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THE ROLE OF SPACE DESIGN IN PREDICTION OF OCCUPANCY IN MULTI-FUNCTIONAL SPACES OF PUBLIC BUILDINGS

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ABSTRACT

In building energy predictions, the default occupancy is defined by the space function with fixed schedules. However, the occupancy of public buildings, such as galleries, recreational and educational buildings, have great variations during high and low seasons. In multi-functional public spaces, occupancy is related to space design features, which would determine the types of activities and occupants' duration of presences. This research investigates the impacts of space design on occupancy in multifunctional spaces of public buildings using multiple cases. This study confirms that considering actual space design features will contribute in improving the accuracy of energy predictions in public buildings.

1. INTRODUCTION

With buildings accounting for almost one third of the total energy consumption, there is an increasing demand to reduce the energy consumption in buildings. Over the past century, intensive research have been conducted with the aim to provide more accurate building energy performance prediction to ensure that the energy consumption anticipated during the design stage is achieved under building's operation. However, studies evidenced there is a large gap between actual and predicted building energy performance (De Wilde, 2014) which is partly due to the impact of occupants' behavior on the energy consumption (Fabi, Andersen, Corgnati, & Olesen, 2012).

The occupants' behaviours and their interactions with buildings are reflected into energy simulation tools with a limited set of variable parameters causing a high level of uncertainty in building energy performance prediction. Understanding what drive occupant's energy consumption behaviours in buildings is important to support decisions about how to reduce the building energy performance gap. Particularly, in public buildings, in which research has widely acknowledged and explored the significance of the occupants and their impact, with an aim to utilize the building energy use (Kang et al., 2018).

Consequently, it is imperative to identify and comprehend the occupant's behaviors, the parameters behind these behaviors, and the influence of design parameters as an initial step in determining the occupant's impact on building energy consumption (Wei, Jones, & De Wilde, 2014).

It's noted that occupant's roles in buildings determine their type of activities and provides an urge to move within different spaces to perform their different role during their presence in buildings (Feng, Yan, & Hong, 2015). The accurate consideration and integration of occupant's energy consumption behaviors in building energy simulation tools can improve the accuracy of building energy predictions. Occupant's behavior can be broken up into passive and active behaviors (Page, Robinson, Morel, & Scartezzini, 2008). Passive behaviour refers to occupants' presence and the production of metabolic heat, and active behaviour include using appliances, opening and closing windows, hot water use, lighting, changing control settings, etc. The way the occupants interact with the building have a great influence on its energy performance (Delzendeh, Wu, Lee, & Zhou, 2017). Occupants and their behaviors are of stochastic and complex nature (Alaaeddine & Wu, 2017), and their influence is often overlooked, misinterpreted, underestimated, or depends on hypothetical default values for occupancy (Pan et al., 2017) in buildings especially in public and educational buildings (Amore et al., 2016). This is due to the irregularity in occupant's presence and their use of public space, which make it more complex to predict.

Early research (Agle & Galbraith, 1991) noted out the essential need to acquire knowledge regarding the space utilisation and occupancy rate for building indoor quality assessment. In addition to indoor air quality (IAQ), building occupancy and density rate have been essential parameters in building evacuation and fire safety and risk assessments. However, it is a relatively new subject in building energy consumption assessment. Recently a number of studies have managed to shed the light on the direct connection between occupancy rates and building energy consumption (Kim & Srebric, 2017; Martani, Lee, Robinson, Britter, & Ratti, 2012).

In order to estimate the energy consumption of a building, after modelling the building and adjusting the location/weather data, depending on the inputs provided by the energy simulation tool, the energy modeller inputs all the available data and modifies the presumption of the software. However, if any information is unavailable, the energy modeller will rely on the software default values. Occupants' behaviors and the occupancy patterns in a building are crucial inputs for building energy consumption assessment, which are predicted based on the building/ space function. Several studies highlighted the impacts of building design features, architecture, interior design and space layout on occupancy and occupants' energy consumption behaviours. In addition to occupancy density, other design related parameters such as lighting and appliances are incorporated into energy simulation tools as space function-related inputs (figure 1).

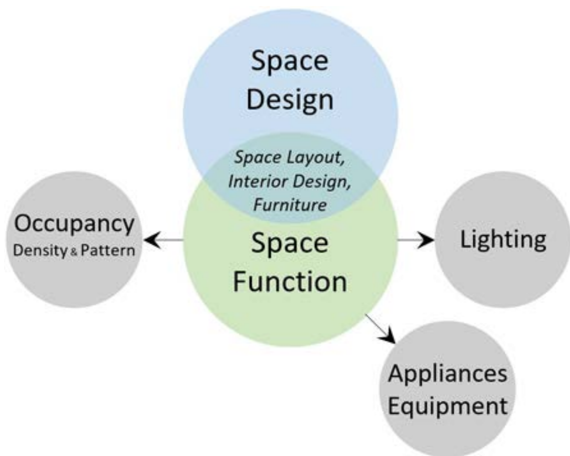

Figure 1: Space design inputs in energy simulation

2. ENERGY PREDICTION IN MULTI-FUNCTIONAL SPACES OF PUBLIC BUILDINGS

Most of the existing studies on the influence of occupants on energy consumption in buildings have focused on residential and offices, followed by commercial buildings (Delzendeh, Wu, Lee, & Zhou, 2017). There aren't as much studies on other building types such as: galleries, recreational facilities and multi-functional institutional buildings. Gul and Patidar (2015) highlighted the complex nature of energy consumption predictions in multi-functional buildings and the need for further studies on this domain.

In the aforementioned public buildings, most of the occupants are autonomous with various semi-regular and non-regular visits to the building. Therefore, occupants of such buildings are also referred to as "visitors". One of the limitations in predicting occupancy schedules in multi-functional spaces of public buildings is the various types of activities that take place within the space which consequently attract different number of visitors at different times. Several factors affect the number of visitors which makes it difficult to have an accurate occupancy density assumption.

In such buildings, occupants have limited access to building systems such as: HVAC set-points, windows, shading devices, etc. Therefore, their impacts on the energy consumption of the buildings are limited to few interactions with building elements (e.g. opening the entrance door) and passive energy consumption behaviours (e.g. presence and occupancy sensitive lighting). It can therefore be hypothesized that in public buildings with high number of visitors, passive energy consumption has noticeable impacts on the energy consumption of the buildings, however, there is a need for more quantitative analysis in this regard.

2.1. Seasonal Occupancy

In the most leading building energy prediction tools, the default occupancy of a space is defined by its function with fixed schedules. The number of visitors in public buildings such as: galleries, recreational facilities and multi-functional institutional buildings, have high variations during high and low seasons which is not fully contemplated into default occupancy schedules of energy simulation tools. According to UK governmental data regarding the monthly visits of museums and galleries in UK (Delaney, 2017), there is 33% seasonal visitor difference between high-season and low-season.

2.2. Occupancy in multifunctional spaces and the role of space design

As mentioned above, building energy simulation tools have presumptions regarding the occupancy and density (number of people per square meter) of each space based on its main function. Most of the leading energy simulation tools use ASHRAE 90.1 User's Manual standard (ASHRAE, 2016), COMNET appendix B (COMNET, 2016a), and COMNET appendix C (COMNET, 2016b) as their main sources of occupancy density and schedule presumptions in energy modelling. However, when it comes to multi-functional spaces, there isn't a specific main function or purpose, instead, a number of activities take place: sitting, standing, walking, etc. Therefore, to assign more accurate occupancy rate to multi-functional spaces, the space should be divided to different zones based on similar activities. Space furniture is a key element to take into consideration while defining the type of activity in multi-functional spaces. Thus, there is a need to provide data and specifications on the actual space furniture and interior elements, as this interior setup and layout in a multifuncctional space contributes in defining fuction purpuse and activity zones, consequently, leading to more accurate occupancy rate for these zones.

3. METHOD OF STUDY

Two large public multi-functional buildings with the total of 38 zones are studied in this research. The first case is a multi-functional gallery building (Manchester art gallery) and the second one is a central institutional building (student central building, University of Huddersfield), both located in North England.

The first case study of this research is Manchester art gallery, one of the most important galleries and art museums in North England with over half a million visitors per year, located in the heart of Manchester. The building volume is like a cube containing 3 floors with various connected spaces. The ground floor consists of: an entrance hall, two exhibition areas, a shop, an information desk (reception) and another entrance area, a café with two sitting areas, teaching and learning rooms and toilets. The first and second floors accommodate various exhibition and gallery spaces and circulation areas.

The second case study is a multi-functional lobby space located at the ground floor of the student central building at the University of Huddersfield. The space contains different zones including: the main entrance, reception, shop, food preparation and canteen, offices, services and circulation zones (Figure 2). Such spaces in institutional buildings contain constant flow of people as they accommodate several essential functions. Besides, the lobby space is directly connected to some other substantial spaces including: library, computer room, bank and gym.

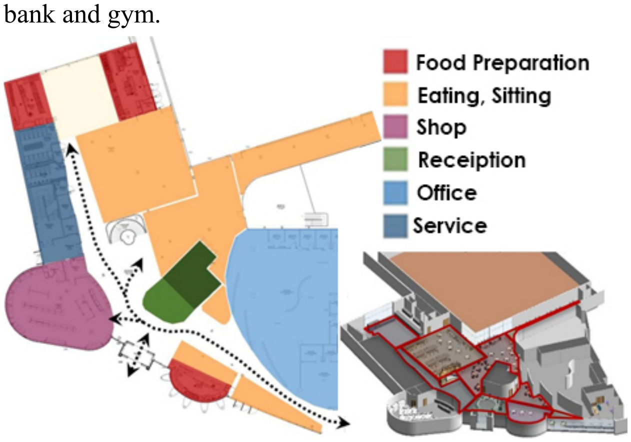

Figure 2: In-use space layout analysis: entrance, circulation and space functions

3.1. Data collection

In this research, to capture the actual occupancy of each zone within the multi-functional spaces, hourly observations were recorded. In addition to observation, other types of available data were used to capture occupancy. For instance, Google offers a weekly/hourly occupancy data for popular buildings, showing the peak hours and occupancy in real time. This new Google feature is shaped by large data from Google users and their real-time locations, and provides an accurate occupancy prediction due to access to a wide range of data.

3.1.1. Manchester art gallery: data collection

A comprehensive occupancy data of a building incorporates hourly, daily and monthly patterns. In this study, 3 sources of data were used to capture occupancy rate and pattern of each zone: UK governmental statistics of monthly visits of museums and galleries (Delaney, 2017), Google "popular times" feature and observation.

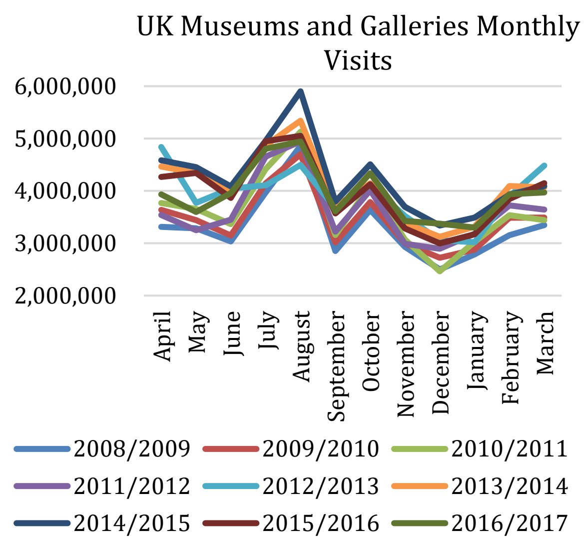

Figure 3: Total museums and galleries monthly visits in UK: 57 centres

According to the UK governmental data (Delaney, 2017), August, July and October have the most monthly visits of museums and galleries in UK respectively, and the least visits happen in January (figure 3). The statistics (Delaney, 2017) show 33% difference between high-season and low-season. The monthly occupancy differences in buildings are sometimes considered by "summer and winter design" schedules in energy simulation tools. However, the actual monthly visits of galleries and museums follow other distinctive patterns which are shown above.

Total of 25 hours of cross-sectional data was collected from Manchester art gallery. Data collection included using the same route every hour, counting the number of people in each zone, observing occupants' interactions with the space, noting the space transformation and measuring door opening time ratio.

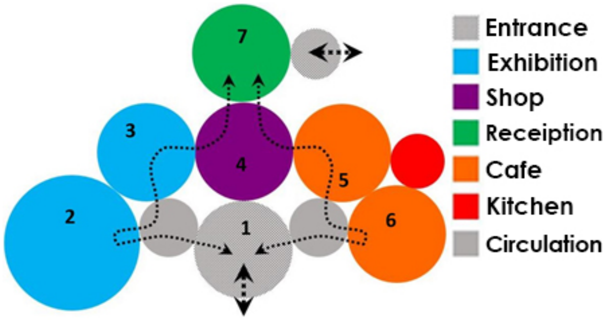

Figure 4: Data collection circulation route diagram, ground floor, Manchester art gallery, UK

Both site observations and the Google "popular times" graphs of hourly and daily visits of Manchester art gallery show that weekends have around 35% higher occupancy numbers in comparison to weekdays. Also, weekdays have quite similar occupancy numbers and patterns, except on Thursdays the longer working hours result different occupancy rates.

3.1.2. Student central building, Huddersfield: data collection

The zones are all connected and contiguous and are not physically divided which makes the entire multi-functional space act as one energy zone in the energy simulation process. However, the analysis of the space density shows different occupancy patterns in different parts. In this regard, a diagram of space functions and circulation spots was drawn with the aim to reach higher accuracy in prediction of the space occupancy (Figure 5).

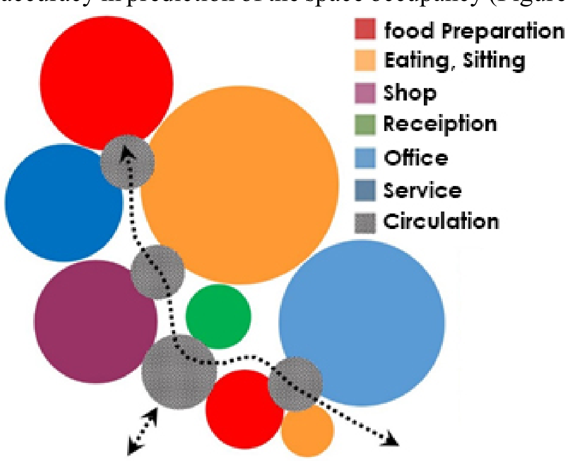

Figure 5: Space function and circulation diagram, student central building, Huddersfield, UK

4. Research findings: Actual VS predicted and lessons learned

4.1. The role of space design

One of the challenges in running energy simulation for multifunctional spaces, is how to specify the space function. The information given to the energy modeller to predict the energy consumption of a building is not often detailed enough in terms of space furniture and the actual function of the space (Figure 6). As an example, in the plans used for energy modelling of the second case study (student central building, Huddersfield, UK) the reception area was not clearly specified. Also, various activities (such as: socialising, studying, playing games, eating, etc.) that take place in different zones of the space could not be predicted without having more detailed space design and furniture data.

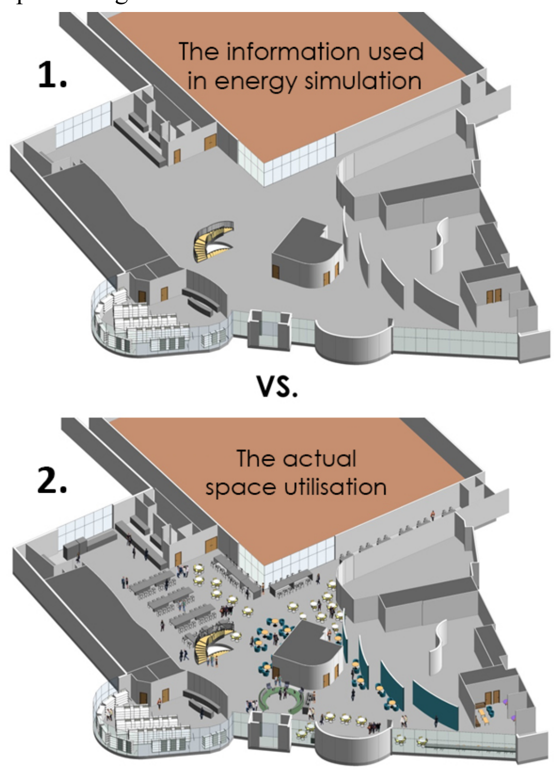

Figure 6: Information given to energy modeller VS. actual space utilisation, Student central building, Huddersfield, UK

In this study, observation of the post-occupancy transformations of the spaces, confirmed the essential role of space design in defining the type of activity in multi-functional spaces. In the first case study (Manchester art gallery, UK), two new exhibitions started in the Ground floor and the data was collected to see how the occupancy changes when new exhibitions start. Exhibition 1 transformed from a typical gallery space to a display area consisting some seating areas and four monitors: two very large (2m *3m), one large (1m* 2m) and one medium size (0.5m* 1m). The monitors consume around 150 watts every hour. The sitting areas in the main space were not enough for all the visitors, so, some audience were sitting on the floor and watching the short film. Most of the visitors spent around 8-9 minutes in this space which was the duration of the film being displayed. Changes to the space not only increased the electricity consumption, but also, increased the occupancy of the space significantly. Also, exhibition 2 got a special design, related to the exhibition theme full of plants, and contained a medium size screen. The space did not propose any type of interaction with visitors and mainly functioned as a pathway to get to other spaces, therefore, occupancy did not increase significantly. Analysis of the changes made to spaces, confirm the role of space design in creating activities and having impacts on the occupancy of spaces.

4.2. Occupancy Data and Working Hours

Occupancy assessment is not only important to predict passive energy consumption, but also, it is a crucial requirement to estimate occupants' active energy consumption patterns (Stazi, Naspi, & D'Orazio, 2017). The findings of this study show various gaps between the actual and predicted occupancy and working hours in various zones of the cases which are shown in tables 1 and 2. The "actual maximum occupancy" data are the average number of the occupancy at peak hours for each space.

Table 1 Predicted VS actual occupancy of Manchester art gallery (November), UK

Types of spaces in "Libraries, galleries and museums "	Standard ASHRAE maximum occupancy (people/m^2) used in DesignBuilder	Actual maximum occupancy (people/m^2) Manchester art gallery (November)
Display and public areas: public circulation, galleries and exhibitions	0.1497	Various occupancy 10:00 - 17:00 Thursdays 10:00 – 22:00 Heating profile 10:00 -17:00
		Circulation: 0.034
		Galleries: 0.058
		Exhibitions: 0.078
		Entrance: 0.122
Eating/drinking area	0.32	0.65 and 0.106
Reception	0.0947	0.025
Shop	-	0.156

Table 2 Predicted VS actual occupancy of student central building, Huddersfield, UK

Types of spaces in "Universities and colleges "	Standard ASHRAE maximum occupancy (people/m^2) used in DesignBuilder	Actual maximum occupancy (people/m^2) student central building, University of Huddersfield	
		Non-semester Low season	School Semester High Season
Circulation Areas	0.1065	Various occupancy 7:00 – 23:00	
		0.06	0.13
Eating/drinking area	0.2062	Canteen	
		0.179	0.52
		Sitting, socialising and eating areas	
		0.14	0.333
Reception	0.1122	0.110	0.202
Shop	-	0.083	0.209

The analysis of the gaps suggest that the presumptions regarding occupancy and working hours of some buildings types are oversimplified and outdated. Some of the gaps could be easily prevented, however, due to the great number of influential parameters, some errors seem to remain if the real-time data is not available. Most of the galleries and museums are not open till after 9 or 10 in the morning, while in the predictions their working hours start at 7 am and heating profile at 8 am. Also, these types of buildings are usually open and the most crowded during weekends which by default values are considered to be non-working days in energy prediction tools.

Large multi-functional buildings (such as: institutional buildings) have exceptionally more complex occupancy patterns which have been overlooked in most of the existing studies (Ahn, Kim, Park, & De Wilde, 2017). Sekki, Andelin, Airaksinen, and Saari (2016) confirmed that energy consumption of schools are highly related to building age and occupancy rates. However, prediction of occupancy in institutional buildings is challenging due to the large number of occupants and great occupancy variations at different times (Yang, Santamouris, & Lee, 2016). Also, another challenge in predicting energy consumption in educational buildings is that the working hours are not clear, some parts of the buildings are in use 24 hours a day.

4.3. Door opening data

Heating is one of the main sources of energy consumption in a cold climate. In public buildings, a great portion of energy is wasted through doors. Even air curtains which are used on top of entrance doors to prevent unwanted air exchange, consume energy (Basarir, 2010). Despite the considerable impact of the unwanted airflow caused by entrance door opening, it has not been fully calculated in building energy predictions due to its complicated nature. In DesignBuilder, one of the most prominent and accurate energy simulation tools, airflow caused by external doors are not calculated in heating and cooling design, and its effects on simulation are considered through ventilation (DesignBuilder, 2009).

The findings of this study show that entrance door opening time ratio depends not only on the number of people entering and leaving the building, but also, on entrance door features including its type (manual or automatic) and design. In automatic doors, the opening time setting can have a considerable impact on the door opening time ratio. For example, Karlsonn (2013) explored the energy performance and the air infiltration of different building entrance doors. He established that entrance doors are a main source of air infiltration which is affected by the frequency of use and different entrances have different impacts.

For the first case (Manchester art gallery) total of 23 set of hourly data was conducted in November. In Manchester art gallery, the main entrance door is a historic heavy wooden door and it is almost never fully open due to its weight. People just open it to the extent that lets them get in and get out. The door directly opens to the entrance/lobby space. That is why, in cold seasons the lobby area is considerably colder than other spaces.

The analysis of the observed daily/hourly door opening ratio together with the existing occupancy data of the building is shown in table 3 and figure 8.

Table 3 Average daily door opening ratio in Manchester art gallery (November)

Door opening ratio, Manchester art gallery			
Days	Maximum door opening ratio	Minimum door opening ratio	Average daily door opening ratio
Monday to Friday	50 % From 14:00 to 15:00	10 % From 10:00 to 11:00	30 %
Saturday and Sunday	65 % From 14:00 to 15:00	10 % From 10:00 to 11:00	45%

For the second case (student central building) two sets of hourly data of weekdays were collected: low season (17 hours in June) and high season (15 hours in September and November). In the student central building, there is a high flow of occupants entering/ leaving the building constantly and passing through its spaces resulting a very high door opening time ratio. The main entrance consists of two automatic doors creating a small buffer zone between outside and inside of the building. However, in cold seasons, when the door opening ratio is high, even availability of an air curtain above the door fails to provide and maintain thermal comfort in the spaces, which are immediately connected to the entrance area such as the reception and information desk. Therefore, extra heating devices are used in the reception area where full-time staff work 10 hours a day.

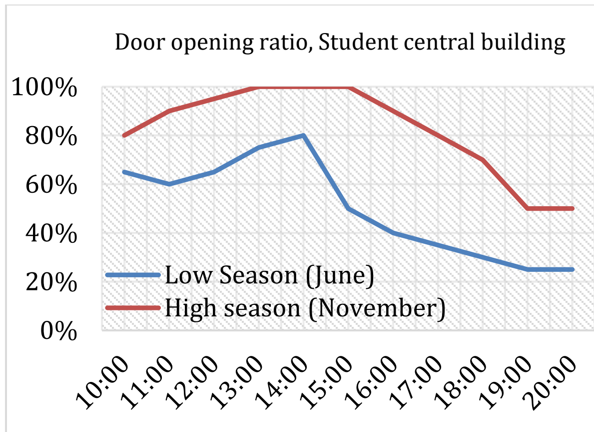

Figure 8: Hourly door opening ratio during weekdays in low and high seasons

5. DISCUSSION

The findings of this study confirm that there is a gap between the actual and predicted impacts of occupants on the energy consumption of public buildings' multifunctional spaces. The gap is due to oversimplified occupancy and outdated working hours presumptions, together with, overlooking seasonal variations in occupancy. Prediction of occupancy in multi-functional spaces of public buildings has not been investigated sufficiently through the existing literature due to its complicated nature, however, various studies have pointed out different influential parameters.

Building attraction factor, building location and target audience which specify the total number of the building visitors directly affect the occupancy density of building spaces. In many public buildings such as galleries, exhibitions, museums and institutions, the total and maximum number of visitors vary significantly in high and low seasons.

This study highlights that insufficiency of actual detailed space design data may lead to unrealistic occupancy assumptions in some building zones. For example, the maximum occupancy of eating areas in crowded buildings is directly related to the type and number of seats and tables, therefore to have an accurate prediction, this study suggests that the actual space furniture used in the space should be the basis for prediction of the maximum occupancy density. Also, This study shows that during peak hours (between 12:00 to 14:00) the eating space is almost fully occupied in both case studies. Just a small number of seats remain empty which are related to the number of people sharing one table. Therefore, it can be established there is a strong link between furniture configuration and the occupancy of eating areas at peak hours in highly visited buildings. In addition to space furniture, which specifies the density capacity of the spaces, aesthetic quality and comfort in the space have an impact on the occupancy of the space. People avoid undesirable conditions and look for pleasant ones (Cabanac, 1971). Occupants tend to spend more time in pleasant places, therefore, the durations of occupant's presence in many spaces are relevant to their design quality (Nasar, Stamps, & Hanyu, 2005). In multi-functional spaces of public buildings, various activities take place at different times. The activities may have fixed or flexible durations, and they range from less to more active. In more active zones, occupants' metabolic heat rate is higher which results greater heat gain and is considered as an input in many energy simulation tools.

Some scholars suggested that in public spaces, such as: galleries and libraries, the building exterior is responsible to communicate its function with the potential visitors, if not, the number of visitors will drop and the building will have less occupancy rates than expected (Nasar et al., 2005). Therefore, both interior and exterior design of the buildings have impacts on the occupancy of spaces.

Figure 5 summarises some of the factors and sub-factors influencing the density of people in multi-functional spaces of public buildings.

In public building with high flow of occupants, the actual entrance door opening ratio may have great impacts on the thermal comfort and energy consumption, which have been overlooked. In some buildings, the entrance door functions as a hole on the building exterier due to its very high opening ratio, which causes constant unwanted airflow. Ventilation rates through building openings (doors and windows) are related to their design features, such as size, type of opening, and their location on the exterior façade (Roetzel et al., 2010). This study shows that entrance door opening ratio is related to number of people entering and leaving the building and design features.

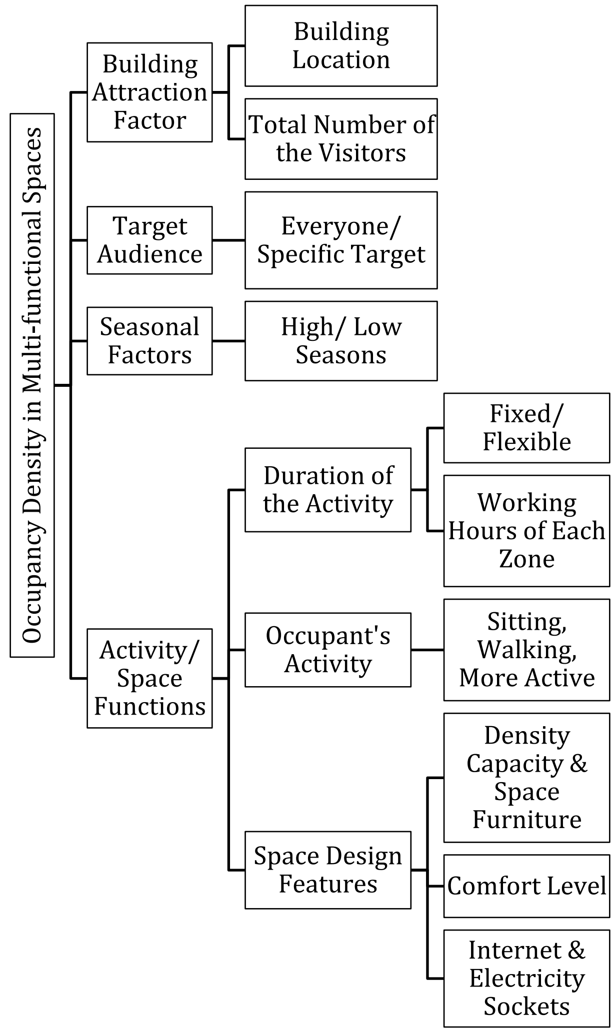

Figure 5 Factors and sub-factors affecting occupancy in multi-functional spaces of public building

CONCLUSION

Occupancy is a key factor in building energy consumption assessment. In multi-functional spaces of public buildings, prediction of occupancy is very complicated due to high number of occupancts and monthly, daily and hourly variations. However, the occupancy estimation has been over simplified in existing energy simulation tools which can be improved. In this study, the total of 38 various zones within two public buildings (one gallery and one multi-functional educational building) were observed in 3 months. Based on the findings of this study, parameters such as: building attraction factor (building location, and the total number of visitors), target audience, seasonal factors and type of activity influence the occupants' density in multi-functional spaces. Also, the gap between actual and predicted occupancy in multifunctional spaces of public buildings are mainly caused by over-simplification of differenct types of activities taking place in these spaces which ,as well, acurratly determining the duration of occupants' presences. This study confirms that, space design features such as: density capacity of the space through space furniture, availability of specific facilities such as wifi and electricity sockets, together with, comfort level influence the occupancy of multi-functional spaces. Future extension of this research aims to quantify the impacts of space design and occupancy on energy consumption in multi-functional spaces to provide a practical outcome for energy modellers and the softwarer developers.

REFERENCES

Agle, E., & Galbraith, S. (1991). *Building Air Quality: A Guide for Building Owners and Facility Managers*. Retrieved from Washington DC.

Alaaeddine, R., & Wu, S. (2017). Application of supervised learning methods to better predict building energy performance.

Amore, M., Rossoni, M., Marengo, M., & de Wilde, P. (2016). Impact of occupancy on energy consumption by an educational facility.

Basarir, M. N. (2010). *Energy Appraisal of Retail Units: Assessing the Effect of Door Operation on Energy Consumption and Thermal comfort.* (MPhil), University of Cambridge.

De Wilde, P. (2014). The gap between predicted and measured energy performance of buildings: A framework for investigation. *Automation in Construction, 41*, 40-49. doi:10.1016/j.autcon.2014.02.009

Delaney, L. (2017). *Statistical data set: museums and galleries monthly visits*. UK Government Retrieved from https://www.gov.uk/government/statistical-data-sets/museums-and-galleries-monthly-visits#summary.

Delzendeh, E., Wu, S., Lee, A., & Zhou, Y. (2017). The impact of occupants' behaviours on building energy analysis: A research review. doi:https://doi.org/10.1016/j.rser.2017.05.264

DesignBuilder. (2009). *DesignBuilder 2.1 User's Manual*. Retrieved from http://www.designbuildersoftware.com/docs/designbuilder/DesignBuilder_2.1_Users-Manual_Ltr.pdf

Fabi, V., Andersen, R. V., Corgnati, S., & Olesen, B. W. (2012). Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment, 58*, 188-198. doi:10.1016/j.buildenv.2012.07.009

Feng, X., Yan, D., & Hong, T. (2015). Simulation of occupancy in buildings. *Energy & Buildings, 87*, 348-359. doi:10.1016/j.enbuild.2014.11.067

Gul, M. S., & Patidar, S. (2015). Understanding the energy consumption and occupancy of a multi-purpose academic building. *Energy & Buildings, 87*, 155-165. doi:10.1016/j.enbuild.2014.11.027

Kang, H., Lee, M., Hong, T., & Choi, J. K. (2018). Determining the optimal occupancy density for reducing the energy consumption of public office buildings: A statistical approach. *Building and Environment*, *127*, 173-186.

Karlsson, N. (2013). Air infiltration through building entrances.

Kim, Y.-S., & Srebric, J. (2017). Impact of occupancy rates on the building electricity consumption in commercial buildings. *Energy and Buildings, 138*, 591-600. doi:10.1016/j.enbuild.2016.12.056

Martani, C., Lee, D., Robinson, P., Britter, R., & Ratti, C. (2012). ENERNET: Studying the dynamic relationship between building occupancy and energy consumption. *Energy & Buildings, 47*, 584-591. doi:10.1016/j.enbuild.2011.12.037

Nasar, J. L., Stamps, A. E., & Hanyu, K. (2005). Form and function in public buildings. *Journal of Environmental Psychology, 25*(2), 159-165. doi:10.1016/j.jenvp.2005.03.004

Page, J., Robinson, D., Morel, N., & Scartezzini, J. L. (2008). A generalised stochastic model for the simulation of occupant presence. *Energy & Buildings, 40*(2), 83-98. doi:10.1016/j.enbuild.2007.01.018

Pan, S., Wang, X., Wei, S., Xu, C., Zhang, X., Xie, J., ... & de Wilde, P. (2017). Energy waste in buildings due to occupant behaviour. *Energy Procedia*, *105*, 2233-2238.

Roetzel, A., Tsangrassoulis, A., Dietrich, U., & Busching, S. (2010). A review of occupant control on natural ventilation. *Renewable and Sustainable Energy Reviews, 14*(3), 1001-1013. doi:10.1016/j.rser.2009.11.005

Stazi, F., Naspi, F., & D'Orazio, M. (2017). A literature review on driving factors and contextual events influencing occupants' behaviours in buildings. *Building and Environment, 118*, 40-66. doi:10.1016/j.buildenv.2017.03.021

Wei, S., Jones, R., & De Wilde, P. (2014). Driving factors for occupant-controlled space heating in residential buildings. *Energy and Buildings, 70*, 36-44. doi:10.1016/j.enbuild.2013.11.001