MOEEBIUS

Modelling Optimization of Energy Efficiency in Buildings for Urban Sustainability

D3.4 MOEEBIUS Comfort Profiling Models

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Glossary

Acronym	Full name
MOEEBIUS	Modelling Optimization of Energy Efficiency in Buildings for Urban Sustainability
HVAC	Heating, Ventilation & Air conditioning
DSM	Demand Side Management
IEA	International Energy Agency
DNAS	Driver, Need, Action, System
IAQ	Indoor Air Quality
HSMM	hidden semi-Markov model
MM	Markov model
ANN	Artificial Neural Nets
SVM	Support Vector Machine
CRF	Contrast Rendering Factor
PMV	Predicted Mean Vote
SET	Standard effective temperature
PPD	Predicted Percentage Dissatisfied
KPIs	Key Performance Indicators
DER	Distributed Energy Resource
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
PDF	Probabilistic Density Function
ISO	International Organization for Standardisation
CEN	European Committee for Standardisation
BEPS	Building Energy Performance Simulation
BLEMS	Building Level Energy Management Systems
MuMo	Multiple Modules

1 Executive summary

The main objective of this task is to define dynamic occupancy and visual/thermal comfort models towards facilitating the definition of accurate comfort profiles for occupants within buildings. These models will be further integrated to the overall MOEEBIUS framework, enabling the holistic optimization of the building performance under constraints imposed by the actual comfort preferences of building occupants.

Thermal comfort models will consider occupants as dynamically interacting entities within their environment through appropriately controlling their HVAC operations (operational mode and temperature settings), mainly driven by the combination of indoor temperature and humidity. On the other hand, Visual Comfort Models will be created towards establishing dynamic user profiles that reflect and more specifically quantify the visual discomfort of occupants based on the analysis of evidence captured exclusively from the observation of users' control actions under specific luminance conditions. The models will further incorporate and correlate occupancy detection and analysis parameters, so as to allow accurate modelling of comfort in relation to occupants' presence and, subsequent, enhanced forecasting of occupancy schedules.

As a side activity, in lack of low level information from indoor building environment, high level price based behavioural profiles will be also defined to further facilitate the extraction of price based demand flexibility profiles and towards this direction the impact of electricity prices on occupants' behaviour is also modelled in MOEEBIUS.

Overall, the main outcome of the task is the definition of **occupancy** and **behavioural** models to be further incorporated in the developments of MOEEBIUS profiling framework. In addition, the models will be further available to the BEPS simulation engine of the project towards the delivery of a fine grained building performance management framework.

2 Objectives of the report

2.1 Introduction

The main objective of this task is to deliver dynamic visual and thermal comfort models towards facilitating the definition of accurate comfort profiles of occupants within buildings. Thermal comfort models will consider occupants as dynamically interacting entities within their environment through appropriately controlling their HVAC operations (operational mode and temperature settings), mainly driven by the combination with indoor temperature and humidity. On the other hand, visual comfort models will be created towards establishing dynamic user profiles that reflect and more specifically quantify the visual discomfort of occupants based on the analysis of evidence captured exclusively from the observation of users' control actions under specific luminance conditions. The models will further incorporate and correlate occupancy detection and analysis parameters, so as to allow for accurate modelling of comfort in relation to occupants' presence and subsequent enhanced forecasting of occupancy schedules. Furthermore, in lack of low level/sensor level information from building environment, price based behavioural profiles will be examined as an additional concept of MOEEBIUS framework. Therefore, the main goal of this document is the definition of occupancy and comfort (& price) profiling models that will further facilitate fine grained user oriented building management framework introduced in the project

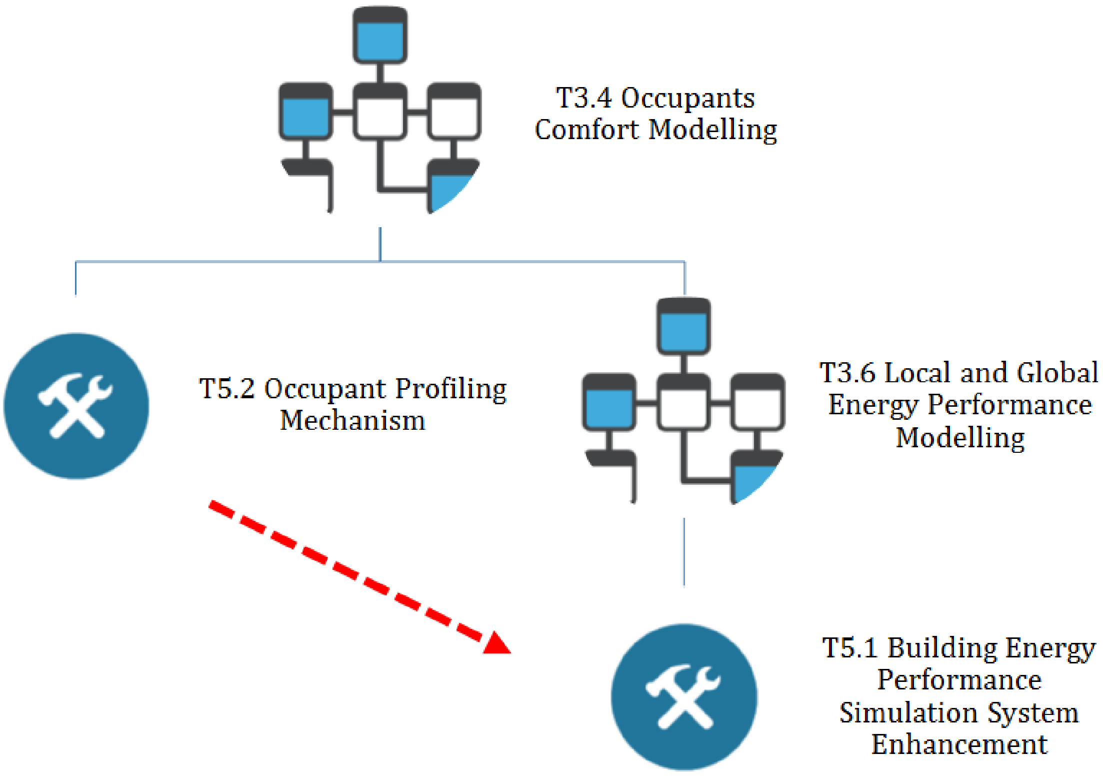
2.2 Relevance with other Tasks

The purpose of this document is to present the models about comfort profiles starting from the definition of occupancy profiles. As a first step, we review the end users and business requirements that define the parameters to be encountered at the modelling phase (D2.1). In addition, the comfort related KPIs (defined in D2.3) are further incorporated in the proposed modelling framework. Furthermore the extraction of the MOEEBIUS Comfort Profiling Models takes also into account the definition of the main elements that consist of the MOEEBIUS framework and place the occupancy profiling mechanism as part of the MOEEBIUS architecture (D2.4 & D3.1).

By specifying the behavioural profiling models, the next step is the incorporation of these models in MOEEBIUS framework. These models set the specifications for the development of the User Profiling engine in D5.2 (T5.2) (MOEEBIUS User Profiling Framework) to be further integrated with DER models towards the extraction of accurate demand flexibility profiles. This is a main innovation of the MOEEBIUS project as the goal is to provide fine grained demand flexibility profiles that incorporate occupants' behavioural patterns.

On the other hand, the identified user oriented models will be further integrated as part of the MOEEBIUS holistic modelling framework (D3.6 (T3.6) - Local and Global Energy performance models) and further incorporated in the BEPS engine

to be developed in D5.1 (T5.1) MOEEBIUS Building Energy Performance Simulation System. The next diagram presents the role of T3.4 as part of the MOEEBIUS work.



The integrated models (as instantiated in T5.2) will be periodically updated in BEPS engine (T5.1) towards the provision of accurate occupants' and preferences parameters in the building energy performance simulation process.

Finally, the extraction of high level price based behavioural profiles, will further enable the extraction of demand elasticity profiles at the Aggregator side; to further facilitate the implementation of price driven DSM strategies.

2.3 Structure of the document

The structure of the document is further provided:

- Chapter 2 documents the main objectives of this document and the relation with other MOEEBIUS tasks
- In chapter 3, we are providing a state of the art analysis of the existing modelling techniques towards the extraction of occupancy and behavioural profiles.
- In chapter 4, the details about modelling of occupancy profiles are provided. Towards the extraction of accurate occupancy models, we take into account the information from occupancy sensors examined in the project.

- The next chapter (Chapter 5) focuses on the definition of comfort profiles, highlighting the models about thermal and visual comfort but further incorporating price aspects as part of the holistic modelling framework.
- Chapter 6 provides a summary of the work along with the main conclusions related to occupants' behaviour profiles.

A series of Annexes are provided to support the documentation of the occupants profiling work as reported in the document. We have to point out that in each chapter apart from specifying the details of each model, we define the modelling parameters that set the structure for the development of the associated components in WP5.

3 Occupants' & Behaviour Profiling Framework - State of the Art

The goal of this section is to provide an indicative state of the art analysis on the work performed towards the definition of accurate occupants' & behaviour models in the building energy management framework. Before going to specific details, the skeleton of the research is defined by IEA Annex 66 initiative.

The IEA Annex 66 Task [1], a large research effort involving several partners has been undertaken towards developing and validating user behaviour models able to describe and predict user actions or user activities that affect the final energy use in a building, thus improving building design optimization, energy diagnosis, performance evaluation, and building energy simulation services. This Section, as well as the user behavior models defined within MOEEBIUS, build-upon and extend the developments and the results of the specific project, in accordance to the project scope towards reducing the gap between predicted and actual energy consumption.

A detailed and extensive State of the Art analysis of most of the aspects of user behavior modeling can be found on the references and publications sections of Annex 66 webpage.[1] (Summary in Annex I). Such an analysis is beyond of the scope of the present deliverable; here selected references will be provided (from Annex 66 as well as other sources) in accordance to the contents of the text.

A comprehensive review of the theory/methodology and the results of Annex 66 can be found in [2]. According to [2], four key components of the human-building environment interaction are identified (Figure 1): Driver, Need, Action, System, i.e. the so-called DNAS framework.

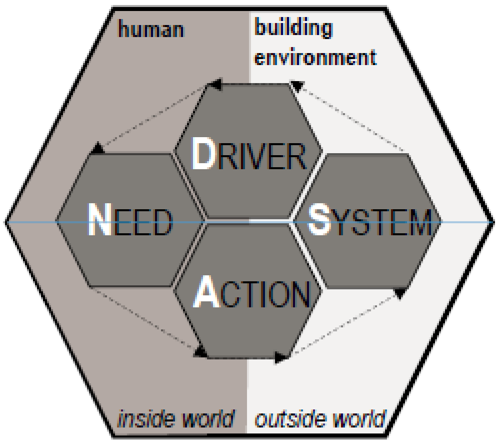


Figure 1 The four key components of the human-building environment interaction, according to Annex 66 results [2]

Based on the theory developed, a set of **drivers** (or events or triggers) are the stimulating factors that provoke energy-related occupant behaviour [2]. A

[1] http://www.annex66.org/

comprehensive list of all the identified divers is shown in Figure 2. From all these, only the dynamic components, allowing the development of near real-time and adaptive user behaviour models are relevant to MOEEBIUS, i.e.: calendar information; indoor/outdoor/weather conditions; and HVAC system state(s).

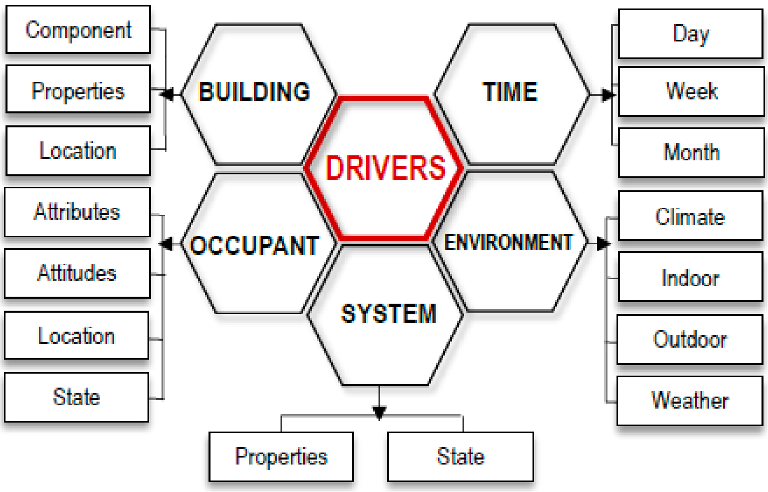


Figure 2 Drivers behind energy-related occupant behavior, according to Annex 66 results [2]

Needs are the requirements of the occupants that need to be met in order to ensure satisfaction with their environment [2]. The main needs identified within Annex 66 are shown in Figure 3; from these only the ones referring to Thermal comfort, Visual comfort and IAQ are relevant to MOEEBIUS project, with IAQ being the outcome of T3.5.

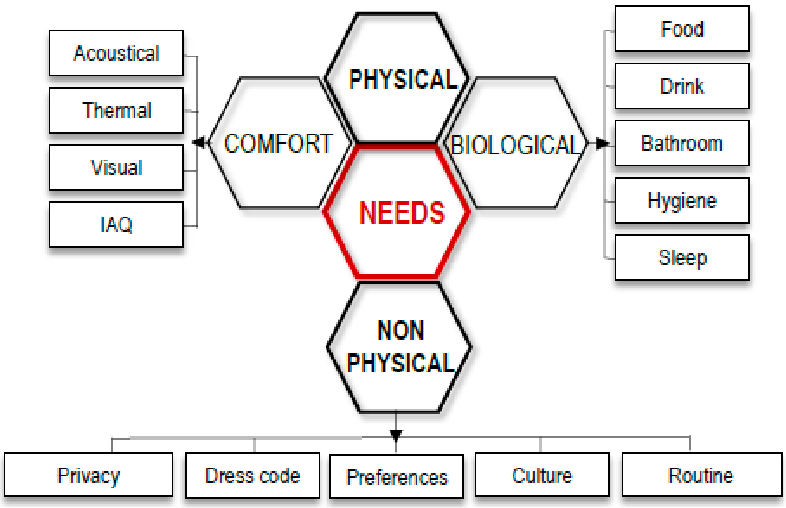


Figure 3 Needs of building occupants that may result in an action that affect the building energy use, according to Annex 66 results [2]

Actions are interactions of occupants with their environment (controllable elements of the building, such as windows, blinds, thermostats, etc.) as well as activities (e.g. changing clothes, drinking water, etc.), in order for the occupants

to satisfy their needs [2]. Within MOEEBIUS project – as also analysed later in the deliverable – all categories of actions identified by Annex 66 (Figure 4) are covered.

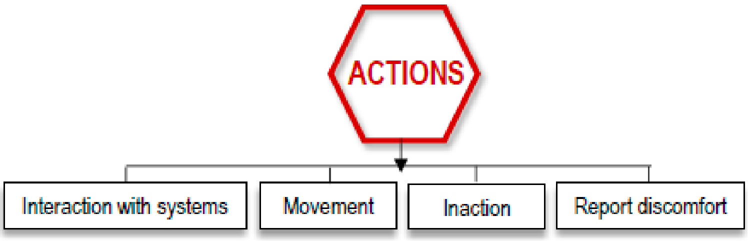


Figure 4 Actions undertaken by building occupants when their needs are not met, according to Annex 66 results [2]

Finally, a set of controllable building elements / building systems have been identified [2] and are shown in Figure 5. Within MOEEBIUS, as will be analyzed in the present deliverable, adaptive/dynamic user behavior models will be developed only for the occupants' interactions with the lights and the HVAC, as well as models for the space occupancy, since the required sensors for the development of these models is (or will be installed) in the target buildings. This is required, since even though Annex 66 contributed several pre-trained user behavior models, it has been evident that adaptive models, trained using real data from the target building will always outperform the static models in terms of accuracy [3].

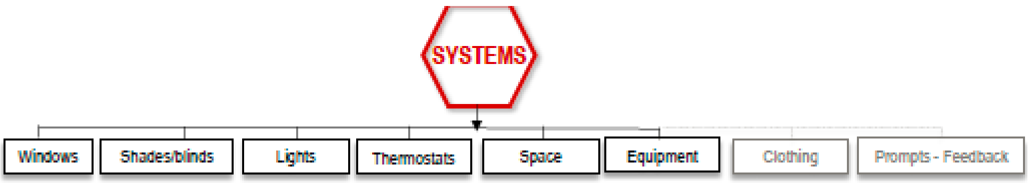


Figure 5 Building systems with which an occupant may interact causing a change in building energy use, according to Annex 66 results [2]

On the other hand, taking into account the feasibility/cost of the final MOEEBIUS solution, as well as the replicability and commercial use of the MOEEBIUS end-product, it has been decided not to develop adaptive user models for user interactions with the windows and blinds of a building. Nevertheless, a set of pre-trained, validated user behavior models have been included in the final library of user models, which will be hard-coded to the BEPS engine. These models, even though they are static, are still more accurate compared to models used in current simulation practice (e.g. windows always closed) [3]. These models are presented/analyzed in Section 5.5.

The **DNAS framework** set the skeleton for the MOEEBIUS Behavioural Profiling Models as defined in the document. The main principles of DNAS are also incorporated in the proposed model towards the delivery of the MOEEBIUS user oriented framework. Based on the above analysis, the scope of the remaining of

the section is to proceed with review of specific approaches and models related to occupants behaviour profiling. These approaches will further facilitate the definition of innovative MOEEBIUS models to be considered in the project. The starting point of this analysis is the review of the latest **occupancy profiling** work while the following step is about typical **thermal and visual profiling models** as examined in the project.

3.1 Occupancy Profiling Models Review

The scope of defining occupancy profiling models is twofold: 1) to extract real time occupancy through correlation of accurate occupancy profiles with raw data as retrieved from WSN occupancy sensors and 2) to enable the extraction of short term occupancy prediction. Therefore occupancy profile modelling is considered a complex (but very important) task as it combines algorithms with data retrieved from sensor devices installed. Various occupancy modelling approaches and prediction algorithms have been proposed in the literature. The most common of them include diversity occupancy profiles, agent-based models, Markov chain models, multivariate Gaussian models and context sources. A brief analysis is provided in the following sections.

3.1.1 Open Reference Models

Open Reference Occupancy Models are typical occupancy models containing occupancy distribution for major types of tertiary buildings/spaces, such as offices, hotels, hospitals, restaurants etc. There are different types of repositories that provide these occupancy models taking into account the past experience. Open Reference Occupancy Models are integrated in building simulation tools towards the evaluation of building performance addressing also the occupancy parameters. These models are not based on actual building conditions and thus are not considered as an option for real time building management processes.

3.1.2 Occupancy Diversity Profiles

While Open Reference Models are defined from previous case studies, diversity profiles are defined from historical analysis over sensor occupancy data. A daily diversity profile is composed of 24 hourly values between 0 and 1, each corresponding to a fraction of the maximum peak occupancy value. Several types of occupancy diversity profiles are defined.

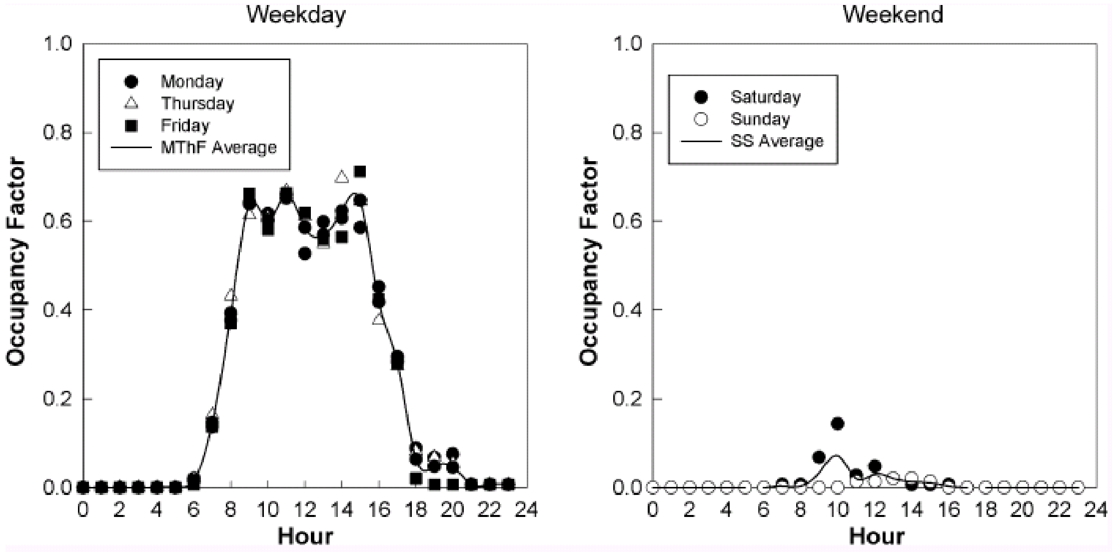


Figure 6 Weekday and weekend observed occupancy factors for administrative university building

An indicative example is provided in Figure 6. The occupancy factor is defined taking as parameter the maximum occupancy level [4]. Although this approach offers a holistic view of building occupancy, it is simple and non-accurate approach as the overall modelling process is time dependent.

3.1.3 Agent based Occupancy profiling models

This is a category of occupancy models where software agents simulate the behaviour and movement of individuals based on combination of static and sensor data. Multiple rules are defined for each agent generating probabilistically next states. This method is unsuitable for real-time data fusion due to its high-degree of complexity. The literature review defines different types of agent based approaches.

A stochastic agent-based model of occupancy dynamics in a building through the definition of an arbitrary number of zones and occupants is proposed by authors in [5]. The proposed model, defines the location of an agent at a given time through a set of rules specified by a number of modules. The modules adopt Markov-like dynamics so that the location of an agent at a given time depends on its location in the previous time. Simulation of the model generates a time-series state of each occupant's location, which can then be collected to generate zone-level occupancy information. In order to specify the input parameters of the model data from occupants' surveys and measured sensor data are considered. The predictions of the model have been compared against measured occupancy data in commercial buildings for three distinct scenarios: single-occupant single-zone, multi-occupant single- zone and multi-occupant multi-zone. A typical case study for evaluation of agent based model is presented:

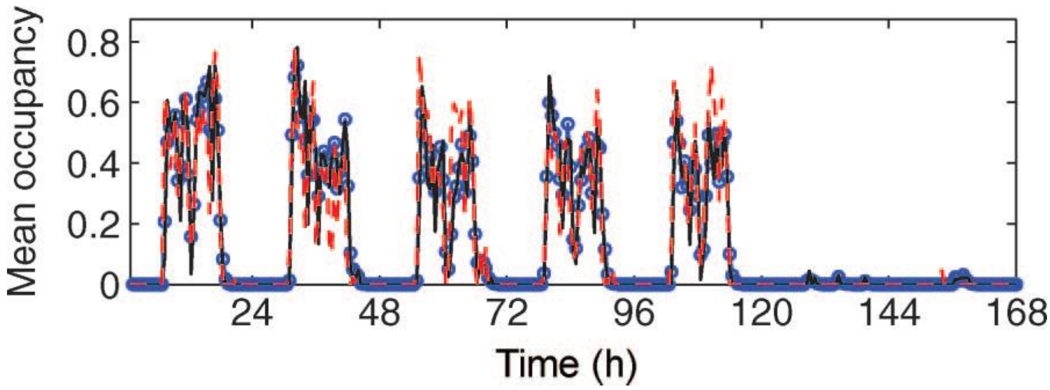


Figure 7 Model based vs. Real time occupancy profiling data

By using the building space layout, the multi-occupant single-zone and multi-occupant multi-zone scenarios were evaluated. It was found through comparison with measured data (actual usage) that MuMo model predicts certain variables (e.g. mean occupancy) with high accuracy. The proposed agent-based model can be used in conjunction with building performance simulation tools in order to provide accurate estimation of building performance. Though, the proposed model generates time-series of data and thus missing the perspective as examined in the project (user driven and not time drive model).

An alternative version was proposed by Mamidi et al [6], called BLEMS. This version follows the common principles of agent based logic but further extends the list of input parameters towards the extraction of accurate occupancy profiles. The BLEMS system relies on accurate occupancy estimation (current number of occupants in a room) and occupancy prediction (a prediction of how many occupants will be in the room in the next 15, 30, 45, 60 minutes) in order to adjust the operation of the HVAC system to conserve energy while maintaining occupant comfort.

The BLEMS Sensor Agent creates a set of features that are based on the original raw sensor readings, but transformed and projected onto useful axes such as the number of times motion was detected in the last minute. The Estimation Agent adds additional knowledge to this feature vector, such as domain knowledge that biases the classification or collaborative knowledge from other agents operating in nearby or similar rooms. The device has the following raw sensors: sound, wide-field motion detection, narrow- field motion detection, ambient light, temperature, humidity, carbon dioxide, and door state (open/closed). The combination of data as coming from different sources define the occupancy profiling mechanism.

A 3rd version of agent based occupancy profiling models is proposed by Robinson et al in "Multi Agent Simulation of Occupants' Presence and Behaviour" [7]. The agent based logic for occupancy profiling is similar to the one proposed by Liao et al [5], though the idea is to integrate also the behavioural modelling under a common framework.

The above models are designed to predict profiles of presence during periods in which occupants are not absent from their vocational occupation for long periods of time. The reasons for such absences include planned vacations, planned work-related trips and unplanned illnesses. Aside from bank holidays the timing and duration of these absences, whether planned or otherwise, tend to vary from one person to the next and from one year to another; they are stochastic in nature. There are stochastic models which address this problem in a convincing way and this is the main innovation of the proposed agent based model.

A pre-processor then determines the periods during which those agents that are employed or in study are absent, whether due to illness, vacation or for some vocational reason. A further pre-process then predicts the chain of arrivals and departures at each of the target destinations throughout the period of interest, taking into consideration whether the agents are in a period of vocational absence or not and whether this absence entails their departure from our scene (because they're on vacation).

Agents' activities whilst present at each destination are then simulated. Depending upon the degree of internal building spatial resolution, the probable location corresponding to these activities may also then be simulated; likewise the associated metabolic heat gains and gaseous pollutant emissions.

There are different agent based approaches as defined in the bibliography. All of them start from the representation of a single occupant and further aggregate the information towards the extraction of time series zone based occupancy profiles. The complexity of these models along with the fact that require detailed personalized information set main boundaries for the cases examined in the MOEEBIUS project.

3.1.4 Markov Chain Models

The extraction of occupancy profiles is based on statistical analysis over input data towards the definition of occupancy patterns. Therefore, non-parametric statistical models like Markov chain models should be considered as an alternative for the extraction of accurate occupancy models.

A Markov Chain is a system of known states where the state changes probabilistically at discrete steps. Multiple Transition Matrices govern the state changes within different slots of time. The next state is selected based on the current state and the probabilities of the corresponding Transition Matrix. A Typical transition matrix is presented where ***S*** vector defines the different states and ***p*** defines the transition probabilities.

	s_0	s_1	…	s_m
s_0	$p_{0,0}$	$p_{1,0}$	…	$p_{m,0}$
s_1	$p_{0,1}$			
⋮	⋮		$p_{i,j}$	
s_m	$p_{0,m}$		…	

Table 1 Markov Chain Transition Matrix

While Markov Chain define static models where there is no Variation through time, we need to extend the current concept in order to address additional aspects related to occupancy profiles. In [7] an inhomogeneous Markov Approach is applied based on observed occupancy data collected from a sensor network. The state of the chain is defined as a vector containing the occupancy at each space on each specific time. Therefore, given the occupancy state at time t, the occupancy distribution at time t + Δt can be predicted by multiplying the current state with the associated Transition Matrix. The probabilities of the Transition Matrix are given by the following equation:

$$p_{i,j} = \frac{n_{i,j}}{\sum_{k=1}^{m} n_{i,k}}$$

where $p_{i,j}$ is the probability of moving from state i to j, $n_{i,j}$ is the number of times a transition from state i to j has been observed in the historical data set and m is the total number of states.

Wang et al. [8], define the current state as the location of an occupant. Therefore, a Location Transition Matrix for each group of occupants containing the probabilities of location changes. The next location is randomly selected based on the current location and the corresponding probabilities of the Location Transition Matrix. As the goal of the project is the delivery of group based occupancy profiles, the aforementioned approach should be considered as the basis for the proposed framework.

While typical Markov models refer to paradigms where the states are already known, this is not the case when we are handing data coming from different sensor devices. In that case, Hidden Markov Models are considered. In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a hidden Markov model, the state is not directly visible, but the output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states. The adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a 'hidden' Markov model even if these parameters are known exactly.

A hidden Markov model can be considered a generalization of a mixture model where the hidden variables (or latent variables), which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other. Recently, hidden Markov models have been generalized to pairwise Markov models and triplet Markov models which allow consideration of more complex data structures and the modelling of nonstationary data. The next figure presents a typical representation of Hidden Markov Model.

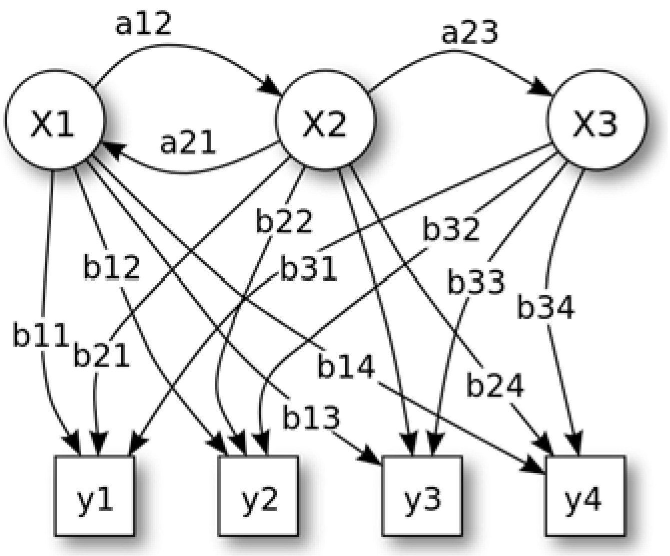


Figure 8 Hidden Markov model Representation

Probabilistic parameters of a hidden Markov model are defined:

- X — states
- y — possible observations/ sensor data
- a — state transition probabilities
- b — output probabilities

While this approach fits to our needs, the extracted models are also time based and thus different types of transition matrices should be defined for the whole project period. Therefore, a different type of Hidden Markov Models is examined.

A commonly used approach for occupancy modelling and prediction is the hidden semi-Markov model (HSMM) [9][10]. This method allows for each state to have any arbitrary duration distribution governing the number of times it remains unchanged. A pivotal point in the use of HSMM is the choice of distribution family for the state duration (e.g. multinomial, Coxian, exponential). Therefore, in this case we define a time independent model, where the time duration parameter is inherited to HSMM. A typical representation of this model as proposed by Dong et al. [10] is presented:

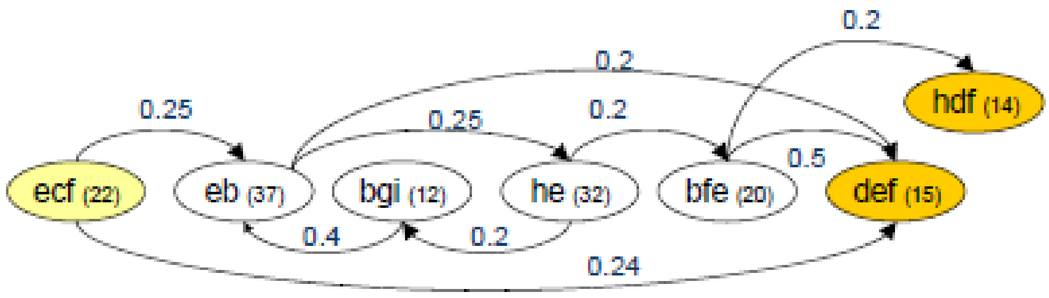


Figure 9 Hidden Semi Markov model Representation

In this case, the transition table represents the time duration for the next transition. Therefore, this representation of the time duration in a single state as a logarithmic function further enables the implementation of the proposed model. This approach is close to MOEEBIUS needs as the goal of the project is to accurate extract occupancy profiles taking as input parameters data from sensor devices installed. In addition, and as the goal of the project is to extract location based profiles, this model will cover the dependencies among states, expressed in terms of space zones.

3.1.5 Non parametric models by exploiting ML techniques

Following the definition of Markov Models as a technique for the extraction of occupancy models, alternative stochastic based statistical models may be considered for occupancy modelling.

Erickson et al[11] retrieving occupancy data from a large building, set a multivariate Gaussian Model in order to predict user mobility patterns and building room usage. An occupancy state is defined as a vector in which each element represents the occupancy in each room. Hourly defined PDFs (Probability Density Functions) give the probability of an occupancy state to occur within a given hour. Given a starting state, the probability of each possible occupancy state for the next time-step is calculated using the current PDF. The drawback of this model is that it causes a great deal of pacing behaviour. For example, if a person leaves the office to enter a hallway at one time-step, there is a high probability that the person will re-enter the office in the next time-step. This occurs since the distribution does not take into account the behaviour observed in the previous time-step. This can cause predictions to favour parts of the distribution that have high probabilities. This is particularly pronounced for rooms rarely occupied. In these cases the model rarely allows room entry and vacates the room too quickly.

In addition to non-parametric statistical models, machine learning techniques have been considered for the extraction of occupancy profiling models. Yang et al [12] proposed a Non-Intrusive Occupancy Monitoring System based on neural nets. An ANN (Artificial Neural Network) is a highly complicated and large-scale nonlinear adaptive system for simulating human neural network. It consists of huge amounts of simple processing units, and is often used to do massively parallel

data processing through continuously adjusting the relationships between inner variables. Some of the advantages of ANN include storage of distributed information, fault tolerance and strong ability of learning and association.

The specific model of ANN used in this study is error back propagation ANN. As one of the most widely used ANN models, the BP network is a typical multilayer feedforward neural network. It is known for its ability to transfer signal forward and transfer error backward, and can be infinitely approximated to an unknown continuous system. The BP network can learn and store large amounts of relations between input and output data without any predefined mathematical functions to describe them. The schematic representation of ANN is provided along with the results from the evaluation of ANN.

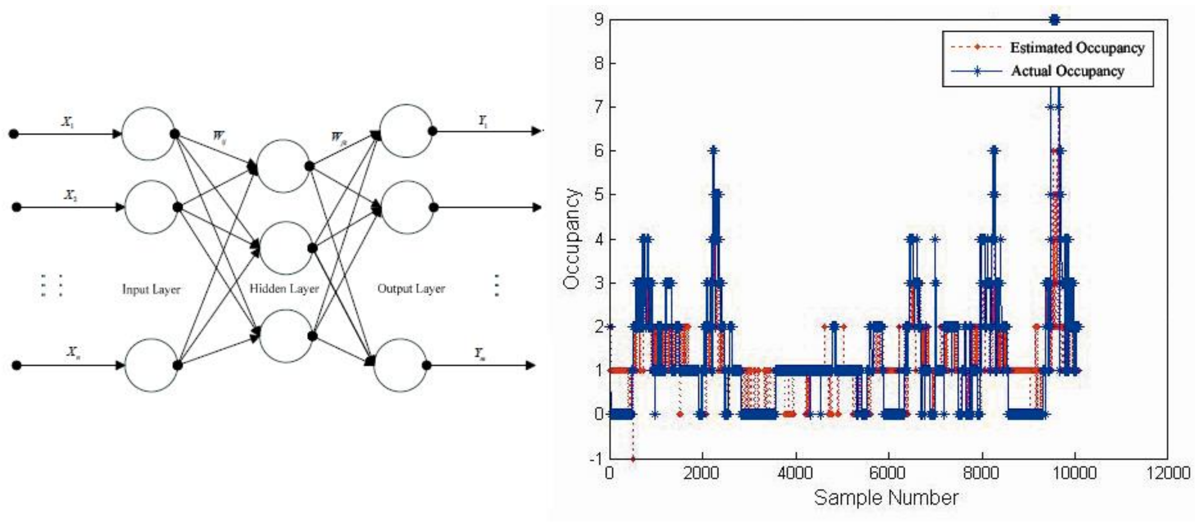


Figure 10 Non-Intrusive Occupancy Modelling with ANN

As an alternative, genetic algorithms are also considered for modelling occupancy profiles. Guillemin by using "Genetic Algorithms to take into Account User Wishes in an Advanced Building Control System" [13] proposed a model based on genetic algorithms.

Among the numerous optimization techniques, Genetic Algorithms have become quite popular thanks to their robustness and their capabilities over a broad range of problems. In our case scenario, the different states of the approach define the occupancy patterns while the overall approach models the transition among states.

An additional technique examined is the Support Vector Machine (SVM) engine, proposed by Lam et al in "Occupancy Detection through an Extensive Environmental Sensor Network in an Open-Plan Office Building" [14]. Support vector machines, developed by Vapnik have been widely applied in classification, forecasting and regression of random data sets. One of the primary features of SVM is to map non-linear functions in a low dimensional space to a higher dimensional space through the use of a kernel function.

A SVM with a Gaussian kernel is applied to sensor network data for the extraction of occupancy profiling models. The LibSVM toolkit developed by Chang and Lin (2001)[15] was then used to train and test the data sets. In order to avoid overfitting, a ten-fold cross validation was conducted on the data sets. The results from SVM simulation in a single zone is present:

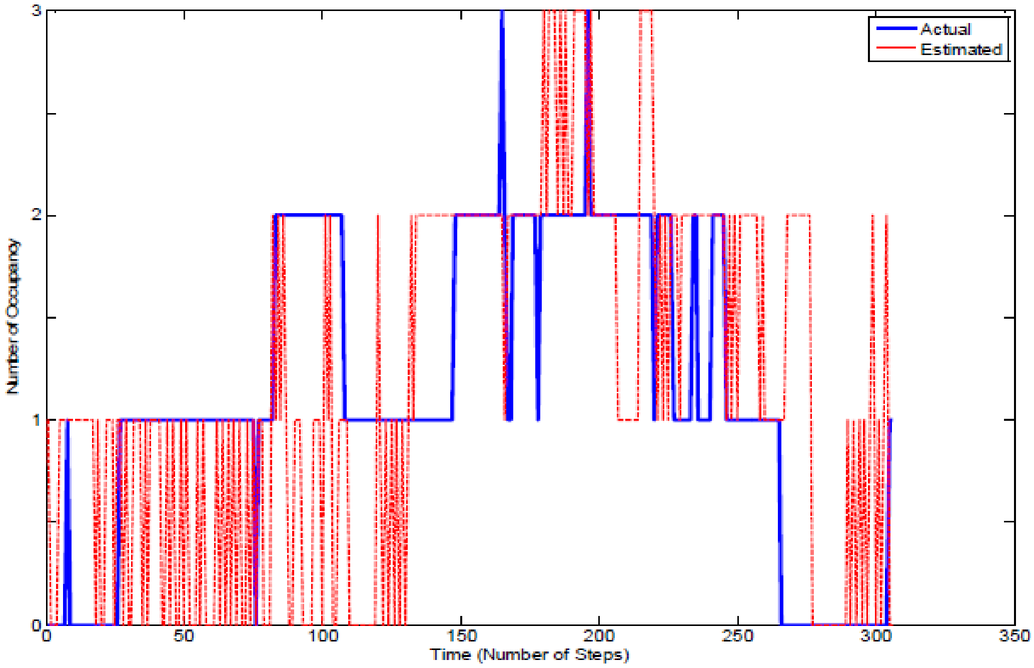


Figure 11 Occupancy Detection through Support Vector Machine

The state of the art analysis highlights that different machine learning techniques are utilized for modelling occupancy profiles. Input parameters, as derived from occupancy sensors and user settings are associated with occupancy state analysis towards the extraction of accurate occupancy profiles. The analysis is in line with the occupancy modelling work performed under Annex 66.

For the MOEEBIUS project, and taking into account the availability of input data from different sensor devices, a mixture of diversity profiles and Hidden Markov models will be considered for the extraction of occupancy profiles.

3.2 Comfort Preferences Models - State of the Art

Following the review of occupancy profiling models, the goal of this section is to present the current work towards the extraction of comfort preferences profiles. The next step is to mix occupancy profiles with user preferences models for the extraction of accurate occupants' behaviour profiles.

Within MOEEBIUS, and due to non-individual occupancy information, group (zone based) behaviour profiles will be analysed tracing back spatio-temporal aspects of activities and operations, fully exploiting the dynamic behaviour (typical, periodical, etc.). Two different types of behavioural profiles are defined, though the main focus of the project is for the 1st category:

- For distributed energy resources affected by environmental conditions (e.g. HVAC and lighting), an enriched behavioural analysis is provided. Occupancy preferences and control actions along with environmental conditions are incorporated in model towards the extraction of a concrete user profiling framework.
- For the non-context operating distributed energy resources (e.g. PCs, printers, EVs etc.), the behavioural/operational modelling framework is delivered taking as main parameter the occupants presence/absence. This is also the case of defining price elasticity profiles where the patterns are directly associated with external energy prices.

The focus of the literature is for the 1st type of devices, where a detailed overview of available visual and thermal comfort models is provided. Prior to this, an introduction to similar behavioural models is provided.

3.2.1 Visual Comfort Analysis

Almost all aspects of human behaviour depend heavily on the light exposed to. Apart from the role of light in visual processes, light also turns out to play a major role in a wide variety of non-visual processes as well (e.g. Health and safety, aesthetics). The focus of this section is to address specific parameters related to visual comfort of building occupants (The visual performance defines whether the lighting solution in a room is suitable for the performed tasks).

Overall, for the area in which a specific task is performed, the lighting level should fulfil the maintained illuminance, the uniformity of illuminance, the colour rendering, and the absence of glare. The arrangement of the lighting should avoid distracting hard shadows, discomforting sources of glare and reflections. The lighting should not flicker, should avoid larger dark zones in the room, and should meet the conditions of uniformity of illuminance in the area in the surroundings of the visual task. Regarding the visual performance, the recommendations and standards for lighting design in workplaces adequately address visual needs and visual comfort. The European standard BS EN 12464-1 [16], presents the requirements for lighting in the task areas of a building concerning intensity level, colour, glare, luminance ratios, and daylight entrance. These standardized parameters are further analysed taking into account the initial review of visual comfort indicators as presented in T2.2.

The core requirement related to visual performance is to ensure a sufficient level of illuminance for the activities carried out in a zone. The illuminance level is considered as the amount of light falling on a given surface and measured as the luminous flux per unit area.

Another parameter to be examined is the relative position of the light source along with the visual task and the observer which determine how effectively the task contrast is rendered (**Contrast Rendering Factor-CRF**). Ideally, the CRF is

measured by comparing the contrast of the object under the ambient lighting with its contrast under reference lighting (completely diffuse, unpolarised illumination). Generally, the higher the CRF, the more acceptable the visual performance is.

A further consideration in lighting uniformity is the illuminance distribution over a workplace. The arrangement of the lighting in a room should avoid distracting hard shadows, discomforting glare sources, and distracting reflections. Large differences in illuminance in a room may lead to visual stress and uncomfortable situations. The **luminance ratio** is the luminance of one area divided by the luminance of another area. Luminance ratio limits are recommended to prevent excessive contrast between light and dark.

Finally, additional parameters related to visual glare, colour and flickering are defined as aspects that affect the visual comfort. It is obvious, that the establishment of a visually comfort environment is a main task with different parameters and thus special interest is delivered on the definition of models that cover the aforementioned aspects.

3.2.2 Thermal Comfort Analysis

Human's thermal comfort is mainly related to the thermal balance of the body as a whole. This balance is influenced by physical activity and clothing, as well as the environmental parameters. Thus, however this comfort feeling is measured and controlled, the same value does not need to be satisfactory for different people. So, any system designed to achieve thermal comfortable conditions should not be driven by a static goal, but it should be user adaptive without prior knowledge about the user; that is, the system should be able to learn on-line the expectations of any new user. Thermal comfort is a complex term which depends on several parameters. In general, variables which affect human heat dissipation and consequently thermal comfort, can be grouped into three categories:

- Environmental, like air temperature, humidity, air speed etc.
- Personal, such as metabolic rate and clothes isolation
- Others (e.g. age, fitness)

Numerous indices for the assessment and design of thermal comfort conditions have been developed during the past 50 to 60 years. One of the most widely used indices in moderate thermal environments, the PMV index (predicted mean vote), predicts the mean value of the overall thermal sensation of a large group of persons as a function of activity (metabolic rate), clothing insulation, and the four environmental parameters: air temperature, mean radiant temperature, air velocity, and air humidity [17]. PMV may take labelled values from −3 to +3, respectively, referred as to: Cold, Fresh, Slightly Fresh, Neutral, Warm, Hot, And Very Hot. Thus, a PMV equals to 0 stands for a neutral feeling of individuals respect to thermal sensation.

Alternatively, other methods [18][19]for the assessment of moderate thermal environments could be used, such as the new effective temperature (ET) and the standard effective temperature (SET). Thermal comfort assessment includes the unambiguous definition of performance indicators (PI) based on the notion of objectively quantifiable performance measures. Different algorithmic techniques are addressed in bibliography towards the definition of occupants thermal comfort preferences.

The goal of the next section is to provide a thorough literature on domains and methodologies, to extend the existing research and provide the MOEEBIUS Behavioural Profiling framework.

3.3 Behavioural Profiling Modelling Approaches

Following the short introduction in the comfort aspects examined in the project, the focus is on the definition of the associated behavioural profiling models as defined in the literature.

3.3.1 Diversity Behavioural Profiling Models

This approach has already been presented for diversity occupancy profiles. The same approach is delivered also for the extraction of Behavioural Profiling Models. The anchor point of this model is to define daily diversity profiles of 24 hourly values between 0 and 1, each corresponding to a fraction of the usage of each device depicting in that way the preferences on different devices. This is a stochastic approach where the different configuration parameters are defined through statistical analysis over historical data.

The AIM project [20][21] is presenting a diversity Behavioural Profiling model where the operational characteristics of an HVAC unit are defined through statistical analysis. A time series graph is extracted showing the probabilistic density function of each device.

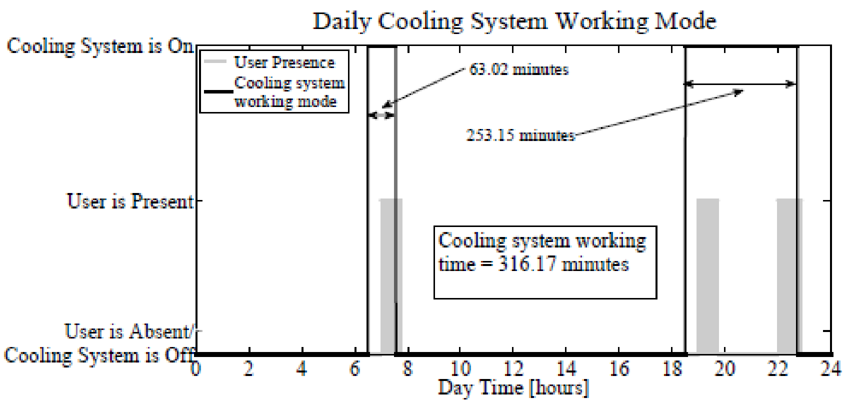


Figure 12 Diversity Behavioural Profile for a single device

The structure of this model is given in the following figure. The first part of the model defines the fluctuation of consumption levels and segments it to appliances of each household. The second part of the algorithmic framework is composed by the main building processes, simulates separately the usage of each individual appliance in household and then aggregates the simulation data for the extraction of the holistic energy consumption.

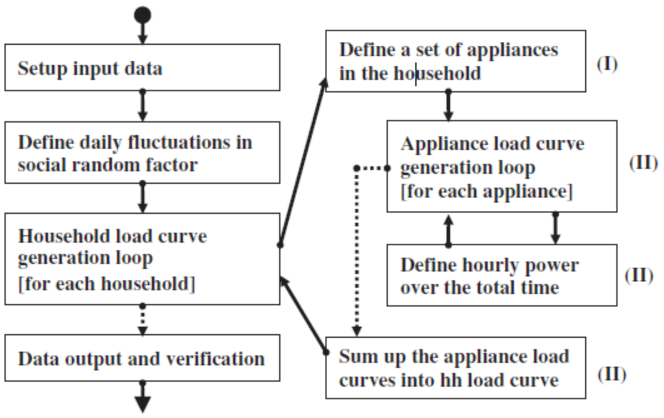


Figure 13 Top down Diversity Usage profile [22]

Therefore, the overall modelling framework is based on measuring energy consumption data and further extrapolating these data taking into account the list of available devices.

A similar approach is provided by Richardson et al.[23]. This is a bottom up approach where the extraction of diversity profiles is based on the actual usage of devices from end users. For each household we need to define the daily activity profiles and then, taking into account occupancy patterns and list of available devices, to emulate the operational patterns of end users.

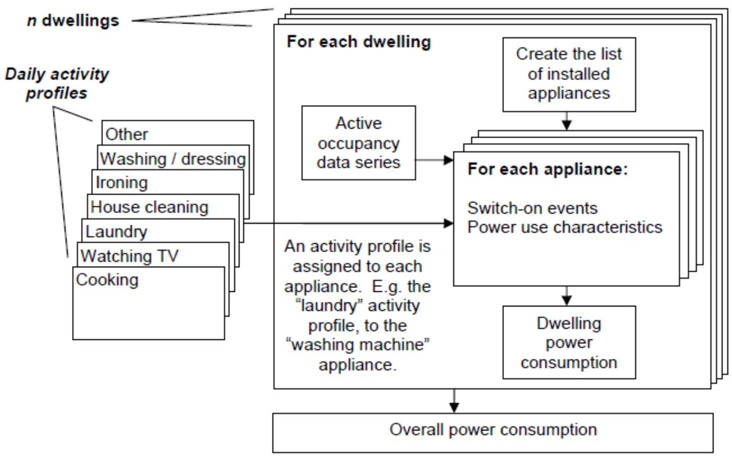


Figure 14 Bottom up Diversity Usage profile

The structure of the model is presented in Figure 14. Each appliance is mapped to one of the daily activity profiles. When an appliance switch-on occurs, the appliance power use characteristics are used to determine its electricity demand (including the reactive power demand). Adding the power demands of all appliances within a building gives the whole v demand.

The diversity profiling framework offers a direct and precise correlation of energy consumption data to individual users. However, it is mainly based on the statistical analysis of huge volumes of data and thus it is considered as a "black-box" approach towards the definition of Behavioural profiles in building premises.

3.3.2 Adaptive user profiling models

Following the definition of diversity profiles, the definition of adaptive profiles taking into account user preferences and needs is one of the approaches examined in bibliography.

The goal of thermal models is to simulate the behaviour and preferences of individuals, either taking into account standardized patterns or through direct interaction with building occupants. One way or another, the goal of these models is to correlate data about environmental conditions and user settings towards the extraction of thermal preference models.

As a first alternative, standardized comfort models are considered as the baseline for optimal management and control of environmentally related distributed energy resources. In HVAC operation, a thermal comfort model is used as feedback by the control algorithm, so as to keep the user thermal sensation in the comfort zone, while minimizing the energy consumption with energy-saving functions coordinating the HVAC systems. Such human thermal sensation models were developed long before the development of these modern HVAC control strategies. Some were based on physiological theory (Gagges et al. [24]; Stolwijk [25]) and others on experimental data measures in climatic chamber (Fanger 1970). The global thermal comfort of P. O. Fanger [17] and the Adaptive Comfort Standard developed by Humphreys and Nicol [26] received most attention from the HVAC world. With its ability to calculate a statistical thermal sensation (called predicted mean vote or PMV) the global thermal comfort model, or PMV model, has been integrated into numerous regulation algorithms of HVAC systems. PMV may take labelled values from −3 to +3, respectively, referred as to: Cold, Fresh, Slightly Fresh, Neutral, Warm, Hot, And Very Hot. Thus, a PMV equals to 0 stands for a neutral feeling of individuals respect to thermal sensation

The PPD index (predicted percentage dissatisfied) is derived from the PMV index and predicts the percentage of thermally dissatisfied persons among a large group of people. Occupants of buildings are not alike, and therefore the individual thermal-sensation votes of the occupants of a given environment will be scattered around the mean. The PPD index predicts the number of people likely to feel

uncomfortably warm or cool. When the PMV value is known, the PPD index can be calculated.

$$PPD = 100 - 95e^{-0.03353PMV^4 - 0.2179PVM^2}$$

The aforementioned review, shows thermal sensation models that are closely related to global comfort indicators as defined in standardization. Therefore, the focus of these models is on the way of calculating PMV and PPD indicators and not on the actual meaning of this indicator (and if actually fit to individual characteristics).

As a recent alternative, there are different approaches that try to define non parametric models taking as input parameters the context conditions. Therefore these approaches are not exclusively defined for thermal aspects but also address visual preferences of occupants. The main objective of these models is to define personalized and adaptive comfort related models, taking into account the specificities of each occupant through one/several personal parameters. Typical metrics are utilized (Temperature levels, adaptive PMV & PPD, luminance levels) for quantification of comfort and discomfort values. In these cases, interaction with users is mandatory in order to retrieve their preferences and non-preferences on environmental conditions.

A personal user interface has been conceptualized for this analysis. It is made up of mainly command buttons which are analogous to the sensation scale. The main scope of this framework is to evaluate in real time the comfort status of occupants and re-adjust the operation of the devices in an optimal way. By allowing each user to signal an eventual uncomfortable sensation and using it to coordinate device systems around, this solution goes beyond the typical comfort controls, sharing artfully the comfort control between the algorithm and each occupant. The main drawback of this approach is the direct enrolment of the occupants on comfort definition process. This is the main reason for consideration of utility function models in the next section.

In lack of low level information, different price based models are defined in order to express the willingness of costumers in specific conditions. Price is considered as the common denominator for the quantification of users' willingness on different goods. In most of the models the utility function curve is the function that quantifies users comfort on different price levels.

3.3.3 Utility function based behavioural models

The previous analysis considers typical standards and KPIs for the extraction of thermal preference models. Although these models are based on globally accepted standards, it has been found that these are problematic in practice as they don't reflect the individual preferences. Thus, in order to define fully adaptive models that also characterize the individual preferences and needs, the theorem of "Utility

Function" is adopted. The concept is an important underpinning of rational choice theory in economics and game theory, because it represents satisfaction experienced by the consumer of a good. A good is something that satisfies human wants. Since one cannot directly measure benefit, satisfaction or happiness from a good or service, we have devised ways of representing and measuring utility in terms of economic choices that can be measured. Therefore, utility function [27] is mentioned as the function that specifies the utility (well-being) of a consumer/individual for all combinations of goods consumed (and sometimes includes other considerations).

In the case study examined in MOEEBIUS project, each customer operates a set of appliances such as air conditioner, lighting device, water heater etc. For each appliance of the customer, an amount that models how much a customer values the device operational status is delivered. The willingness to use a specific device is transformed to the Utility function value. An abstract model approach of the Utility function estimation is provided. [28]

"Each customer $i \in N$ i ϵ N *operates a set* $Ai, i \in N$ *of appliances such as air conditioner, lighting device, water heater. For each appliance* $a \in Ai$ *of customer* i*, we denote by* $p_{i,a}(t)$ *its operational draw at time* $t \in T$*, and by* $q_{i,a}(t)$ *the vector (* $p_{i,a}(t)$*,* $t \in T$ *) of operational draws over the whole period examined."*

A typical representation of Utility function formalism for a specific device is given in Figure 15.

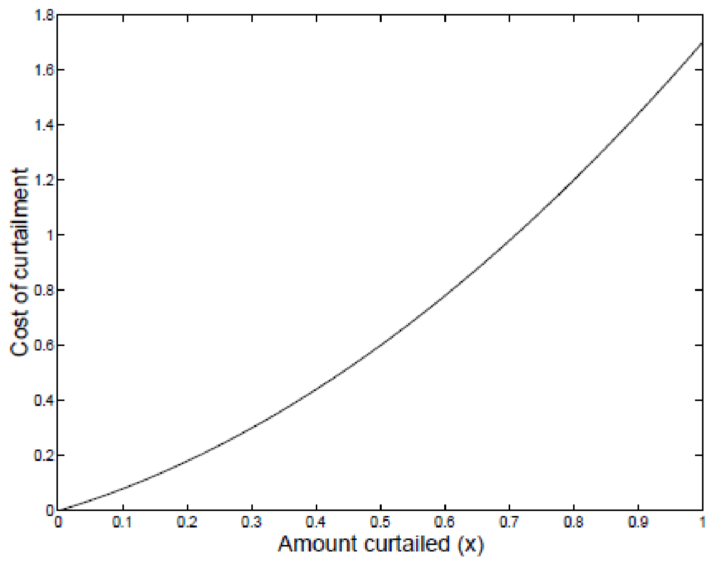


Figure 15 Utility function representation

There are different approaches in bibliography that adopt the Utility function principle in order to quantify users' willingness to operate specific devices [29]. On the energy domain examined in the project, a high level categorization of the

typical Distributed Energy Resources is considered in order to provide fitted utility functions that optimally characterize the behavioural patterns of individual users:

- Type 1: The first DER type includes those appliances such as air conditioner and refrigerator whose operation is closely related to temperature of customer’s environment. The value of the Utility function is maximized out of the technical operational limits of the devices.
- Type 2: The second DER type includes appliances such as PHEV, dish washer, clothes washer. For these appliances, a customer only cares about whether the task is completed before a certain time. These devices are characterized as demand shiftable devices and thus the total value of utility function is increased at the end period of the scheduled operation.
- Type 3: The third DER type includes the appliances that must be on for a certain period of time, such as lighting. A customer cares about how much light they can get at each time t but different operational states can be considered on the time period. Type 3 devices combine the environmental and operational conditions in an integrated framework and the Utility function is delivered as a parameter of these input settings.
- Type 4: The fourth DER type includes appliances that a customer uses in a non-continuous-essential mode, such as TV and computers. The status of these devices is considered as on/off and thus an extra parameter (e.g. price) has to be examined in order to estimate the utility function.

There are two approaches on the “Utility function” model as defined through state of the art analysis:

- Utility curve as a function of operational characteristics: In this case, the willingness to use a specific device is based on user control settings. This approach is close to diversity profiles as defined above.
- Utility curve as a function of price: This is the most common approach defined in bibliography and the core principle for implementation of automated price driven demand response strategies. In this case, the willingness to use a specific device is related to a specific price. The main drawback from this approach is the difficulty to train this model type by establishing different price schemas.

The main objective of this framework, is the extraction of utility function curve for each specific device. The utility function curve is differentiated for each occupant and building operational conditions. Therefore, the "utility function" approach is considered as the most thorough one, as it incorporates several heterogeneous aspects under an integrated methodological framework. Within MOEEBIUS, we will try to extent the "utility function" framework by incorporating also building environmental conditions as part of the model. The utility function approach as examined in MOEEBIUS project is not device specific but is further extended to address user settings, environmental conditions and device operational characteristics.

The aforementioned analysis intends to serve as the baseline for our research in MOEEBIUS and will be used as a reference state-of-the-art in the topics related to the role of occupants. In this context, this section provided a set of recommendations as guidelines for the development of the integrated MOEEBIUS occupancy profiling and behavioural preferences modelling framework.

4 MOEEBIUS Occupancy Profiling Modelling Framework

We first define occupancy profiling models that describe occupants' in building premises. This is a complex task as in most of the cases these patterns are characterized by high levels of uncertainty. In addition, the lack of precise sensing equipment (to preserve privacy concerns and due to project budget limitations) limits us to the definition of abstract occupancy models. The next section provides an overview of the proposed MOEEBIUS Occupancy Profiling framework accompanied by the associated data models and the algorithmic framework to be considered at the development phase.

4.1 Occupancy Profiling Overview

Within MOEEBIUS, occupancy models will be created representing the spatio-temporal distribution of occupancy. These models will depict regular occupancy patterns and will be constantly updated in order to reflect changes that may occur on building's occupancy levels.

The main constrains about the identified objects are coming from the installation types in building premises. By utilizing low cost occupancy sensors with low accuracy levels (PIR), we are lacking of critical information and thus the definition of occupancy patterns remains at zone-level (taking into account the final installation set up). Different zones (by taking into account the BIM definition and the physical topology) are defined and further aggregated to enable the extraction of hierarchical occupancy profiles.

The MOEEBIUS **Occupancy Profiling Model** has two main aspects, occupancy and flow. **Occupancy** refers to the static representation of the occupants found at each space or zone (similar to diversity profiles), while **flow** represents the dynamic occupancy variation at building's zones. Therefore a mixture of diversity profiles with machine learning techniques is considered as the occupancy modelling framework in the project

For the 1st part and the static representation, the proposed models will contain information such as **occupancy density** along with arrival and departure, defined per space or zone. The diversity profiling analysis will be dynamic in order to address special days and events and further will be continuously calibrated addressing that way the seasonal character of the buildings.

The 2nd part of the analysis is the extraction of occupancy variations during the day addressing that way the dynamic nature of occupancy profiles. The goal is to examine (with Markov Models) the possibility of occupancy change at a specific time period and thus modification of occupancy range through time. In order to extract these probabilities, a long training period over historical data is required. According to the Markov Model [30], an **Occupancy State** is defined as a vector in which each element represents the occupancy in each space/zone of the

building. Occupancy could be represented by the exact number of occupants in the space/zone (not applicable in the project), or a range of the proportion of occupants defining categories such as empty, low occupied, medium occupied and full occupied. Within MOEEBIUS project, and taking into account project requirements, abstract occupancy ranges will be defined per zone of the building (or further aggregated). An example of the state representation is given in Figure 16.

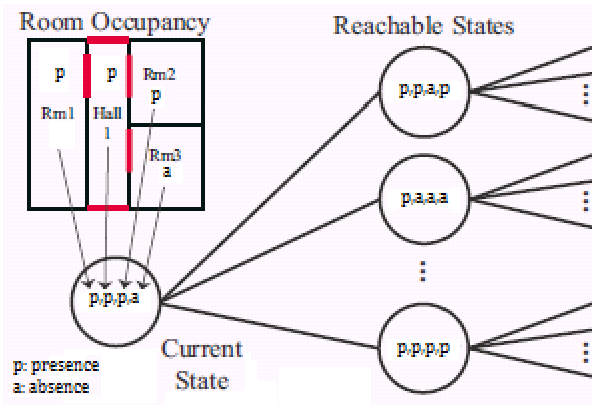


Figure 16 Example of Occupancy State representation [30]

Additionally, an **Occupancy Transition Matrix** is defined as the matrix where each element represents the probability of moving from one occupancy state to another. An example representation is given in Table 2, where s_0, s_1,…, s_m declare occupancy levels (vector with range of occupancy) and $p_{i,j}$ is the probability of moving from occupancy state s_i to s_j.

Table 2 Occupancy Transition Matrix (Markov Model)

	s_0	s_1	…	s_m
s_0	$p_{0,0}$	$p_{1,0}$	…	$p_{m,0}$
s_1	$p_{0,1}$			
⋮	⋮		$p_{i,j}$	
s_m	$p_{0,m}$		…	

By defining Occupancy Transition Matrices**, flows** among occupancy levels are modelled. Each transition matrix will be available for a specific type of day (e.g. weekday, weekend), season and time period (e.g. hourly) and will be continuously updated. It is obvious that we need to incorporate at the decision process the time of the day as the parameter affecting the transition flow probability. Thus, a specific type of Markov Models (that incorporates in the model the timeperiod for each transition → Semi Markov Models) will be evaluated. All transition matrices will be calibrated and trained over time. Initial values for occupancy states and

flows will come from empirical data, typical schedules, pilot surveys, and open reference models. An open reference occupancy models repository containing occupancy models from other projects will be utilized for the initialization of the MOEEBIUS building occupancy and flow models.

As a first step, each space will be matched to the available open reference models, in order to select the best fitted occupancy model. The model values will be manually adapted to fit the proposed MOEEBIUS framework. Then the values should be adapted to the actual building conditions by taking into account occupancy data. Apart from open reference occupancy models**,** typical schedules will be used when applicable. Zone specific schedules contain information about typical events taking place, such as working hours, holidays, typical meetings etc. These schedules will be provided by the pilot representatives in a standardized way to further enhance the extraction of occupancy information.

After this initial phase, building's occupancy and flow models will be updated on a regular basis (e.g. once bi-weekly/month) based on pilot site observations and possible updates of typical schedules.

4.2 Occupancy Prediction Modelling Overview

Along with the extraction of real time occupancy data, MOEEBIUS will provide **short-term** (near real time) occupancy and flow prediction allowing for more efficient management of building's energy resources and providing the essential information for short term forecasting of demand flexibility. **Short-term prediction** provides occupancy range per building space for few minutes after current situation per a specified time-frame.

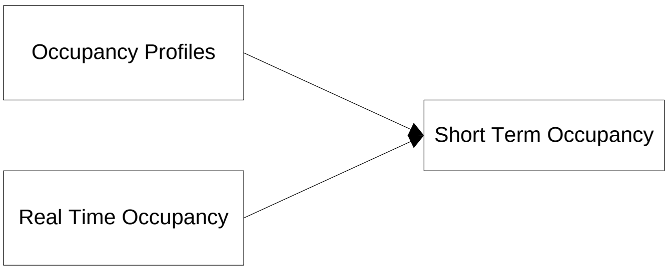


Figure 17 Occupancy Prediction Modelling Overview

The idea is to utilize real time occupancy sensor data with the extracted occupancy and flow models in order to estimate the expected occupancy densities.

4.3 Occupancy and Flow Model Specifications

Following the definition of MOEEBIUS occupancy modelling framework, the detailed specifications of the model are provided. The analysis takes into account the data syntax as defined in MOEEBIUS Common Information Model.

4.3.1 Real-time Occupancy Modelling

MOEEBIUS will provide real-time occupancy data per zone in predefined ranges. Real time information is a meta-information as derived from occupancy and flow modelling. The real time occupancy data will be further available to Building Management Tools (e.g. Demand Flexibility Engine, Facility Manager UI) for further exploitation. The next table presents the modelling parameters for real time occupancy data.

Parameter	Description	Type
Space/Zone	The space/zone real-time detected occupancy refers to.	ID, enumeration
Occupancy range	Real time Occupancy Range in the specific space/zone.	float or integer

Table 3 Real-Time Detected Occupancy Parameters

This is the typical representation of a sensor event type as defined also in MOEEBIUS CIM in D2.2. Time-stamped information will be available as the output from real-time occupancy framework.

4.3.2 Occupancy Profiling Model Specification

In this section, the detailed specifications of MOEEEBIUS occupancy modelling are provided. The summary view MOEEEBIUS Occupancy framework is presented in the Annex. The different elements that consist of the overall framework are specified.

4.3.2.1 Occupancy Profiling Parameters

In this section we present the detailed list of occupancy metrics, which consist of the steady state representation of the model. The core of the model as presented above is:

Parameter	Description	Type
Occupancy range as a temporal distribution	The range of occupants in a building/space/ of that building/space/zone per a specified time frame (e.g. per hour).	complex
First Time	The time the first occupant arrives.	time
Last Time	The time the last occupant leaves.	time

Table 4 Static Occupancy Parameters

Occupancy range type is a complex type that is further defined as the vector of: {occupancy value (float), time-period (time)}. The metrics described in Table 4 can be defined per building, space or zone as well as per type of day and season.

Therefore, occupancy metrics granularity has two dimensions: spatial and temporal. This segmentation is further analysed in Table 5 and Table 6

Parameter	Description
Building	Metrics refer to the whole building.
Space	Metrics are defined per building space.
Zone	Metrics are defined per building zone defined (virtual or physical)

Table 5 Spatial Granularity

The aggregation of zone level data defines the static occupancy data for the building and spaces based on the hierarchy designated in BIM models. The next table presents the temporal segmentation for the occupancy model.

Parameter	Description
Day Type	Defines the type of day refer to. The enumerated values of this parameter will be updated according to the extracted occupancy patterns. Typical values are: weekend, weekday, special events, bank holidays
Season	Defines the season that metrics refer to. The typical taxonomy is: Autumn, Winter, Spring, Summer

Table 6 Temporal Granularity

Therefore, the spatio-temperal granularity of the project set constrains for the state occupancy representation (in terms of diversity profiles). The flow modelling part is further combined as an aspect of the model towards the provision of the enhanced MOEEBIUS Occupancy modelling framework.

4.3.2.2 Flow Modelling Parameters

The matrix presented above contains the typical diversity occupancy profile of the zone. To address the stochastic nature of this aspect, probabilities of moving from one occupancy level to another (and therefore specific transition paths) are defined to depict occupants flow. The transition table that incorporates these flow parameters of the model:

Parameter	Description	Type
Transition Probability	The probability value for each transition at a specific time-period/ timestamp of the day	complex
Start Point	The time the first occupant arrives.	time
End Point	The time the last occupant leaves.	time

Table 7 Flow Modelling Parameters

The transition probability is modified through time and thus the complex type ("Transition Probability") is segmented to {probability value (float), time-period (time)}. The values of this flow matrix are continuously updated taking into account the training process of the occupancy profiling engine. We have to point out that huge volumes of data and a long training period is required for modelling the transitions. Therefore, the main focus of MOEEBIUS demonstration is on the extraction of accurate diversity profiles.

4.3.2.3 Open Reference and Schedule models specifications

As mentioned above, the definition of open reference models and typical pilot schedules has to be defined in a standardized way. These input parameters are further incorporated in the occupancy profiling framework and thus modelling specifications are provided for these initial configuration settings. A representation of the specifications about **Open Reference Occupancy Models** is given in the next figure.

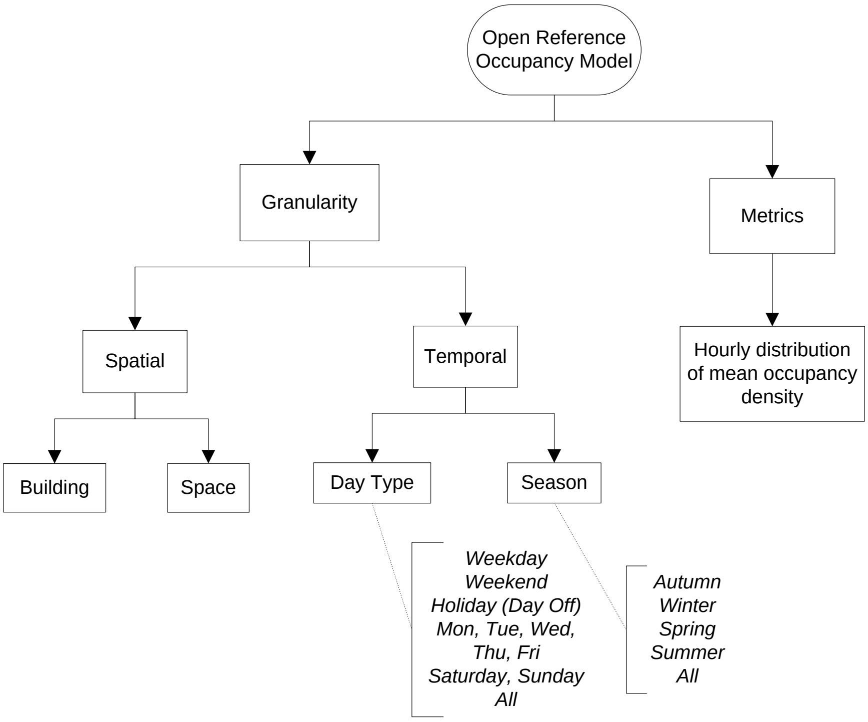


Figure 18 Open Reference Occupancy Model Specification

The model contains the hourly distribution of the occupancy density for the whole building or per space and may be different depending on the type of day and season. Therefore the modelling aspects for open reference models are similar to them presented for occupancy profiles, considering these diversity profiles as the baseline for open reference models.

For typical schedules we refer to events concerning either the whole building (e.g. operating hours, holidays, special activities) or particular spaces (e.g. meeting room, lab). Furthermore, schedules may contain either **typical** or **dynamic** information. Typical schedules refer to typical events/tasks, such as working time,

holidays, lunch break hours, common meeting times, while dynamic schedules refer to more special events/tasks that do not happen on a regular basis (e.g. extra meetings/conferences, organized events, planned trips, planned vacations etc.). Scheduling information will be provided during pilot evaluation phase in order to further enhance the extraction of occupancy profiling models (manually incorporated in the associated user profiling engine). The general parameters used for zone schedules are given in the next Table.

Parameter	Description	Type
Space	The space/Zone where the event is going to take place	ID
Event Name	A description of the event e.g. meeting/conference, holiday, lunch	string
Start Time	The time the event is expected to start	time
End Time	The time the event is expected to end	time
Occupancy Range	The occupancy range that expected to participate in the event	float or integer

Table 8 Scheduling parameters

As mentioned above we define different types of schedules (typical and dynamic events) that also considered as part of the model. For typical model, an enumeration is defined to specify the periodical character of the event (Season or Day_type) while for dynamic events we have to define the specific date that this event is going to happen. Indicative paradigms for schedules are defined:

Parameter	Typical event	Dynamic event
Space	Building	Meeting room
Event Name	Working period	Meeting
Start Time	8:00	13:00
End Time	19:00	14:00
Occupancy Range	3	1

Season	Autumn, Winter	-
Day Type	Weekday	-
Date	-	23/12/2016

Table 9 MOEEBIUS Schedules examples

We have presented above the different structures that consist of the occupancy profiling framework. Occupancy diversity profiles associated with occupancy flow profiles set the MOEEBIUS occupancy profiling framework, further incorporated with information from open reference models and typical schedules in building premises.

By defining the data parameters that consist of the models for occupancy profiling, we further proceed with the definition of models for short term occupancy prediction.

4.4 Occupancy Prediction Model Specifications

The occupancy prediction modelling specifications are further provided as an instance of the occupancy model presented above. Following the common modelling principles of the different structures defined as part of the occupancy profiling engine, the occupancy prediction is modelled in a similar to real time occupancy. The modelling specifications are presented in the next Table:

Parameter	Description	Type
Space/Zone	The space/zone real-time detected occupancy refers to.	ID, enumeration
Occupancy range as a distribution	The range of occupants in a building/space/ of that building/space/zone per a specified time frame (e.g. per hour).	complex

Table 10 Occupancy prediction modelling parameters

Again, the occupancy range data type is defined as a complex type, with the occupancy range and the short term time-period forecasting. The analysis is delivered for a short period in order to provide accurate results. By taking into account the probabilities for occupancy variation – occupancy flow modelling-, the occupancy prediction values are further associated with a reliability level.

4.5 BEPS tool Occupancy Model parameters

Along with the definition of the occupancy profiling parameters in building premises (as part of MOEEBIUS occupancy profiling engine), we need to further define the data structures for interfacing this information to BEPS modelling framework (in T3.6) and subsequently the BEPS tool (in T5.1). The goal of the MOEEBIUS BEPS tool is to provide accurate building performance simulations, by incorporating in the simulation process dynamically updated occupancy profiles as defined by MOEEBIUS occupancy profiling engine. Therefore, we need to specify the data structures that incorporate occupancy profiling attributes required for the simulation process. The definition of interfaces /methods and the associated data models are reported in deliverables D3.1" MOEEBIUS Architectural Design and Technological/ Functional Specifications" & D3.2 "Common Information Model Definition"; here the specific viewpoint of occupancy profiling models is reported. The representation of the methods defined for interfacing is provided below, while a typical .xsd incorporating this information is provided in Annex II.

Method	Description
getOccYearAvg (depth=null)	Returns hourly occupancy average for a period of one year. Depth is the number of years to consider for the avg. calculation. If null last year
getOccSeasonAvg (season= <val>,depth=null)	Returns hourly occupancy average for a certain season. Depth is the number of years to consider for the avg. calculation. If null last year
getOccMonthAvg (months= <listval>,depth=null)	Returns hourly occupancy average for certain months. Depth is the number of years to consider for the avg. calculation. If null last year
getOccMonthAvg (stardate= <val>,enddate=<val>)	Returns hourly occupancy average between certain dates.
getOcc24h ()	Returns the hourly occupancy forecast for 24h ahead

Table 11 BEMS tool occupancy modeling incorporation

This list is an indicative one, while the actual implementation of these interfaces will be performed in WP5 along with the development of Building Energy Performance Simulation System Enhancement (T5.1) & Occupant Profiling Mechanism (T5.2). The goal of this section was to provide the modelling framework about occupancy profiles as agreed among the partners participating in the development process. These, will be further incorporated with behavioural aspects, towards the extraction of MOEEBIUS behavioural profiles. The detailed framework for the extraction of these profiles is provided in the next section.

5 MOEEBIUS User Preferences Modelling Specification

In this section, the detailed specifications of MOEEBIUS User Preferences Models are provided. First, we set the algorithmic framework for the extraction of the different behavioural profiles. Then, the detailed behavioural profiling modelling aspects are defined.

As mentioned above, the behavioural model analysis is mainly focusing on two core aspects: thermal and visual preferences (considering operational and price elasticity profiles as part of the proposed framework). The principles of the process are the same, though differentiations will be highlighted at the modelling analysis. Within MOEEBIUS (taking into account the limited number of equipment installations), zone specific occupancy and therefore behavioural profiles will be extracted.

5.1 Behavioural Preferences Modelling Overview

We have already highlighted ASHRAE as the initiative to specify the comfort aspects for building occupants. ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) [31] points out in its handbook four factors which affect the final inner comfort in a building:

- Thermal comfort, which is the most widely examined factor through the aggregation of heterogeneous parameters, such as humidity, air-conditioning temperature, external temperature, and air speed
- Visual comfort which depends on illumination level
- Air quality, based on the CO2 measurement within the infrastructure examined
- Noise level, which is a measurement of the noise within the infrastructure

From these, thermal and visual comfort parameters are examined in this document. Air quality models are examined in Task 3.5 while noise level analysis is out of the scope of the project. In this section, we present the approach for modelling behavioural preferences at building zones. Along with the definition of the modelling principles, we are further defining the algorithmic framework for the extraction of user preferences (in the next section).

As a high level picture for the proposal, we have to say that we are not providing a static model rather a dynamic one continuously updating to reflect changes that may occur in occupants' behaviour. The occupants will not have to explicitly define their operational profiles, instead these will be defined by continuously monitoring user control actions and also reactions (corrective control actions) to specific contextual conditions. The evaluation of the user profiling framework will be based on the selection of specific events that affect occupants' preferences. The different types of events examined for the user preferences framework are:

- **Environmental Events**: The reduction of the luminance or the increase of external temperature may trigger the generation of different types of events

- **Control Actions**: The events triggered by the reaction of the users to the internal conditions through actuators.
- **Occupancy events**: These types of events are considered as the events triggered by the variation of the number of occupants within the infrastructure. We have already specified occupancy event types in previous section.

Following the initial segmentation of events (environmental, control actions, occupancy) required for the behavioural profiling framework, the core part of the work is the definition of the types of preferences to be examined in the project. We have already specified through the literature review the most important features that set the baseline for the MOEEBIUS framework:

- **Thermal Comfort Profiling.** Thermal comfort is the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation (ANSI/ASHRAE Standard). Maintaining this standard of thermal comfort for occupants of buildings or other enclosures is one of the most important goals of HVAC (heating, ventilation, and air conditioning) design engineers. The **Predicted Mean Vote** (PMV) model, as presented above, is the main model considered for the quantification of comfort level. In addition, adaptive models about thermal comfort preferences are also mentioned in State of the Art Analysis to further consider occupants as dynamic entities of the building. The combination of these two modelling frameworks set the baseline for the proposed MOEEBIUS thermal behavioural profiling model.
- **Visual Comfort Profiling**. Visual comfort and discomfort levels of occupants is an obscure concept because of the multiplicity of variables involved and the difficulty of reconciling aesthetic and physiological elements. Most visual discomfort metrics have been derived under controllable conditions in lab environment and represent an average over the subjects, without making any provision for adaptation to individual needs. Therefore, it is mandatory to develop a framework in which visual discomfort can be expressed addressing individual needs and preferences. In the MOEEBIUS framework, we propose a method to calculate a visual comfort probability in a specific zone, relying exclusively on the observation of the users' actions in premises. This user-adaptive approach is delivered as part of the MOEEBIUS Behavioural Profiling framework and defines the visual comfort and discomfort levels of individuals under different environmental conditions.
- **Device Profiling**. Along with the extraction of thermal and visual profiles, we extend the framework in order to cover typical devices whose operation is not affected by environmental conditions. These devices are dependent only from user settings and operational characteristics. The most typical example of this device type is the charging process of electric vehicles. This is the case of shiftable devices where user preferences and non-preferences are directly affected by the operational characteristics of devices.

In addition, and in lack of low level information from specific building devices, aggregate price driven behavioural profiles should be defined. This is the initial step of the work towards the extraction of price elasticity profiles, to be further incorporated at the decision process of Demand Side Aggregator.

By defining the types of behavioural profiles examined in the project, we need to define the contextual framework for the delivery of these models. A short overview of the semantic elements that set principles for the profiling framework is provided in the following Table.

MOEEBIUS Semantic Element	Dependency
Building Information Model	BIM model provides the structural characteristics of the infrastructure. A list of areas and sub-areas within the buildings are defined setting the physical layer for the extraction of Behavioural Profiles
Occupancy Profiling Model	The occupancy flow model provides to the Behavioural profiling model information related to occupancy patterns. This close dependency has been already highlighted in previous section.
Events Model	As mentioned before, different types of context events are triggered by the occupants on specific BIM zones. These events will further enable the extraction of Behavioural Profiles
DER Model	Behavioural Profiles are defined for specific devices and therefore detailed DER models should be considered for the overall modelling representation of MOEEBIUS framework
KPI Model	Behavioural Profiling framework is further associated with comfort and discomfort KPIs. This work is documented in T3.6.

Table 12 Context Framework for Behavioural Profiling

The aforementioned analysis provided an overview of the profiling types examined in the project, highlighting the input parameters to be considered for the profiling mechanism and further define the context for MOEEBIUS Behavioural analysis. This initial analysis sets the layer for the definition of the algorithmic framework to further define the aspects/data attributes of MOEEBIUS Behavioural modelling framework.

5.2 MOEEBIUS User Preferences Algorithmic Framework

We have already highlighted in the literature, the preferable approach for MOEEBIUS user preferences framework. A preferences framework expressed in terms of utility function is considered as the baseline for the proposed profiling Engine. We have to point out that different viewpoints of the same algorithmic

approach are considered for the specification of the different profiling types. More specifically we define:

Algorithmic Framework for context based devices: A Bayesian formalism is proposed to estimate objectively occupants' visual and thermal discomfort as a function of the environmental conditions at one or more locations. Expressed as a discomfort probability, it is based on an analysis of past history of user's interactions with lighting and HVAC devices (devices associated with visual and thermal comfort respectively).

Algorithmic Framework for operational devices: These are the devices that are not directly related to environmental conditions and thus user preferences are device operation driven. The algorithmic approach for these device types is the extraction of an abstract utility function taking as input parameters the interaction of users with these devices.

In addition, the **algorithmic framework for the extraction of behavioural profiles as a function of tariff schemas** is provided as part of the work. This is a parallel activity towards the extraction of accurate price elasticity profiles and is presented as an Annex (Annex IV). Following the distinction among the different types of devices, the detailed algorithmic framework is presented.

5.2.1 Algorithmic Framework for context based devices

We have already highlighted the Bayesian networks as the principle for the behavioural analysis [32]. The anchor point of the proposed framework is the estimation of user's discomfort from a statistical study of his past behaviour. More specifically, Bayes' theorem is applied to estimate a Bayesian Discomfort Probability as a function of the temperature/luminance distribution in each building zone. We first set a review of Bayesian statistics and then we discuss how these can be applied in our case.

In statistics, Bayesian inference is a method of inference in which Bayes' rule is used to update the probability estimate for a hypothesis as additional evidence is acquired. Bayesian updating is an important technique throughout statistics, and especially in mathematical statistics. Bayesian inference has found application in a range of fields including science, engineering, philosophy, medicine and law.

A more concrete description of the Bayesian inference follows. Bayesian inference is what we do when we infer that a state A must be true because we have observed state B and that A and B usually happen together. For example, if we see a lion at a circus show we can infer that it must be tame, because all tame lions we have seen were part of a circus show, and we have never seen a wild lion in such a show. Series of experiments have successfully demonstrated that the brain carries a built-in prior probability curve for different kinds of events, which is updated as new evidence becomes available.

It was Reverend Thomas Bayes (1702–1761) who first discovered what is now known as Bayes' theorem: given two events, denoted by A and B, the following holds:

$$\Pr(A \mid B) = \frac{\Pr(B \mid A) * \Pr(A)}{\Pr(B)}$$

Where Pr(A) stands for the probability of event A and Pr(A|B) stands for the conditional probability of A knowing that B has happened. Pr(B) can be expanded, yielding the same theorem in another form:

$$\Pr(A \mid B) = \frac{\Pr(B \mid A) * \Pr(A)}{\Pr(B \mid \bar{A})\Pr(\bar{A}) + \Pr(B \mid A)\Pr(A)}$$

Where Pr(Ā) stands for the probability of A not happening. Bayes' theorem deals with only two events, but Bayesian networks link together an arbitrary number of events believed to exert a probabilistic influence on each other. Consider the following example, adapted from Korb and Nicholson (2004) [33]: a patient's chances of developing lung cancer are assumed to depend exclusively on whether they live in a polluted area, and on whether they smoke. Similarly, having cancer will determine the chances of an X-ray test to be positive and will also affect the chances of the patient developing a breathing condition known as dyspnoea. The probabilistic influences exerted among these events are shown in Figure 19.

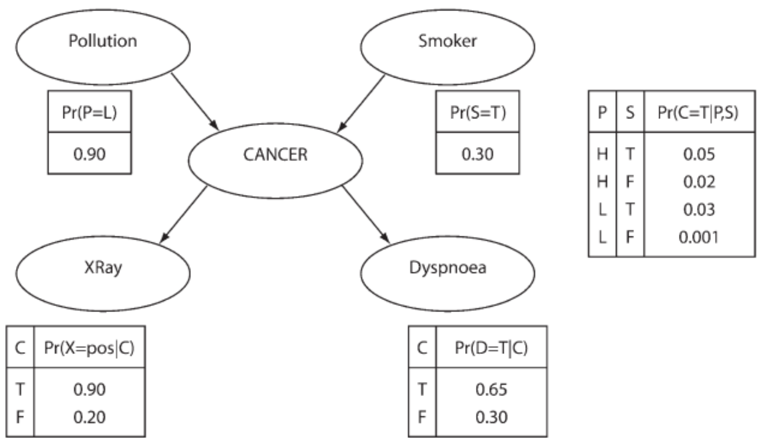


Figure 19 Bayesian Inference Approach- Reference Example

Here the conditional probabilities are given explicitly, and successive applications of Bayes' theorem allow us to determine any other probability. For example, without knowing whether the patient exhibits dyspnoea and without the results of an X-ray test, the probability of any patient having cancer (with symbols as defined in Figure 19) is:

$$
\begin{aligned}
\Pr(C=T) = {} & \Pr(C = T \mid P = H, S = T)\Pr(P = H)\Pr(S=T) + \\
& \Pr(C = T \mid P = H, S = F)\Pr(P = H)\Pr(S=F) + \\
& \Pr(C = T \mid P = L, S = T)\Pr(P = L)\Pr(S=T) + \\
& \Pr(C = T \mid P = L, S = F)\Pr(P = L)\Pr(S=F)
\end{aligned}
$$

Where,

- $\Pr(C = T)$: The probability of cancer.
- $\Pr(P = H)$: The probability of high air pollution.
- $\Pr(S = T)$: The probability of being a smoker.

Based on the above mentioned statistical values as depicted in the schema, we calculate the probability Pr(C = T) = 0.012.

Bayesian inference has emerged in recent years as a particularly promising form of artificial intelligence and has gained a solid foothold in different application domains.

The anchor point of our claim in MOEEBIUS project is that if (even naive) Bayesian classifiers are so good at calculating probabilities, then they should also be able to calculate the probability for a certain environment of being comfortable or uncomfortable to its occupant. Such a classifier should base its judgment on the physical variables it measures and classify the zone examined as comfortable or not. In particular, this classifier will look for correlations between different types of discomfort levels and environmental parameters towards the extraction of accurate behavioural profiles. The principle for the extraction on behavioural profiles based on zone settings and user preferences is provided:

Environment Conditions, Controls& Settings → [Profiling Engine] → Comfort parameters

The following of this section highlights the applicability of Bayesian networks in MOEEBIUS case towards the definition of visual and thermal preference profiles.

Visual Comfort Bayesian networks

As an initial step, we continuously record the measured illuminance levels after each user action. If we denote as:

- C: Event "User being comfortable"
- E: Illuminance level
- T: True Indication & F: False Indication as the possible values for C
- E: possible illuminance value for E parameter

We can estimate based on the available data the following parameters:

- $\Pr(E = e|C = F)$, which is the PDF when an abnormal comfort situation is considered.
- $\Pr(E = e|C = T)$, which is the PDF when a normal comfort situation is considered.

If *E* is a discrete variable we should simply count the number of times it realized each value and divide by the total number of events. If *E* is a continuous variable, it is, strictly speaking, a probability density we must estimate. The simplest density estimator is a classic histogram but the choice of bin width can influence the resulting density estimate. The details of this segmentation is not the scope of this deliverable but part of the development of user preferences engine.

In Figure 20 we show an example of the estimated density of illuminance level for a typical building zone when discomfort, $\Pr(E = e|C = F)$. The data points are represented beneath each density curve as small ticks.

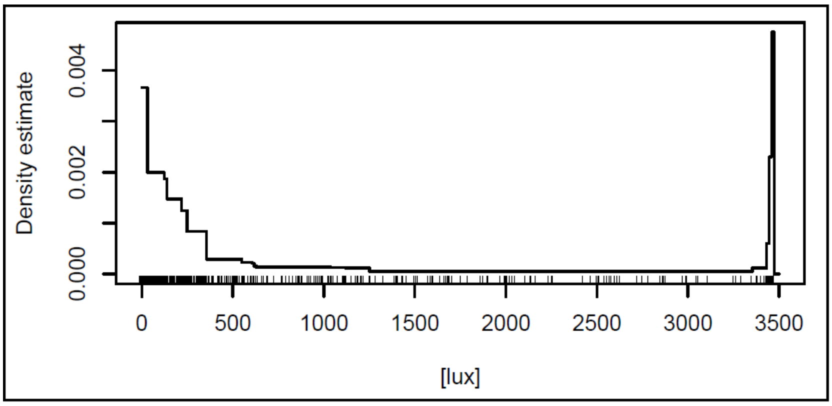


Figure 20 Probabilistic Density Function for true comfort settings

The users are remarkably consistent in that the illuminances most often seen to trigger a user action are below about 200 lux, or higher than 3000. In other words, only very dark or very bright situations prompt user actions. Similarly, the distribution of illuminances resulting from user actions tends to cluster around a value of about 400-500 lux. Again, the users are consistent among each other.

From the aforementioned two curves, we may now apply Bayes' theorem and derive Pr(C = False | E = e), i.e. the probability of user discomfort as a function of illuminance level. The estimation of PDF function is depicted:

$$\Pr(C = F|\, E = e) = \frac{\Pr(E = e|C = F) * \Pr(C = F)}{\Pr(E = e|C = F) * \Pr(C = F) + \Pr(E = e|C = T) * \Pr(C = T)}$$

The $\Pr(C = F)$ term, named to Bayesian formalism as the prior, has been the cause of much controversy in the statistical community. A couple of years ago the dust settled and the consensus seems now to be that in the absence of any prior information it is safe in most cases to set $\Pr(C = F) = \Pr(C = T) = 0.5$.

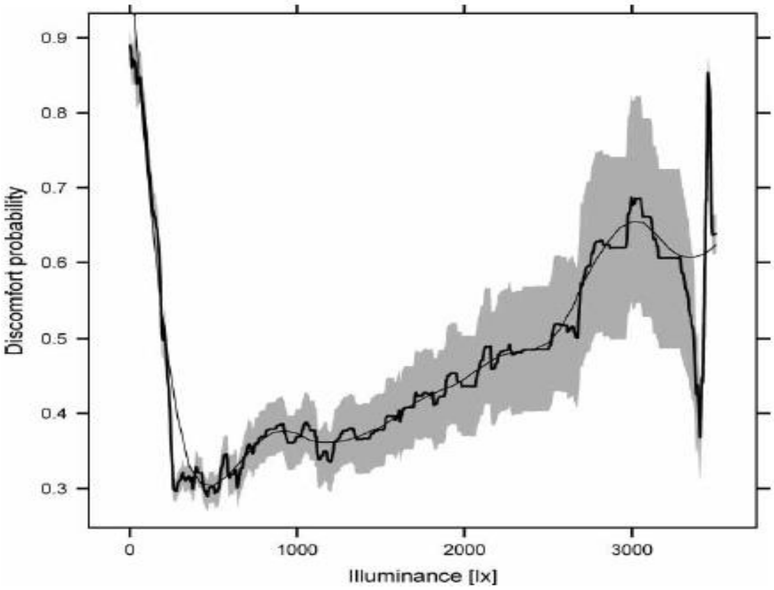


Figure 21 Discomfort Probability Function [20]

The output curve, smoothed with a "lowess" function, is shown in Figure 21. A global minimum at about 500 lux is depicted showing the maximum comfort/ minimum discomfort level.

It is obvious from the curve that for the average user, the preferred horizontal illuminance should be at 500 lux. This is for the specific case taking into account the illuminance level as tracked by the luminance sensor. An overview of algorithmic framework for the extraction of visual comfort behavioural profiles is presented:

<u>Input Parameter</u>

Illuminance value (lux: as measured by luminance sensor). User control actions on lighting devices trigger environmental events. Based on correlation of control action with luminance events we can define comfort and discomfort states.

<u>Algorithmic Framework</u>

Extraction of probability functions: $\Pr(E = e|C = T)$ & $\Pr(E = e|C = F)$ based on available data. Input parameters for probability functions estimation are:

- E: illuminance state
- e: illuminance data
- C: Event "user being comfortable"

<u>Output</u>

The PDF function $\Pr(C = F|\, E = e)$ expresses the discomfort value on a state condition for the single occupant.

Thermal Comfort Bayesian networks

Thermal comfort is defined in terms of the perception of satisfaction that a subject experiences in a given thermal environment. Probably, the most influential standards for designing an indoor environment of thermal comfort have been developed by ASHRAE, the International Organization for Standardisation (ISO) [34], and the European Committee for Standardisation (CEN) [35]. The sensation of thermal comfort is found to be dependent on six environmental and physical factors: air temperature, radiant temperature, air speed, air humidity, and metabolic rate as well as clothing level of the subject. Based on these factors, mathematical expressions of a thermal sensation index, the Predicted Mean Vote (PMV) is delivered, for predicting the percentage of dissatisfied occupants against certain indoor environments were proposed.

The aforementioned model is generic enough and cannot cover the specificities of each case scenario. Therefore, an adaptive thermal approach is proposed to optimise the comfort acceptance of end users. A Bayesian adaptive comfort temperature approach is proposed for MOEEBIUS in order to predict the desired temperature set point for an air-conditioned space according to the occupants' complaints about thermal discomfort. The basis for this model remains the PMV indicator as the commonly selected indicator in the domain, though an adaptiveness of this parameter is defined as part of the personalization process of the project. In particular, measured system settings and complaint records are used as input parameters to demonstrate the proposed algorithm in determining the optimum temperature set point for the HVAC system.

The main differentiation from luminance framework as presented above is that parameter E is a discrete variable. Subsequently, the thermal discomfort function is extracted as a discrete probability density function and each value defines the utility parameter (Utility function) as thermal preference. The next table presents the details of the algorithmic framework for thermal (dis)comfort profiling.

Input Parameter

Indoor Temperature value (as measured by temperature sensor) and **indoor humidity value** (as measured by humidity sensor) further combined and expressed in terms of PMV. The user control actions on HVAC units trigger an environmental event. Based on correlation of control action with temperature & humidity events we can define comfort and discomfort states.

Algorithmic Approach

Extraction of probability functions: $\mathrm{Pr}(\mathrm{E} = \mathrm{e}|\mathrm{C} = \mathrm{T})$ & $\mathrm{Pr}(\mathrm{E} = \mathrm{e}|\mathrm{C} = \mathrm{F})$ based on available data. Input parameters for probability functions estimation are:

- E: Temperature/ Humidity state
- e: Temperature/ Humidity data
- C: Event "user being comfortable"

Output

The PDF function $\mathrm{Pr}(\mathrm{C} = \mathrm{F}|\ \mathrm{E} = \mathrm{e})$ expresses the discomfort value on a state condition for the single occupant.

As an intermediate step of the framework, is the extraction of PMV values from temperature and humidity data. The ASHRAE standard specifies the equation for PMV calculation (presented also in D1.3 as part of KPIs definition), though a non – parametric machine learning technique is adopted in the project for the direct calculation of PMV values. A fuzzy based model as proposed by Hamdi et al. [42] is followed to express the PMV values as a synthesis of context dependent and personal dependent parameters.

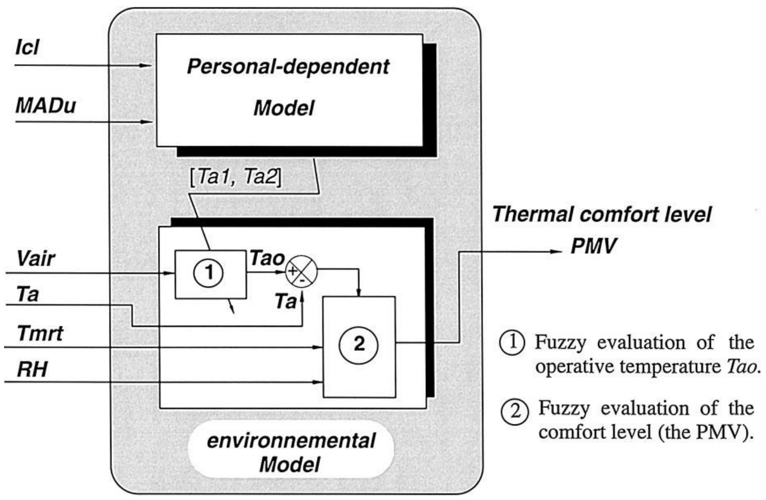


Figure 22 Architecture of the fuzzy thermal sensation index

Following the definition of the algorithmic framework for context based devices, we further proceed with the adaptation of the framework for operational device types.

5.2.2 Algorithmic Framework for operational devices

The algorithmic framework for defining comfort and discomfort boundaries of operational devices is slightly different and customized to each device type. First, we have to define the list of device types integrated in MOEEBIUS project:

- The first type includes shiftable devices such as water heaters. For these device types, the end user cares whether the task is completed before certain time. Therefore, the objective is to ensure users' preference levels at the end of operational period. Following the ex-ante pilot analysis water heater is the only device to be considered in the project, though a generic model is provided to facilitate the easy transformation in any case scenario.
- The second type includes the devices that must be in ON mode when present, such as monitor PC. The utility function of these devices is expressed by the following formula:

Operational Status = {1, when present || 0, when absent}

This is the simplest case where the user preferences are occupancy (presence/absence) driven.

We examined the definition of discomfort states as a function of control actions and configurations and thus we express the algorithmic framework for operational devices through:

As a side activity, we defined also the algorithmic framework for the extraction of price elasticity profiles. This analysis is not at the core work of this task and thus the preliminary analysis is provided as part of the Annex.

We have presented in this section the **holistic algorithmic framework** for the extraction of behavioural profiles. The main focus is on the extraction of context based behavioural profiles (thermal and visual) though the analysis covers also operational device types. By having defined the algorithmic framework for the extraction of behavioural profiles, we extract the modelling specifications that explicitly characterize occupants' behaviour. This is the scope of the next section; to define the detailed modelling parameters of MOEEBIOUS Behavioural Profiling Mechanism.

5.3 Behavioural Profiling Modelling Specifications

In previous sections, we presented the detailed analysis (algorithms) for the extraction of user preferences and here we are providing the associated modelling specifications. As an Annex (Annex IV), we are documenting the associated model parameters for price driven behavioural profiles.

5.3.1 User Preferences Model Input Parameters

The occupancy events, as extracted from aforementioned occupancy profiling engine set input parameter for the MOEEBIUS user preferences framework. In addition within MOEEBIUS framework, different types of events as captured from pilot sites are handled towards the extraction of user preferences. Therefore, the list of events considered as input parameters for the model are presented:

Event Types	Description
Environmental	Events triggered due to significant changes on environmental conditions
Control Actions	Events triggered through the interaction of occupants with devices
Occupancy	Events as triggered from real time occupancy extraction mechanism

Table 13 Types of events

Following the definition of event types, a summary of events structure is presented, following the definition of event type in MOEEBIUS CIM. The event type is modelled as:

Parameter	Description	Type
Id	An index that express the sequence of events	ID
EnvironmType	The ID of the environmental parameter examined.	Complex
Value	The measurement value of the environmental type	Float
Space/Zone	The area of the infrastructure related to the specific event	ID
Time	Time period of the event	time

Table 14 Environmental event Type

The complex datatype "EnvironmType" is analyzed as:

- Type: The ID of the environmental parameter examined
- Type unit: The unit of the measurement value.

These data are extracted from MOEEBIUS Middleware Layer. The metrics and the units are defined:

- Temperature: °C
- Humidity: %
- Luminance: lux

Furthermore, control actions (on different DER types) are defined. The event model is presented:

Parameter	Description	Type
Id	An index that expresses the enumeration of Control Events	ID
DER_Id	The Id of the device triggered from a control action of the user/group of users	ID
Space	The Id of the space that the respective device is placed	Float
User	The ID of the user that activate this control action or if automated	ID
Control Act	The respective Control Action on the actuator, triggered in	Complex
Time	Time period of the event	time

Table 15 Control action event Type

The datatype "ControlAct" is a complex type defined as:

- Control Status: On/Off setting of the device
- Control Mode: The actual control settings of the device

This event model is generic enough to cover the full list of control actions but the focus of the user profiling framework is on manually driven control actions.

Details about the modelling representation of real time occupancy events types have been already provided in previous sections. Here we present the data structure of occupancy events as requested by the user preferences model.

Parameter	Description	Type
Id	An index that express the enumeration of occupancy events	-

Space	The area/zone of the occupancy event	ID
Time	Time period of the event	time
Occupancy Range	The total number of occupants within the area examined	Float or integer

Table 16 Occupancy event Type

This model representation is the enhancement of real time occupancy status with timestamp and a unique ID for managing historical data. By defining the input parameters of the model, we can proceed with the detailed modelling of user preferences framework.

5.3.2 User Preferences modelling – Generic specifications

The structural specifications for the user preferences model are provided. These specifications are covering the different models defined in this section, further presented in the following table:

Parameter	Description	Type
Id	Id of the zone/space examined	-
Space	The area/zone with the specific ID	ID
Occupancy Range	Occupancy Range in the area/zone	Float or integer
ExtPreferences	External Preferences as defined by the interaction of Building occupants with the platform	ExtPreferences
Control Actions	The list of historical control actions as derived from the specific group	ControlAct
EnvConditions	The list of environmental conditions considered for the extraction of user preferences	EnvironmType
Preferences	The list of preferences as extracted from User Profiling mechanism	Preferences

Table 17 Group of Users Characteristics

We have already defined the complex types: ControlAct & EnvironmType. The complex type "ExtPreferences" defines user settings as provided by building occupants' interaction with the MOEEBIUS platform (through Mobile UI). This complex type is presented:

Parameter	Description	Type
Luminance	Selection among predefined modes for luminance level	string
Temp_Summer	Preference temperature during summer/spring period	float
Temp_Winter	Preference temperature during autumn/winter period	float
Device Set point	Operational preference about each specific controllable device	float

Table 18 ExtPreferences Type Model

By providing the high level structure of User Preferences modelling, we further proceed with the detailed framework for each modelling aspect examined in the project. A schematic representation of the MOEEBIUS holistic behavioural profiling model is also provided in Annex.

5.3.3 User Preferences modelling – Thermal Comfort

For thermal models we first specify the input data types considered for the model. Therefore, the environmental types of: **temperature** and **humidity** are considered along with control actions on the different types of HVAC units integrated in the project.

The "Preferences" data type for thermal comfort profiling is further defined in the next table.

Parameter	Description	Type
maxPMV	The parameter/value for the upper boundaries of the thermal comfort type examined. A predefined PMV value is considered for the specific group of occupants.	PMV
minPMV	The parameter/value for the lower boundaries of the thermal comfort type examined. A predefined PMV value is considered for the specific group of occupants.	PMV
Current PMV	The parameter/value for the current value of the thermal comfort type examined. (PMV value)	PMV

Average	The average PMV value as defined from Thermal Profiling framework	PMV
DiscomfortCurve	The non-parametric vector that defines the discomfort utility function as a function of input environmental conditions	Complex

Table 19 Thermal Preferences Model

The complex "DiscomfortCurve" type is modeled as a table with input parameters: {temperature, humidity} and output parameter: {Utility Function}.

The same process is considered for the definition of visual preferences model

5.3.4 User Preferences modelling – Visual Comfort

For visual comfort analysis the environmental type of: **luminance** is considered along with control actions on the different types of lighting devices integrated in the project.

The next table presents the list of parameters that specify the visual preferences model parameters:

Parameter	Description	Type
maxLum	The parameter/value for the upper boundaries of the visual comfort type examined. A predefined luminance value is considered for the specific group of occupants.	Float
minLum	The parameter/value for the lower boundaries of the visual comfort type examined. A predefined luminance value is considered. A predefined luminance value is considered for the specific group of occupants.	Float
CurrentLum	The parameter/value for the current value (most recent analysis) of the visual comfort type examined.	Float
AverageLum	The parameter/value for the average value of the comfort type examined. A predefined performance indicator is considered.	Float
DiscomfortCurve	The non-parametric vector that defines the discomfort utility function as a function of input environmental conditions	Complex

Table 20 Visual Preferences Model

Again, the complex "DiscomfortCurve" type is modelled as a table with input parameter: {luminance} and output parameter: {Utility Function}.

5.3.5 User Preferences modelling – Operational Comfort

Along with the definition of context based profiles, we define preferences profiles for operations driven devices. In this case, there is no external parameter affecting users' preferences and thus occupants control actions and control events trigger the analysis for the extraction of operational preferences.

The "Preferences" type for operational profiling is defined in the next table.

Parameter	Description	Type
maxDER	The parameter/value for the upper boundaries of DER operational setting.	DER_Setpoint
minDER	The parameter/value for the lower boundaries of DER operational settings.	DER_Setpoint
CurrentDER	The parameter/value for the current value of DER operational settings.	DER_Setpoint
AverageDER	The parameter/value for the average value of DER operational settings.	DER_Setpoint
DiscomfortCurve	The non-parametric vector that defines the discomfort utility function as a function of DER operational settings	Complex

Table 21 Operational Preferences Model

The complex "DiscomfortCurve" type is modeled as a table with input parameters: {DER Set point} and output parameter: {Utility Function}. We have to point that this approach is defined for a limited number of controllable devices, explicitly examined in MOEEBIUS project.

We have defined the different classes and attributes that consist of the MOEEBIUS behavioural profiling framework. We first model the input parameters for each case. Environmental conditions, occupancy and control events are considered as input parameters of the model. Then, following the algorithmic process for the extraction of user preferences, the different behavioural profiling types (Thermal, Visual, and Operational) are defined. Along with statistics (as extracted from algorithmic process), the **DiscomfortCurve** is the outcome that estimates the discomfort utility function for building occupants.

5.4 User Preferences Model- Reference Specification

In order to clearly specify the different parameters of the holistic behavioural profiling model, a typical example is provided. The parameters are defined for a specific zone of the building, focusing on the parameters of visual profiling model. The same approach should be considered for thermal profiling model.

Parameter	Description	Value
Id	Id of the zone/space examined	1_12
Space	The area/zone with the specific ID	Adminstrative_ Office
Occupancy Range	Occupancy Range in the area/zone	3 (medium occupancy range)
ExtPreferences	External Preferences as defined by the user	ExtPreferences
Control Actions	The list of historical control actions as derived from the specific Space	ControlAct
EnvConditions	The list of environmental conditions (luminance) as derived from the specific Space	EnvironmType
Preferences	The list of visual preferences as extracted from User Profiling mechanism	Preferences

Table 22 Adminstrative_Office Visual Preferences Root

The External Preference settings associated with the visual preferences model are presented:

Parameter	Description	Value
Luminance	Luminance settings	Bright

Table 23 External Preferences – Visual Comfort

A list of luminance events and control actions over lighting devices is associated with the modelling framework but are not presented in this section. Indicative events per each category are presented:

Parameter	Description	Value
Id	An index that express the sequence of events	01
EnvironmType	The ID of the environmental parameter examined.	Luminance

Value	The measurement value of the environmental type	200
Space/Zone	The area of the infrastructure related to the specific event	1_12
Time	Time period of the event	hh:mm:ss

Table 24 Luminance event

Parameter	Description	Value
Id	An index that expresses the enumeration of Control Events	01
DER_Id	The Id of the device triggered from a control action of the user/group of users	Light_01
Space	The Id of the space that the respective device is placed	1_12
Control Act	The respective Control Action on the actuator, triggered in	{ON, 70%}
Time	Time period of the event	hh:mm:ss

Table 25 Control action event Type

The next table presents the list of parameters as extracted from Visual Preferences model:

Parameter	Description	Value
maxLum	The parameter/value for the upper boundaries of the visual comfort type examined	500
minLum	The parameter/value for the lower boundaries of the visual comfort type examined	100
CurrentLum	The parameter/value for the current luminance level value	250
AverageLum	The parameter/value for the average value of the visual comfort type examined	240
DiscomfortCurve	The non-parametric vector that defines the discomfort utility function as a function of input environmental conditions	Complex

Table 26 Visual Preferences Model

The visual discomfort curve is further presented:

Input Value (luminance)	Output Value (Utility Function)
10	1.0
30	1.0
50	1.0
70	1.0
90	0.9

Table 27 Visual Discomfort Curve

The output of the model is the extraction of **visual discomfort** utility function that expresses occupants' (non) preferences for a specific building zone.

This was an indicative instantiation of the model values for the core models defined in the document. A more detailed analysis of these models and how these will be further exploited in the project will be presented in D3.6: Local and Global Energy performance models (integration of occupancy profiling model as part of the holistic modelling framework) and D5.2 MOEEBIUS User Profiling Framework (development of component integrating the aforementioned profiles)

5.5 Pre-trained windows/blinds control models based on IEA Annex 66

As analysed in Section 3, in order to maintain an acceptable balance between modelling accuracy and feasibility/cost of the final solution, a set of pre-trained user behaviour models for windows and blinds control are utilised, developed or evaluated within IEA Annex 66. These models should be incorporated in the integrated MOEEBIUS modelling framework (D3.6: Local and Global Energy performance models) though no further processing is expected.

As with the adaptive models developed within MOEEBIUS project, the blinds and windows control user behaviour models are considered as *stochastic models*. This means that based on some indoor and/or outdoor drivers/triggers (e.g. indoor/outdoor temperatures, rain, etc.), the adopted models allow calculating the *probability* a user (or a group of users residing in the same building space) will interact with the windows or the blinds (e.g. open or close).

Towards designing a probability distribution for the entire range of indoor and outdoor drivers, all the models utilize logistic regression. This means that the probability distribution $p(\theta)$ is calculated as follows:

$$\log\left(\frac{p(\theta)}{1-p(\theta)}\right) = \alpha\theta + b,$$

meaning that the actual probability distribution is given by:

$$p(\theta) = \frac{\exp(\alpha\theta + b)}{1 + \exp(\alpha\theta + b)}.$$

Here, the parameters α and b are identified using regression [36], while θ is a vector containing all the necessary values for the indoor/outdoor drivers/triggers. A typical example of such a function is shown in Figure 23 [36].

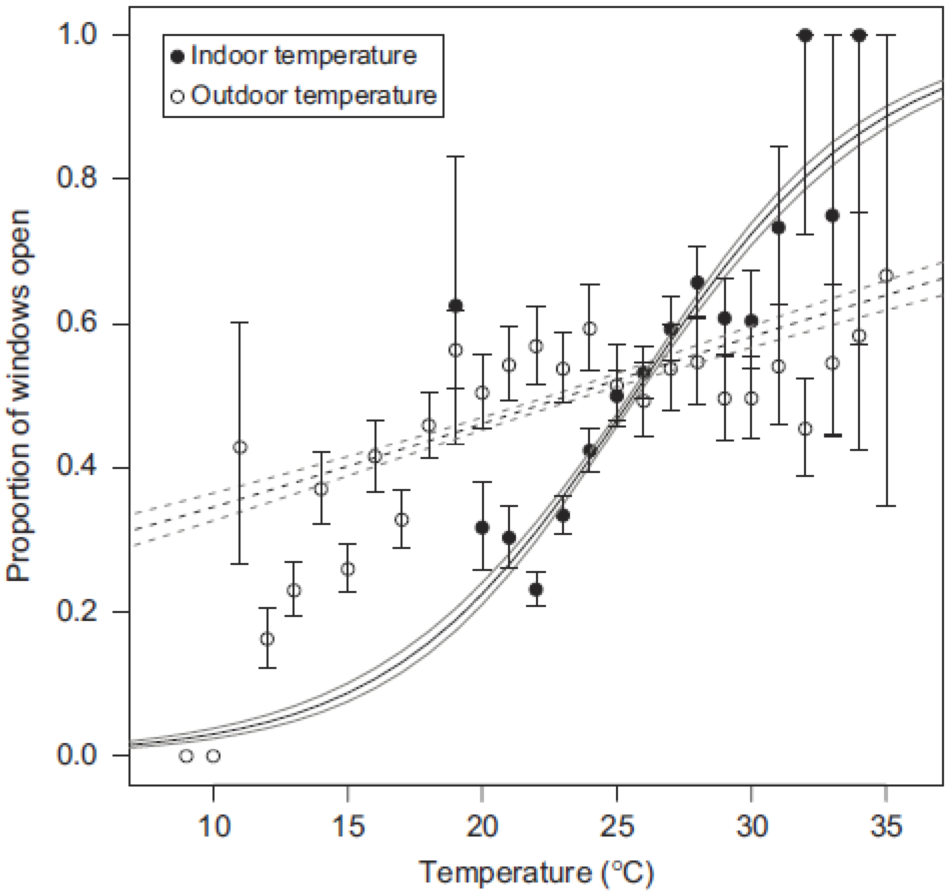


Figure 23 Window opening probability as a function of indoor and outdoor temperature [36]

Following, a brief overview of the selected windows and blinds control models is provided.

5.5.1 Blinds Control

For the blinds control modelling, three models developed in [36] are provided. This study used 5-years data from a Swiss office building for the model training phase and the models *predict the probability a user (or a group of users) will deploy the blinds* based on the specific values of the driving factors. For the first model, the driver is the indoor air temperature, for the second model the driver is the outside air temperature, while for the third model the drivers are both the indoor and outdoor air temperatures.

5.5.2 Windows Control

For the windows control, a larger number of models is available and is included here, some of which facilitate increased complexity.

Starting with the simplest (in structure) models, three models developed in [38] are included. The study used 1.5-year data from 15 UK office buildings for the model training phase and the models *predict the probability a user (or a group of users) will open a closed window* based on the specific values of the driving factors. For the first model the driver is the outdoor air temperature, for the second model the driver is the indoor globe temperature and for the third model the driver is both the indoor globe and outdoor air temperature.

A similar study in [39] utilized 1.5 year data from 33 commercial and office buildings in different climatic zones in Pakistan, and using the indoor globe and outdoor air temperature as drivers, develops a model for *predicting the probability a user (or a group of users) will open a closed window.*

Note that for the two models defined above, one of the driving factors for opening the window is the indoor globe (or mean radiant) temperature, instead of the indoor air temperature. Such a measurement in the actual building would require the installation of a black-globe thermometer in each space. The black-globe thermometer consists of a black globe in the centre of which is placed a temperature sensor. On the other hand, since these models will be coupled to the detailed building thermal simulation model, the mean radiant temperature will be calculated by the building simulation model for each space automatically and can be provided directly as input to the window control models.

Moving to more complex models, in [40] seven models are developed using data from 3 summer months and from two office buildings in UK – one with natural ventilation and one without. For the first two models, the driver is indoor air temperature and they are trained using data from the building without natural ventilation. Here, one model *predicts the probability a user (or a group of users) will open a closed window* while the second model *predicts the probability a user (or a group of users) will close an open window*, using as driving factor the indoor air temperature. The next two models predict the same actions for buildings without natural ventilation, but using as driving factor the outdoor air temperature, while the final three models use the indoor air temperature as driving factor and are trained using the naturally night-time ventilated building data and *predict the probability a user (or a group of users) will i) close an open window; ii) open a closed window; and iii) leave an opened window as is*, respectively.

A far more complex model is trained in [37]. Here, one sub-model for each combination of Markov transition occupancy states (as defined above) and system interaction actions (i.e. from closed to open and from opened to closed) is trained,

using the same data as [36] (see Figure 24). The following divers/triggers/parameters are defined in the model:

- Indoor air temperature;
- Outdoor air temperature;
- A binary input indicating preceding absence longer than 8 hours;
- A binary input indicating rainfall;
- Ongoing presence duration (in minutes);
- Daily mean outdoor air temperature;
- A binary input indicating following absence longer than 8 hours;
- A binary input indicating if the office is on the ground floor.

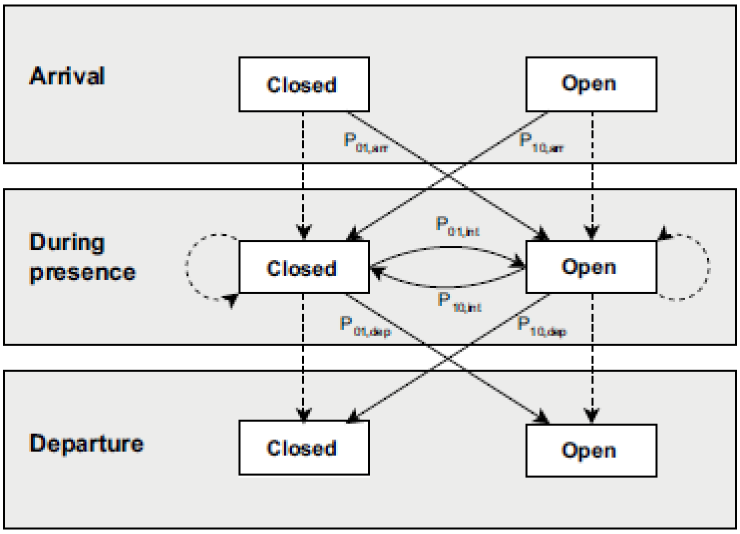


Figure 24 General scheme of the Markov process [3]

Finally, the most complex model is defined in [41], using the data from the naturally-ventilated building of [40]. Here the driving factor is the indoor air temperature, but different logistic regression sub-models are defined based on specific user types and Markov transition states for occupancy.

The three Markov occupancy states defined are: *Arrival, Presence and Departure*, while also four user types defined: *Active, Medium, Passive and Unknown*, depending on how frequently they interact with the system (windows). Of course, the defined user types can be extended to groups of users occupying the same building space.

The first sub-model *predicts the probability an Unknown-type user (or a group of users) will open a closed window when the Markov transition state for occupancy is Presence.*

The second sub-model *predicts the probability an Unknown-type user (or a group of users) will close an open window when the Markov transition state for occupancy is Presence.*

The remaining three sub-models *predict the probability an Active-, Medium- and Passive-type user (or a group of users) will open a closed window when the Markov transition state for occupancy is Arrival.*

In the following Table, a more detailed illustration of the windows and blinds control models described Section 5.5 is presented.

Pub	Data Source	Models / Driving Factors	Action	Markov State	User Type
Blinds					
[2]	5-years data from a Swiss office building	• Indoor air temperature	Open -> Close	(All)	(U)
		• Outdoor air temperature	Open -> Close	(All)	(U)
		• Indoor Air Temperature • Outdoor Air Temperature	Open -> Close	(All)	(U)
Windows					
[4]	1.5-year data from 15 UK office buildings	• Indoor Globe Temperature	Close -> Open	(All)	(U)
		• Outdoor Air Temperature	Close -> Open	(All)	(U)
		• Indoor Globe Indoor Globe Temperature • Outdoor Air Temperature	Close -> Open	(All)	(U)
[5]	1.5 year data from 33 commercial and office buildings in different climatic zones in Pakistan	• Indoor Globe Indoor Globe Temperature • Outdoor Air Temperature	Close -> Open	(All)	(U)
[6]	3 summer months from a UK building without natural ventilation	• Indoor Air Temperature	Open -> Close	(All)	(U)
		• Indoor Air Temperature	Close -> Open	(All)	(U)
		• Outdoor Air Temperature	Open -> Close	(All)	(U)
		• Outdoor Air Temperature	Close -> Open	(All)	(U)
	3 summer months from a UK building with natural night-time ventilation	• Indoor Air Temperature	Close -> Open	(A)	(U)
		• Indoor Air Temperature	Open -> Close	(P)	(U)
		• Indoor Air Temperature	Open -> Open	(D)	(U)
[3]	5-years data from a Swiss	• Indoor air temperature • Outdoor air temperature	Close -> Open	(A)	(U)

	office building	• A binary input indicating preceding absence longer than 8 hours • A binary input indicating rainfall • Ongoing presence duration (in minutes) • Daily mean outdoor air temperature • A binary input indicating following absence longer than 8 hours • A binary input indicating if the office is on the ground floor	Close -> Open	(P)	(U)
			Close -> Open	(D)	(U)
			Open -> Close	(A)	(U)
			Open -> Close	(P)	(U)
			Open -> Close	(D)	(U)
[7]	3 summer months from a UK building with natural night-time ventilation	• Indoor Air Temperature	Close -> Open	(A)	(A) (M) (P)
			Close -> Open	(P)	(M)
			Open -> Close	(P)	(M)
Markov States: (A)rrival, (P)resence, (D)eparture, (All) States **User Types: (A)gressive, (M)edium, (P)assive, (U)nknown**					

Table 28 Synopsis of pre-trained models for windows and blinds control

In summary, windows and blinds control models are models that emulate the control actions performed by building users under specific contextual conditions. An extensive analysis was performed for the selection of the best fitted model. The incorporation of these parameters in the MOEEBIUS simulation tool, will further enables us to mimic the actual building conditions providing a more accurate calculation of building energy performance.

5.6 BEPS tool Behavioural Preferences parameters

Following the definition of modelling framework for the Profiling Engine, we proceed with the incorporation of model parameters in MOEEBIUS BEPS modelling framework (in T3.6) and subsequently the BEPS tool (in T5.1). MOEEBIUS Building energy performance simulation is performed on the basis of dynamically updated occupancy profiles and thus behavioural profiles should be also incorporated in the simulation process. The table depicts the methods to be incorporated in BEPS tool for accessing the updated behavioural profiling values, while a detailed presentation of .xsd schema to be considered for interfacing the tools is presented in Annex II.

Method	Description
getThermal (stardate=<val>,enddate=<val>)	Returns profiling values about thermal comfort associated with a previous period
getVisual (stardate=<val>,enddate=<val>)	Returns profiling values about visual comfort associated with a previous period
getThermal ()	Returns the latest profiling values about thermal comfort
getVisual ()	Returns the latest profiling values about visual comfort

The aforementioned analysis presents the different methods for retrieving behavioural profiling data. Each request is associated with a specific occupancy profiling and building zone, considering the definition of the different semantic elements of behavioural profiling as presented above.

On the other hand, we presented above the windows and blinds control models as static models that emulate the actions of the users in these specific device types. These models will be provided once and their parameters will not be subject to change / adapting to specific occupants, due to the lack of specific sensors in the buildings Therefore, these model are not periodically updated and thus directly incorporated in the BEPS engine defined in the project (also part of the overall integrated MOEEBIUS framework presented in D3.6). Still, the richness and variety of the models allows for determining the most suitable ones for each building/occupant types, based on the building manager experience and/or on-field surveys. A java-based library (Annex III) is developed using the models presented above and is provided as input in Task 3.5.

This chapter documents the models about preferences profiling, focusing mainly in thermal and visual profiles. The extraction of the behavioural profiles will further enable the delivery of a user oriented building management framework, fully preserving end users’ needs and requirements. The next step is the incorporation of these models in MOEEBIUS Occupants Profiling Engine (WP5) and further integration of this engine in MOEEBIUS platform.

6 Conclusions

This report presents the MOEEBIUS occupancy and behavioural modelling framework with the associated specifications. A state of the art analysis was performed as the starting point for the definition of the proposed framework. Then, the two main aspects of the modelling framework were presented: the occupancy profiling model framework and the user preferences modelling framework. Detailed specifications were given for each of these concepts.

Within MOEEBIUS, detailed occupancy models will be created representing the spatio-temporal distribution of occupancy in building zones. These models will depict regular occupancy patterns and will be periodically updated in order to reflect changes that may occur on building's occupancy patterns. The extraction of occupancy patterns takes into account data as retrieved from low cost occupancy sensors incorporated in the selected algorithmic process.

On the other hand, MOEEBIUS user preferences modelling framework covers mainly the core comfort parameters: thermal comfort preferences and visual comfort preferences. These models are defined at a zone level granularity by taking into account occupancy profiles and building contextual conditions. Along with the context based behavioural profiles, DER specific profiles, windows and blinds control models and price elasticity profiles are also defined in order to cover the different case scenarios examined in the MOEEBIUS project.

Apart from the extensive documentation of the modelling framework, a live repo is available storing the associated classes of the model: [43]

Although no major modifications are expected to the MOEEBIUS occupancy and preferences modelling framework, this report can be considered as a living document, adopting minor refinements during the development of the occupancy and behavioural profiling engine. By defining the profiling models, the next step is the incorporation of these models in MOEEBIUS platform. These models set the specifications for the development of the user profiling engine in D5.2 MOEEBIUS User Profiling Framework. In addition, occupants' profiling models will be further integrated in the BEPS engine (to be specified as a whole in D3.6 and developed in D5.1 MOEEBIUS Building Energy Performance Simulation System).

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8 Annexes

8.1 Annex 1: Annex66 overview

Occupant behaviour is complex, stochastic and multi-disciplinary (Figure 1). Having deep understanding of occupant behaviour and being able to model and quantify its impact on use of building technologies and energy performance of buildings is crucial to design and operation of low energy buildings. Due to the complexity and the great district discrepancy of occupant behaviour, it is prerequisite for researchers to work together to define and simulate occupant behaviour in a consistent and standard way.

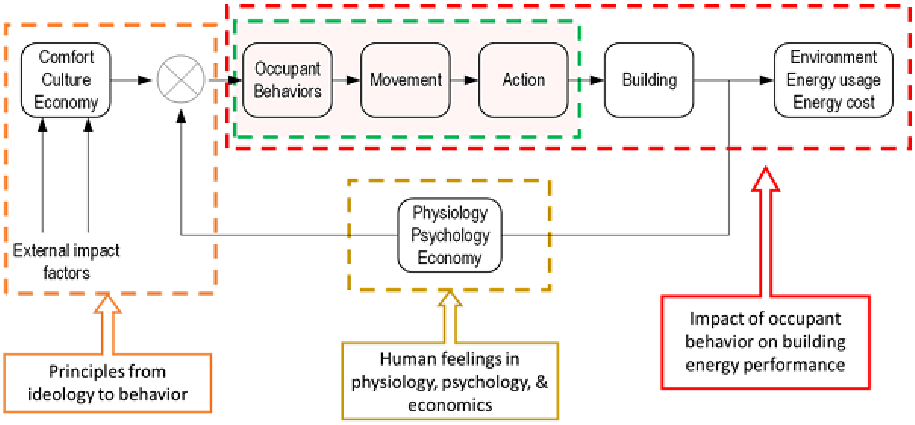

Figure 25 Relationship between occupants and buildings

The Annex 66 aims to set up a standard occupant behaviour definition platform, establish a quantitative simulation methodology to model occupant behaviour in buildings, and understand the influence of occupant behaviour on building energy use and the indoor environment. The project has five subtasks:

<u>Subtask A - Occupant movement and presence models.</u> Simulating occupant movement and presence is fundamental for occupant behaviour research. The main objective of the subtask is to provide a standard definition and simulation methodology to represent how an occupant presents in his/her office and moves between spaces.

<u>Subtask B - Occupant action models in residential buildings</u>. Occupant action behaviour in residential buildings affects building performance significantly. This subtask aims to provide a standard description for occupant action behaviour simulation, systematic measurement approach, and modelling and validation methodology in residential buildings.

<u>Subtask C - Occupant action models in commercial buildings</u>. Some specific challenges of occupant behaviour modelling exist in commercial buildings, where occupant behaviour is of high spatial and functionality diversity. This subtask aims to provide a standard description for occupant action behaviour simulation,

systematic measurement approach, and modelling and validation methodology in commercial buildings.

Subtask D - Integration of occupant behaviour definition and models with current building energy modelling programs. This subtask will bridge between Subtasks A-C and Subtask E, enable applications by researchers, practitioners, and policy makers and promote third-party software development and integration.

Subtask E - Applications in building design and operations. This subtask will provide case studies to demonstrate applications of the new occupant behaviour definition and models. The occupant behaviour definition and models can be used by building designers, energy saving evaluators, building operators, and energy policy makers. Case studies will provide verification of the applicability of the developed definition and models by comparing the measured and the simulated results.

8.2 Annex 2: MOEEBIUS Behavioural Profiling Model

Two different views of the model are provided. The first version covers the aspects when low level building information is available, while the second approach cover the case of aggregated price based behavioural profiles.

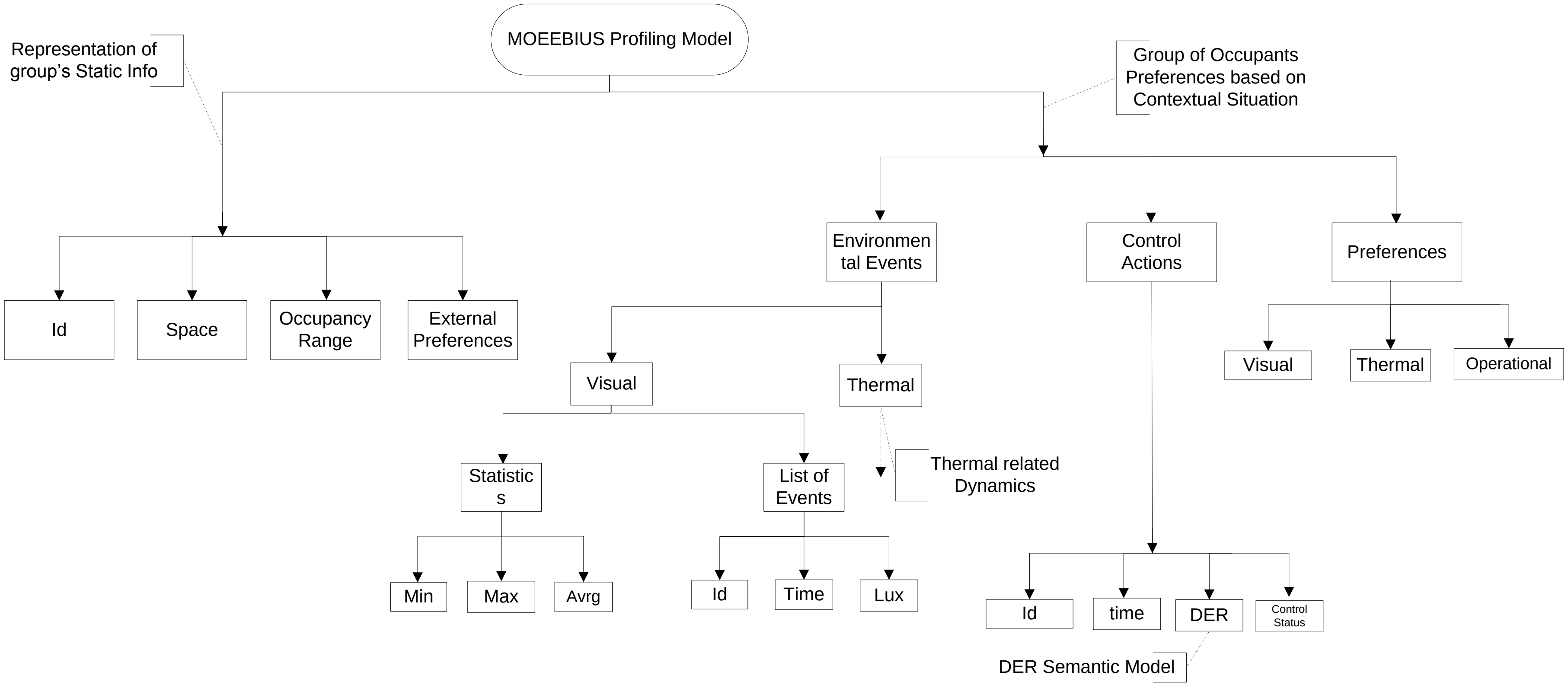

Figure 26 MOEEBIUS Behavioural Profiling Model

The associated XSDs with the model parameters are presented

```xml
<?xml version="1.0" encoding="UTF-8"?>
<!-- edited with XMLSPY v5 rel. 4 U (http://www.xmlspy.com) by TEAM (RENEGADE) -->
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema" elementFormDefault="qualified"
attributeFormDefault="unqualified">
    <xs:element name="Building_Zone">
        <xs:annotation>
            <xs:documentation>Comment describing your root element</xs:documentation>
        </xs:annotation>
        <xs:complexType>
            <xs:sequence>
                <xs:element name="ID" type="xs:ID"/>
                <xs:element name="name" type="xs:string"/>
                <xs:element name="description" type="xs:string"/>
                <xs:element name="occupancy" type="xs:ID"/>
                <xs:element name="space" type="xs:ID"/>
                <xs:element name="behavioural_Profile" maxOccurs="unbounded">
                    <xs:complexType>
                        <xs:sequence>
                            <xs:element name="id" type="xs:ID"/>
                            <xs:element name="dateTimeStamp" type="xs:dateTime"/>
                            <xs:element name="description" type="xs:string"/>
                            <xs:element name="min_value" type="xs:float"/>
                            <xs:element name="max_value" type="xs:float"/>
                            <xs:element name="average_value" type="xs:float"/>
                            <xs:element name="unit" type="xs:string"/>
                            <xs:element name="curve" maxOccurs="unbounded">
                                <xs:complexType>
                                    <xs:sequence>
                                        <xs:element name="input" type="xs:float"/>
                                        <xs:element name="output" type="xs:float"/>
                                    </xs:sequence>
                                </xs:complexType>
                            </xs:element>
                        </xs:sequence>
                    </xs:complexType>
                </xs:element>
            </xs:sequence>
        </xs:complexType>
    </xs:element>
</xs:schema>
```

We have to point out that the environmental and control action events are the input parameters of the models and thus no part of the output model as presented. The {input, output} fields specify the non-parametric values of the model (PMV value for thermal comfort & lux for visual comfort).

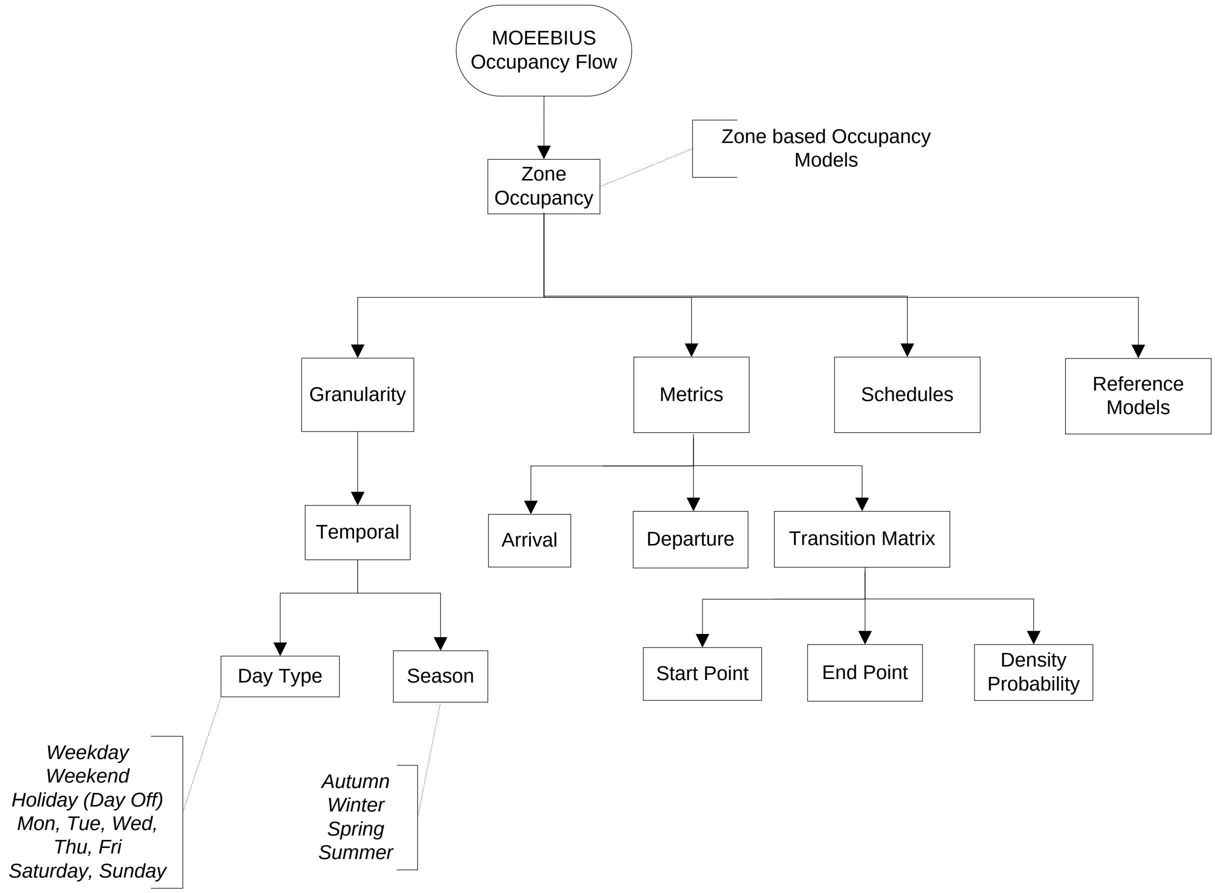

Figure 27 MOEEBIUS Occupancy Profiling Model

The associated XSD focusing on the model parameters (schedules & reference models are not part of the model).

The same analysis is provided for occupancy profiling model parameters:

```
<?xml version="1.0" encoding="UTF-8"?>
<!-- edited with XMLSPY v5 rel. 4 U (http://www.xmlspy.com) by TEAM (RENEGADE) -->
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema" elementFormDefault="qualified"
attributeFormDefault="unqualified">
    <xs:complexType name="Building_ZoneType">
        <xs:sequence>
            <xs:element name="ID" type="xs:ID"/>
            <xs:element name="name" type="xs:string"/>
            <xs:element name="description" type="xs:string"/>
            <xs:element name="occ_Profile" maxOccurs="unbounded">
                <xs:complexType>
                    <xs:sequence>
                        <xs:element name="id" type="xs:ID"/>
                        <xs:element name="dateTimeStamp" type="xs:dateTime"/>
                        <xs:element name="season" type="xs:string"/>
                        <xs:element name="dateofweek" type="xs:string"/>
                        <xs:element name="occ_range" maxOccurs="unbounded">
                            <xs:complexType>
                                <xs:sequence>
                                    <xs:element name="firsttime" type="xs:integer"/>
                                    <xs:element name="starttime" type="xs:integer"/>
```

```
                        <xs:element name="range" maxOccurs="unbounded">
                          <xs:complexType>
                            <xs:sequence>
                              <xs:element name="value" type="xs:float"/>
                              <xs:element name="transition_prob" type="xs:float"/>
                            </xs:sequence>
                          </xs:complexType>
                        </xs:element>
                      </xs:sequence>
                    </xs:complexType>
                  </xs:element>
                </xs:sequence>
              </xs:complexType>
            </xs:element>
          </xs:sequence>
        </xs:complexType>
</xs:schema>
```

8.3 Annex 3: Class Diagram of the pre-trained windows/blinds control models java library developed, based on IEA Annex 66

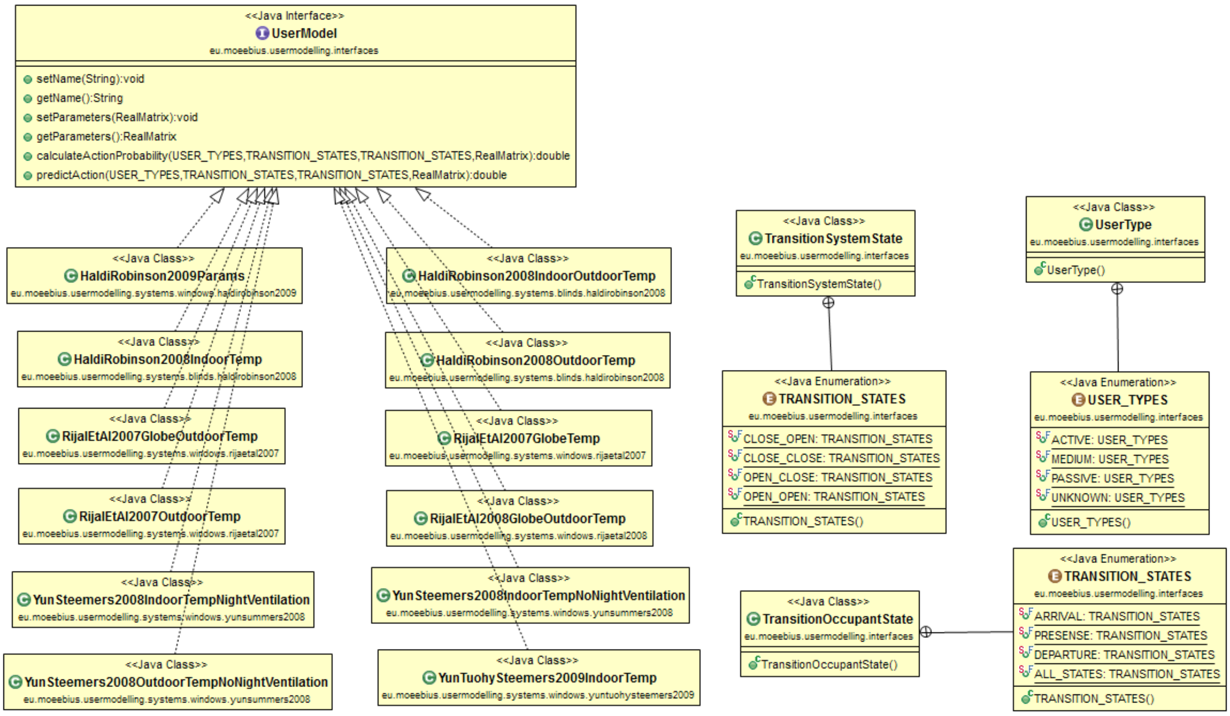

Figure 28 Class Diagram of pre-trained windows/blinds control models

8.4 Annex 4: Algorithmic & Modelling Framework for price based behavioural profiles

As a parallel activity, we are defining the algorithmic framework for the extraction of behavioural profiles as a function of price. This is the approach in lack of low level information from sub-building environment (lack of information about environmental conditions & user setting), further supporting the aggregator role, where the objective is the extraction of price based demand flexibility profiles to further facilitate the implementation of accurate DSM strategies.

For the extraction of price based behavioural profiles, we consider **price elasticity** as the parameter that specifies the impact of price in energy usage. Price elasticity of demand (PED or Ed) is a measure used in economics to show the responsiveness, or elasticity, of the quantity demanded of a good or service to a change in its price, ceteris paribus. More precisely, it gives the percentage change in quantity demanded in response to a one percent change in price (ceteris paribus, i.e. holding constant all the other determinants of demand, such as income). Therefore, **price elasticity** is the representation of utility function, expressing the willingness of customers to accept a modification in energy prices. The algorithmic process is specified:

Input Parameter

Different **Tariff schemas** (as defined by external stakeholders) and external **temperature** values (as provided by weather providers). By taking into account the tariff schemas along with the impact on building **energy consumption**, we define the price elasticity to be incorporated in the proposed framework.

Algorithmic Approach

The definition of comfort and discomfort levels is inherited on the extraction of **price elasticity** data along with historical input conditions. Input parameters for price elasticity were presented above with the associated calculation formula

$$e_p = \frac{\mathrm{Tariff\_Variation} / \mathrm{Current\_Tariff}}{(Actual - Baseline)/Baseline}$$

The analysis is performed for different groups of external environmental conditions.

Output

The **price elasticity** expresses the discomfort value on a state condition of a single occupant.

8.4.1 User Preferences modelling – Price based model

This approach is differentiated from previous analysis as we are lacking low level information about customers. In that case, energy consumption and price data are considered as the input parameters towards the definition of price elasticity values. The updated version of root model table in order to define the MOEEBIUS price based behavioural profiling framework is presented:

Parameter	Description	Type
Id	Id of building	-
Space	The area/zone with the specific ID (This is optional in MOEEBIUS framework as we define price based profiles at building level)	ID
Tariff Schemas	Tariff schemas as defined from external stakeholders. This type defines only the tariff change events triggered by external stakeholders	Tariff
Energy Consumption	The list of historical consumption data related to building operation	Consumption
EnvConditions	The list of environmental conditions considered for the extraction of user preferences	EnvironmType
Preferences	The list of preferences as extracted from User Profiling mechanism	Preferences

Table 29 Root Parameters - Price based behavioural profiling

For the complex types defined, we specify the associated classes and attributes. For **Tariff classes** we consider the baseline tariff policy and the variation from current status:

Parameter	Description	Type
Id	An index that expresses the enumeration of price triggered Event	ID
Space	The Id of the building triggered with this price event	ID
Current_Tariff	The actual price defined by the contract with end user	Float

Tariff_Variation	The price variation event triggered by external stakeholder	Float
Time	Time period of the event	time
Duration	The total duration of Tariff_Variation	Float

Table 30 Tariff Type Schema

The same approach is considered for "**Consumption**" type, where the baseline and actual energy consumption set the modelling parameters. We have to point out that the baseline definition is a process handled internally in order to define the impact of price on total energy consumption. Therefore the correlation of energy consumption data (both actual and baseline) to specific price event is considered.

Parameter	Description	Type
Id	An index that expresses the enumeration of price triggered event	ID
Space	The Id of the building triggered with this price event	ID
Baseline	The baseline energy consumption as defined through an internal estimation process	Float
Actual	The actual energy consumption due to modified price event.	Float

Table 31 Consumption Type Schema

By handling as part of the model the parameters about: {Current_Tariff, Tariff_Variation, Baseline & Actual}, we can further define the price elasticity parameter through:

$$e_p = \frac{\mathrm{Tariff\_Variation}/\mathrm{Current\_Tariff}}{(Actual - Baseline)/Baseline}$$

Then, we proceed with the algorithmic framework as presented in previous section, towards the extraction of behavioural profiling model parameters. We define the Discomfort Curve as the non-parametric vector that estimates the discomfort utility as a function of price elasticity in different external temperature conditions.

The DiscomfortCurve curve is a complex type which is further defined as a no-parametric function that takes as input parameters: {external temperature, Tariff_Variation & Consumption} towards the calculation of price elasticity and subsequently Utility function value

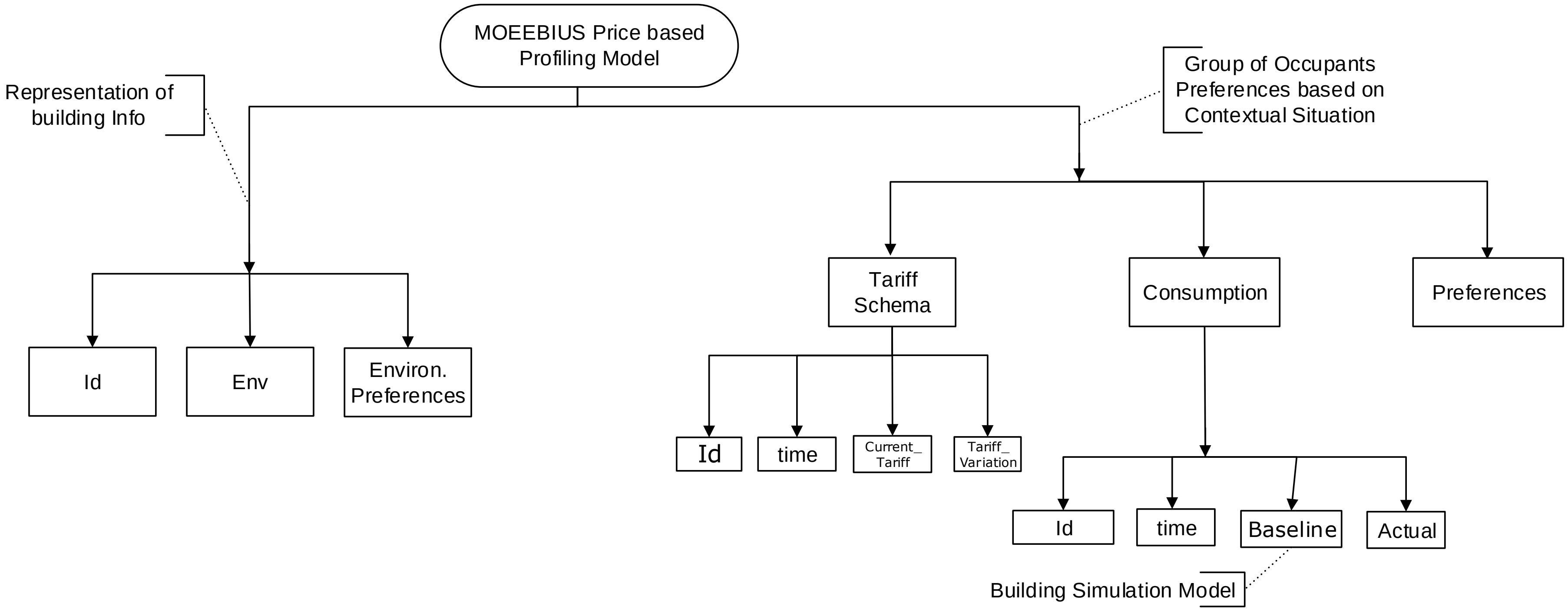

Figure 29 MOEEBIUS Price based Behavioural Profiling Model

For price driven behavioural profiles an indicative instance of the model is presented:

Parameter	Description	Value
Id	Id of building	Building_1
Tariff Schemas	Tariff schema as defined from external stakeholders	Tariff_12
Energy Consumption	The list of historical consumption data related to building operation	Consumption_12
EnvConditions	The list of environmental conditions considered for the extraction of user preferences	EnvironmType_12
Preferences	The list of preferences as extracted from User Profiling mechanism	Preferences_4

Table 32 Users Characteristics- Price based behavioural profiling

The input parameters for the model are {Tariff Schemas, Energy Consumption & EnvConditions types} which are further specified:

Parameter	Description	Value
Id	An index that expresses the enumeration of price triggered Event	ID_1
Space	The Id of the building triggered with this price event	Building_1
Current_Tariff	The actual price defined by the contract with end user	130 euro/MWh
Tariff_Variation	The price triggered event from external stakeholder	20 euro/MWh
Time	Time period of the event	hh:mm:ss
Duration	The total duration of Tariff_Variation	60 (minutes)

Table 33 Tariff Type Example

For "Consumption" event, which is further associated with the specific tariff event we have the typical example:

Parameter	Description	Value
Id	An index that expresses the enumeration of price triggered event	Tariff_12
Space	The Id of the building triggered with this price event	Building_1
Baseline	The baseline energy consumption as defined through an internal process	300 (Wh)
Actual	The price triggered event from external stakeholder	250 (Wh)

Table 34 Consumption Type Example

The results from the algorithmic framework (Bayesian analytics over historical data) are further presented:

Parameter	Description	Type
DiscomfortCurve	The non-parametric vector that defines the discomfort utility function as a function of price elasticity and external temperature conditions	Complex

Table 35 Price based Preferences Example

An instance of the complex class "Discomfort Curve", as extracted from Price based Preferences model is presented:

Input Value (Price Elasticity)	Input Value (External Temperature)
-0.5	15
-0.6	15
-0.7	20
-0.9	20
-1.1	25

Table 36 Price based Discomfort Curve

This was an initial abstract representation of **price elasticity** as the behavioural profile of building occupants under different price based conditions. The detailed model and how this approach can be further incorporated in the decision process of Aggregator (calculation of demand flexibility potential and further incorporation in DSM strategies implementation) will be presented in D6.1.