A conceptual framework to simulate building occupancy using crowd modelling techniques for energy analysis

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Abstract
The causes of the performance gap between the predicted energy demand and actual End Use Energy Demand (EUED) are seen to be underpinned by two main issues. The first issue is the assumptions for the modelling tools in term of physical attributes of buildings, building system and occupants. The second issue, which is more problematic, is whether the given inputs to the modelling tools are realistic or not, in particular, business requirements (fixed or flexible schedules), occupancy (level, pattern & behaviour) and Building Management System (BMS) which can be overly simplified and are unable to address the dynamism between factors within buildings. This over-simplification (often necessary to run the model) is seen the major cause of the performance gap. In this paper, the authors attempt to address one of the issues with regards to the occupancy in large public buildings with significant people movement, such as subway station, museums, public library. The traditional approach is using statistical benchmarking data to establish the basic occupancy schedule, such approach is often not reliable and doesn't reflect the operational reality which is dynamic and unpredictable. However, the challenges of dynamics of people movement have been tackled in the other areas such as crowd modelling and people moving analysis. Techniques and tools have been developed to simulate people movement in different environment. This paper proposes an approach of employing people movement modelling technique to simulate the occupancy in public buildings.

Keywords: Crowd modelling, Energy simulation, Occupancy analysis, Energy demand

1 Introduction

The 'performance gap' between predicted energy demand and End Use Energy Demand (EUED) has long been evident in many studies. In the Probe studies, Bordass et al (2001) reported that the actual energy consumption in buildings was usually twice higher than predicted. Research by Demanuele et al (2010) discovered that the measured electricity demands are approximately 60% - 70% (schools and general offices) and 85% (university campus) higher than model predictions. The Carbon Trust report from five case study buildings also showed that there are substantial differences between actual energy consumption and the building regulation compliance modelling outputs – the actual consumption can be five times higher than predicted (Carbon Trust 2011). Thus, the causes of the performance gap are seen to be underpinned by two main issues. Firstly, it is argued that as all modelling tools are based on assumptions about the relationship between a range of factors including buildings, systems and occupants: these assumptions tend to introduce embedded numerical errors compared with the real world, although this aspect could be partly addressed by choosing modelling tools that are validated by industry benchmark standards. The second argument, which is more important to address, is whether the given inputs to the modelling tools are realistic or not, in particular, business requirements (fixed or flexible schedules), occupancy (level, pattern & behaviour) and Building Management System (BMS) can be overly simplified and are unable to address the dynamism between factors within buildings.

This over-simplification (often necessary to run the model) is seen the major cause of the performance gap (Menezes et al 2012). Studies have also shown that occupant behaviour can have strong impacts on building energy usage. The detailed energy audits of commercial buildings discovered that more than half of the total building energy was wasted due to occupant behaviour (Masoso & Groblera 2009); the sensitivity analysis of NBI (2011) showed large variations of overall building energy use due to tenants' preferences on the given control variables – the difference can be as much as 80%. More emerging research evidences in recent years showed great emphasis on the need for improvements in modelling the business requirement and occupant behaviour for commercial premises (in contrast to the traditional schedule based inputs) in order to reduce the 'performance gap'. One particular attempt on a high density office building by Menezes et al (2012) was to use a full-year's monitored data, including real occupancy level, actual annual lighting consumption and actual hourly use per individual equipment, in order to refine the energy model inputs. With these monitored inputs (accurately reflecting how occupants interacted with the building and how its lighting and appliances were used) the predicted EUED was proved to be within 3% difference with the actual monitored EUED. Thus, it was clearly demonstrated that with more realistic inputs data the accuracy of energy modelling tools can be improved significantly.

However, using monitored data as inputs is not often practical as we want to know what is likely to happen in terms of EUED for a building 'in advance' rather than rewind what has happened. In order to acquire more realistic inputs in advance, it is essential to have good understanding of occupant behaviour in term of occupancy, business requirement for the proposed building. In this paper, the authors are aimed to address one of the issues, occupancy in public buildings where the movement of people or circulation is the key factor. People movement or crowd modelling has been studied extensively in the past 20 years in the areas of public safety, emergency evacuation, and computer gaming and animation. This paper is an attempt to adopt the crowd modelling techniques developed in those areas to provide a more realistic building occupancy input for energy demand analysis.

2 Building Occupancy

Feng et al., (2015) defined building occupancy as "occupied status or number of occupants present in a building or space which is time dependant". They divided existing occupancy studies into four groups based on the space scale and the level of required details: (1) the number of occupants in building scale, (2) occupied/ non occupied status of a space, (3) the number of occupants in a space, and (4) occupant's localization within the space. The complication in occupancy simulation relied on its stochastic nature both in time and space (Feng et al., 2015; Wang, Yan, & Jiang, 2011). Also, the patterns of movement within spaces that occupants choose, varied by their individual characteristics and different roles they played which should be considered in modelling the probabilistic circulations and localisations (Feng et al., 2015). The direct relationship between occupant's movement and occupancy in different building zones has been remarked in various studies (Page, et al., 2008; Wang et al., 2011). Therefore, different methods used in indoor localisation and movement tracking have also been used in occupancy studies. For instance, Vlasenko et al., (2015) generated a model of indoor movement patterns for a single occupant in a "smart home" using a number of passive infrared (PIR) motion sensors to assess how frequent the living spaces are visited. Also, Azghandi et al., (2015) suggested a combined method using PIR and RFID for multi-occupant location tracking. They also used special destinations as starting/ending points to capture people's movement, while defining a circle of radius as people's possible future location. In another study, Yu, Wu, Lu, and Fu (2006) emerged an algorithm to locate people's positions by integrating information from multi-camera and floor sensors. Knauth, et al., (2009) proposed an accurate localisation system based of ultrasound using electronic badges given to visitors of their lab. However, although movement tracking together with stochastic analysis could generate occupancy profile for specific type of building, it will be difficult to apply generally for a new building.

2.1 Building occupancy in energy simulation

Building occupancy profile is one of the key inputs for building energy simulation. Building energy simulation engines such as TRNSYS, IES Virtual Environment or EnergyPlus, incorporate the physical model of the building as well as other parameters such as building location, weather data, the physical properties of building elements and the building occupancy profiles. For example, in DesignBuilder (EnergyPlus engine), a leading energy simulation tool, occupancy is considered in the "activity" section of the software. Before running the simulation, the activity section should be modified for all building zones. This section includes: occupancy (to modify the density of people within each zone), activity factor, gender adjustments, clothing and use of computer and other equipment (Figure 1). The energy analysis outputs are heating/ cooling/ ventilation design data, lighting data, CO2 emission, the total energy consumption and cost. The reliability of the final output, in the first place, is strongly related to the accuracy of the initial energy model (which is sometimes a simplified version of a complex volume) and additional data input for the required parameters. While majority of the parameters are based on hard physical data, such as geometry based energy model, weather data, physical attributes of building material, the occupancy profiles can only be based on modeller's experience, statistical analysis that might not be available or reliable for every building. Martinaitis et al. (2015) confirmed the importance of the reliability of default occupancy for the energy efficiency assessment of residential household. He also believed there was a direct relationship between the importance of occupancy information in energy simulation and the "complexity" factor of the energy performance assessment.

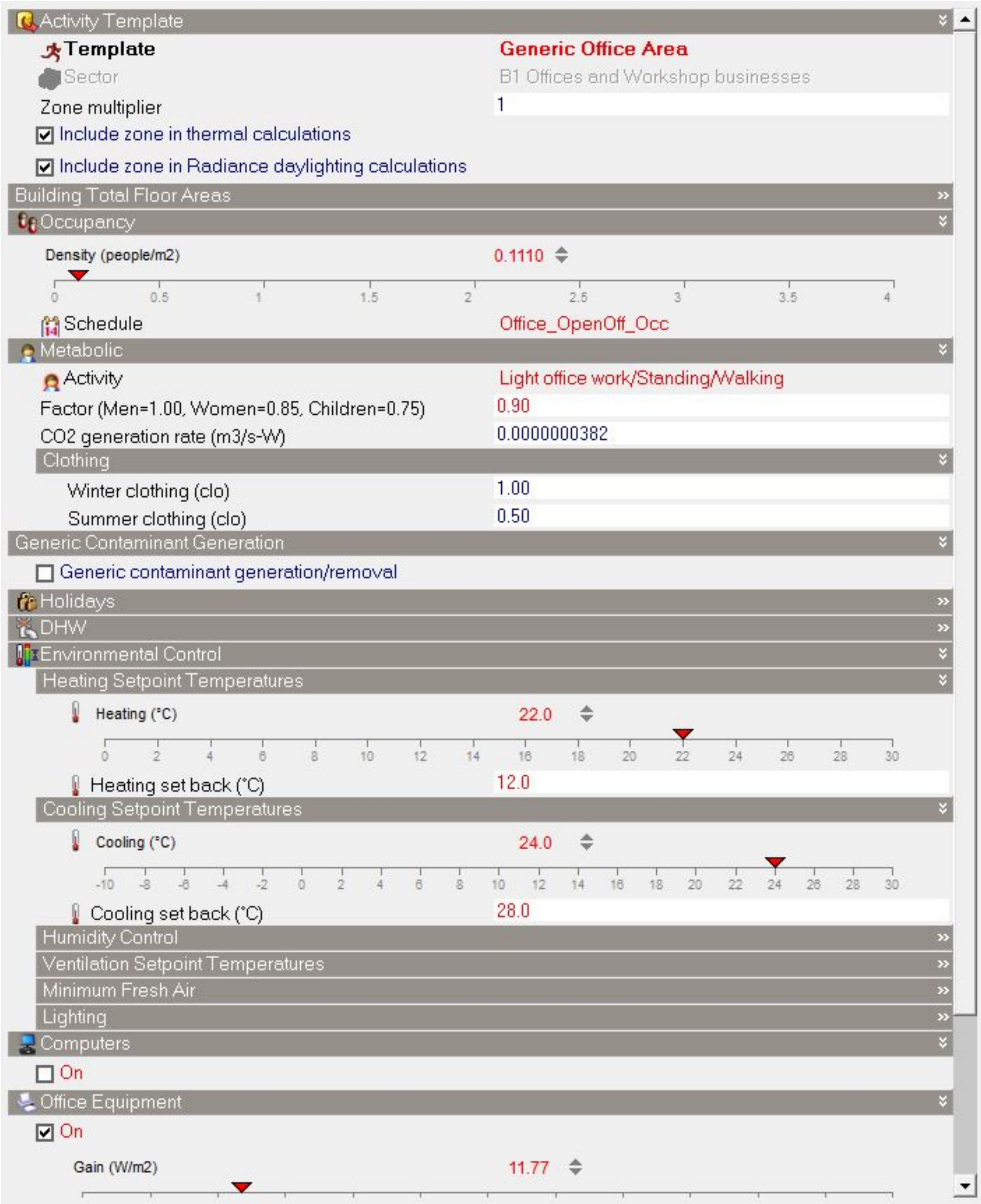

Figure 1 Occupancy input section in DesignBuilder

Furthermore, Yang et al. (2015) highlighted the critical importance of occupancy information in indoor environmental quality, energy consumption and building energy simulation. At present, occupant's impact on building energy consumption is only considered through occupancy section of energy simulation software. Input data regarding occupancy in energy simulation software, was limited to occupants' presence in fixed and scheduled patterns which was not reality (Fabi et al., 2013; Martinaitis et al., 2015). As an example, in residential buildings, the default occupancy is measured based on floor area (HUB, 2015). The ROWNER research project (HUB, 2015) showed that use of electricity in residential buildings was highly related to occupant behaviour and lifestyle which demonstrated that neglecting occupants' interactions with building systems in building energy calculations led to inaccuracies. Therefore, there is a strong need to have a methodical approach to establish occupancy profile to take into account occupant behaviours and interactions with building system. In large public buildings, the building operation is usually beyond the control of occupants and their impact on energy demand are mostly affected by their presence or movement. In this paper, the authors attempt to use crowd modelling techniques to simulate the occupant movement in such buildings in order to provide more realistic occupancy profiles for energy analysis.

3 People movement / Crowd modelling

Crowd models refers to a system that describes crowds' behaviours and their movements via predefined mechanisms (e.g. a set of formulas, a collection of rules, etc.). In the past 20 years, crowd models and simulations (Santos & Aguirre 2004; Kuligowski & Peacock 2005; Zheng et al. 2009; Chu 2009; Ng et al. 2010) were developed to provide a better understanding of crowd behaviours for the emergency services, designers and planners. Several typical crowd phenomena (e.g. clogging, pushing, and "faster-is-slower" effect) have been successfully demonstrated by various models (Zheng et al. 2009; Cheng et al. 2008; Musse & Thalmann 1997; Ebihara et al. 1992). A number of modelling approaches have been established over the years. The most recent approaches are the force-based models, Cellular Automata (CA) models, and agent-based models.

The force-based models consider that individuals in a crowd are affected by some force alike effect and their motions can be determined by the total effects of those forces. This concept was first introduced in the 'Boids' programme (Reynolds 1987) which simulated the motion of a flock of birds. In 1995, the Social Force model (Helbing & Molnar 1995) was proposed to describe the movements of pedestrians that are determined by the forces which are generated from nearby crowd and physical objects. This model was further developed (Helbing et al. 2000) to simulate panic situations by interpreting social psychology issues, and was then further tested by Parisi and Dorso (2007) in a room exit scenario. The force-based models can provide precise position and orientation information on individuals as they have continuous time and spatial representations of a crowd. However, individual behaviours (e.g. following, communications, or interactions) are often ignored as the processes of thinking and decision-making are difficult to be interpreted by mathematical equations alone.

The Cellular Automata (CA) model was another popular method which was originally invented by Von Neumann (1966) in order to create self-replicator machines in 1966. It was subsequently introduced into crowd modelling by Wolfram (Wolfram 1983; Wolfram 1986; Wolfram 2002). In the CA model, the fields (e.g. buildings, streets, etc.) are represented by a collection of equal size cells. Each cell can only be occupied by one individual at one time and a cell updates its state depending upon the states of adjacent cells. The CA modelling approach were widely used in the simulations of evacuation processes (Kirchner & Schadschneider 2002; Perez et al. 2002; Zhao et al. 2006) and in the studies of crowd movement in a bi-directional counter flow (Yu & Song 2007; Wang et al. 2012). Although the CA model has the strength of simplicity in its representation of field and crowd movement, it has some limitations. For example, the maximum crowd density is limited by the total number of cells; flow rates through doors could be inaccurate because the cells may not perfectly align with the environment geometrically (Pelechano & Malkawi 2008); and an individual's physical size has to be the same size as the cell thus the movement is not continuous in terms of time and space.

Agent-based modelling was introduced to integrate the human decision making process in crowd simulation (Dijkstra et al. 2000; Macal & North 2007). It was considered as an appropriate approach because the agents were designed to be autonomous, independent, interactive and intelligent. Agent-based models could be combined with CA modelling to represent the movements of agents (Hamagami & Hirata 2003; Bandini et al. 2007). They could also be integrated with force-based models in order to take into account individual behaviours. For example, intelligent autonomous agents can be implemented on top of steering behaviours (Reynolds 1999). Or agents could be used to simulate group behaviour alongside with the Social Force model (Braun et al. 2003). It has been suggested (Pelechano & Badler 2006) that an agent-based model can be created at the top level for communication, navigation and decision making, while the Social Force model can be applied at the bottom level to represent the crowd local motions. For occupant movement simulation, such approach will be most advantageous.

4 Conceptual framework for the integration of crowd modelling and building occupancy

As described in the previous section, the established crowd modelling techniques are offered methods to simulate the occupant movement in buildings. It is envisaged that the occupant movement model can be developed and implemented into a simulation to generate occupancy profiles and subsequently incorporated into an energy simulation tool, such as DesignBuilder. Figure 2 illustrates the key elements of the integration.

4.1 Occupants movement

There are many factors affecting the occupant movement in building, such as building layout, main function of the building, interior design, and occupant behaviour. In large public buildings, we are focusing on the building layout and occupant behaviours. The building layout will be translated from the building plans, function of each space, architecture circulation requirement and business requirement. This will determine the potential movement paths of occupants. In certain public buildings, such as airport, train/subway station, the main movement paths can be pre-determined. Localised movement in specific space can be modelled together with occupant behaviour, such as children follow parents, attraction from shopping area, use of coffee area /resting area, etc. However, such detailed level of modelling might not be necessary as the energy calculation is based on zones and movement within the zone might not be so important.

Occupant behaviours are very much dependant on the type of buildings and main function of space. In certain type of buildings, i.e. subway station, the occupant behaviours will be relatively simple, i.e. entering the station, getting on the platform or exiting the station. In other type of buildings with mixed function, occupant behaviours can be quite complex which require further study.

4.2 Occupants movement logics

The occupant movement logics is to model how the occupant is going to respond the environment and determine the direction, speed of the movement. It uses the crowd modelling techniques such as flow based discreet event method (Figure 3) for simple behaviours or agent based modelling for more complex behaviours to incorporate decision making process. Microscopic modelling techniques such as social force model, or Cellular Automata (CA) model can be used to represent the local motion of the occupants, so the speed, direction of each simulated occupant can be calculated.

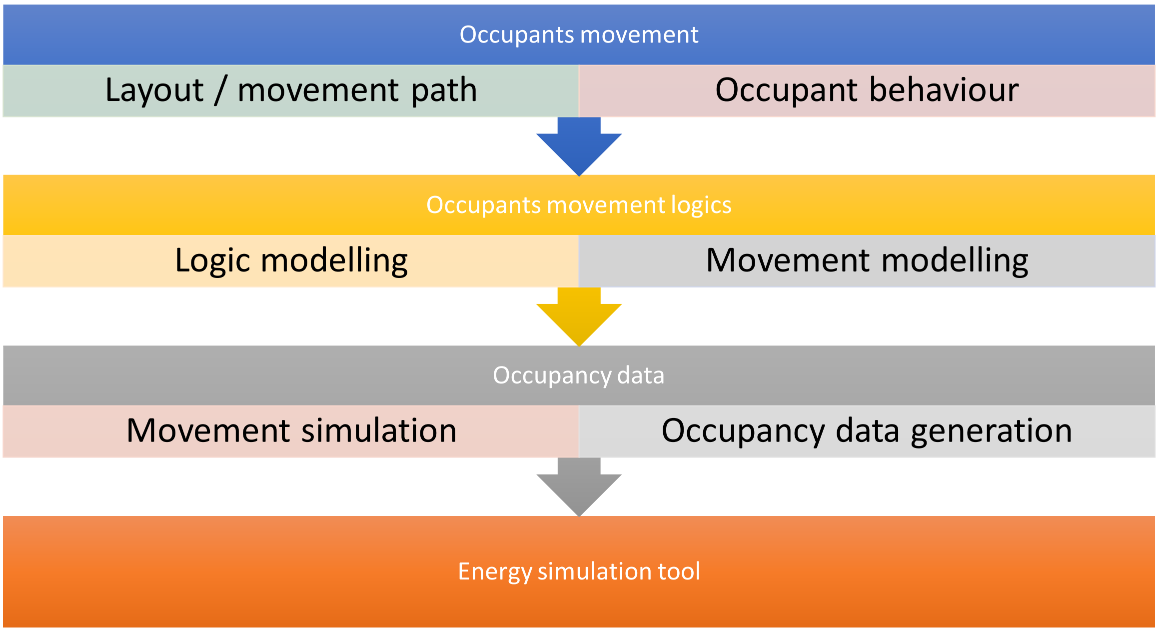

Figure 2 Conceptual framework for integrating crowd modelling and energy analysis

4.3 Occupancy data

Once the occupant movement logic is formulated, it can be implemented in a simulation environment, such as Anylogic, a multimethod simulation tool. The simulation can be carried out for a set building operational period (month, year). The microscopic crowd models are able to record positions of every occupant continuously. Data from simulations then can be used to establish dynamic occupancy profiles which will serve as input for energy simulation tools.

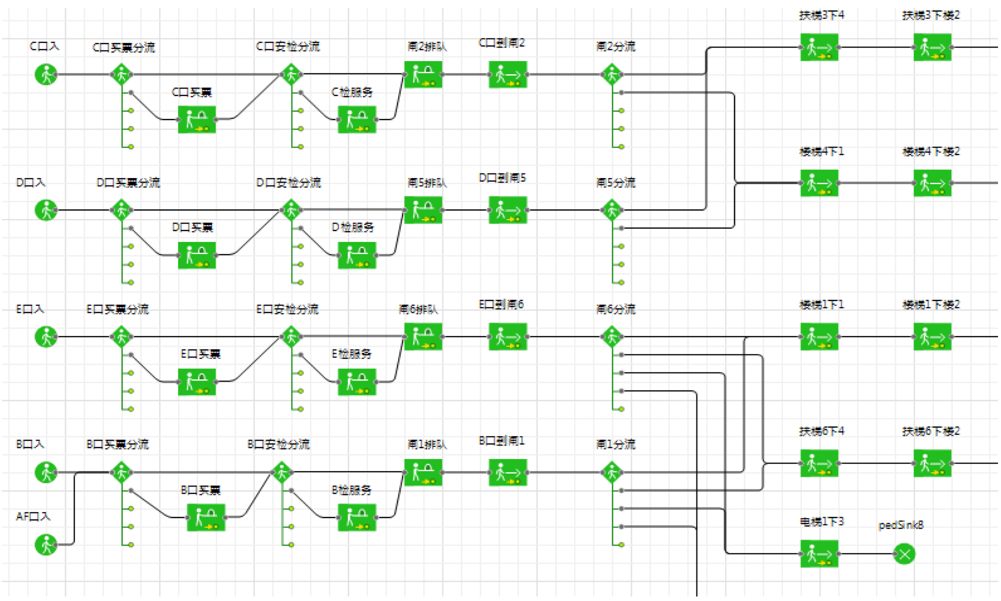

Figure 3 Example of people movement logic in a subway station

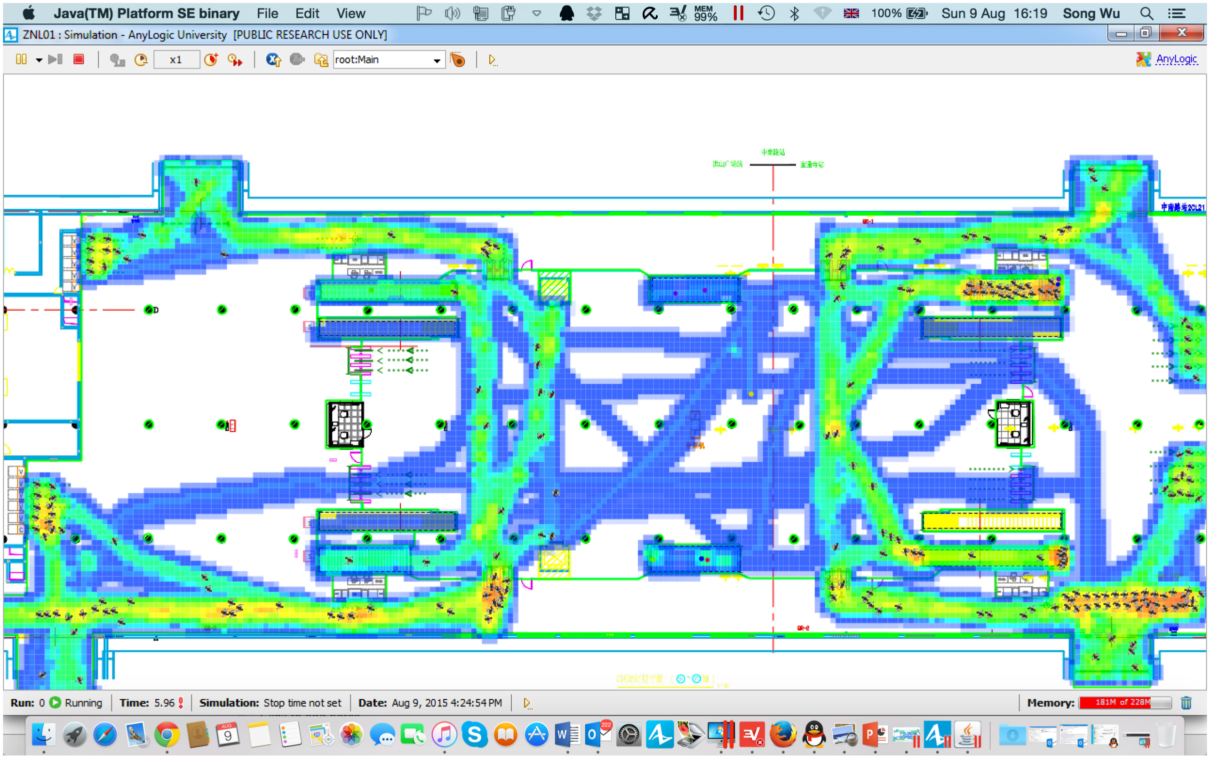

Figure 4 Example of people movement simulation in a subway station

5 Summary

This paper outlines a novel method of employing crowd modelling techniques to generate dynamic occupancy profile for energy simulation tools. It offers to develop dynamic occupancy model for large public building where people movement is one of the key factors for energy demand analysis. Crowd modelling techniques can provide more realistic people movement in building by incorporating occupant behaviours and the microscopic modelling approach can also produce high resolution occupancy profile i.e. hourly or even minutely. At the moment, this paper only presents a conceptual framework of such method. A number of challenges have been identified for the next stage of the research.

- Complex occupant behaviours representation in mixed uses environment, such as airport.
- Random movement where main movement path cannot be established.
- Data optimisation with large datasets generated by the simulation
- Dynamic integration with energy simulation tool

Further case studies also need to be carried out to assess the impact of the dynamic occupancy profile on energy demand. The authors are working on a number of case studies and the results will be reported in the future publications.

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