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# D3.7

## Design of the GreenSoul Analytics and Decision Support Engine

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# Abstract

The overall goal of this deliverable is to define the main functionality of the GreenSoul Decision Support System, along with the description of its integrated components. The DSS is the core element that analyses data coming from various GS-ed things and deducts the necessary decisions to be undertaken for increasing energy savings in the building. It performs this task while respecting the comfort requirements of the occupants, regarding their thermal and visual preferences. The DSS communicates to the GS elements through the LinkSmart Middleware and also acquires needed historical data through the GIM database. Then, the core DSS mechanism calculates the optimal building (devices) states before deploying the persuasion mechanisms to be used from GS web and mobile applications.

## Changes History

| VERSION | DATE | DESCRIPTION |
|---|---|---|
| V0.1 | April 2017 | CERTH (ToC) |
| V0.2 | May 2017 | CERTH (Initial draft) |
| V0.5 | June 2017 | CERTH (Major update) |
| V0.6 | July 2017 | CERTH (ready for review) |
| V0.7 | July 2017 | CERTH (peer review) |
| V1.0 | July 2017 | CERTH (final version) |

## Executive Summary

The present document is a deliverable of the GreenSoul project, funded by the European Commission's Directorate-General for Research and Innovation (DG RTD), under its Horizon 2020 Research and innovation programme (H2020), reporting the results of the activities carried out by T3.4, namely the "*Analytics and Decision Support Engine*".

The purpose of this Task is thus to design and implement the GreenSoul Decision Support mechanisms that will be integrated along with the physical GS-ed devices and other subsystems, identifying energy inefficient behaviours and motivating respective changes to the building occupants.

The main objective of this deliverable is to describe the current state of DSS technical functionalities and how they can be utilized in the GS pilot premises. The DSS is the "brain" of the GreenSoul architecture, the component which is responsible for accessing data from the GS-ed things, analyze them and evaluate the current energy consumption state against the forecasted optimal one. Finally, it should identify and send the best persuasive mechanisms to the end-users via the web and mobile interfaces. Through the persuasion mechanisms deployed in the final implementation, the building users will have the opportunity to understand their energy behaviour and perform actions to achieve more energy savings.

## List of Definitions & Abbreviations

| Abbreviation | Definition |
|---|---|
| **API** | Application Programming Interface |
| **ARMA** | Auto Regressive Moving Average |
| **BEMS** | Building Energy Management System |
| **BIM** | Building Information Model |
| **CRF** | Conditional Random Field |
| **DSS** | Decision Support System |
| **DG-RTD** | Directorate-General for Research and Innovation |
| **GIM** | GreenSoul Information Model |
| **GS** | GreenSoul |
| **HVAC** | Heating Ventilation and Air-Conditioning |
| **MPC** | Model Predictive Control |
| **NREL** | National Renewable Energy Laboratory |
| **OWA** | Ordered Weighted Averaging |
| **PDF** | Probability Distribution Function |
| **PID** | Proportional Integral Derivative |
| **PIR** | Pyroelectric/Passive InfraRed |
| **PMV** | Predicted Mean Vote |
| **REST** | Representational State Transfer |
| **SVM** | Support Vector Machines |
| **XML** | eXtensible Markup Language |

# Contents

# List of Figures

# 1 Introduction

The traditional approach to address energy efficiency improvement in buildings is the replacement of consuming equipment with newer and more efficient one. A small electric motor, an incandescent lamp, a water boiler are typical examples of energy consuming devices for which the above-mentioned approach takes place. However, with the advent of IoT communication capabilities, new opportunities arise and make a new approach available: the more intelligent “systemic” approach. Now, the various consuming devices are seen as part of a larger interconnected system and their operation is optimized based on the collective systemic needs. The GreenSoul project dives directly into this research area and aims to propose an innovative solution for optimal coordination of several energy consumption loads inside tertiary building spaces, mainly through mechanisms that engage end-users to change their energy behaviour.

This document presents the current state of the Decision Support System (DSS), which is going to be the core of decision making processes in the GreenSoul platform. The DSS will retrieve data from various heterogeneous sources, whether from physical devices and sensors, or historical data stored in databases. Then it will undertake the algorithmic procedures needed in order to analyse this information and evaluate the energy efficiency of the current building state. Also, it will try to encourage users to set in motion certain actions upon building loads, in order to reach targeted energy savings. The system design will respect the comfort preferences of the occupants and will propose actions that reduce consumption while maintaining desired levels of comfort.

The DSS is considered as a live component that will be continuously adjusted and updated during the project lifetime, since there are other tasks running which may have an impact on it and induce modifications in a future project period.

## 1.1 Outline of the Deliverable

The presented deliverable is structured and organised in the following chapters:

- **Section 2** provides a state of the art analysis of current approaches on building energy management and solutions to motivate an behavioural energy change on building occupants.
- **Section 3** describes how DSS is currently integrated into the GreenSoul framework. The role of the LinkSmart Middleware is exemplified and the flow of information is depicted.

- **Section 4** delivers the proposed mechanisms that are needed to:
    - Gather valuable data from sensors to identify occupancy flow inside a space
    - Predict occupancy in future time frames, in order to identify and evaluate the status of devices such as the HVAC; in the current state of the document, the prediction methods that are going to be examined and evaluated are presented
    - Model the visual and thermal comfort inside that occupants are experiencing inside a space
- **Section 5** presents the most important component inside the DSS; the Building Optimal Status Engine checks current indoor environmental conditions and various systems' status and decide whether the current system state achieves optimality
- **Section 6** describes the conceptual model of the Persuasion Engine, which is needed to incorporate the behavioural change-techniques of GreenSoul.

# 2 State Of the Art

## 2.1 Energy Management in Commercial Buildings

Several approaches exist in the literature, which try to leverage new opportunities for energy savings in public buildings. In most cases, thermal, lighting and air quality comfort are considered as the three most major factors that affect occupants' quality of living in a building environment [1]. Occupancy status also plays a central role in energy behaviour of humans inside a building and, as authors in [2] report, significant energy savings are possible, by only utilizing occupancy measurements.

HVAC systems typically present a considerable share (~30%) of electricity consumption in a building. Thus, optimal HVAC control tends to be the most effective way to achieve energy savings [3]. Developing optimal strategies to control HVAC and lighting systems is not a trivial task; at first, it requires a detailed modelling of the air quality requirements, as well as the respective thermal and comfort levels that the occupants desire. Then it needs to estimate the current comfort conditions, based on environmental measurements (air temperature, humidity, illumination etc.). Studies exist that exclusively target the HVAC efficient control, such as in [4], where the authors have developed an adaptive controller for thermal and visual comfort.

As lighting systems is considered the second most energy consuming load inside tertiary buildings, various control strategies can be found in literature used for efficient lighting management, that focus in:

i) reducing wasted hours of electricity in unoccupied spaces
ii) adjusting devices' lighting levels according to respective changes in available daylight inside spaces (daylight harvesting)
iii) selectively shedding lighting loads during periods of peak demand

Building Energy Management Systems (BEMS) are currently the usually employed systems that building managers use for energy and comfort management in large commercial and tertiary buildings. BEMS. The objective of such systems is to achieve overall high energy-efficiency, low emissions, and economic feasibility, without compromising consumers' comfort.

However, these systems pose some issues that need to be addressed:

- The operational settings of the HVAC and lighting systems are usually determined through assumed occupied periods of the day.

- There is no use of real-time information from dynamically changing factors, such as occupancy and occupants' activities
- The intelligence in these systems is based on hard-coded rules for defining comfort ranges for building occupants, therefore making unfounded assumptions about occupants comfort preferences. Temperature set points, for instance, are generally uniform for a building and therefore do not take into account space dependent activity or sun exposure or occupant preferences. Recent studies, in fact, have shown weak and context dependant correlations between code-defined comfort ranges and occupant reported comfort ranges [5,6,7].

Current analysis techniques of energy efficiency in buildings used for decision support are limited to a few data sources. The most common ones are those provided by BMS systems. However, other parameters, such as occupancy are omitted. Other approaches are more advanced, such as the DSS proposed in OPTIMUS [8], which considers data from five heterogeneous data sources (i.e., weather conditions, social, building energy management systems, energy prices, renewable energy production) in order to suggest short-term action plans to the public authorities for energy saving.

Many solutions in literature propose systems for energy monitoring, such as the one developed by Kim et al. [9] for fine-grained monitoring of domestic energy consumption. It provides real-time appliance-level energy use estimation without the need for external calibration. It does this by means of indirect magnetic, acoustic, or light sensors placed near each appliance. Data is collected from heterogeneous sensors, and a machine-learning algorithm is used to learn and estimate the energy consumption of every appliance. This is a self-calibrating method that requires little human intervention, but it does require a sensor to be deployed with each and every device. The system is easy to install and run long-term and supports information integration from various sources. However, it does not provide manual, programmable, or intelligent control of devices, and also offers no security feature.

Several studies have tried to improve building energy management through advanced control algorithms (e.g.10,11,12,13) which include conventional controllers, computational intelligence, optimization-based controllers and rule-based systems. Other literature studies have focused on multi-agent systems (14,15,16,17,18,19,20), as they provide an interesting framework for learning occupancy trends and reacting to real-time conditions.

Conventional controllers are commonly used in commercial buildings, and usually do not use occupancy measurements although they may use predefined occupancy schedules [21]. They include thermostats [22], PID controllers [23], adaptive controllers [24] etc. Conventional controllers may not always be feasible and present various limitations. In addition, this approach only works with energy savings and wastage (in fact not in all cases), and does not address the aspect of occupants' comfort.

Computational intelligence in building control embraces fuzzy systems [25] (e.g. fuzzy controllers of type P, fuzzy PID controllers, fuzzy cognitive maps controllers), neural network controllers [26], synergistic neuro-fuzzy techniques [27], artificial intelligence [28] and combined approaches [29]. This approach usually generates more energy savings but it is more complex.

Optimization-based controllers typically use a receding horizon optimization approach, which is also known as model predictive control (MPC). Petersen et al. [30] examine the use of MPC in the design stage to decide on HVAC control strategies, while approaches of [31] and [32] use occupancy predictions. MPC-based control requires more information compared to the other approaches mentioned above and involves huge costs for modelling, data collection, expert monitoring and deployment. Although interesting results have been presented, it has been argued that with the current standards, MPC controllers do not provide significant energy savings over much simpler feedback-based schemes, even when perfect occupancy predictions ahead of time are available [citation needed].

A recent trend towards incorporating more intelligence in the development of building control systems is the utilization of multi-agent technology, which has gained increasing attention due to its ability in tackling complex systems as well as to allow using distributed intelligence approaches. Such systems have been thoroughly investigated in the literature both for managing thermal [33] and electrical loads [34], but also overall for other types of energy [35]. In [36] a multi-agent system is proposed for energy and comfort management which can be applied to enable the building to interact with its occupants for user-centered control. Wang et al. [36] propose a building indoor energy and comfort management system based on information fusion using ordered weighted averaging (OWA) aggregation, while in [37], the proposed multi-agent system is coupled with an intelligent optimizer (particle swarm optimization -PSO-) in order to optimize building energy management.

Furthermore, Yang et al. [38] focus on balancing the conflict between energy consumption and environment comfort. Towards this direction, they propose a multi-agent based framework utilizing two different multi-objective optimization methods to find the Pareto-optimal solutions. In [39] a multi-agent semi-centralized decision making control methodology is utilized, while [40] present a multi-agent comfort and energy system which coordinates both building system devices and occupants through direct changes to occupant meeting schedules using multi-objective Markov Decision Problems. Although agent technology has enabled the improvement of building control systems, its main drawback is its high degree of complexity, which may render it unsuitable for real-time applications. This is also true for large buildings' modelling, where the number of agents, rooms and interactions increases exponentially.

Within this context, Goyal et al. [3] investigate the performance of energy-efficient building climate-control algorithms as a function of their complexity (e.g. information requirements, computational complexity). It seems that when more information is available there is the potential of more energy savings. However, the control algorithm may become more complex.

A simpler but quite efficient approach in building energy management is the utilization of rule sets. A rule-based controller usually uses "if-else" logic for decision making. It may also use other forms of information, such as occupancy measurements, that the conventional controllers do not use. A number of papers have proposed rule-based controllers that use occupancy measurements, concluding that significant energy savings are possible. The controller in [41] uses occupancy measurements to turn off the HVAC system, while the controllers in [42] and [43] modulate the ventilation rate based on measured occupancy. In [3], a decision support model is presented which uses rule sets for intelligent building energy management. However, this system is not fully-automated since users inside the building should define themselves their preferences for indoor conditions, setting values to the control parameters.

## 2.2 Behavioural change mechanisms

Persuasion techniques explicitly aim to convince people to take certain actions. With persuasion, there is no assumption that "the data speak for themselves" (i.e., that information will lead to action). Persuasion methods seek to convince people to change their behaviour more explicitly than either information or feedback. Several articles focus on the energy efficiency improvement through behavioural change. However, current research efforts and solutions to promote behavioural change in users of public buildings are not yet fully exploited [44], despite the fact that such change in occupants' habits can have a considerable impact on energy savings, up to 40% of the total building's consumption, as argued in [45]. In order to engage the users into a more energy efficient lifestyle, they should first be more aware of the benefits that such theme attains [46]. The methods used to achieve such awareness vary through several literature studies; sending feedback through email or similar communication channels [47], presenting interactive posters [48], giving energy-saving prompts and goal-setting targets [49].

Studies such as [50], focus on promoting behavioural change in social housing through serious game mechanisms where the users design their own virtual home based on a drag-and-drop interface. Users earn in-game rewards to upgrade their home (by retrofitting) and buy more in-game objects. Another serious game dealing with the energy efficiency problem is the “2020 Energy”, supported by Energy Europe. Also a set of 8 mini-games is developed by the “SAVE ENERGY” project. SMART IHU is an ambient intelligence application developed and applied in International Hellenic University premises in Greece. The system consolidates data from wireless sensors and some high level management applications into a middleware, which then provides SWASDL annotated semantic web interface endpoints. The annotations mostly contains terms from the project’s context ontology. ENTROPY project aims in creating a platform that provides the appropriate tools and methods in order to change the end-users’ behaviour on daily routine. In [51], a platform is described that enables energy awareness.

The most common drawback of the aforementioned approaches is that they view the persuasion mechanisms in a static-non interactive manner, focusing on short-term benefits of behavioural change, rather than pushing on long-term commitment of users towards energy efficiency. Typically, the persuasion messages are not validated, in terms of their effectiveness and also how socio-demographic reasons affect users’ response to these signals.

# 3 DSS Architecture

The GreenSoul DSS represents an unsupervised mechanism (i.e. no human intervention is required) for efficient building energy management, under utilization of information from various sources; GS consuming systems' current and previous state, occupants' preferences, environmental conditions obtained through a multi-sensorial network. Furthermore, the DSS respects occupants' energy-related decisions and propose methods to improve their energy behaviour, based on an innovative persuasive approach. The interaction of DSS with the various GS components can be seen in the architectural schema shown in Figure 1.

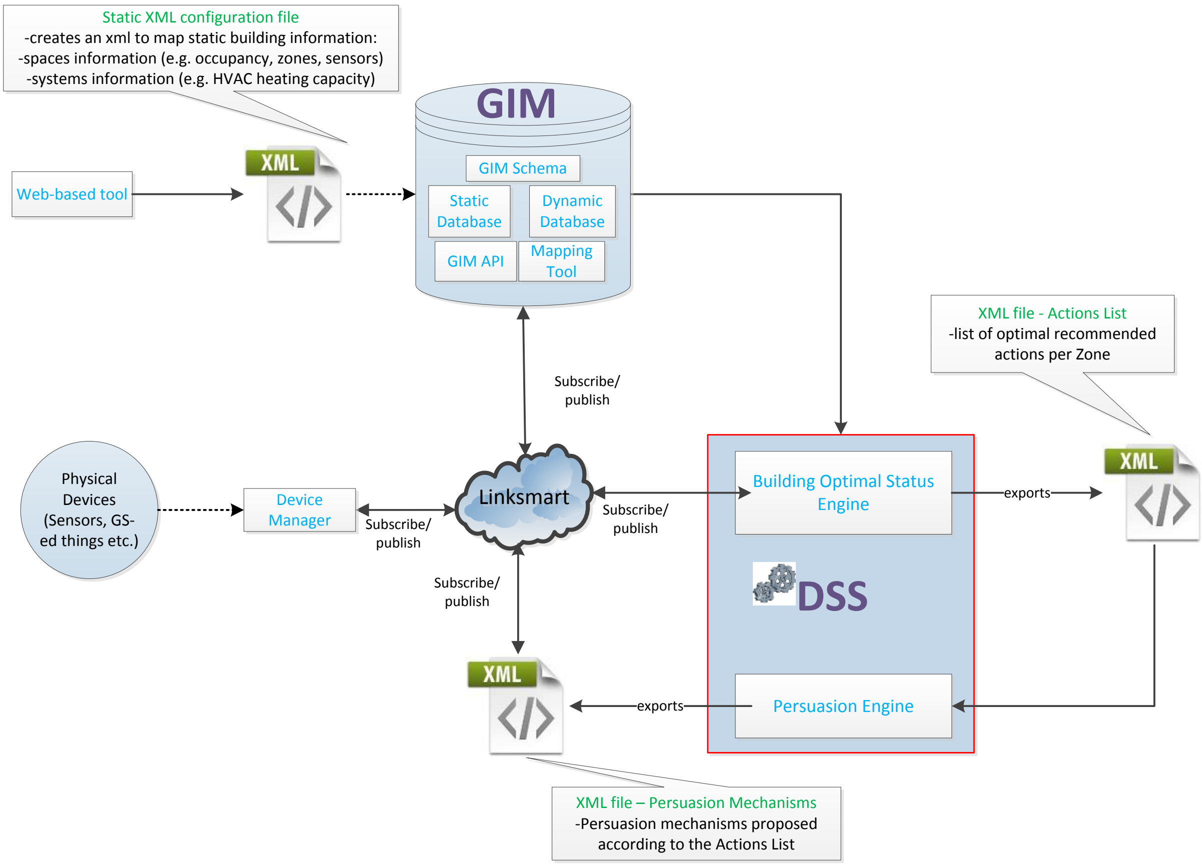


**Figure 1 Overall DSS communications schema**

The typical flow of data is described below:

1. Physical devices used in GS framework publish their data on LinkSmart, through an MQTT/RESTful API. The Device Manager is the component responsible to extract this raw information and translate it to GIM compliant messages for publishing them to LinkSmart.
2. The Building Optimal Status Engine component of the DSS subscribes to LinkSmart Event Manager' topics to gather its required data (e.g. "temperatureSensorData" topic).

3. It also gathers required static (e.g. building spaces dimensions) and historic dynamic information (e.g. indoor temperature, occupancy) from GIM through a RESTful API (shown in more detail in Figure 2)
4. Through a rule-based deterministic mechanism, described in Section 5, the DSS evaluates the optimal actions to be followed per device and exports them in XML-schema formatted messages.
5. The Persuasion Engine obtains the actions' list and proposes the persuasion mechanisms, which again are published to LinkSmart in order to be retrieved from mobile and web applications.

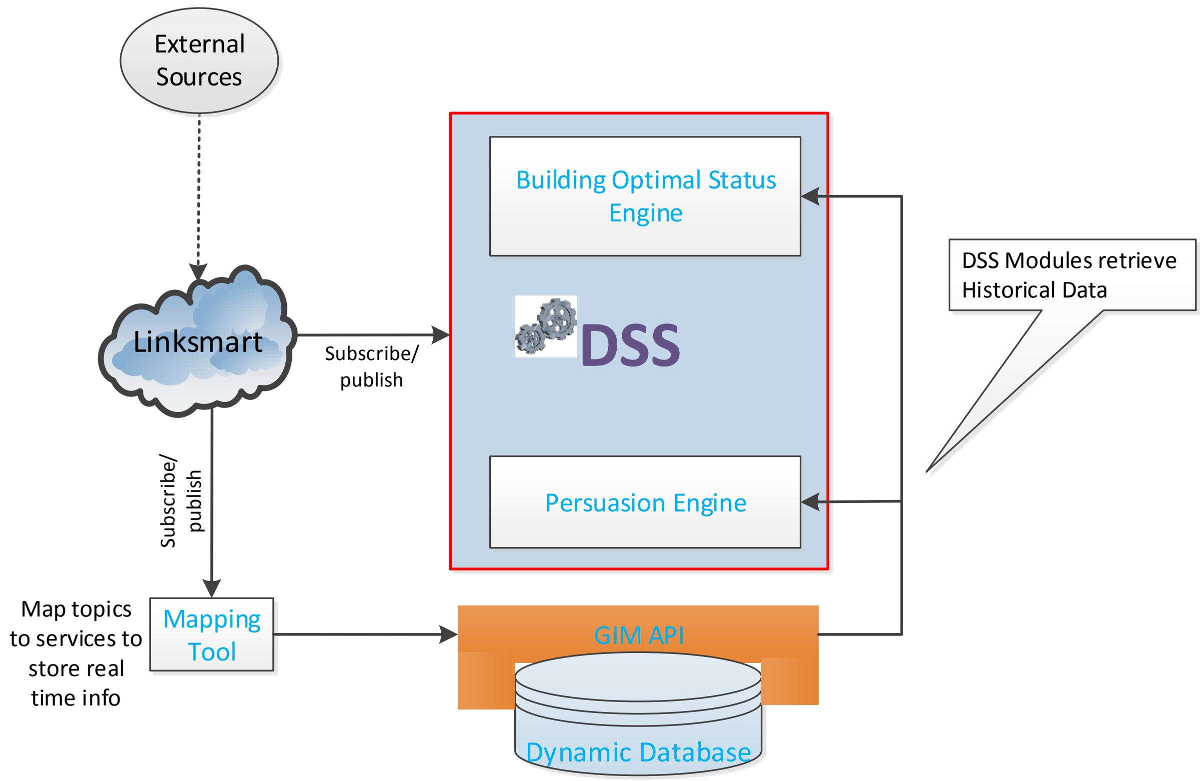


**Figure 2 DSS-to-GIM Database detailed communication**

The DSS supports a set of operations for monitoring and analysing the building assets (light, HVAC, appliances), while respecting occupants' comfort. It achieves this by combining historical information stored in GIM databases, along with real-time data derived from the multi-sensorial-cloud and the various GS-ed consuming devices. Such data include historical and current occupancy state, indoor and outdoor environmental conditions (e.g. temperature, luminance), users' actions upon devices, current operational status of devices and energy consumption current and future states. The core element of the DSS is the Building Optimal Status Engine, which aims to analyse gathered information and evaluate the optimal building status in real-time. It will accomplish this by devising a set of deterministic rules to reach GS-ed devices' optimal state, in order to find the optimal balance between energy savings and occupants' comfort.

Basically, the Building Optimal Status Engine would monitor the current status of the system and identify whether improvements can be made in energy efficiency, without compromising users' comfort. Its final output would be the list of actions that need to be followed from each device in the system, in order to achieve comfort and consumption targets.

The exported list of actions would serve as an input to the 2nd critical module inside the DSS framework, the Persuasion Engine. This would be responsible for utilizing the user profiles and the socio-economic factors identified in D4.1 and D4.2 and facilitate the mathematical model derived in D4.4. Then, a self-learning approach will be followed that would make the model unique in its implementation, compared to other similar approaches; the persuasion mechanisms will be validated considering their effectiveness on users' behaviour and will be calibrated accordingly in the next timeframes.

The conceptual architecture of the Persuasion Engine will be defined in Chapter 6 and will be later on updated with the final implementation in the next version of the document.

# 4 Data Extraction

## 4.1 Occupancy Extraction Module

The occupancy extraction module, as its name implies has the scope to retrieve real-time occupancy information for each building space. It will achieve this by relying on the network of sensors installed in GS pilots. In the following paragraphs, the components needed and the extraction process are described.

The functionalities of the occupancy extraction module include:

- Exploitation of the detection capabilities of different sensor types (preferably low-cost sensors)
- Real-time occupancy extraction based on raw data retrieval from various occupancy sensors inside the spaces of interest. Occupancy presence/absence detection for the building and its zones should be evaluated.

### 4.1.1 *Flow of Information*

The occupancy extraction mechanism is a completely automated procedure that is utilized upon data provided from the installed occupancy detection infrastructure (sensors). Each sensor participating in the multi-sensorial cloud is assigned with a unique ID.

The module subscribes to sensor-change events which are produced from the LinkSmart Event Manager and refer to the sensors assigned with occupancy extraction.

When a change is detected, the component evaluates and then publishes new occupancy-change events to the Event Manager, so that this information can be used from other GS components.

### 4.1.2 *Definition of Zones/Spaces*

In order for the occupancy extraction module to function properly, each building space has to be divided in occupancy zones. Through the GIM ontology, each zone is characterized by a unique ID string and the maximum number of expected occupants,

### 4.1.3 *Physical sensors requirements*

***Double beam sensors***

The basis of such sensors is on infrared technology creating beams across a entrance/doorway. They are usually installed in pairs therefore, when the beams are broken by a person passing through the doorway a person is counted and the timing of when he/she breaks the second beam indicates direction, entering or exiting.

For the testing purposes, the kitchen area in the ground floor of CERTH/ITI main building was used. More specifically, in order to extract movement direction through an entrance, 2 separate beam sensors (double beam) are used. A beam sensor consists of the IR transmitter and the IR receiver and it works as a switch. The emitted beam is broken when the receiver losses optical sight with the transmitter. The two beam sensors are connected to an Arduino UNO microcontroller board, which is programmable. These are placed side by side at an approximately 3 cm distance, at a height about 1.20 m, as suggested in [52].

Dedicated software was developed at Arduino level in order to read the states of the two beam sensors and log the break and reset times of each beam. When both beams reset, the break and reset times of the two beams are compared and a decision is made with four possible outcomes:

- an entry
- an exit
- only one beam was broken
- someone indented to pass (enter/exit) but finally returned back

An entry event is sent for case 1 and an exit event is sent for case 2. This approach is followed because real-life observations showed that standing at the door step and then returning back is a not very rare scenario. We decided to such logic and extract semantically–enhanced information at low-end Arduino level, due to the short time difference between beam sensor events, which are usually around a few hundreds of milliseconds.

Double counts can occur when someone passes holding an object, and missed counts are possible in the case two occupants pass at the same time. The selected installation height prevents extra counts caused by the movement of legs or the movement of arms. Some true entries/exits falsely recognized as returns were observed.

**PIR motion sensors**

Pyroelectric/Passive InfraRed (PIR) motion sensors are widely used for non-individualized occupancy detection purposes, as they are a low cost and simple to install solution. Their main functionality is the delivery of binary information about whether a room is occupied or not. Sometimes though, they fail to detect stationary occupants, leading in false conclusions.

When movement is detected from the PIR sensor, an activation event is sent by the sensor. After a specified period (configured to a few seconds) of no movement detection, a deactivation event is sent. At each time step, the feature extracted from a PIR motion sensor is either 0.0 or 1.0, based on its state. If during the period of the last time step the sensor was activated (activity detected), the value 1.0 is assigned. Instead, in the case where the PIR remained in off state during the whole duration of the last time step, the value 0.0 is assigned as no activity is considered.

More accurate results can be extracted when data from double-beam and PIR sensors are combined. When such implementation is followed, the occupancy extraction mechanism can be regarded as a classification problem, meaning that based on the data collected from the multi-sensorial network, the actual 'class' (occupancy level) is inferred. To solve this task, a Conditional Random Field (CRF) classifier could be selected. This method is going to be examined in a later stage on whether it can have a valuable impact on the GreenSoul framework

## 4.2 Occupancy Prediction

Predicting building occupancy is an important aspect in order to facilitate energy efficient behaviour. For example, if the HVAC system can be turned on and pre-heat or pre-cool a room, prior to its use from the occupants, it could help facilitate more energy savings and better comfort inside the space.

A common solution to predict occupancy inside a space is to follow the guidelines of occupancy open reference models. Such models present standardized occupancy schedules based on specific building/space types. Examples of such models can be found in the building component library of NREL53, in the Autodesk 360 Energy Analysis - Vasari54, or in standardized ASHRAE 90.1-2013 building schedules55 which are recommended for use in energy simulation programs.

More advanced methods to predict occupancy would include learning models that process data coming directly from sensors. In [56], the authors use a modified Bayesian approach combined forecasting approach to forecast occupancy a short time into the future. Also, authors in [42] make use of semi-Markov processes to model the spatial and temporal movement of tourists in order to understand, predict, control for and optimise the decisions made by tourists in their choice of attractions. Another popular predictive method used in numerous forecasting applications from economics to vehicle traffic systems is based on the Auto Regressive Moving Average Model (ARMA). Support Vector Machines (SVM) offer another method to predict time series information. The Semi-Markov Model was used in [57] for reliability and survival analysis. Furthermore, in [58] the authors model the spatial and temporal movement of tourists in order to understand, predict, control for and optimise the decisions made by tourists in their choice of attractions.

For GreenSoul purposes, we are going to adopt a hybrid mechanism, based on each pilot occupancy prediction needs. At an early design stage, the standardized occupancy templates are going to be adopted, considering the specific spaces examined. Then, more sophisticated methods would be considered, in order to train the occupancy template models and adjust them based on real data from each pilot, in order to get a more accurate prediction per use case. This can be achieved by utilizing the algorithmic methods discussed above.

## 4.3 Indoor Comfort Profiles Modelling

The Indoor Comfort Profiles module seeks to define the levels of comfort that occupants are experiencing inside a particular space, based on environmental conditions and devices-related status. A detailed model is going to be presented, which reflects the constant users' comfort preferences inside building spaces, but also fine-tunes them by taking into account the changes made by users upon specific devices. The idea is that occupants do not have to explicitly define their operational profiles; these will be inferred through monitoring of their control actions/reactions to specific environmental and operational changes.

As ASHRAE [59] points out, the typical four factors that affect inner comfort inside a building are the air quality, the noise level, the visual and the thermal comfort. For the GS purposes, the main parameters that are examined are the visual and thermal comfort, as they have a greater influence on the building energy consumption. As such, GS focuses on estimating the visual and thermal comfort experienced by the occupants, considering the environmental conditions that relate with these values.

**Thermal comfort** [60,61,62] can be an obscure concept because of the multiplicity of variables involved and the difficulty of reconciling aesthetic and physiological elements. Even if a "perfect" set of thermal discomfort metrics was to be found, differences between users' preferences with respect to temperature would make the analysis controller solely based on that index difficult to be accepted by all users, unless an adaptation of this index to the individual user was achieved. Usually, thermal comfort conditions are typically expressed in the literature by using the Predicted Mean Vote (PMV) Model [63]. However, as it is derived from data collected in a controlled environment, it is not suitable for applications in naturally ventilated spaces which have high levels of air movement. Thus, the GS uses adaptive models of thermal comfort, which set occupants as dynamic entities with their environment, controlling their thermal comfort by themselves. Therefore, the PMV index and its parameters (at this stage only temperature is considered) is dynamically defined in GS in an adaptive manner. This process will be explained in the next paragraphs.

**Visual comfort** [64,65]: Within GS, we set a method to compute a visual comfort probability in a building, relying exclusively on the observation of the users' actions in premises-similarly as in the thermal comfort case. This user-adaptive approach is delivered as part of the Indoor Comfort profiling approach and defines the visual presences of individual users (or group of users) under different environmental conditions.

In order to identify the visual comfort per environment, we set a method to evaluate visual discomfort, based exclusively on users' actions upon light control units.

Different types of events are considered to be monitored in order to extract the indoor comfort profiles:

- Occupancy events, which illustrate the variation of the number of occupants inside a building space
- Environmental events (e.g. the temperature or luminance reduction), which would lead to a change in comfort perceived by the building occupants.
- Operational events, which represent the users' response to changes in indoor conditions, through actuator mechanisms (e.g. changing temperature set point). Such actions would define the operating limits of devices (e.g. HVAC systems) and they will also trigger the learning mechanism, for re-evaluating of user preferences.

The profile is going to be derived per space of interest. This will be driven by the one-to-one assignment of each event to each specific zone, group ID etc. In a next DSS implementation, this could be also utilized automatically by a self-adjusted mechanism.

**Algorithmic Approach**

In order to estimate the thermal/visual discomfort profiles of occupants as a function of environmental conditions, a Bayesian adaptive comfort approach is proposed to be used for GS needs [66]. Bayesian classifiers are very good at calculating probabilities and thus can be utilized for probability estimation for a certain environment of being comfortable or uncomfortable to its occupant. Such a classifier should base its judgement 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 and the environmental parameters distribution in the zone. Therefore, a user(s) discomfort probability is going to be derived, given a set of physical variables. This part of examination will set the basis for the control approach as the user preferences define the main parameters that have to be accomplished with GreenSoul. The implementation of the Bayesian nets in GreenSoul project case is described below:

Pr(*Env* | ComfortLevel): Defines the environmental conditions when a Comfort Level is already established.
Pr(*ComfortLevel* | Env): Defines the Comfort level for predefined Environmental Conditions.
Pr(*ComfortLevel*): Defines the probability of being in comfort/discomfort mode.

$$Pr(ComfortLevel|Env) = \frac{Pr(Env|ComfLev)Pr(ComfLev)}{Pr(Env|NotComfLev)Pr(NotComfLev) + Pr(Env \vee ComfLev)Pr(ComfLev)}$$

These probabilities set the basis to calculate the

**Thermal Comfort modelling and learning mechanism:** As previously noted, the main purpose of the algorithm is to extract the discomfort probability inside a space as a function of the environmental conditions. An adaptive Bayesian comfort approach is utilized to predict the desired temperature state for a known space, according to how they react to the current conditions through traditional control units:

At first, the new values of PMV (temperature) are monitored, after a new temperature set-point is delivered to the HVAC actuator (an environmental event is triggered, after an operational event is issued by the user or automatically from the system). Then, we need to evaluate both the previous state of the environment (not desirable situation) and the after control event state (desired situation); if we denote by *C* the user comfort index, by *E* the workplane value (temperature), by *T=True* and *F=False* the possible values for *C*, and by *e* a possible value that *E* can take, we need to estimate based on the available data the following parameters:

Pr($E = e \mid C = F$) which is the probability distribution function (PDF) of *E* taking the value of *e*, when we know that comfort is not satisfied. On this scenario, we need to obtain the control events triggered and the environmental conditions on the relevant situations.

Pr($E = e \mid C = T$) which is the PDF of *E* taking the value of *e*, when knowing that comfort is the desired one. On this scenario, we need to obtain the environmental conditions on the relevant situations after the control actions and when no new event is triggered.

Based on the above PDF functions, the PDF function Pr($C = F \mid E = e$) would be the model's final output. This would express the discomfort value on a specific state condition, thus predicting the discomfort probability upon different levels of the desired temperature set-point for an air-conditioned space according to occupants' complaints on thermal discomfort (reactions through traditional actuators). The parameter *E* is a discrete variable and we should simply count the number of times it realized each value and divide by the total number of events. Thus, the thermal related discomfort function is extracted as a discrete probability density function and each value will define the utility parameter (Utility function) for the thermal preferences.

**Visual Comfort modelling and learning mechanism:** A similar approach is followed, as the one described in the thermal comfort modelling section. Here, the *E* parameter is the luminance value. *E* is a continuous variable and therefore it is 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. As a further analysis, we should examine the "taut-string" non-parametric density estimator. The details of its inner workings are beyond the scope of this document, but it may be seen as a histogram whose bin widths adapt to the data in an optimal manner.

**Appliances Operational Comfort modelling mechanism:** Devices such as PC monitors, printers and projectors are considered in this initial stage of the DSS implementation. Contrary to the previous methodology, the comfort modelling mechanism in this case is very straightforward and is directly related to the occupancy measurements inside the space where the device is located. Specifically, when there are no occupants inside the space, then the Discomfort Factor is assigned with value = 0 (no discomfort). When occupancy ≠ 0, then Discomfort Factor is assigned with value = 1.

### 4.3.1 *Physical Sensors Requirements*

In this section, the sensors responsible to capture the data related to the environmental conditions events and is going to be installed in the GS pilot buildings are described.

**Temperature Sensors**: Temperature sensor is a device that gathers data concerning the temperature from a source and converts it to a form that can be understood either by an observer or another device. These sensors come in many different forms and are used for a wide variety of purposes, from simple home use to extremely accurate and precise scientific use.

**Luminance Sensors:** A light sensor, as its name suggests, is a device that is used to detect light. There are many different types of light sensors, each of which works in a slightly different way. A photocell or photoresistor, for example, is a small sensor that changes its resistance when light shines on it; they are used in many consumer products to determine the intensity of light.

### 4.3.2 *Flow of Information*

The Indoor Comfort Profiling component communicates with GIM in order to receive all the essential data needed for extraction of the comfort profiles. Subsequently, the below communication flow is performed:

1. The component gets historical data (environmental conditions and control actions for groups of users/zone) from the GIM.
2. Updates visual/thermal comfort model parameters based on the actions/ reactions of the users with the system.
3. Disseminates the results from the comfort profiling analysis (per user/ context/ condition) for enabling the respective analysis needed.

# 5 Building Optimal Status Engine

The Building Optimal Status Engine is the most critical part of the proposed holistic building decision support mechanism. The end user of the DSS can configure the lowest minimum and average comfort level (thermal-visual comfort) allowed at any building area (comfort_threshold). This value is configurable and can be modified at any time in order to serve for different occasions, e.g. normal operation, special events, weekends, holidays etc. For instance, the facility manager may define a higher threshold for a special event or a lower threshold for weekends during which building occupancy may be lower too.

The building is divided into lighting zones and thermal zones based on topology and usage. Appliances, (e.g. monitors and printers), are also considered as a separate category. The overall flow diagram shown in Figure 3 depicts the general operation of the Engine. At each time step, the system checks in parallel all lighting zones, thermal zones and building appliances, and delivers the (best) necessary control actions on available lights, HVAC units, devices, if any. This procedure is repeated at each time step.

An efficient human sensing mechanism is also incorporated into the system taking into account the temporal correlation of actions, in order to serve for respecting occupants' choices on devices operation and receiving feedback from any manual user action during automated building control. This mechanism regards some devices as “locked” and thus does not permit the DSS to affect them for a particular time period. This happens under the following conditions:

- Following an incentive from the DSS Persuasion Engine, an occupant applies a control action upon a specific device (e.g. HVAC). It should be noted here that after such action, the system calibrates users' comfort preferences towards optimally adjusting to occupants' choices.
- An occupant changes the operational status of a device, without a prior system control action as in the first case (e.g. an occupant arrives first in the morning and turns on a light). Here, the aim is to respect occupant's choice by not affecting the device for some time afterwards.

The decision making for HVAC, Lighting and building appliances is depicted in Fig. 3 and is described in detail in the following sections.

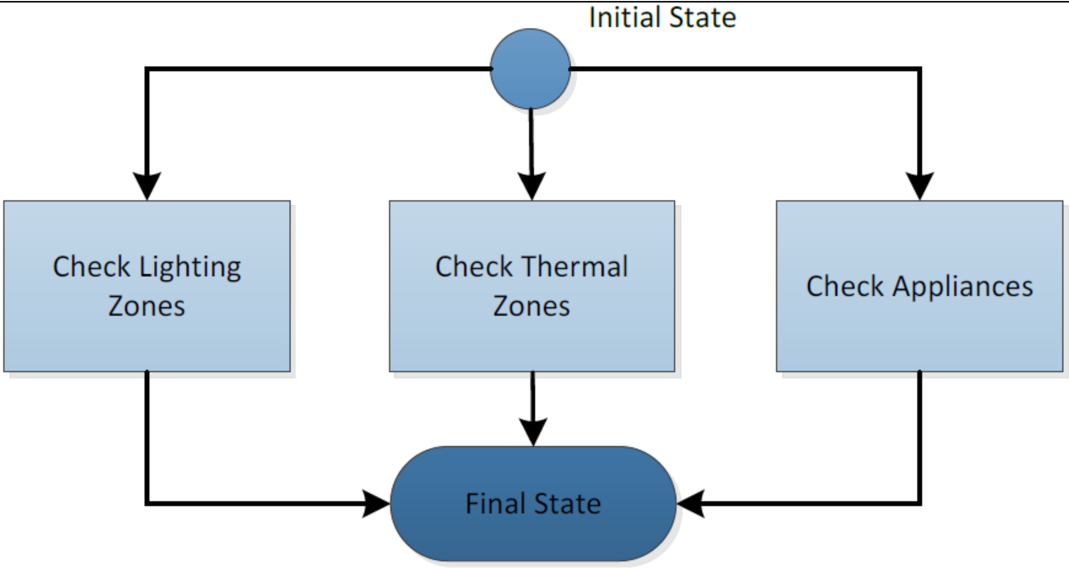


**Figure 3 Overall flow diagram for the operation of the Building Optimal Status Engine**

**Lighting zones**

The decision making process for each lighting zone is described in this section. This process is illustrated in Figure 4. At first, the module receives the current occupancy status from the occupancy extraction mechanism discussed in Section 4.1, in order to decide its next actions. If the zone is empty, the system automatically turns off any lights that have been left open. In case there are people in the zone, the context is further checked in terms of occupants' visual comfort. Specifically, the currently measured visual conditions in the examined area (luminance) are correlated to the comfort level, based on the respective discomfort probability function extracted through the comfort profiling component. If the comfort is within accepted levels, no action is performed by the system. Otherwise, the optimal list of applied actions is evaluated:

A series of iterations is performed for each combination of not-locked lighting units in the examined zone, thus simulating various system states; combinations of available lights are considered and the respective lighting conditions are evaluated. From this process, the thermal comfort probability for each of the states is evaluated, based on the comfort profiles extracted from the environmental comfort profiling mechanism. Thus, depending on the actual environmental conditions per use case, the system can select the optimal set points to be applied to the respective lighting units, so as to reach comfort satisfaction.

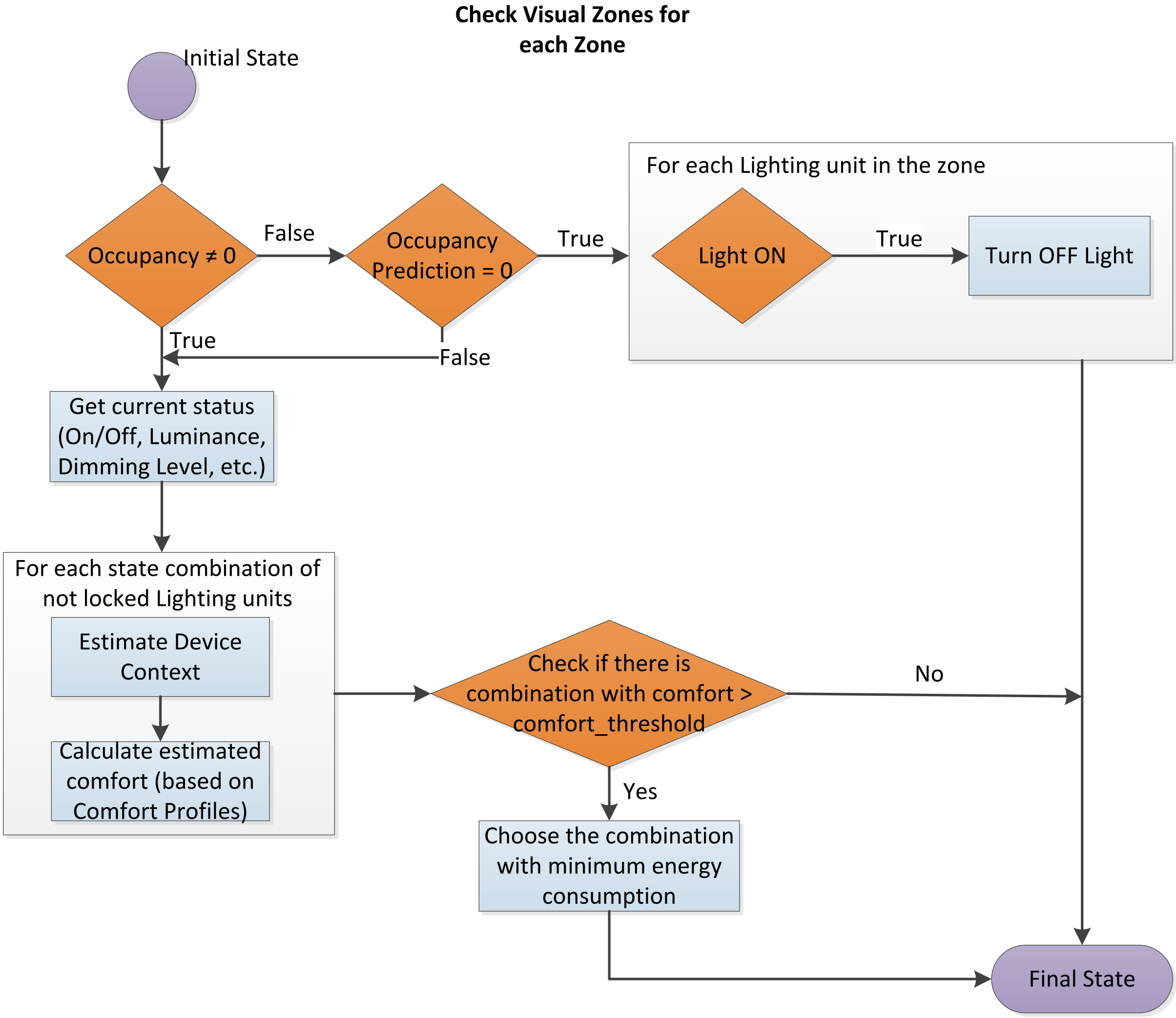


**Figure 4 Overall Flow Diagram for the lighting zones decision process**

More analytically, the aforementioned process is described below:

Initially, the overall luminance of the zone ($L_{Z_i}$) is retrieved by the Middleware as reported by the corresponding luminance sensor. Then, the luminance coming only from the artificial lighting of the zone ($L_{Z_i}$(lights)) is calculated based on the lights' operational state (i.e. open/closed, dimming level), as well as on measurements collected during the initialization of the system (determining how much luminance is derived by each light and for each state). The system handles on/off light units as dimmable units with 2 states (0% and 100%). The luminance coming from the external environment or from adjacent zones can be calculated as:

$$L_{Z_i}{}^{ext} = L_{Z_i} - \sum_{k=1}^{N_{Z_i}} L_{Z_{i,k}} \qquad (1)$$

where$L_{Z_i}$: overall luminance of zone Zi,

$L_{Z_{i,k}}$: luminance in zone Zi which is due to light k.

$N_{Z_i}$: total number of available lighting devices in zone Zi,

$L_{z_i}{}^{ext}$: luminance in zone Zi which comes from the external environment (e.g. through windows).

The occupants' visual comfort inside the examined zone is considered as a function F(.) of the zone's overall luminance which is defined through the Indoor Comfort Profiling component:

$$VC_{z_i} = F\left(L_{z_i}\right) \tag{2}$$

where,

$VC_{z_i}$: visual comfort in zone Zi,

$L_{z_i}$: overall luminance of zone Zi.

Thus, the target luminance level in order to reach the comfort threshold for the occupants in the zone can be calculated as:

$$L_{Z_i}{}^{des} = F^{-1}\left(VC_{Z_i}{}^{thres}\right) \tag{3}$$

where,

$L_{Z_i}{}^{des}$: desired overall luminance in zone Zi and

$VC_{Z_i}{}^{thres}$: comfort threshold in zone Zi.

The luminance level which should be contributed by the lights towards achieving the desired visual comfort (comfort_threshold) is:

$$L_{z_i}{}^{des} - L_{z_i}{}^{ext} = \sum_{k=1}^{N_{Z_i}} L_{Z_{i,k}}{}^{des} \tag{4}$$

where,

$L_{z_i}{}^{des}$: desired luminance in zone Zi coming from light k,

$N_{Z_i}$: total number of available lights in zone Zi,

$L_{z_i}{}^{ext}$: the luminance coming from the external environment and

$L_{Z_{i,k}}{}^{des}$: the desired overall luminance.

Finally, the corresponding increase/decrease in the luminance which should be derived by each available light (defining also the consequent change in its operational state) is determined as follows:

$$LumPerLight_{Z_i} = \frac{\sum_{k=1}^{N_{Z_i}} L_{Z_{i,k}}{}^{des} - \sum_{k=1}^{N_{Z_i}} L_{Z_{i,k}}{}^{cur}}{N_{Z_i}} \quad (5)$$

where,

$LumPerLight_{Z_i}$ is the increase or decrease in the luminance which should be derived by each light in zone Zi,

$L_{Z_{i,k}}{}^{des}$: luminance to be reached in zone Zi by light k,

$L_{Z_{i,k}}{}^{cur}$: current luminance in zone Zi due to light k and

$N_{Z_i}$: total number of available lighting devices in zone Zi.

It should be noted here that in case the total availability of a lighting device is reached based on the calculation of equation (5), the remaining luminance is distributed evenly to the rest lights in order to achieve the total $\sum_{k=1}^{N_{Z_i}} L_{Z_{i,k}}{}^{des}$.

The same procedure is repeated consecutively for all the lighting zones of the building.

**Thermal Zones**

The overall procedure is similar, yet more complex, to that for the lighting zones and it is illustrated in Figure 5. The main difference here is that in case of occupancy absence, occupancy prediction is also taken into account in order to decide whether to turn off HVAC units in operation. The DSS turns off any HVAC unit which has been left open only if both current and predicted occupancy for the next minutes equals to zero. This differentiation is due to the fact that HVAC systems present thermal GreenSoul in contrast to lights which reach their final state instantaneously. Moreover, in this case occupants' thermal comfort is considered (instead of visual comfort) in relation to the current zone temperature. Finally, the possible control actions include increase or decrease of the HVAC temperature set point. The basic aspects of the implemented methodology are summarized below.

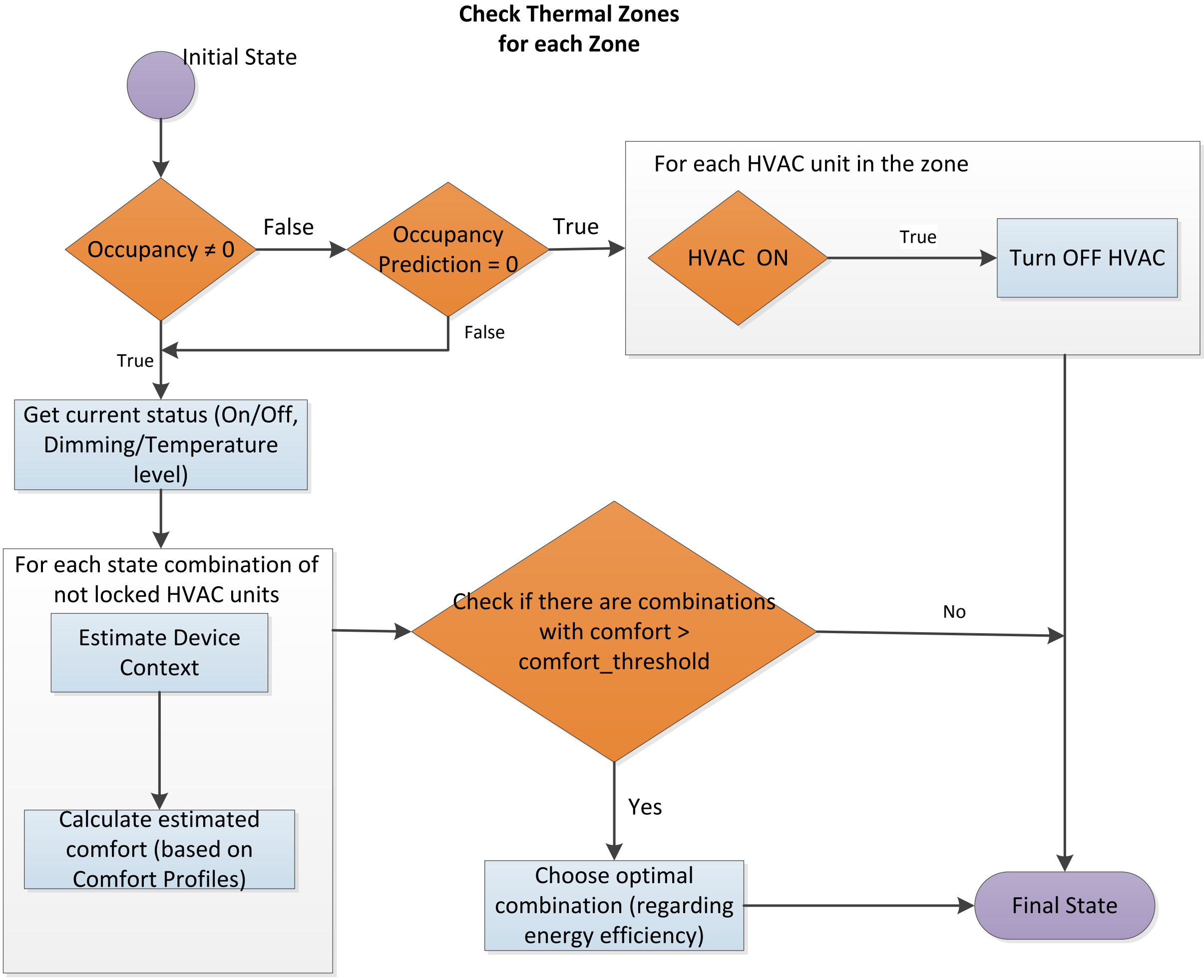


**Figure 5 Overall Flow Diagram for the thermal zones decision process**

Initially, for each HVAC unit of the zone various set points around the current setting are examined based on a predefined constant:

$$setPoint_{Z_i}{}^{exam} = setPoint_{Z_i}{}^{cur} \pm k \tag{6}$$

where,

$setPoint_{Z_i}{}^{cur}$: current set point of the HVAC in zone Zi,

$setPoint_{Z_i}{}^{exam}$: set of possible set points to be examined for the next time step, and

k: constant defining the range around the current set point which will be examined by the system (since not all possible settings can be inspected).

Then, the estimated zone temperature and HVAC energy consumption are calculated for each set-point resulting from equation (6) based on the corresponding device model. The model for HVAC takes as input the current context (e.g. temperature, zone occupancy), as well as static information (e.g. construction materials, building structure). The inputs and outputs of the model are presented in the following equation:

$$\{temp_{Z_i}{}^{est}, hvac_{cons_{Z_i}}{}^{est}\} = Model\big(currentContext_{Z_i}, staticInfo\big) \quad (7)$$

where,

$temp_{Z_i}{}^{est}$: estimated temperature of zone Zi for the next time step,

$hvac_{cons_{Z_i}}{}^{est}$: estimated energy consumption of the HVAC in zone Zi for the next time step, *Model(.)*: represents the function of the model for HVAC (Specified based on the heat demand of the examined thermal zone and its respective model [67]),

$currentContext_{Z_i}$ is current context information for zone Zi such as temperature, humidity, occupancy etc.,

$staticInfo$: static information about the zone, such as the construction materials, building structure etc.

The occupants' thermal comfort inside the examined zone is considered as a function G(.) of the zone's overall temperature which is defined through the Indoor Comfort Profiling component:

$$TC_{Z_i} = G\big(temp_{Z_i}\big) \quad (8)$$

where,

$TC_{Z_i}$: thermal comfort in zone Zi and

$temp_{Z_i}$: temperature of zone Zi.

Thus, the estimated occupants' thermal comfort ($TC_{Z_i}{}^{est}$) for each of the estimated temperatures ($\mathrm{temp}_{\mathrm{Z_i}}{}^{\mathrm{est}}$) resulting from the examined set points can be calculated as:

$$\mathrm{TC}_{\mathrm{Z_i}}{}^{\mathrm{est}} = \mathrm{G}(\mathrm{temp}_{\mathrm{Z_i}}{}^{\mathrm{est}}) \quad (9)$$

Finally, the selected set point is the one which results in comfort above the comfort threshold and has the minimum energy consumption:

$$\mathrm{setPoint}_{\mathrm{Z_i}}{}^{\mathrm{new}} = \{\mathrm{setPoint}_{\mathrm{Z_i}}{}^{\mathrm{exam}}\}_{(\mathrm{TC}_{\mathrm{Z_i}} > \mathrm{comfort\_threshold}), \min(\mathrm{hvac\_cons}_{\mathrm{Z_i}})} \quad (10)$$

where,

$setPoint_{Z_i}{}^{new}$ : HVAC set point finally applied by the system for the next time step,

$setPoint_{Z_i}{}^{exam}$: is the set of set points examined for the next time step,

$TC_{Z_i}$ : thermal comfort in zone Zi,

$hvac_{cons_{Z_i}}$: energy consumption of the HVAC in zone Zi, and

*comfort_threshold*: threshold defined by the user of the DSS

**Appliances**

This section describes the decision making process for building appliances (e.g. printer, PC monitor, ice maker, coffee maker etc.). Here, the concept of "controllable" appliances is introduced. Non controllable appliances are those which are not affected by the DSS because they should remain open regardless of occupancy presence, such as PC towers, servers, fridges etc.

Initially, the system checks current occupancy state. In case the area is empty and the examined appliance is open, controllable and not-locked, the system turns it off when occupancy prediction is zero. Otherwise, i.e. if there are occupants in the related area, an open appliance will remain open, while a closed appliance will be turned on (as long as it is controllable) to serve occupancy presence.

The system will also check devices' future schedule of use, because some devices (such as a printer or a coffee machine) should be controlled according to their planned use and not only depending on the space occupancy.

# 6 Persuasion Engine

An interesting debate between automation and behaviour change solutions has recently been established [68]. Following literature findings on this topic, it is still difficult to reach a decisive conclusion in favour of one or the other method. On one hand, automation systems have proven to reduce electricity requirements in many real-world scenarios, as depicted in the previous sections of this work. However, preliminary findings [69] from questionnaires distributed to various agencies/organisation within tertiary buildings have provided indications that occupants are sometimes keener to interact with the building's infrastructure themselves than having an automated solution that suddenly makes changes to their working environment.

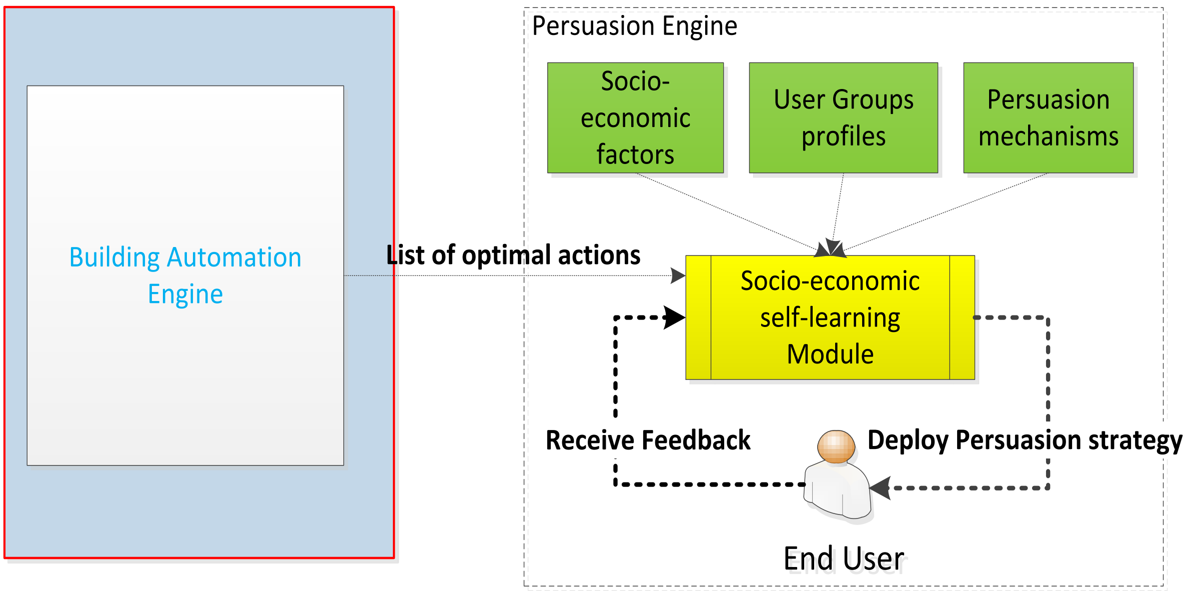


Figure 6 DSS schema including Persuasion Engine

Following the discussion above, this work proposes the incorporation of a persuasive mechanism along with the already illustrated automation methodology.

As Fogg states in [70], the persuasive technology is broadly defined as a technology that is designed to change attitudes or the behaviour of the users through persuasion and social influence.

The persuasion mechanism proposed in this article poses several conceptual benefits, compared to previous similar attempts:

- Messages will be validated in terms of their effectiveness, through a user-feedback adaptive mechanism, advancing from the typical generic message in one-size-fits-all approaches.

- Socio-economic and demographic reasons that affect the users' sensitivity to each message is examined through targeted surveys.

More specifically, through the use of enhanced occupant energy-related behaviour models (i.e. obXML [71]) and socio-economic factors that influence the former, the most suitable persuasion strategy will be deployed for end-users to directly interact with energy consuming devices within the premises of tertiary buildings. This approach represents the persuasion engine that will be integrated along with the building optimal status engine which was described in the previous sections as can be seen in

Figure 6. Taking as input the optimal control actions that will affect the least the occupant comfort in terms of visual and thermal conditions, the persuasion engine will be called to find the means that will motivate each occupant group (or individual if supported from the infrastructure available, i.e. RFID technologies) to take action and reduce energy waste.

Through a sophisticated adaptive process, the persuasion strategy adopted -for each time the system identifies an inefficient energy behaviour- will be fine-tuned, in order to reach optimal acceptance from the end-user. The process in analysed in the following list of actions:

1. Import list of actions (e.g. decrease temperature) for each appliance/HVAC/lighting unit, from Building Optimal Status Engine.
2. Import collected socio-economic factors and persuasion techniques stored in GIM static database.
3. Deploy holistic model (described in T4.4) to prioritize persuasion mechanisms based on users' profiles and socio-economic factors; assign weighted factors to the criteria affecting users' response to persuasion strategies.
4. Adopt a self-learning mechanism, in order to fine-tune the weights accordingly, based on positive or negative feedback from the end-user to each persuasive technique.

Several modelling approaches can be used in order to utilize the self-learning module. Some examples would be the Markov models (if the future state depends only from the current state) or the Semi Markov models (if the future state depends on the current state and a number of past states) or even rule based mechanisms. However, at the current state of this conceptual approach, it seems that the most suitable methodology is the reinforcement learning technique due to the fact that, in general, software agents ought to take actions in an environment so as to maximize some notion of cumulative reward.

# Conclusion

The presented deliverable reflects the current state of the GreenSoul Decision Support System. The DSS conceptual design lies on top of two main data acquisition mechanisms:

- Data retrieval from various physical sources through LinkSmart Middleware in a fast and efficient manner
- Acquisition of static and historical data related to building past energy behavior through the GIM databases and schemas' APIs, defined in [72]

The information gathering would be needed for actualizing the core DSS processes that will drive energy behavior change.

- Obtain current status of energy consumption and associated comfort that occupants perceive inside their working environment.
- Predict the association between devices' setpoints and environmental conditions
- Propose the best actions/device to be followed by the occupants
- Employ persuasive mechanisms to engage occupants in actually delivering those actions

It is obvious that at this state of the project, the DSS is not yet finalized as a complete system that performs all the tasks needed and identified in the functional and non-functional specifications of GreenSoul [73]. Several aspects are going to be addressed in the next versions of the DSS, including the implementation and finalization of the occupancy prediction mechanisms, the better calibration of occupancy extraction methods and examination of using different granularities when monitoring occupancy and finally the development of the Persuasion Engine, along with its interaction with the rest DSS sub-systems. These tasks will coincide with the preliminary installations into the pilot premises, where new challenges will arise and handled on the fly.

# Comments from External Reviewers

## External Reviewer #1

July 9th, 2017

| Issue | Yes | No | Score (1=low to 5=high) | Comments |
|---|---|---|---|---|
| **Is the architecture of the document correct?** | X | | 5 | |
| **Does the architecture of the document meet the objectives of the work done?** | X | | 5 | |
| **Does the index of the document collect precisely the tasks and issues that need to be reported?** | X | | 5 | |
| **Is the content of the document clear and well described?** | X | | 4 | |
| **Does the content of each section describe the advance done during the task development?** | X | | 4 | |
| **Does the content have sufficient technical description to make clear the research and development performed?** | X | | 5 | |
| **Are all the figures and tables numerated and described?** | X | | 5 | |
| **Are the indexes correct?** | X | | 5 | |
| **Is the written English correct?** | X | | 5 | |
| **Main technical terms are correctly referenced?** | X | | 5 | |
| **Glossary present in the document?** | X | | 5 | |

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## External Reviewer #2

July 10th, 2017

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|---|---|---|---|---|
| **Is the architecture of the document correct?** | X | | 5 | |
| **Does the architecture of the document meet the objectives of the work done?** | X | | 5 | |
| **Does the index of the document collect precisely the tasks and issues that need to be reported?** | X | | 5 | |
| **Is the content of the document clear and well described?** | X | | 4 | |
| **Does the content of each section describe the advance done during the task development?** | X | | 4 | |
| **Does the content have sufficient technical description to make clear the research and development performed?** | X | | 4 | |
| **Are all the figures and tables numerated and described?** | X | | 5 | |
| **Are the indexes correct?** | X | | 5 | |
| **Is the written English correct?** | X | | 5 | |
| **Main technical terms are correctly referenced?** | X | | 5 | |
| **Glossary present in the document?** | X | | 5 | |

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