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PHD THESIS BOOKLET

*Analysis and Modelling of Occupant Behaviour to Support  
Building Design and Performance Optimisation*

**Zsófia DEME BÉLAFI**

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## ABBREVIATIONS

ACR	Air Change Rate
AHU	Air Handling Unit
ASHRAE	American Society of Heating, Refrigerating, Air-Conditioning Engineers
BCVTB	Building Control Virtual Test Bed
BEM	Building Energy Modelling
BMS	Building Management System
BPS	Building Performance Simulation
CBE	Center for the Built Environment, Berkeley
DHW	Domestic Hot Water
DNAS	Drivers-Needs-Actions-Systems
FMI	Functional Mock-up Interface
FMU	Functional Mock-up Unit
HVAC	Heating, Ventilation and Air-Conditioning
IAQ	Indoor Air Quality
IDA ICE	IDA Indoor Climate and Energy
IDP	Integrated Design Process
IEA EBC	International Energy Agency, Energy in Buildings and Communities Programme
IRB	Institutional Review Board
LEED	Leadership in Energy and Environmental Design
MODE model	Motivation and Opportunity as Determinants
NMBE	Normalized Mean Bias Error
OB	Occupant Behaviour
OBFMU	Occupant Behaviour Functional Mock-up Unit
OXML	Occupant Behaviour eXtensible Markup Language
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
SCT	Social Cognitive Theory
SFH	Single Family House
SHOCC	Sub-Hourly Occupancy-Based and Complex Control Models
TPB	Theory of Planned Behaviour

## NOMENCLATURE

$N_s$ =	completed sample size needed (notation often used is $n$ )
$N_p$ =	size of population (notation often used is $N$ )
$p$ =	proportion expected to answer a certain way (50% or 0.5 is most conservative)
$B$ =	acceptable level of sampling error (0.05= $\pm$ 5%; 0.03= $\pm$ 3%)
$C$ =	Z statistic associate with confidence interval (1.645=90% confidence level; 1.960=95% confidence level; 2.576=99% confidence level)
$y_i$	measured data
$\bar{y}$ .	averaged measured data
$\hat{y}$ =	modelled data

## 1. Background, Motivation

In recent years, both legislative instruments and market demand drive the construction industry towards high-performing, low-energy consuming buildings [1] [2]. However, without considering the human dimension, technologies alone do not necessarily guarantee high performance in buildings [3] [4]. Occupant behaviour is a leading factor influencing energy use in buildings [5]. Occupant behaviour in buildings primarily refers to occupants' comfort preferences, presence and movement, and adaptive interactions with building systems that have an impact on the performance of buildings (e.g., thermal, visual and acoustic comfort provision; indoor air quality; energy use). Such interactions include adjusting thermostat settings, opening or closing windows, dimming or turning on/off lights, pulling up or down window shades and blinds, switching on or off plug loads, and consuming domestic hot water.

To represent our buildings' energy balance and indoor environmental conditions and also to lower the energy consumption of buildings, the use of building performance simulation (BPS) tools is essential in the design process in case of both new construction and retrofitting projects [6] [7] [8] [9] [10] [11]. There is a performance gap observed between real and predicted energy consumption of buildings. The core issues are not with deterministic factors, such as the physical characteristics of building envelope, HVAC systems, lighting and electrical equipment, which have been investigated for the past few decades. Rather, this gap was found to be mostly caused by over-simplifying occupants' behaviour and presence patterns in buildings during the design process [6].

Occupant behaviour is currently represented in BPS software via oversimplified and predefined deterministic schedules or fixed rules, which result in deterministic and homogeneous results that do not reflect the stochastic nature, dynamics, and diversity of occupant behaviour. For example, occupants can open windows due to various reasons: (1) feeling hot (thermal comfort driven), (2) feeling stuffy (indoor air quality driven), and (3) arriving in a space (event driven) [12]. Such determinants of window opening actions have been confirmed through multiple large-scale surveys and field studies [13]; probabilistic models developed from these studies have in turn been adopted by several BPS programs. These stochastic behaviour models are data-driven, and they generally improve the representation of realistic adaptive occupant activities in BPS programs [6].

This research work was intended to build upon existing research findings and to enhance the current understanding and modelling of energy-related occupant behaviour in buildings.

## 2. Research Questions

- I. What is the quantifiable impact of energy-related occupant behaviour in commercial and residential buildings? What could be the depth of occupant behaviour analysis in case of market-driven building design and performance optimisation projects?
- II. What are the drivers and trends in energy-related building occupant behaviour in the office environment?
- III. Is the energy-related behaviour of office occupants affected by a change in the physical office environment, namely, changes in seating layout, environmental control options and corporate communication about sustainability?
- IV. What motivating factors drive window use behaviour in a school building?
- V. How can stochastic occupant behaviour models used to support building performance simulation practise?

### 3. Methods Used

Firstly, I conducted literature review work at the very beginning of research. This was followed by two real-life case studies where I investigated and modelled occupant behaviour in an office and in a residential building project within the constraints of two typical Hungarian construction-market sustainable consultancy projects using dynamic building performance simulations.

Findings of these case studies lead me to the conclusion that although the energy performance predictions became more precise with my methods applied there (within a strict resource and time constraint), there is a strong need to gain more information about human behaviour in our buildings. Also, it is important to enhance our current occupant behaviour modelling methods to make them suitable for market-driven projects as well.

Therefore, in my following work I focused on addressing these issues. I conducted three data collection campaigns where I applied different methods to gain information on occupant behaviour in office spaces and in a primary school building: Time-Series Data Collection and Analysis, Questionnaires and Interviews.

After obtaining more information on the behaviour of people in different physical settings, I continued my work on the integration of this knowledge into building performance simulation software programs to enhance the applicability of occupant behaviour modelling in real-life design projects as well. At this part, I conducted modelling method categorization works and compiled a library of occupant behaviour models.

#### 3.1 Literature Review and Critical Analysis

As a first step of research, I conducted a literature review and critical analysis to identify gaps and missing pieces of knowledge in the field of energy-related occupant behaviour in buildings. Major part of currently relevant literature can be found in literature databases of international IEA EBC projects Annex 53 and 66 [14][15]. Also relevant international journals were identified and scanned to find the current state-of-the-art knowledge of the field. Furthermore, I could identify current hot topics and trends in the field by attending relevant international conferences, symposiums and project meetings where I had the chance to get to know ongoing research works by experts in building occupant behaviour. Short and long-term international student exchange programs (to University of Nottingham, Norwegian University of Technology (NTNU) and Lawrence Berkeley National Laboratory) allowed me to get insights into the work conducted in this field and also helped to identify the direction of my research.

Serving as the basis of my work on occupant behaviour modelling in building performance simulation, I **reviewed stochastic occupant behaviour models in literature** to identify and compile a list of 127 currently available stochastic occupant behaviour models in the field, covering the following categories:

##### *Occupant Behaviour Types:*

occupant movement and different types of occupant interactions with windows, doors, shading, blinds, lighting systems, thermostats, fans, HVAC systems, plug-loads; having hot/old beverages and adjusting clothing levels.

##### *Building Types:*

office, residential and school buildings.

*Publication Date of the Models Reviewed:*

1970-2015.

The review of these models helped me to identify gaps in the current modelling techniques and focus areas.

### 3.2 Dynamic Building Performance Simulation

I used dynamic building performance simulation in the case studies summarized in main result I. For simulations I chose the commonly used and trusted dynamic, zonal simulation tool IDA ICE [16] [17] (Figure 1) for annual energy saving estimation. For a dynamic energy model, it is essential to use appropriate parameters to represent the building.

In case of **the office building case study** (main result I/I), I used two types of models for different purposes: a partial (one-floor) model and a whole-building energy model. Data input to the two types of energy models:

*The partial building energy models*

I carried out occupant behaviour-related sensitivity analyses using a partial one-floor model representing an average floor (2nd floor) of the building. Based on results from the onsite walk-through, interviews, and fan coil (FC) valve state investigations, I could build up a real thermostat-use case. This case was compared in energy consumption to a base-case where thermostat setpoint modifications were not allowed for users, i.e., the system was controlled by fixed setpoints: with a minimum 22.5 °C and a maximum 24 °C. I used the same partial building energy model for a window-opening sensitivity analysis where window opening frequencies and durations were evaluated in terms of heating energy consumption during the winter season. This analysis supported the calibration process of the whole-building energy model.

*The whole-building energy model*

I determined physical parameters related to the construction materials and installation quality based on a comprehensive building audit of the case study office building. As-built plan drawings were used to establish the building's geometry and construction materials. Thermographic images were used to identify thermal bridges and leaking windows and doors that were installed in low quality. HVAC parameters were determined based on the audit of the primary HVAC equipment including the boiler, chillers and air handling units (AHU), as well as the secondary systems such as FC units. The building audit results enabled me to do an indirect analysis of occupant behaviour (occupancy, FC usage (valve states), window opening, manual shading control overwrite frequency, plug loads, lighting, personal heaters).

For model calibration, the owner provided five years (2009–2013) of utility bills and monthly submeter logs. The calibration process included monthly analysis and fine-tuning of operational patterns due to the effect of occupants' behaviour and control actions (see Section 5 as well). As an indicator of the model calibration quality, I used normalized mean bias error (NMBE), which is defined in ASHRAE Guideline 14-2002 [18]. This guideline is widely used for building energy model calibration. The NMBE acceptance threshold is 5% if monthly calibration is used. NMBE is calculated as

$$\text{NMBE} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{n \times \bar{y}_i} \times 100\% \quad (1)$$

where  $y_i$  is the measured data with  $n$  data points, which is averaged in  $\bar{y}$ . This is compared to the modelled values ( $\hat{y}$ ).

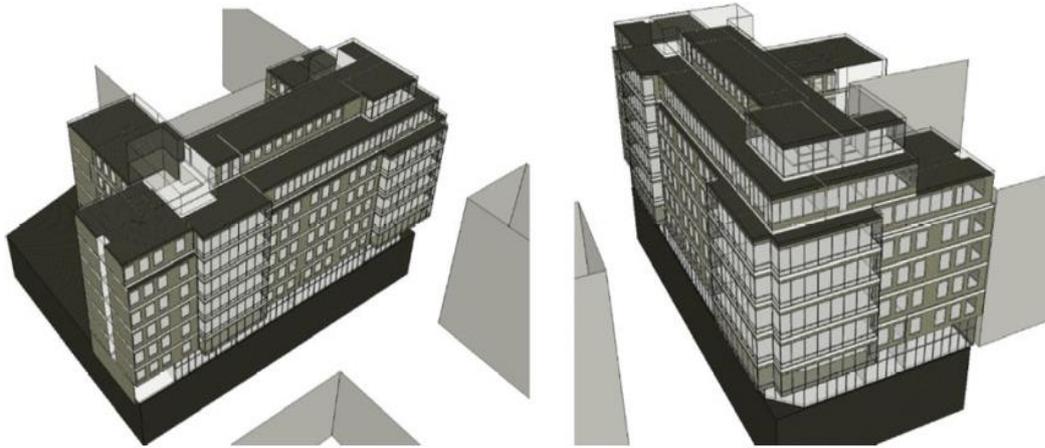


FIGURE 1 - 3D VIEW OF THE OFFICE BUILDING ENERGY MODEL IN IDA ICE

In case of **the residential case study** (main result I/II), I minimised the yearly energy demand of the building by means of passive energy efficiency measures. I conducted a parametric study using dynamic building energy modelling for yearly energy consumption estimations in software IDA Indoor Climate and Energy (IDA ICE).

I investigated the order of magnitude of change in annual energy consumption patterns after a possible change in occupant behaviour. As part of this set of sensitivity analysis, the effect of total occupant number change and heating/cooling setpoint adjustments were considered. I compiled the following household composition scenarios:

- *2 residents: 2 adults, both working*
- *3 residents: 2 adults and one child*
- *4 residents: 2 adults and 2 children*
- *5 residents: 2 adults and 2 children and one grandmother*

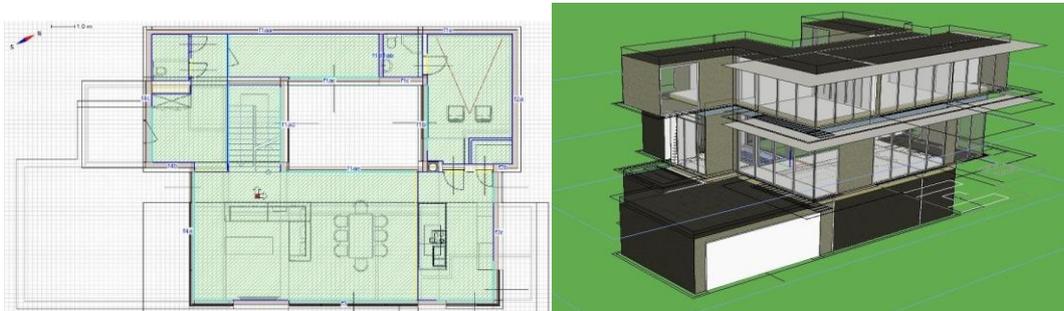


FIGURE 2 - FLOOR PLAN ZONING AND 3D VIEW OF THE MODEL IN IDA ICE SOFTWARE

### 3.3 Questionnaires and Interviews

It is often the case when investigating occupant behaviour in buildings that objective measurement data are not available or not understandable on its own. In these cases questionnaire surveys and interviews are useful tools to complement an existing dataset (see project summarized in main result IV as an example) or even to get new knowledge on a larger sample in a poorly researched area (see projects summarized in main results II and III). I conducted **transversal questionnaires and interview campaigns** to support my data-collection projects:

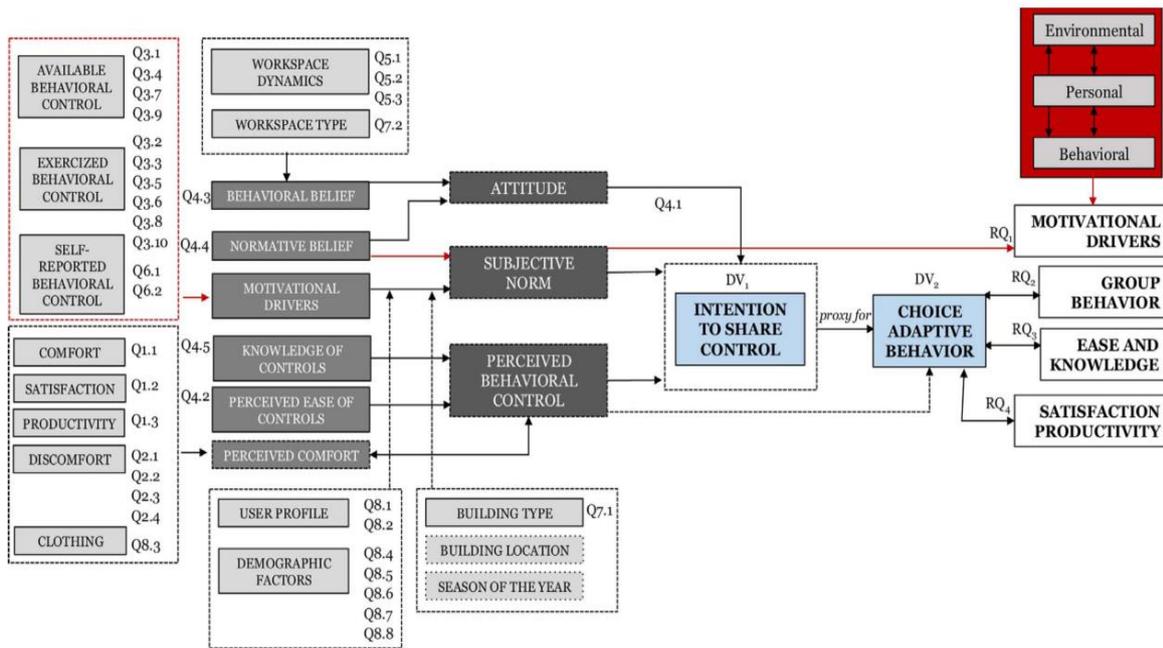
I conducted **qualitative individual interviews** with teachers using the classrooms under investigation. Classroom 1 (English language) has been used by two English teachers, one of them was interviewed. Classroom 2 (German language) has been used by only one teacher who could not be interviewed. Instead, the headmaster of the school has been interviewed who had several decades of work experience with the above mentioned German teacher and knew her way of thinking and daily routine. Both interviews have been conducted by telephone at a predefined appointment to allow interviewees the freedom to choose the appropriate timing for the interview. This way the interview could be conducted in a comfortable environment, where respondents appeared to speak freely. Interviews have been conducted after the data collection campaign, in November 2017. The interview guide protocol was flexible enough to allow respondents to discuss other topics that they felt were important. Nevertheless, I checked that the topics in the interview guide were covered throughout the discussions.

Although the sample size does not allow for statistical generalization, it gives a very precise picture with an appropriate resolution on the behaviour, daily schedule and attitude of different teachers.

Based on an interdisciplinary research framework developed by us (team of four: social scientist, architects and HVAC engineer), a **cross-sectional survey** was designed consisting of 37 questions. Results of the Hungarian data collection campaign is summarized at main result II. The online survey was designed to investigate how social-psychological and demographic factors (i.e., independent variables) are related to occupants' behavioural intention in sharing the control systems (i.e., dependent variables) and identify occupants' choice of adaptive actions from a group of occupants by analysing the statistical inference of the estimated parameters and the relative importance of each of these factors. Additionally, the survey results are expected to provide important social-psychological (e.g., group norms) findings to building efficiency solution and simulation modelling by considering both building technology and social context.

The survey was designed to collect responses from the targeted administrative staff and faculties among 14 universities and research centres across four continents (America, Asia, Europe, Australia) and six countries (USA, China, Italy, Hungary, Poland, Australia). The survey was conducted already in three university institutions in Italy, in one university in the USA and in Hungary. The survey is currently open in several other countries (USA, three institutions in Poland, Australia, and China). The survey is anonymous and no personal identification has been/will be collected. Each survey response was/will be recorded in the Quatrics software together with the date of compilation and geographical coordinates.

Every survey question in the questionnaire represents one or more independent variables to articulate the 37 measures of the investigation (Figure **Hiba! A hivatkozási forrás nem található.**3). Two additional variables (building location and season of the year) can be directly inferred from the survey without compromising data privacy issues. All measures except for control variables are estimated by participants' responses to the items with a five-point Likert-type scale [19].



**FIGURE 3 - THE PROPOSED QUESTIONNAIRE TO MEASURE THE RESEARCH QUESTIONS, CONSISTING OF 37 QUESTIONS CONNECTED TO DEPENDENT AND INDEPENDENT VARIABLES [19]**

To ensure future quality of international comparison results, it was crucial to apply a rigorous survey translation process. The survey instrument, originally developed in English, was translated into national questionnaires, in diverse languages (Italian, Polish, Hungarian, Chinese). I developed a translation guideline protocol to ensure equivalence across languages. Semantic, conceptual, and normative equivalence of survey questions is guaranteed by re-translating survey questions back into English before finalizing translated versions, by following a double translation process (DTP) [20], one of most adopted translation processes for survey questionnaires.

The interdisciplinary framework introduced above and the questionnaire itself was worked out by a team of 4: a social scientist, two building energy professionals and myself. Whereas I conducted the Hungarian data collection campaign. The Qualtrics survey link was sent to the Hungarian sample through the institutional e-mailing list of six universities during the hot, summer season (from April 18th to November 13th, 2017). Two reminders were sent to the participants. I provided incentive raffle opportunities (3x5000 HUF gift cards for stationary) to increase response rate. A total number of 207 valid responses were collected from the online questionnaire.

As part of the study summarized in main result III, I developed and conducted two cross-sectional surveys both before and 1 year after the office moving, in the summer season. The questionnaire was developed to collect information on the use of environmental controls. I used the survey data to discover the differences in the very same office workers' environmental perception and behaviour in the different office settings.

### 3.4 Time-Series Data Collection and Analysis

I conducted long-term measurements in a school building targeting the investigation of window use behaviour on a multi-season time-series dataset.

Based on the complaints of teachers, two classrooms were identified where there are thermal comfort issues perceived during winter season. IAQ and window opening monitoring devices were installed in these classrooms to investigate the problem. Along with the indoor condition monitoring sensors, energy consumption and outside condition monitoring devices were installed (see full list of measurement points below) in February 2017. In the framework of this project, 8 months of data from the system was available: 15/02/2017-20/09/2017 with a summer break in the middle (15/06/2017-31/08/2017). See Table 1 for more details on the parameters of the two classrooms.

TABLE 1 - MAIN CHARACTERISTICS OF THE TWO CLASSROOMS INVESTIGATED

Classroom	1 (English)	2 (German)
Floor	2nd	1st
Net floor area	28.6 m <sup>2</sup>	28.6 m <sup>2</sup>
Room height		
Room volume	109.6 m <sup>3</sup>	109.6 m <sup>3</sup>
Orientation	South-East	South-East
Nr. of windows	2	2
Type of windows	Historic double skin box-type	Historic double skin box-type
Maximum nr. of pupils	20	20
Nr. of teachers using the room	2	1

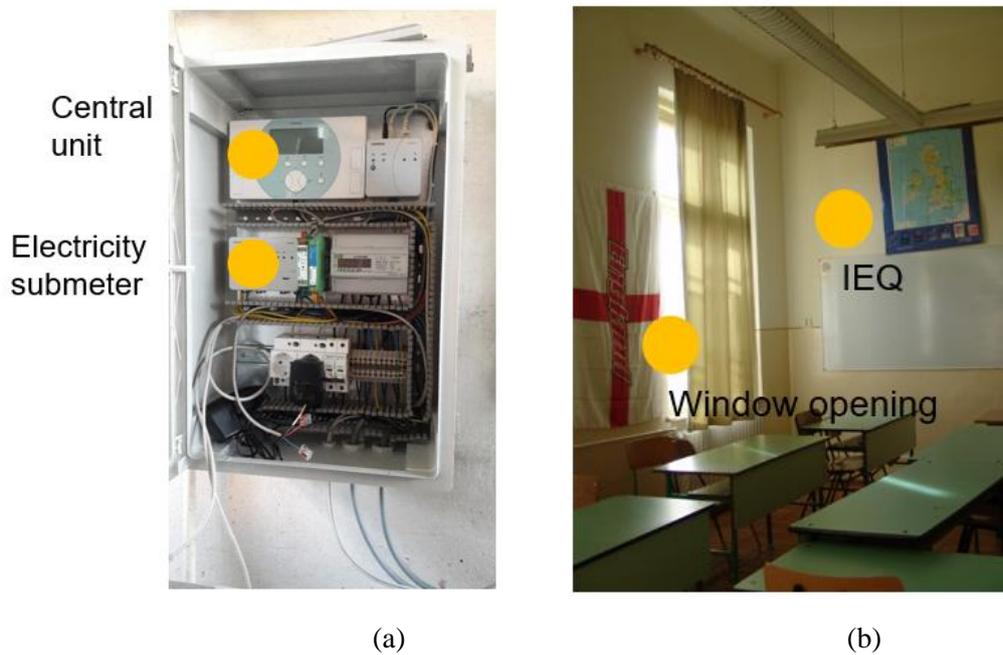
Continuous monitoring points in the elementary school building:

- Weather station on site: outdoor temperature (T<sub>out</sub>), frequency: 15 mins;
- Whole building electricity consumption, frequency: 15 mins;
- Whole building natural gas consumption (all used by heating system), frequency: 15 mins;
- Electricity submeter for heating consumption, frequency: 15 mins;
- Air temperature, and window opening sensors in two classrooms, CO<sub>2</sub> sensor in one of them, frequency: 30 secs.

TABLE 2 - IEQ MONITORING SENSOR SPECIFICATIONS (SIEMENS, SYNCO LIVING CALIBRATED SYSTEMS)

Measured parameter	Applied sensor	Nr. of sensors	Range	Accuracy	Acquisition rate
Indoor dry-bulb air temperature	QAA 910, NTC 10 kOhm resistor	2	0...50 °C	±2%	30 s
Outdoor dry-bulb temperature	QAC 910, NTC 10 kOhm	11	-50...50 °C	±2%	15 min
Indoor CO <sub>2</sub> level	QPA 2000, NDIR Symaro	1	0...2000 ppm	≤± (50 ppm + 2 %)	30 s
Window opening	Gamma wave	4 with 2 signals	0 (closed), 1 (open)	N/A	30 s

See Figure 4 for photographs of the installed monitoring devices at the central electricity meter (a) next to the main entrance and indoor sensors in the English language classroom on the second floor.



**FIGURE 4 - MONITORING SYSTEM COMPONENTS (A) CENTRAL MONITORING UNIT AND ELECTRICITY SUBMETER, (B) INDOOR MONITORING DEVICES IN A CLASSROOM**

Time-series data processing and analysis: after a thorough data cleaning, the association process was followed of behavioural control actions with time of the day, environmental variables and social, contextual parameters. The dataset was analysed using correlation analysis on to assess the influence of recorded parameters on behaviour and employing goodness-of-fit estimators to evaluate the level of statistical significance of the correlations.

After good statistical correlations were found, a stochastic occupant behaviour model could be developed with the method described below. This method has been developed by UNIVPM (Università Politecnica delle Marche).

**TABLE 3 - THE GENERAL WEIBULL FORMULA [21]**

Increasing form	Decreasing form
$P_{\tau}\{A\} = F(x_{\tau}) = \begin{cases} 1 - e^{-\left(\frac{x_{\tau}-u}{l}\right)^k \frac{\Delta\tau}{\tau}} & \text{if } x_{\tau} > u \\ 0 & \text{if } x_{\tau} \leq u \end{cases}$	$P_{\tau}\{A\} = F(x_{\tau}) = \begin{cases} 1 - e^{-\left(\frac{u-x_{\tau}}{l}\right)^k \frac{\Delta\tau}{\tau}} & \text{if } x_{\tau} < u \\ 0 & \text{if } x_{\tau} \geq u \end{cases}$

The formula F in Table 3 is a discrete C Weibull cumulative function. The parameters u, l, and k are three undetermined constant coefficients that are independent of the environmental stimulus and time;

$\Delta\tau$  is a discrete time step in the measurement or simulation; and  $\tau_c$  is a known time constant (e.g., 1 h). The coefficients in the formula have a physical meaning:

- $\mathbf{u}$  is a threshold parameter that represents the threshold characteristic of the occupant's physical response to the environmental stimulus.  $\mathbf{u}$  has the same dimension as  $\mathbf{x}$ ;  $\mathbf{x}-\mathbf{u}$  represents how far the environmental condition  $\mathbf{x}$  exceeds the occupant's threshold  $\mathbf{u}$ ;
- $\mathbf{l}$  is a scale parameter that represent the linear effect of the environmental stimulus.  $\mathbf{l}>0$  and has the same dimension as  $\mathbf{x}$ ;  $\mathbf{x}-\mathbf{u}/\mathbf{l}$  is a dimensionless measure of the environmental parameter  $\mathbf{x}$ ;
- $\mathbf{k}$  is the shape parameter that represents a power exponent for the effect of the environmental stimulus.  $\mathbf{k}>0$ , and  $\mathbf{k}$  is dimensionless.

The three parameters  $\mathbf{u}$ ,  $\mathbf{l}$ , and  $\mathbf{k}$  quantify how the occupants react to a certain environmental discomfort.

### 3.5 OBXML Library Development

My **method to develop a stochastic occupant behaviour model library** in the XML programming schema (obXML library) is introduced in Figure 5.

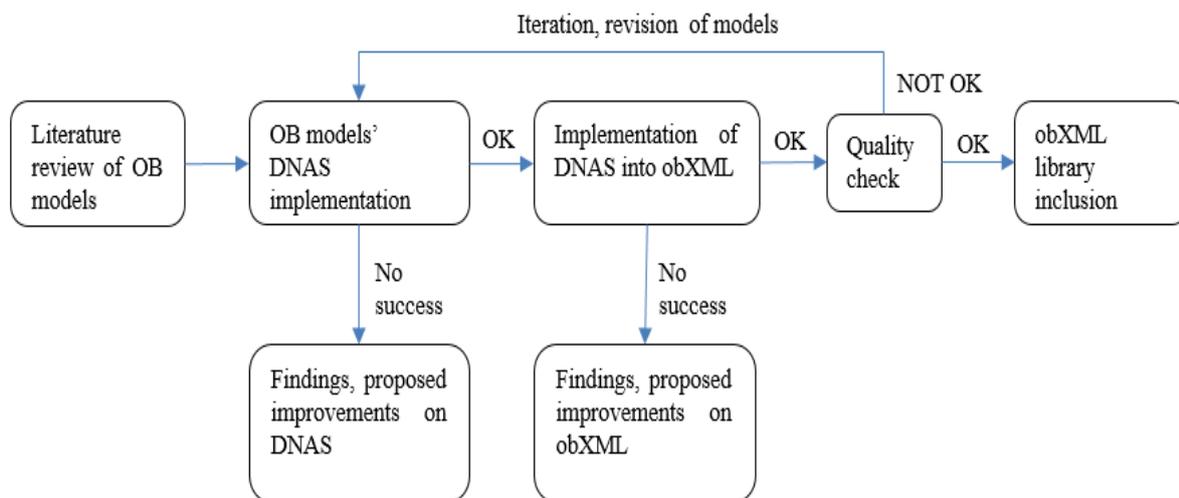


FIGURE 5 - THE PROCESS TO DEVELOP THE OB LIBRARY

After the model review, I processed the models and implemented into the DNAS framework. Drivers, Needs, Actions and Systems were identified. Then I used the obXML schema to represent these models in a standardized way. Elements of DNAS were implemented into respective obXML schema elements. Both of these implementation tasks were followed by logging limitations of the framework and schema and future improvements were proposed also. At the obXML implementation process, I used meta-data attribute fields to mark the basic information in case of each model for categorization and sorting purposes. These fields include information on the building, action and system types, reference information to the paper where the model was published, data collection region, data types and sample size of the database which served as a basis for the model. I represented each OB model in a separate XML file, but multiple OB models can be combined into a single XML file if needed. After the implementation works, I checked the internal validity of XML files with the most recent version of the obXML schema. Also the model implementation was manually double-checked in case of each library item.

## 4. Main Results

### *Main Result I*

#### *on Occupant Behaviour Modelling Opportunities in the Current Design Process*

I investigated and modelled occupant behaviour in an office and in a residential building project within the constraints of two typical Hungarian construction-market sustainable consultancy projects: a design and an operation optimization project in real construction industry situations. Although the energy performance predictions became more precise with my methods applied in case of the performance optimisation project, there is a strong need to gain more information about human behaviour in our buildings and also to develop modelling methods that are more precise and easier applicable.

#### I/1

In case of an existing Hungarian office building, I used calibrated, dynamic building energy simulation models to represent the building's energy use patterns. As an example, a semi-automated (automatic shading and lighting, fancoils with thermostats, manually operated windows) office building was used from the Váci út, Budapest office corridor.

**I found that the heating and cooling (fan-coil) usage patterns of office workers detected in the building causes +10% heating and +5% cooling energy consumption increase in a year compared to the scenario where occupants have no control over the heating and cooling system [22].**

#### I/2

Through a single family house design project, I managed to show the influence of family setup on the yearly energy consumption by means of dynamic building energy simulations. Occupancy scenarios with 2, 3 and 5 occupants were compared to the baseline, 4-occupant family composition. Occupants were represented in the simulations by occupancy schedules, automatic thermostat setbacks for un-occupied periods and user interactions: manual overwrite of the shading, lighting system and window opening.

**My simulation results show that a family composition change means -6% to +10% deviation in annual heating energy consumption and -20% to +16% change in cooling energy consumption [23].**

### *Main Result II*

#### *on Hungarian office worker behaviour*

As part of an international office building occupant behaviour survey study [15] [19] [24], according to my best knowledge, I established the first representative Hungarian office occupant behaviour dataset.

Based on the data analysis results [25], the following main result statements can be made on motivation and knowledge of control use, group behaviour, and preferred order of actions:

#### **II/1 Motivation and knowledge of control use**

**Based on the respondents' survey answers, I showed that the primary driving factor of window opening behaviour is to have fresh air in all seasons (90%, 86%, 88%, 80% in spring, summer, autumn and winter seasons respectively).**

The regulation of indoor temperature levels is a dominant secondary driver (56%) during the summer season whereas in other seasons it shows less importance (36%, 28%, 28% in spring, autumn and

winter seasons). Respondents' votes on the knowledge of different control usage showed that the sample was most confident in using the light switches (4.72 average vote on the scale from 1 to 5 where 5 indicates the full agreement with the statements on knowledge) and window opening/closing (4.71). Whereas thermostat or heating control valve was used less confidently (4.18). This shows the lack of education programs on more complicated environmental controls. [25]

## **II/2 Group behaviour**

As 70% of the sample worked in a shared or open office environment, I managed to show group behaviour trends in environmental control use which adds new knowledge to the field. 53% stated that they operate the controls by meeting the needs of those who express discomfort.

**According to my analysis results, 23% experienced group discussion on control use in the office environment. Negotiations over control use take place most often on window (69% of the sample experienced) and lighting (65%) use. In case of windows, the negotiation frequency is more than once a day whereas in case of lighting control it is less than once a week. [25]**

## **II/3 Preferred order of actions**

**Occupants preferred to open the window first (111 votes out of 207) when they were feeling hot during summer season and then secondly they prefer to have a cold drink (38 votes). This is followed by shading closing and clothing level adjustments. Whereas in case they feel cold during summer season, respondents indicated that they first increase clothing levels (59 votes), then close the windows (42 votes) and these are followed by having a hot drink. [25]**

This is a new area of research in this field which allows us to determine the share of active (e.g. window, shading use) and passive (e.g. drinks, clothing level adjustments) environmental control usage in office environments.

This dataset introduced here can be a basis for future building performance optimisation projects as occupant behaviour can be modelled more precise using these results.

## ***Main Result III***

### ***on Office Occupant Behaviour Change***

I conducted two rounds of cross-sectional survey campaigns on the population of a firm before and after their headquarter change. Based on the comparison of the two datasets, I showed that the energy-related behaviour and energy-saving intention of the office population changes significantly after the move due to the different perception of the new physical office environment and due to the different corporate communication on the importance of sustainability [26]. According to well-known behavioural models [27] [28] [29] [30], a person's behaviour depends on both internal and external factors. The following main result statements can be made based on the analysis:

#### **III/1 Heating and cooling use, knowledge on controls**

Regarding the observed efficiency of the cooling and heating system, I investigated the frequency of usage and the knowledge on controls.

**I showed that cooling is observed to be more efficient by the occupants, therefore less time switched on in the new office (decrease from 66% to 30% daily usage). However, heating is switched on more often in the new office (increase from 18% to 30% daily usage). I showed that due to the more complex environmental controls (complicated thermostat and lighting switch), occupants reported that they are less confident in using these controls and they use them less effectively. [26]**

**III/2 Window opening**

I conducted an analysis what environmental control options do occupants prefer in the office spaces investigated to restore thermal comfort and with what frequency they open the window.

**In the old office, occupants preferred to open the window to control their thermal sensation whereas in the new office space, clothing level adjustments are preferred. Also, in the old office window opening was more frequent (88% daily opening) than in the new one (55.2%). [26]**

**III/3 Intention to save energy**

Using the datasets, I showed the effect of moving to a new, environmentally-friendly office on the occupants' attitude change to energy-saving behaviour both in the office and at home.

**According to my analysis results, occupants consider their behaviour much more environmentally friendly after the move (before: 3.46 mean vote on a scale from 1 to 7, 7 meaning the full agreement of environmental statements; after: 4.41) due to the environmental certification system advertisement and updated company communication. [26]**

By this study, I managed to identify what is the exact impact of external factors (such as change in secondary HVAC systems for example) in case of the behaviour of an office population. This can add information to ongoing debates in the field on the generalizability of occupant behaviour representation models.

***Main Result IV******on window use drivers in a school building***

I set up an environmental and behavioural monitoring system in a Hungarian school building. Based on the analysis of an 8 months long time-series dataset of two classrooms, I found that window opening and closing behaviour drivers differ significantly due to the different habits, schedules and general school rules applied by different teachers using the same type of classrooms [31].

In case of the first classroom (English language, 2<sup>nd</sup> floor), I developed stochastic occupant behaviour models for window opening and closing behaviour based on indoor and outdoor temperature levels.

**In the first classrooms, behavioural models show strong connection between environmental temperature levels and window use (R<sup>2</sup> values of models for window opening: 0.91 and 0.30 for indoor and outdoor temperature respectively, same values for window closing: 0.89 and 0.71). [31]**

**In case of the second classroom (German language, 1<sup>st</sup> floor), I showed that window use behaviour is driven by habitual actions, it is connected to a scheduled behaviour pattern and it does not show strong correlation (<15% probability change) to environmental parameters (indoor, outdoor temperature, CO<sub>2</sub>). [31]**

By means of the interviews with teachers using the classrooms, I managed to identify essential internal and social differences that might be the reason between the different behavioural patterns observed in the two classrooms.

Classroom 1 was operated by two teachers constantly changing classrooms in breaks.

**Teachers could open the windows only during classes based on the observations and complaints of children being, for example, thermal discomfort-driven. [31]**

Classroom 2 was occupied by only one teacher during all classes held in there.

**This teacher was not leaving the classroom during the day and she opened the windows in all of the breaks to “let enough fresh air in”, independently from the outdoor or indoor temperature levels. Children’ complaints were not considered during the classes. [31]**

Phenomena like this are rarely described in the literature yet. Therefore, this study highlights for researchers in this field that future studies and investigations on the effect of contextual and social behavioural aspects in case of energy-related occupant behaviour studies are extremely needed.

### ***Main result V***

#### ***on Occupant Behaviour Modelling in Building Performance Simulation***

**Based on a review of building energy modelling tools, I established a new categorization for the different occupant behaviour (OB) modelling approaches currently applied in building energy modelling software tools: (1) direct input or control, (2) built-in OB models, (3) user function or costume code and (4) co-simulation. [12]**

I determined as well which tool has the capabilities to use which approach. Given these four approaches to simulate OB models, energy modellers must decide which is the most appropriate to select.

To support this selection process, I provided recommendations on the usability of deterministic and stochastic approaches.

**Direct input or control is most often used conveniently with deterministic schedules whereas co-simulation is used with stochastic models. Built-in OB models can be both deterministic or stochastic. User functions or customized user codes are applicable with both methods as well but not convenient to use. [12]**

Building on top of my previous model and software tool review and categorization work, I developed conveniently usable library of stochastic occupant behaviour models. A stochastic occupant behaviour model can be used in building performance simulation by selecting and co-simulating a fit-for-purpose model from this library.

**I reviewed and classified and then implemented 52 stochastic occupant behaviour models into an internationally accepted, standardized computer schema (occupant behaviour XML – obXML) forming an obXML library. [32]**

## 5. Summary, Future Work

Building on top of existing research findings of this field, I've added new knowledge and comprehensive datasets to the field based on my observation of energy-related occupant behaviour in different building types. Human behaviour has been found to be highly influenced by contextual and social factors such as the office environment or daily habits of occupants.

Although the general usability of stochastic occupant behaviour models in building performance simulation is proved and enhanced by this work, due to the variation observed in behaviour in different cultures and contexts, it is questionable to use generally these models for performance optimisation.

As a future direction of this research, I would like to point out that a multidisciplinary approach is needed to address future challenges of this research field. Namely, a better understanding of human behavioural differences can be achieved only by better analysing the human part of the equation by using the knowledge of other behavioural, social and psychological disciplines.

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