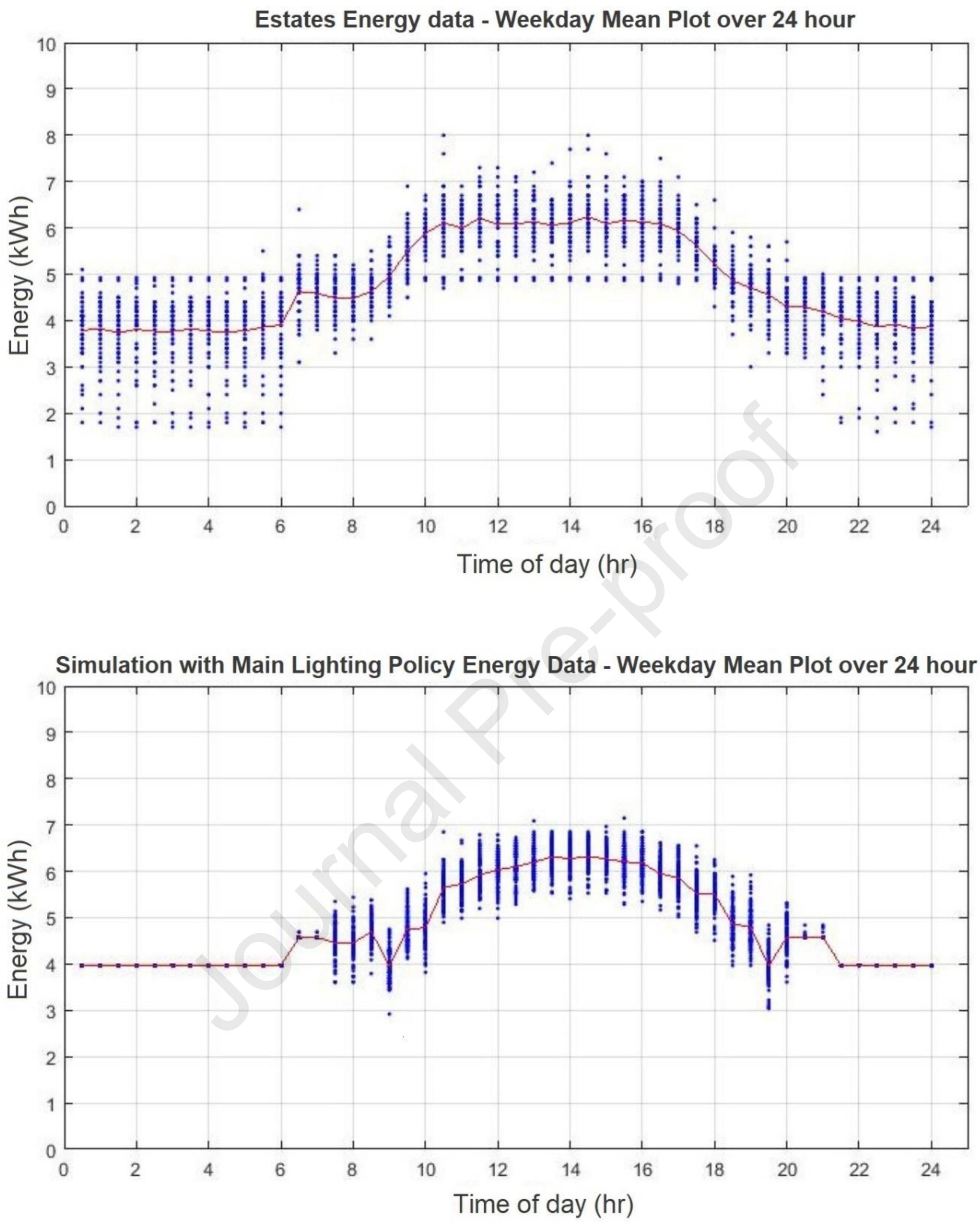


Fig 11: Simulation result after 100 repetitions compared against Estate's data every 30 min over 24 hours.

In general, the simulation results show the similarity of the simulated electricity output and the Estate's pattern. Although the variability is very different the mean of total simulated electricity consumption (230.65 KWh) is almost equal to that of Estates (231.65 KWh) thus satisfying the objective of model validation outlined in case study 1 which can now be used as a base model for further analysis.

4.2 Case Study 2: Impact of Trajectory Route Choice in Occupant Model

In the agent-based occupant model developed by [13] agent movement between rooms implied teleporting the agent to their destination through one corridor. In reality, to travel between rooms an agent might need to pass through multiple corridors; this means none of the corridor's electricity consumption from lighting usage is used in the calculation except one even though looking at the floor plan it was evident that some of the transition would require an agent to cross multiple corridors. As a result, the electricity consumption was always underestimated. The model also only investigated a single floor scenario; on multiple floors, especially in large commercial buildings, there can be more than one stairway, multiple corridors, and rooms to go through. The NGB is a perfect example with three stairways exiting at different zones of the building with multiple corridors and stairs.

The undergoing research investigated the impact of passing through one or more corridors, stairs, rooms etc. during the transition by introducing trajectory routes for agent movement between rooms. The validated model is used as a base model for case study 2. With the existing lighting policy, most of the NGB lights are always in active mode, so there is no way to determine the impact on electricity consumption due to the agent's occupancy throughout the building. As such, all the default settings of the model were kept and only changed the lighting configuration to smart lighting, i.e. PIR sensor controlled. The updated model is then used to compare and contrast simulation results with and without trajectory route choices during agent movement.

Simulation results illustrated in Figure 12 show the electricity consumption difference between the two scenarios for the same period of occupied hours. The experiment was replicated 100 times with random seeds for each of the two scenarios, and the aggregate results are plotted, as shown in Figure 13. For simplicity of the model, any kind of lighting such as emergency lights that might be continuously kept switched on during unoccupied hours were ignored. So, with the adoption of a smart lighting policy, zero lighting electricity is consumed when the building is empty, and the lights respond to agent presence only. As seen in Figure 13, electricity consumption starts to rise from 6 am morning and goes to zero by 9 pm as defined by the agent stereotype in Table 6. The peak energy consumption every half hour in the model without trajectory route choice is just over 3KWh which when introduced goes over 4KWh, thus showing a significant underestimation of lighting energy consumption prediction when modelling without trajectory route choice.

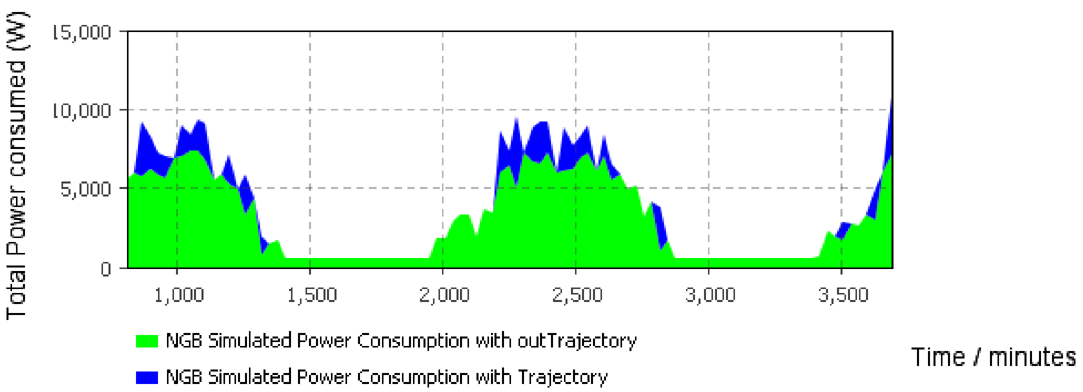


Fig 12: The difference between power consumption when using and not using trajectory route choice during agent movement is seen above. The blue is the extra energy usage when route choice is introduced.

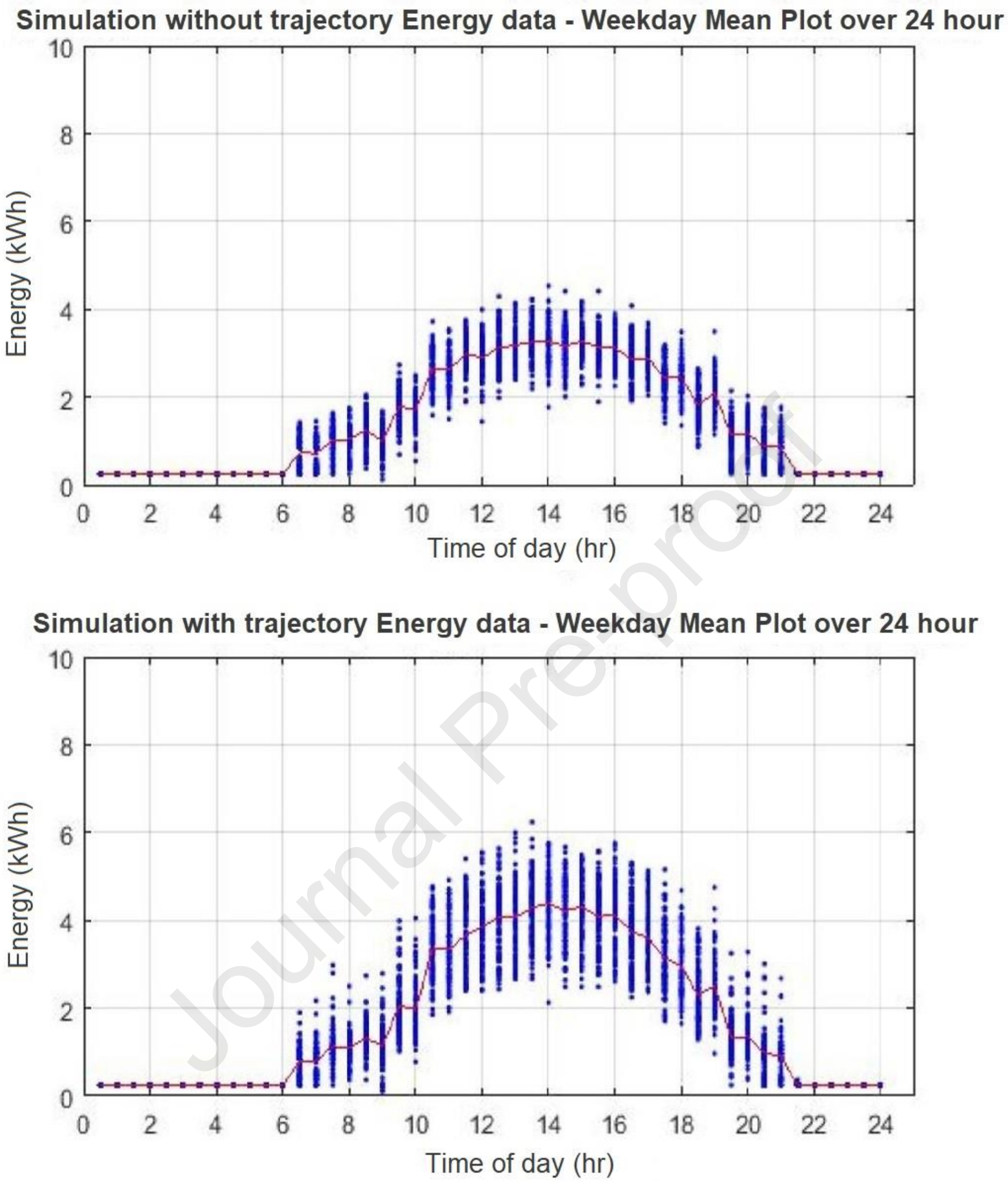


Fig 13: Showing lighting energy consumption data without using trajectory and using trajectory information.

Although trials were run to identify route choice preferences and derive their probabilities for our test site it might not be possible to do so everywhere. The model was simplified slightly, and the simulation was run again with trajectory included but with random route choice instead of probabilities. Simulations were run with 100 replications for both the cases and the results were plotted, as shown in Figure 14. The lighting energy consumption illustrated in Figure 14 shows very little difference between the two cases, but using probability-based route choice makes the simulation outcome more realistic and gives more confidence in the result.

The total lighting energy consumption differences between the three scenarios over 100 replications were; without trajectory (68.91KWh), random trajectory (85.36 KWh) and probability-based trajectory (83.54 KWh). It can be seen there is a significant difference, approximately 19% between including trajectory and not including trajectory during agent movement but a minimal difference between random and probability specific route choice. The results will not be comparable with the base model result in case study 1 since the lighting configuration was mostly manually controlled, always switched on, did not include trajectory and required model calibration.

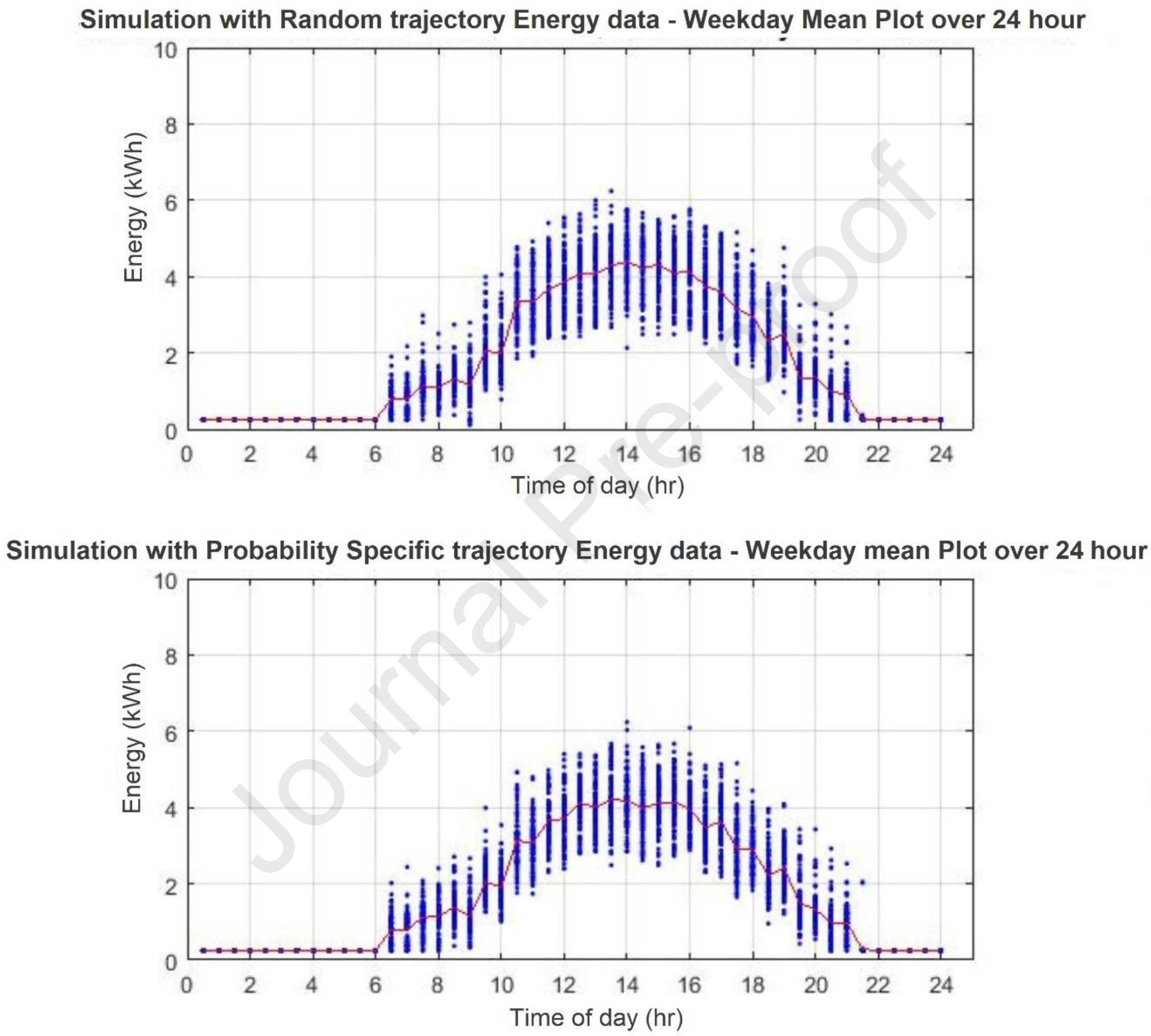


Fig 14: Showing the energy consumption between random and probability-based route choice.

5 Discussion

In case study 1 the base model was implemented following NGB lighting policy. It can be seen in Figure 11 that the mean base energy consumption every half hour is around 4 KWh, which moves up to a little over 6 KWh during the peak times of the day. The energy consumption starts to rise from 6 am and starts to fall gradually from 6 pm. The variance of the electricity consumption data from the Estate's record throughout the month is fairly high. The model was slightly calibrated to ensure we have the same baseline for electricity consumption during the night. The lights in hallways, corridors, stairs etc. in the simulation environment were kept switched on mimicking the lighting policy of NGB but it was not possible to identify exactly how many since not all facilities were accessible at night for observation. As a result, the simulated electricity consumption was still falling below the mean consumption of the Estate's data at night (near 4KWh) as seen in Figure 11. So, to ensure a similar baseline for comparison during the night time a constant value was introduced as miscellaneous electricity consumption in the base model. The simulated electricity output, although stochastic, shows less variance since it is less unpredictable compared to the real-world scenario. The mean electricity consumption from the simulation shown by the red line is around 6 KWh during peak times, nearly similar to Estate's data but the pattern varies slightly and seems flatter during the rise and fall. This difference can be explained due to various real-life factors such as intermittent absence by occupants, whereas during the simulation, they are not considered and all agents are present during weekdays. As a result, all the personal office spaces in the simulation are always occupied at some point of the time during the day, which might not be true in real life. Also, some of the major rooms listed for agent movement during simulation might not be occupied every day in real life. These and various other unforeseen everyday situations impact real-life energy consumption, which is evident from the significant variance in the Estate's energy data.

In case study 2 the simulation at first considered typical agent state transition (teleporting) as seen in [13] and then introduced trajectory routes. The route choice probabilities derived from the trials as discussed in the methodology section are used by the agents when making route choices within the transit states when the trajectory is introduced in the model.

The results showed a significant difference between the two cases, approximately 19%. Simulation results without trajectory showed 68.91 KWh consumption compared to 85.36 KWh consumption with trajectory per day for the whole office during weekdays. This shows a typical underestimation of 16.45 kWh per day or 4277 kWh per year (only considering weekdays). Considering the average variable unit electricity price of 31.42 pence / KWh for a medium business according to the census provided in powercompare.co.uk, 2023, the model prediction underestimates roughly 1343 GBP annually without incorporating trajectory. Thus, it proves the case that incorporating trajectory information during agent movement between rooms helps to minimise underestimation and predict more realistic electricity consumption data.

The proposed modelling approach using the EABSS framework helps to develop a high level conceptual model with clearly defined relationships and activities related to agent interaction and behaviour before implementing the model. Although the main novelty of the proposed methodology lies in incorporating intra-state transition routes during agent movement to any destination it can make the model implementation quite complex. This is because the model needs to add almost all possible combinations of transition routes leading to any agent destination and this may not be feasible for larger buildings such as hospitals and corporate offices where there may be too many corridors, stairs and hallways crisscrossing. Nevertheless, the methodology can still be applied by simplifying the model and generalising the transition routes. Also, to make the model prediction more credible and realistic, transition probabilities were used by agents when choosing a particular route, which was computed from the extensive occupancy trial using indoor positioning system, but this can also be simplified by making random route choice as an alternative as shown in one of the experiments in case study 2. This ensures the proposed modelling approach is applicable for any type of building to predict realistic energy consumption during the design stage to evaluate post-occupancy performance.

6 Conclusion

6.1 Summary

In this paper, an alternative methodological approach to agent based modelling is proposed which takes into account the trajectory of the agent's movement during building simulation for predicting electricity usage. The trajectory incorporates potential states of transition through various office spaces before the agent reaches its destination thus making the modelling more realistic and adding credibility to the prediction. Two case studies were implemented. The first case study discussed developing the baseline model following the EABSS framework which was validated against actual electricity usage data provided by Estates. The predicted electricity consumption was 230.65 KWh compared to that of Estates 231.65 KWh per day. The base model was then updated to implement the proposed approach by introducing transition routes and compared against the existing practice of teleporting agents during the transition to their destinations. The model made use of the trials conducted earlier in previous studies [32], [33] to identify route choice preferences of occupants during office hours in NGB and used those probabilities as input. Results show the proposed approach helps to predict lighting electricity usage with more confidence and identified an underestimation of 19% when compared to previous approaches without incorporating transition routes.

6.2 Limitations and Future Work

In this study, a simplified version of the simulation environment was implemented and investigated the electricity consumption of occupants from building lights only. The first two floors of the NGB were used to simulate occupant movement although it was a three-storied building due to access limitations. Agent movements mimicking building occupants were also simplified to some extent by allowing occupancy and movement between own office rooms and other rooms commonly used such as toilets, presentation/seminar rooms, laboratory/equipment, and kitchen areas. The floors were arbitrarily divided into zones to ease the process of modelling and identifying zones of occupancy. Communication between agents was very limited typical of group activities or movement, especially out-of-office movement. Weekends were avoided due to limitations of accessibility.

Nevertheless, we have successfully demonstrated the value of incorporating transition routes in agent based building occupancy model to predict more realistic energy consumption at design stage. The results showed previous approaches underestimated the consumption prediction significantly which highlights the issue of “Performance gap” discussed in [9]. The proposed approach can also be applied in any model related to building performance evaluation and reduce the discrepancies related to design and model assumptions. Furthermore, the design and implementation of the real world occupancy trial to derive the probability-based route choice adds credibility and validation in the prediction results objectively.

In the future, additional activities can be added in the model for the agents such as the use of additional electronic appliances such as microwave, fridge/freezer, and laptops to make the simulation environment more realistic and also include weekend activities. If possible, evaluate electricity consumption across different seasons by modifying the occupant behavioural pattern based on observation during Fall, Spring and Summer. All the above will help to improve the model significantly and make it more robust and credible.

Author Contributions: The lead author, Md Shadab Mashuk is responsible for the entire research which is part of his PhD. Apart from supervising the PhD, Peer Olaf Siebers contributed to writing this paper. All the other authors provided significant guidance and advice in their capacity as academic supervisors during the PhD.

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Highlights

- Incorporating transition routes improve electricity consumption prediction
- 19% electricity consumption is underestimated when transitions are not incorporated
- Proposed methodology is applicable for any office buildings
- Probability based route choice adds confidence compared to random route choice
- Detailed occupancy can be observed using indoor positioning system

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: