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D4.2 – Energy Comfortness Tool v1

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Executive Summary

The Energy Comfortness Tool (ECT) introduces a new framework for assessing indoor environmental quality in connection with energy performance. It introduces the new concept of “comfortness”, an integrated indicator that combines thermal, visual, acoustic, and air-quality comfort into a single, interpretable measure. By linking these comfort dimensions with energy simulation results, ECT enables a balanced evaluation of both human well-being and building efficiency. This report highlights the first operational release of ECT (standalone version), which implements this concept through a modular standalone software solution. It integrates data ingestion, prediction of indoor conditions via Machine-Learning models, standards-based comfort calculations, and Building Energy Modelling (BEM) using Building Information Modelling (BIM) -derived inputs. The workflow transforms sensor data into comfort indices and energy indicators that can be visualised and compared across building spaces.

Comfort is quantified using a class-based scoring system that aligns with international standards. Thermal comfort follows ISO 7730 (Predicted Mean Vote - PMV - and Predicted Percentage of Dissatisfied - PPD), visual comfort uses EN 12464-1, acoustic comfort applies NF S 31-080, and indoor air quality is based on EN 16798-1 with particulate limits from Directive 2008/50/EC. Each domain is normalised on a four-class scale (A to D, plus NC for non-classifiable), and an overall comfortness score is obtained through weighted aggregation. This unified approach ensures consistency across measurements and supports inclusiveness by incorporating occupant profiles that reflect age, gender, and sensory characteristics. Comfortness is evaluated at the individual level, with ECT incorporating representative profiles that reflect both the general population and groups with diverse accessibility needs, such as older adults and people with visual or mobility limitations. A key feature of ECT (standalone version) is its interactive dashboard, which presents comfort and energy data through clear visualisations. Users can review thermal, visual, acoustic, and air-quality conditions individually or as a combined comfortness index, gaining direct insight into the trade-offs between comfort quality and energy demand. The interface provides meaningful information for both technical and non-technical users, facilitating evidence-based design and operational decisions. ECT (standalone version) has been initially validated through a demonstrator at the CERTH/ITI nZEB Smart House, confirming its functionality and reproducibility. The tool represents a milestone in linking comfort research with building-energy analysis and offers an open, extensible foundation for future development.

As a unifying framework, ECT bridges the gap between data collection, simulation, and actionable insight. ECT (standalone version) demonstrates this capability as a standalone tool (public version) with manual data ingestion via CSV files, providing a reproducible environment for research and individual analysis. This establishes the foundational service that is extended in ECT (integrated version) as described in D4.5 Energy Comfortness Tool v2, which integrates seamlessly within the AccesS Suite via automated data provisioning and authentication mechanism through the Suite's API. This common core, adaptable to different deployment contexts, underscores the ECT's role as a versatile service for optimizing both energy efficiency and occupant comfort.

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List of Acronyms and Abbreviations

Term	Description
AI	**Artificial Intelligence**
ASHRAE	**American Society of Heating, Refrigerating and Air-Conditioning Engineers**
API	**Application Programming Interface**
BIM	**Building Information Modelling**
BEM	**Building Energy Modelling**
BOMS	**Building Operation and Management Systems**
CatBoost	**Categorical Boosting**
CSV	**Comma-Separated Values**

ECE	**Energy Comfortness Engine**
ECD	**Energy Comfortness Dashboard**
ECT	**Energy Comfortness Tool**
EPW	**EnergyPlus Weather file**
HVAC	**Heating, Ventilation and Air Conditioning**
IAQ	**Indoor Air Quality**
IDF	**Input Data File (EnergyPlus format)**
IEQ	**Indoor Environment Quality**
IFC	**Industry Foundation Classes**
IoT	**Internet of Things**
MAE	**Mean Absolute Error**
ML	**Machine-Learning**
MSE	**Mean Squared Error**
LightGBM	**Light Gradient-Boosting Machine**
NGO	**Non-Govermental Organization**
$PM_{2.5}$ / PM_{10}	**Particle Matter (diameter < 2.5 µm / <10 µm)**
PMV	**Predicted Mean Vote**
PPD	**Predicted Percentage of Dissatisfied**
TVOC	**Total Volatile Organic Compounds**
Q-Q Plot	**Quantile – Quantile Plot**
XGBoost	**eXtreme Gradient Boosting**

1 Introduction

1.1 Scope and objectives of the deliverable

This deliverable (D4.2 Energy Comfortness Tool v1) presents the standalone version of the Energy Comfortness Tool (ECT), which was conceived as a demonstrator integrating Machine-Learning (ML) models, comfort assessment with energy performance analysis. The scope of the document is to describe in detail the design, implementation, and functionalities of ECT as a standalone version, and to show how the conceptual framework of comfortness - a new concept - has been translated into a working software package. Comfortness, as defined in the project, represents the overall assessment of indoor environmental quality across four domains (i.e., thermal, visual, acoustic, and Indoor Air Quality (IAQ)), while at the same time linking these assessments with energy loads. The deliverable therefore marks the transition from theoretical definition to practical application, demonstrating how comfort can be consistently quantified, visualised, and communicated to a wide range of users.

The objectives of D4.2 are closely aligned with the commitments set out in the project's proposal. The primary goal is to provide a standalone, reproducible tool that embodies the comfortness framework and that can be deployed by both project partners and external users. ECT (standalone version) has been implemented as a modular software system that combines ML models for the prediction of indoor environmental variables with standards-based comfort calculations and physics-based building energy simulations. The outcome is a holistic assessment of comfort that can be presented in an accessible format and contextualised in terms of energy consumption. By packaging the tool as a ready-to-use image, the project ensures that the demonstrator can be easily adopted without extensive technical preparation, thereby supporting both research experimentation and practical applications.

In addition, the deliverable provides evidence of the tool's operation through a demonstrator case at the CERTH/ITI nZEB Smart House that acts as project's testbed in alignment with T7.3 activities. The Smart House offers sufficient historical data for all comfort domains while AccesS pilot cases have recently started building their datasets. This allowed to initially validate the software and illustrate its value for stakeholders ranging from technical experts to decision-makers. The report thus establishes ECT (standalone version) as a milestone in the development of the Energy Comfortness Tool, providing the foundation for future updates that will expand integration and scalability.

1.2 Structure of the deliverable

The present document is organised to provide both the conceptual background and the technical details necessary to understand the design and implementation of the Energy Comfortness Tool. Following this introductory chapter, Chapter 2 presents the theoretical underpinnings of the work. It reviews the literature and standards that define comfort within the thermal, visual, acoustic and IAQ domains, and introduces the project's new integrative framework of comfortness as an overall concept. Chapter 3 then turns to the Energy Comfortness Tool itself, describing its architecture, the role of ML in predicting indoor environmental variables, the application of standards-based comfort calculations, and the integration of energy simulations. The chapter concludes with a detailed overview of the simulation dashboard that serves as the main user interface. Chapter 4 offers complementary discussion and additional sections relevant to the tool's positioning within the broader project. Chapter 5 provides the conclusions, highlighting the achievements of the current version and outlining the perspectives for further development. Finally, Annex A provides technical information on requirements, installation, and operation. In this way, the deliverable moves from context to implementation and from demonstration to documentation, ensuring both accessibility for non-technical readers and sufficient depth for technical experts.

1.3 Relation to Other Tasks and Deliverables

D4.2 is coupled with D4.5 Energy Comfortness Tool v2, which demonstrates the Energy Comfortness Tool v2, a version of the tool integrated within the AccesS Suite platform. Task 4.2 whole rationale and methodology are based on the developed architecture as described in D1.2 while user needs have been considered as defined within D2.1 that highlights each pilot sites roadmap.

The work from this task is also linked with the final integration and implementation of ECT in the AccesS Suite through T7.2 AccesS Inclusive Toolbox: Integration of Components, and its testing under T7.3 Inclusive Toolbox: Testing. The deployment and assessment of the AccesS Suite and integrated tools takes place within WP10-WP12 and in that sense, results are also linked.

2 Background and Concept of Energy Comfortness

2.1 Defining Comfortness

Indoor comfort has emerged as a central theme in the evaluation of building performance, reflecting its profound impact on human health, well-being, and productivity. Humans spend the majority of their lives indoors, commonly cited as 80 to 90% of time in modern societies[1], and are therefore continuously exposed to the environmental conditions maintained within residential, commercial, and institutional spaces. Studies have shown that indoor conditions greatly impact brain function, with a poor environment recognized as the cause of behavioural and mental issues, cognitive problems and even neurodegenenarative diseases [1]. The importance of comfort has historically been acknowledged across separate disciplines: thermal comfort in building physics and Heating, Ventilation and Air-Conditioning systems (HVAC) engineering [2], visual comfort in architectural lighting [3], acoustic comfort in environmental acoustics [4] , and indoor air quality (IAQ) in environmental health [5]. Each of these domains has its own body of research, methodologies, and regulatory standards. This domain-specific legacy has provided clear metrics and compliance pathways, but it has also resulted in a fragmented view of what it means for an indoor space to be truly "comfortable". Multi-domain comfort estimations are gradually being discussed more and more, appearing in recent literature [6, 7]. Moreover, the galloping evolution of Artificial Intelligence (AI) and Machine-Learning (ML) may dramatically alter our perception of comfort and how to evaluate it [8], as well as open new pathways for immediate adaptation to volatile conditions that affect comfort [9].

As mentioned above, several recent reviews have underscored the shortcomings of this fragmented approach. Comfort is rarely determined by a single factor in isolation; instead, it arises from the simultaneous perception of multiple domains, each interacting with and sometimes counteracting the others. A space with optimal thermal conditions may still be experienced as uncomfortable if noise levels are excessive, if lighting is insufficient, or if air is stale and polluted. Yet research and practice continue to prioritise thermal comfort above all others. A systematic review of personalised comfort methods [10] revealed that 97% of AI-based comfort prediction studies focus solely on thermal conditions, with only 3% considering other dimensions such as IAQ, acoustic comfort, or visual comfort. This imbalance has perpetuated a research landscape where thermal metrics dominate comfort assessment, while other critical determinants of well-being remain comparatively underexplored.

The dominance of thermal comfort is partly historical, as HVAC systems have long been designed around temperature and humidity control, and partly methodological, since models like PMV/PPD (Predicted Mean Vote/ Predicted Percentage of Dissatisfied) offered a quantifiable framework early on. However, evidence has accumulated that PMV-based assessments often fail to reflect real occupant perceptions, particularly in naturally ventilated or mixed-mode buildings. As [11] note, the PMV/PPD framework struggles with predictive accuracy and lacks sensitivity to personal and contextual factors. Their hybrid model, which integrates wrist skin temperature with classical indicators, shows that personalisation through physiological data and hybrid modelling significantly improves prediction accuracy. This line of research points to a fundamental limitation of traditional approaches: they assume "average" occupants in "average" environments, whereas in reality comfort is both individualised and context-dependent. Nevertheless, it is important to note that his kind of personalized data acquisiton posses severe practical challenges, such as device installation and proper

[1] https://ec.europa.eu/commission/presscorner/detail/en/ip_03_1278

function and ethical considerations about personal health data. In any case, personalisation has therefore become one of the most active trends in comfort research. [10] map out a wide range of AI techniques - ranging from classical regressions to deep neural networks - that have been applied to predict personalised comfort. These methods exploit not only environmental variables but also physiological signals, contextual data, and behavioural indicators to produce dynamic, individualised predictions. The implication is clear: comfort can no longer be treated as a fixed property of the environment alone but must be understood as an emergent condition shaped by occupants' bodies, activities, and perceptions. Such findings resonate with broader shifts in building science toward occupant-centred design, where the user is no longer a passive recipient of environmental conditions but an active parameter in modelling and control.

Another important dimension of this shift is inclusiveness. [12] conducted an extensive study of older adults in senior living facilities, focusing on how multiple comfort domains interact to shape their perceived well-being. Their findings highlight the inadequacy of one-size-fits-all approaches. Elderly occupants were shown to have heightened sensitivity to thermal variations, reduced tolerance to poor lighting, and distinct responses to acoustic and air quality conditions compared with younger populations. Importantly, they emphasise that comfort evaluations should not only average across populations but should also explicitly integrate vulnerable groups, including the elderly and those with sensory or mobility impairments. Inclusiveness is thus not merely a social aspiration but a technical necessity; comfort assessments that ignore diversity risk producing misleading outcomes that mask discomfort among the very groups most dependent on safe and healthy indoor environments.

Empirical post-occupancy studies further demonstrate how comfort perceptions diverge in practice. [13] examined occupant satisfaction in a Malaysian green-certified building and found disparities across domains, with relatively high satisfaction reported for humidity and noise levels but more mixed responses regarding lighting and temperature. Such studies reveal that comfort is not only multidomain but also culturally and contextually variable, shaped by building design, climate, and user expectations. They also show the need for integrated evaluation frameworks that can capture and reconcile these differences rather than relying on domain-specific snapshots. The role of digitalisation and IoT systems in enabling such frameworks is increasingly recognised. [14] review IoT-based indoor environmental quality (IEQ) systems and note that while sensors can capture real-time data across all four comfort domains, integration challenges remain significant. These include sensor calibration, interoperability of devices, and data privacy concerns. Nevertheless, the integration of IoT sensing, AI-based prediction, and building simulation is widely seen as a promising path toward dynamic, holistic comfort management. Such approaches not only provide finer granularity of monitoring but also allow for adaptive control systems that can balance comfort against energy consumption.

It is within this evolving landscape that the AccesS project introduces the concept of Comfortness. Comfortness is defined as the overall level of indoor comfort across thermal, visual, acoustic, and air quality domains, explicitly linked to energy performance. Unlike previous approaches that treat domains separately, Comfortness normalises each index into a common four-class system (A-D, plus NC for non-classified) and aggregates them into a weighted score. This formulation allows for trade-offs to be quantified, such as recognising when high thermal comfort is achieved at the expense of poor IAQ, or when improvements in visual comfort require additional energy use. By embedding inclusiveness into occupant profiles - accounting for age, impairment, and activity level - the Comfortness framework ensures that assessments are not abstract but grounded in real and diverse human needs.

To summarize, the evolution of comfort research over recent decades has moved from domain-specific metrics to personalised, multidomain, and inclusive frameworks. Yet gaps remain, especially in integrating non-thermal domains and in linking comfort evaluation directly to energy use. The concept of Comfortness addresses these gaps by providing a unified, standards-based, multidomain metric that reflects both the diversity of human occupants and the practical realities of energy consumption. In doing so, it provides a foundation for a new generation of tools - such as the Energy Comfortness Tool developed in this project - that can support decision-making, promote inclusivity, and catalyse innovation in the field of smart and sustainable buildings.

In terms of calculating Comfortness, as this is a new concept, we have defined a weighted class-based system based on homogenizing comfort expression in other domains. The explicit comfort classes that ECT can evaluate are for the following domains:

1. Thermal
2. Visual
3. Acoustic
4. CO_2 (IAQ)
5. CO (IAQ)
6. TVOC (IAQ)
7. $PM_{2.5}$ (IAQ)
8. PM_{10} (IAQ)

In ECT, we are introducing four classes, from D (worst) to A (best). Moreover, we assign a NC (non-classifiable) class to any observation that falls outside the thresholds defined for each quantity (the thresholds and the method for classifying individual domains are described in the following sub-chapters). Hereafter, we interchangeably use the terms "comfortness" and "overall comfort". The overall comfort score ($\overline{S_c}$) is calculated as:

$$\overline{S_c} = \frac{\sum_{i=1}^{N} s(c_i) * w_i}{\sum_{i=1}^{N} w_i} \tag{1}$$

where $s(c_i)$ is the scoring function for each of the different comfort quantities (c) considered in the calculations of the overall comfort, i.e. for use of all comfort indices we have $N = 8$ (thermal, acoustic, visual and the 5 IAQ indices). The weights (w) are obtained from the following weighting matrix:

$$w_i = \begin{bmatrix} 1.0, if\ i = thermal \\ 0.6, if\ i = visual \\ 0.6, if\ i = acoustic \\ 0.2, if\ i = CO_2 \\ 0.2, if\ i = CO \\ 0.2, if\ i = TVOC \\ 0.2, if\ i = PM_{2.5} \\ 0.2, if\ i = PM_{10} \end{bmatrix} \tag{2}$$

According to this weighting schema, thermal comfort has the highest effective contribution to overall comfort with ~31%, acoustic and visual follow with 19% each, while comfort contribution per IAQ index is ~6%. From the above equations, it is evident that while a missing comfort index may affect the final score, the original balance is relatively unchanged. For instance, if two IAQ indices are missing thermal comfort contributes ~36% and acoustic / visual 21%, while remaining IAQ indices participate to overall comfort by ~7%. Higher-weighted indices (thermal) will drastically change this balance if missing, but this represents the actual conditions of occupant comfort. The mapping function of comfort classes (A, B, C, D) to comfort scores is the following:

$$s(c) = \begin{pmatrix} A \rightarrow 4 \\ B \rightarrow 3 \\ C \rightarrow 2 \\ D \rightarrow 1 \\ NC \rightarrow 0 \end{pmatrix} \tag{3}$$

Finally, $\overline{S_c}$ is mapped back to an overall comfort class ($\bar{C}$) according to threshold values:

$$\bar{C} = \begin{pmatrix} A \rightarrow \overline{S_c} \geq 3.5 \\ B \rightarrow \overline{S_c} \geq 2.5 \\ C \rightarrow \overline{S_c} \geq 1.5 \\ D \rightarrow \overline{S_c} \geq 0.5 \\ NC \rightarrow \overline{S_c} < 0.5 \end{pmatrix} \tag{4}$$

The proposed system facilitates modularity, as the results of Eq. (1) are self-adjusted if one or more of the comfort indices are omitted (according to sensor availability), with varying degrees of impact on the comfortness class.

2.1.1 Thermal Comfort

Thermal comfort represents one of the most extensively studied aspects of indoor environmental quality and remains the cornerstone of building environmental design. It is defined by ISO 7730[2] as "that condition of mind which expresses satisfaction with the thermal environment." This definition recognizes that comfort is not purely a physical state but a subjective perception arising from the interaction between the human body, clothing, activity level, and the surrounding environment. In practice, thermal comfort depends on the balance between the heat produced by the body's metabolism and the heat lost to the environment through convection, radiation, evaporation, and conduction. When this thermal balance is achieved without conscious effort, occupants are considered thermally comfortable.

The most widely adopted quantitative framework for evaluating thermal comfort is Fanger's Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) model [15], developed in the 1970s and later formalized in ISO 7730. Fanger's model is derived from heat-balance principles and empirical studies involving controlled laboratory experiments with hundreds of subjects exposed to various thermal conditions. The model predicts the average thermal sensation vote (PMV) on a seven-point ASHRAE scale ranging from -3 (cold) to +3 (hot), with 0 corresponding to thermal neutrality. The PPD index is then used to express the expected proportion of dissatisfied occupants at a given PMV value, acknowledging that even at thermal neutrality some percentage of individuals (typically about 5 %) will still feel slightly warm or slightly cool.

According to ISO 7730, the PMV depends on six primary variables:

1. Air temperature (°C) - the temperature of the surrounding air.
2. Mean radiant temperature (°C) - the average temperature of all surfaces surrounding the occupant, weighted by their view factors.
3. Air velocity (m/s) - the speed of air movement near the occupant.
4. Relative humidity (%) - affecting the rate of evaporative heat loss.
5. Metabolic rate (met) - the rate of internal energy production in the human body, dependent on activity level.
6. Clothing insulation (clo) - the thermal resistance of clothing ensembles, which limits heat transfer between the skin and environment.

[2] https://www.iso.org/standard/39155.html

The first four variables describe the environmental conditions, while the latter two represent personal factors. ISO 8996[3] provides standardized methods for estimating metabolic rate from body mass, height, age, and activity level, and ISO 9920[4] specifies typical clothing insulation values (clo) for different garment combinations. Together, these standards form the foundation for consistent and reproducible comfort evaluation across diverse indoor settings.

Within ECT, thermal comfort is calculated using the ISO 7730 formulation of the PMV/PPD model. Indoor air temperature and relative humidity are taken either from sensor data or from the ML-predicted quantities, while air velocity is assumed constant at 0.1 m/s and mean radiant temperature is set equal to the measured or predicted air temperature. The metabolic rate is estimated dynamically from occupant characteristics - age, gender, weight, and height - following the methodology of ISO 8996, and adjusted by the declared activity level in the occupant profile. Clothing insulation values are obtained from the same profile in accordance with ISO 9920. By using occupant-specific physiological parameters rather than fixed assumptions, the tool ensures that calculated PMV values more accurately represent the diversity of users, including those whose thermal sensations deviate from the "average" adult upon which Fanger's model was originally based.

The resulting PMV values are then converted into PPD values, which quantify the percentage of occupants expected to feel thermally uncomfortable under those conditions. In ECT, the PMV/PPD output is further mapped onto the four-class comfort scale introduced earlier (A-D + NC). The class boundaries correspond to the categories defined in ISO 7730 for buildings of different comfort expectations, as seen in the following table.

Table 1. Classification boundaries for thermal comfort. PMV and PPD conditions must both be met.

Class	PMV Condition (absolute values)	PPD Condition	Description
A	≤ 0.2	≤ 6%	Excellent comfort
B	≤ 0.5	≤ 10%	Good comfort
C	≤ 0.7	≤ 15%	Acceptable comfort
NC	Outside above ranges	Outside above ranges	Not classified

Although the PMV/PPD model is robust and widely validated, several studies have highlighted its limitations [2], [16]. It assumes steady-state thermal conditions, uniform clothing and activity, and homogeneous environmental parameters, assumptions rarely met in naturally ventilated or mixed-mode buildings. Field investigations have shown that occupants often adapt behaviorally (by adjusting clothing or opening windows) and physiologically (through acclimatization) to variable thermal conditions. This has given rise to adaptive thermal comfort models, such as those described in ASHRAE 55[5], which relate neutral temperatures to outdoor climatic conditions and occupant expectations. Nevertheless, for the purpose of establishing a transparent, reproducible, and standard-compliant methodology, ECT (standalone version) employs the ISO 7730 approach while retaining the flexibility to integrate adaptive formulations in future updates.

Fanger's model remains an essential benchmark for thermal comfort because it enables a direct link between objective physical quantities and subjective human response. By combining ISO standardized inputs with occupant-specific profiles, the Energy Comfortness Tool provides a balance between

[3] https://www.iso.org/standard/74443.html
[4] https://www.iso.org/standard/39257.html
[5] https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy

general applicability and personalisation. In this configuration, thermal comfort not only serves as a primary indicator of indoor environmental quality but also as a key driver in the overall comfortness computation, reflecting its dominant contribution to human satisfaction and energy use alike. Thermal conditions that deviate from neutrality increase the predicted dissatisfaction rate and, consequently, lower the overall comfort class, influencing both comfort assessment and the optimization of energy strategies.

2.1.2 Visual Comfort

Visual comfort is a key determinant of indoor environmental quality, directly influencing visual performance, alertness, and psychological well-being. It is defined by EN 12464-1:2021[6] - Lighting of Workplaces - Indoor Workplaces as the condition in which the visual environment allows occupants to perform visual tasks efficiently, accurately, and comfortably. Unlike thermal comfort, which primarily concerns heat exchange, visual comfort depends on the interaction between luminance, illuminance, contrast, glare, color rendering, and daylight availability, all of which affect occupants perceive and respond to the surrounding space. Poor lighting can lead not only to visual fatigue and reduced productivity but also to discomfort, loss of spatial orientation, and negative emotional responses. EN 12464-1 specifies minimum illuminance levels (E, lx) for a wide range of indoor tasks and spaces, from 100 lx for circulation areas to 500 lx or higher for offices and classrooms, together with limits on glare and requirements for uniformity and color rendering. The standard recognizes that visual comfort is not simply a function of absolute brightness but rather of luminance distribution and adaptation - the eye's ability to adjust to changing light levels without strain. Excessive contrast, directional glare from luminaires or windows, and insufficient daylight balance can all compromise comfort even when average illuminance values meet regulatory thresholds. In addition to its physical determinants, visual comfort has a strong psychological dimension related to mood, perceived spaciousness, and connection with the outdoors. These aspects have become increasingly important in modern design approaches emphasizing human-centered and biophilic environments.

Within ECT, visual comfort is evaluated using both standard compliance metrics and a derived visual score that can adapt to specific occupant characteristics. For standard occupants, illuminance levels are compared against EN 12464-1 thresholds corresponding to the space function defined in the BIM input. For example, office spaces target an average illuminance of 500 lx with a minimum uniformity of 0.6, while residential and circulation areas require lower levels. Deviations from these benchmarks are mapped to the class-based scoring system (A-D and NC) introduced earlier, where Category A represents optimal conditions within the recommended range and Category D represents inadequate illumination. Luminance level-based classification for general visual comfort, in the context of ECT, is presented in the following table.

Table 2. Classification boundaries for visual comfort.

Class	Luminance range (lx)	Description
A	300 - 500	Optimal lightning
B	200 - 300 or 500 - 700	Good lightning (slightly too dim or too bright)
C	< 200 or > 700	Poor lightning (too dim or too bright)
NC	Not classified	Not classified

[6] https://www.cibse.org/media/mxymm5no/en12464-2011.pdf

To ensure inclusiveness, ECT also integrates an adapted visual comfort model for occupants with visual impairment, based on the approach of [17], who investigated the perceptual response of individuals with partial sight to varying illuminance conditions. Their results show that the perceived comfort of visually impaired occupants follows a nonlinear relationship with illuminance, increasing rapidly up to a threshold value and then plateauing as light levels approach 2000 lx. In ECT, this relationship is represented by a two-branch piecewise function that converts measured or simulated illuminance (E, lx) into a raw visual score:

$$v_s(E) = \begin{cases} 10^{0.0012*E+0.85}, if\ E \in [125, 391)\ lx \\ 10^{1.32}, if\ E \in [391, 2000]\ lx \end{cases} \quad (5)$$

The function captures the diminishing returns of increased brightness for occupants with reduced vision, acknowledging that illumination beyond a certain point no longer enhances visual perception. To harmonise this model with ECT's unified comfortness framework, the raw visual score is normalised between 1 and 5 according to its attainable range:

$$\widehat{v_s} = 1 + \frac{v_s - \min(v_s)}{4 * (\max(v_s) - v_s)} \quad (6)$$

This transformation ensures that the adapted score aligns numerically with the four-class system used for other comfort domains. In practice, the function allows the tool to translate absolute illuminance values into perceptual comfort scores that reflect both the sensitivity curve of visually impaired users and the overall scale of the comfortness model. When the occupant profile indicates visual impairment, the ECT automatically applies this adapted formulation; otherwise, it uses the standard illuminance-based classification derived from EN 12464-1. By including this adaptation, the Energy Comfortness Tool moves beyond compliance-based lighting evaluation toward personalised and inclusive comfort assessment. It recognises that lighting requirements differ among individuals and that optimal conditions for one group may be uncomfortable or insufficient for another.

Finally, integrating visual comfort into the overall *Comfortness* framework allows trade-off analysis between lighting quality and energy performance. Since artificial lighting contributes substantially to internal heat gains and electrical consumption, maintaining appropriate illuminance while minimizing energy use is a critical design objective. Through its combined use of standard-based classification and adaptive perception models, ECT provides a quantitative yet human-centered means to evaluate this balance. Visual comfort thus represents both a discrete domain within the tool and an essential component of the overall comfortness index, ensuring that comfort evaluation remains comprehensive, inclusive, and energetically efficient.

2.1.3 Acoustic Comfort

Acoustic comfort is an essential but often underestimated component of indoor environmental quality. It is generally defined as the perceived acoustic satisfaction of occupants within an enclosed space, influenced by background noise, reverberation time, sound insulation, and the character of unwanted sounds. Unlike thermal or visual comfort, which can be measured through straightforward physical quantities, acoustic comfort is inherently subjective and context-dependent, shaped by the occupant's age, hearing ability, activity, and expectations. The same noise level that is acceptable in a busy office may be perceived as disturbing in a hospital ward or residential bedroom.

The assessment of acoustic comfort in ECT also draws upon the criteria established by NF S31-080:2006[7], which defines acoustic performance levels for offices and associated workspaces. Unlike measurement-oriented standards that focus exclusively on physical parameters, NF S31-080:2006 introduces comfort-based categories that combine background noise limits, spatial sound insulation, and reverberation control to characterize the overall acoustic quality perceived by occupants. The standard distinguishes four acoustic performance classes (A to D), where Class A represents optimal comfort conditions suitable for concentration or confidential tasks, and Class D denotes minimal acoustic performance acceptable only in non-sensitive areas. Typical target ranges recommended by the standard include background noise levels between 35 and 45 dB(A) in standard open-plan offices, sound insulation between adjacent spaces exceeding 40 dB, and reverberation times below 0.6 s for enclosed offices. Importantly, NF S 31-080 acknowledges that acceptable acoustic conditions depend not only on physical measurements but also on the activity type and the subjective sensitivity of occupants. This makes it consistent with the philosophy of the Comfortness framework, where acoustic satisfaction is interpreted as a perceptual balance between measured noise exposure and user expectations rather than a purely technical specification. Following we offer a summary of the adapted noise levels integrated in ECT.

Table 3. Classification boundaries for acoustic comfort.

Class	Noise range (dB)	Description
A	< 35	Very quiet
B	35 - 45	Quite
C	45 - 65	Moderate noise
D	≥ 65	Significant noise
NC	Unspecified	Not classified

Recent research [13], [18], [19], [20], [21] has emphasized that acoustic annoyance is not uniform across the population but varies systematically with demographic factors such as age. Younger occupants tend to exhibit higher sensitivity to transient or high-frequency noise, whereas older individuals - often experiencing reduced auditory sensitivity - report lower annoyance for the same sound pressure levels. In ECT, this variability is explicitly represented through an age-dependent annoyance model adapted from [20], which relates the perceived annoyance level (AL) to both the occupant's age and the measured or simulated indoor noise level (NL, in dB). For acoustic annoyance, a piecewise linear function is first to calculate the reference annoyance level (AL_r) based on age ranges:

$$AL_r(age) = \begin{cases} 0.944 * age - 9.014, if\ age\ \in [11, 16] \\ -0.353 * age + 11.738, if\ age \in (16, 22] \\ -0.044 * age + 4.650, if\ age\ \in (22, 55\} \end{cases} \tag{7}$$

Then, the annoyance level (AL) for the specific noise level measured (or simulated) is obtained from:

$$AL = AL_r * e^{2*NL} \tag{8}$$

In summary, ECT's acoustic comfort module bridges quantitative acoustic assessment and human perception by employing an age-dependent annoyance function validated in the literature and aligning it with the project's four-class system. The integration of perceptual sensitivity makes the evaluation

[7] https://www.boutique.afnor.org/en-gb/standard/nf-s31080/acoustics-offices-and-associated-areas-acoustic-performance-levels-and-crit/fa142103/740

adaptable across demographic groups, while the class-based normalization ensures compatibility with other comfort domains. By transforming measured or simulated noise levels into perceptual annoyance and then into standardized comfort classes, the tool provides a comprehensive, human-centered representation of acoustic comfort that complements the broader Comfortness framework.

2.1.4 Indoor Air Quality (IAQ)

Indoor Air Quality (IAQ) constitutes a core dimension of the overall comfortness concept and is one of the four domains that determine the perceived environmental quality of a space. It refers to the chemical and physical composition of indoor air that affects both health and sensory comfort. Elevated concentrations of gaseous or particulate pollutants can cause irritation, fatigue, and reduced cognitive performance, while adequate air freshness contributes to well-being, satisfaction, and productivity. In buildings with mechanical or natural ventilation, IAQ also provides an indirect indication of ventilation efficiency and infiltration control, linking environmental quality directly with energy use.

ECT evaluates IAQ according to the framework set out in EN 16798-1:2019[8], which establishes indoor environmental input parameters for the design and assessment of building energy performance. This four indoor environment categories (I-IV) corresponding to different quality expectations: Category I represents high indoor environmental quality suitable for sensitive occupants, while Category IV defines acceptable but low-expectation environments. EN 16798-1 provides reference concentration limits for carbon dioxide (CO_2), carbon monoxide (CO) and Total Volatile Organic Compounds (TVOC), which serve as the primary indicators of ventilation adequacy and pollutant load. For particulate matter ($PM_{2.5}$ and PM_{10}), ECT follows the legally binding limit values established by Directive 2008/50/EC[9] on ambient air quality and cleaner air for Europe, which, although defined for outdoor environments, are widely used as indoor reference levels in building performance assessments. Following, we provide a table of IAQ limits to define the four comfort classes for each metric in the context of ECT. It is noted that the four categories (I-IV) of EN16798-1:2019 are mapped to equivalent classes of the comfortness system (A-D).

Table 4. Classification boundaries for CO_2 classes.

Class	CO_2 concentration (ppm)	Description
A	< 550	Excellent air quality
B	550 - 800	Good air quality
C	800 - 1,350	Acceptable air quality
D	≥ 1,350	Poor air quality
NC	Unspecified	Not classified

[8] https://standards.iteh.ai/catalog/standards/cen/b4f68755-2204-4796-854a-56643dfcfe89/en-16798-1-2019?srsltid=AfmBOorFs-1Hu9hfmeeAranF4xBlTHlaQD2_-EQhandCBl6nl2nH_8jX

[9] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02008L0050-20150918

Table 5. Classification boundaries for CO classes.

Class	CO concentration (ppm)	Description
A	< 35	Safe levels
B	≥ 35	Elevated levels
C	N/A	Not applicable to this metric
D	N/A	Not applicable to this metric
NC	Unspecified	Not classified

Table 6. Classification boundaries for TVOC classes.

Class	TVOC concentration (ppb)	Description
A	< 100	Safe levels
B	≥ 100	Elevated levels
C	N/A	Not applicable to this metric
D	N/A	Not applicable to this metric
NC	Unspecified	Not classified

Table 7. Classification boundaries for PM_{10} classes.

Class	PM_{10} concentration (μg/m^3)	Description
A	< 2,083	Safe levels
B	≥ 2,083	Elevated levels
C	N/A	Not applicable to this metric
D	N/A	Not applicable to this metric
NC	Unspecified	Not classified

Table 8. Classification boundaries for $PM_{2.5}$ classes.

Class	PM_{10} concentration (μg/m^3)	Description
A	< 0.003	Safe levels
B	≥ 0.003	Elevated levels
C	N/A	Not applicable to this metric
D	N/A	Not applicable to this metric
NC	Unspecified	Not classified

The modular structure of ECT allows IAQ evaluation either through real-time sensor measurements or through simulation outputs when such data are unavailable. In naturally ventilated spaces, the tool incorporates outdoor weather information from the Open-Meteo interface to estimate ventilation rates and the resulting indoor pollutant concentrations. This dual approach ensures consistency between measured and simulated analyses, enabling both diagnostic evaluation and scenario testing. From a perceptual standpoint, IAQ interacts closely with the other comfort domains. Elevated CO_2 or VOC levels increase perceptions of stuffiness and fatigue, while particulate accumulation can reduce visual clarity and accentuate thermal discomfort. Studies such as [10] demonstrate that occupants evaluate air freshness and odor intensity as part of their global comfort perception rather than in isolation. Older adults in assisted-living environments associate poor air quality with decreased autonomy and well-being [12]. By grounding IAQ assessment in EN 16798-1:2019 and Directive 2008/50/EC, ECT ensures full regulatory alignment and methodological transparency. The harmonized class-based framework allows for direct comparison with other comfort parameters and maintains the balance between human perception and environmental performance. IAQ thus becomes both a standalone indicator and an integral component of the overall Comfortness metric, linking air purity, ventilation effectiveness, and energy efficiency within a single, standardized assessment scheme.

2.2 Energy Simulations

Building Energy Modelling (BEM) has become an essential methodology for evaluating and optimising the performance of buildings throughout their lifecycle. It provides the analytical framework to estimate heating and cooling loads, evaluate HVAC system efficiency, and predict the energy consequences of design or operational choices. Modern simulation tools combine physics-based modelling, climatic data, and occupancy schedules to reproduce the dynamic thermal behaviour of buildings under real or hypothetical conditions.

Among the most widespread solutions is Autodesk Revit[10], which integrates energy-analysis modules such as Insight. These allow designers to perform early-stage assessments directly within BIM environments, facilitating rapid exploration of façade design, glazing ratios, or orientation effects. DesignBuilder[11], IES-VE[12], and Sefaira[13] provide more detailed interfaces for thermal and daylight simulations, commonly used in professional practice to demonstrate compliance with national energy codes or voluntary certifications. Although these tools deliver accurate energy and carbon estimations, they typically treat comfort only indirectly through fixed thermal setpoints or simplified PMV indices, while not truly considering other comfort domains. Other tools, such as EnergyPlus [22] and Simergy[14], enable advanced modelling of building physics and HVAC systems. They offer high temporal resolution, detailed control of boundary conditions, and the possibility to test novel control strategies. These frameworks, however, are primarily energy-oriented; they quantify heating and cooling demand, not the experiential comfort of occupants. Bridging this divide - linking objective energy performance with subjective comfort perception - is now a key research frontier in building science and forms the conceptual foundation for the “energy comfortness” paradigm addressed later in this deliverable. In any case, these solutions do not integrate actual observations and their patterns through tools such as ML, to identify real-world contributions of phenomena to energy performance.

Energy simulation is grounded in fundamental heat-balance equations that represent the exchange of energy between indoor air, building elements, and external conditions. At each time step, the simulation resolves conduction through walls, convection with air, radiation between surfaces, and internal heat gains from occupants and equipment. The resulting dynamic model predicts indoor temperatures and the associated energy required to maintain specified comfort conditions [22]. The international methodological framework is provided by the ISO 52000 family of standards, particularly ISO 52016-1:2017[15]. This standard defines the procedures for hourly or sub-hourly energy-balance calculations and for translating results into annual energy indicators. Complementary standards such as ISO 52017-1 and EN ISO 13790 govern the calculation of system efficiencies and the aggregation of results into national performance certificates. These documents ensure comparability between simulation outputs and regulatory requirements across Europe.

[10] https://help.autodesk.com/view/RVT/2025/ENU/?guid=GUID-2043E09F-40E5-4155-AE28-134F62E54F54
[11] https://designbuilder.co.uk/
[12] https://www.iesve.com/software/building-energy-modeling
[13] https://sketchup.trimble.com/en/products/sefaira?srsltid=AfmBOoqEL4tKGy9sU3PGpDBlrfxuuK35jhmeChi8_daKzxSpUPLlbMP5
[14] https://d-alchemy.com/products/simergy
[15] https://www.iso.org/standard/65696.html

2.3 Stakeholder and Target User

ECT has been developed as a multi-stakeholder demonstrator, serving both technical experts and non-technical users in the building and urban ecosystem. Its design ensures that outputs are accessible, actionable, and inclusive across different user groups, bridging the gap between advanced computational methods and practical decision-making. For technical experts, such as building engineers, energy modellers, and data scientists, ECT provides a transparent, standards-based environment that integrates machine-learning predictions with physics-based simulations. These users benefit from the ability to test scenarios, validate models against measured data, and explore the trade-offs between comfort and energy performance. The tool's modular architecture, reliance on established standards, and reproducibility through containerisation make it particularly valuable for research and development contexts, where methodological rigour and comparability are essential. For designers, facility managers, and policy makers, the tool functions as an accessible interface to complex analyses. Through the Streamlit dashboard, these users can configure scenarios by selecting spaces, occupant profiles, and time periods, and then view results that are expressed in intuitive categories (A-D and NC). The ability to visualise both detailed domain-specific outputs and aggregated overall comfortness scores allows decision-makers to quickly identify shortcomings in building performance and prioritise interventions. Finally, ECT has also been designed with end-user inclusivity in mind. By incorporating models that account for factors such as age and visual impairment, the tool recognises that comfort is not uniform across all occupants. This ensures that evaluations are sensitive to the needs of vulnerable groups, which is particularly relevant in contexts such as residential buildings, schools, hospitals, or elderly care facilities. Overall, the Energy Comfortness Tool is positioned as a flexible and inclusive demonstrator, capable of serving as a bridge between technical depth and practical usability, and addressing the needs of stakeholders across the building and urban ecosystem.

2.3.1 Primary Stakeholders

ECT has been designed with a clear focus on the primary stakeholders who directly influence the operation, design, and regulation of buildings. By addressing the needs of these groups, the tool ensures that its outputs are not only scientifically rigorous but also actionable in real-world decision-making contexts.

Building managers and operators constitute the first stakeholder group. They are responsible for ensuring that indoor environments remain both comfortable and energy-efficient throughout the building's lifecycle. For these users, ECT (standalone version) provides the ability to monitor comfort and energy-related indicators in real time, drawing on both measured data and model predictions. The system highlights inefficiencies, such as excessive cooling loads or poor indoor air quality, and presents them in a form that facilitates rapid corrective action. In addition, the dashboard supports the generation of compliance and performance reports, which building managers can use to justify operational decisions, demonstrate adherence to standards, and communicate with owners or tenants. Architects and engineers represent a second major stakeholder group. Their interest lies in understanding how design choices affect the balance between comfort and energy performance. ECT (standalone version) supports this need through its integration of BIM data and energy simulation capabilities, which enable the exploration of alternative design scenarios before construction or renovation takes place. By linking EnergyPlus simulations with comfort calculations, architects and engineers can assess comfort-energy trade-offs at the planning stage and refine their designs accordingly. The ability to integrate both sensor-based evidence and BIM-derived simulations provides a robust foundation for data-driven design workflows and ensures that design choices are supported by objective analyses.

Policy makers and regulators form the third group of primary stakeholders. Their responsibilities include ensuring compliance with energy performance and comfort standards such as the Energy Performance of Buildings Directive (EPBD) and relevant ISO and EN standards. ECT (standalone version) provides these users with a transparent framework for evaluating compliance by translating complex comfort and energy indicators into standardized categories. The inclusion of explainable AI features also supports evidence-based policymaking, offering insights into which variables most strongly influence comfort or energy performance. Importantly, the tool also promotes inclusivity by accounting for age- and impairment-related differences in comfort perception, aligning with broader European policy objectives such as the Green Deal and the Sustainable Development Goals (SDGs).
In sum, ECT (standalone version) has been structured to directly support the workflows of building managers, design professionals, and policy makers, ensuring that each group can access the level of detail and type of analysis most relevant to their decisions.

2.3.2 Target Users

In addition to its primary stakeholders, ECT (standalone version) is also tailored to serve a diverse group of target users who engage with buildings from different perspectives, such as consultants and ICT developers. These users benefit either directly from improved comfort and inclusiveness or indirectly through the insights that the tool generates for policy, design, and operational contexts. Occupants, as the end-users of buildings, are the most immediate beneficiaries of ECT (standalone version), even though they do not interact directly with the software. The tool is designed to enhance their well-being by ensuring that comfort is monitored, assessed, and maintained across thermal, visual, acoustic, and air quality domains. A central innovation of ECT (standalone version) is its ability to integrate occupant profiles into the comfort models, enabling personalised assessments that reflect the needs of diverse groups. This includes profiles for elderly users, individuals with mobility limitations, and those with vision impairments, ensuring that comfort evaluations are inclusive and sensitive to vulnerable populations. In this way, occupants indirectly benefit from an improved quality of life and healthier indoor environments. Accessibility experts and Non-Govermental Organizations (NGOs) also stand to gain from the deployment of ECT (standalone version). These groups are often tasked with ensuring that inclusiveness remains central to smart building innovations and that accessibility standards are respected in practice. By providing objective results that incorporate the perspective of impaired or vulnerable users, ECT (standalone version) offers a valuable evidence base for advocacy. Accessibility experts can use the outputs of the tool to argue for more inclusive design practices and to ensure that comfort evaluations extend beyond averages to account for population diversity.

Energy consultants and sustainability officers represent another important category of target users. Their role is to support building certification schemes such as LEED[16], BREEAM[17], or WELL[18], and to align operational strategies with climate neutrality targets. The ability of ECT (standalone version) to link comfort and energy performance within the same framework provides these professionals with a powerful resource. It allows them to quantify comfort-energy trade-offs, support carbon reduction strategies, and generate the documentation needed for certification processes. Finally, ICT developers and integrators are also target users, as they can build upon the ECT (standalone version) demonstrator to develop more advanced applications. This makes ECT (standalone version) not only a tool for assessment but also a foundation for innovation in building digitalization and smart infrastructure.

[16] https://www.usgbc.org/leed
[17] https://breeam.com/
[18] https://www.wellcertified.com/

2.3.3 Benefits per User Group

ECT (standalone version) has been conceived not only as a demonstrator of technical feasibility but also as a practical solution that delivers tangible value to multiple user groups. Its modular architecture, reliance on international standards, and inclusive design approach ensure that benefits are tailored to the diverse roles and responsibilities of stakeholders in the building and urban ecosystem. For building managers and engineers, the primary benefit lies in decision support. ECT (standalone version) translates complex comfort and energy modelling into clear trade-off analyses that can guide operational or design choices. Managers can monitor performance in real time, identify inefficiencies, and justify interventions with transparent evidence, while engineers and architects can use the tool to explore design alternatives and assess compliance with standards. In both cases, ECT (standalone version) serves as a bridge between technical depth and actionable insight, reducing uncertainty in decision-making. For occupants and accessibility experts, the key benefit is inclusiveness and well-being. By embedding occupant profiles into the comfort models and explicitly considering groups such as the elderly or those with mobility or vision impairments, ECT (standalone version) ensures that comfort evaluation is not restricted to a statistical “average” occupant. Instead, it reflects the diversity of building users and supports environments that promote health, safety, and equal access. Accessibility experts and NGOs can leverage these results to advocate for more inclusive design practices and ensure that smart building innovations remain human-centred. For the ICT and research communities, ECT (standalone version) functions as an innovation catalyst. Its open, containerized distribution makes it easy to deploy, extend, and integrate into larger ecosystems such as Building Operation and Management Systems (BOMS). Researchers can validate new models or comfort indices within a working framework, while ICT developers can prototype integrations at pilot sites. In this sense, the tool serves as a validated stand-alone prototype that lowers the barrier to further experimentation and scaling. Together, these benefits ensure that ECT (standalone version) is not only a technical solution but also a platform for supporting decisions, promoting inclusivity, and catalyzing innovation in the wider smart building landscape.

Table 9. Benefits by User Group in ECT (standalone version)

Stakeholder Group	Role in ECT (standalone version)	Benefit	Engagement Level
Building Managers & Engineers	Configure, monitor, and interpret results	Decision support through comfort-energy trade-offs	High - daily/operational
Occupants & Accessibility Experts	Provide profiles and serve as indirect beneficiaries	Inclusiveness and improved well-being	Medium - indirect/advocacy
ICT Developers & Researchers	Extend, integrate, and validate the tool	Innovation catalyst, prototype for scaling	Variable - project-based

3 The Energy Comfortness Tool

3.1 A Unified Architecture with Version-Specific Enabled Modules

The Energy Comfortness Tool (ECT) is architected as a unified framework that bridges data collection, computational modeling, and actionable insights for optimizing both energy efficiency and occupant comfort. It serves as a central unifying framework that integrates heterogeneous data sources and computational methods into a coherent assessment of "Energy Comfortness." This unified architecture is instantiated in two complementary versions: standalone version as detailed in this report and integrated version as presented within *D4.5 Energy Comfortness Tool v2*, that share common core components while employing version-specific enabled modules for data ingestion, Manchine model management, and platform integration. The Energy Comfortness Tool described in this report is a standalone software (public edition) that integrates ML models and energy simulation to evaluate occupant comfort in specific indoor spaces. This way, ECT acts as a bridge between generalized energy simulation algorithms and ML models highly specialized to each space.

3.2 The Unified ECT Framework Concept

The ECT framework is built upon a modular, service-oriented architecture designed for both flexibility and scalability. Its fundamental innovation lies in providing a consistent comfortness evaluation framework that can be deployed across different contexts from standalone research tool (as described in D4.2- public version) to integrated platform component (as described in D4.5- sensitive version) while maintaining methodological rigor and result comparability.

The architecture follows a layered approach with the Energy Comfortness Dashboard (ECD) as the primary user interface, the Energy Comfortness Engine (ECE) as the computational core, and version-specific enabled modules that define the deployment model and data integration approach.

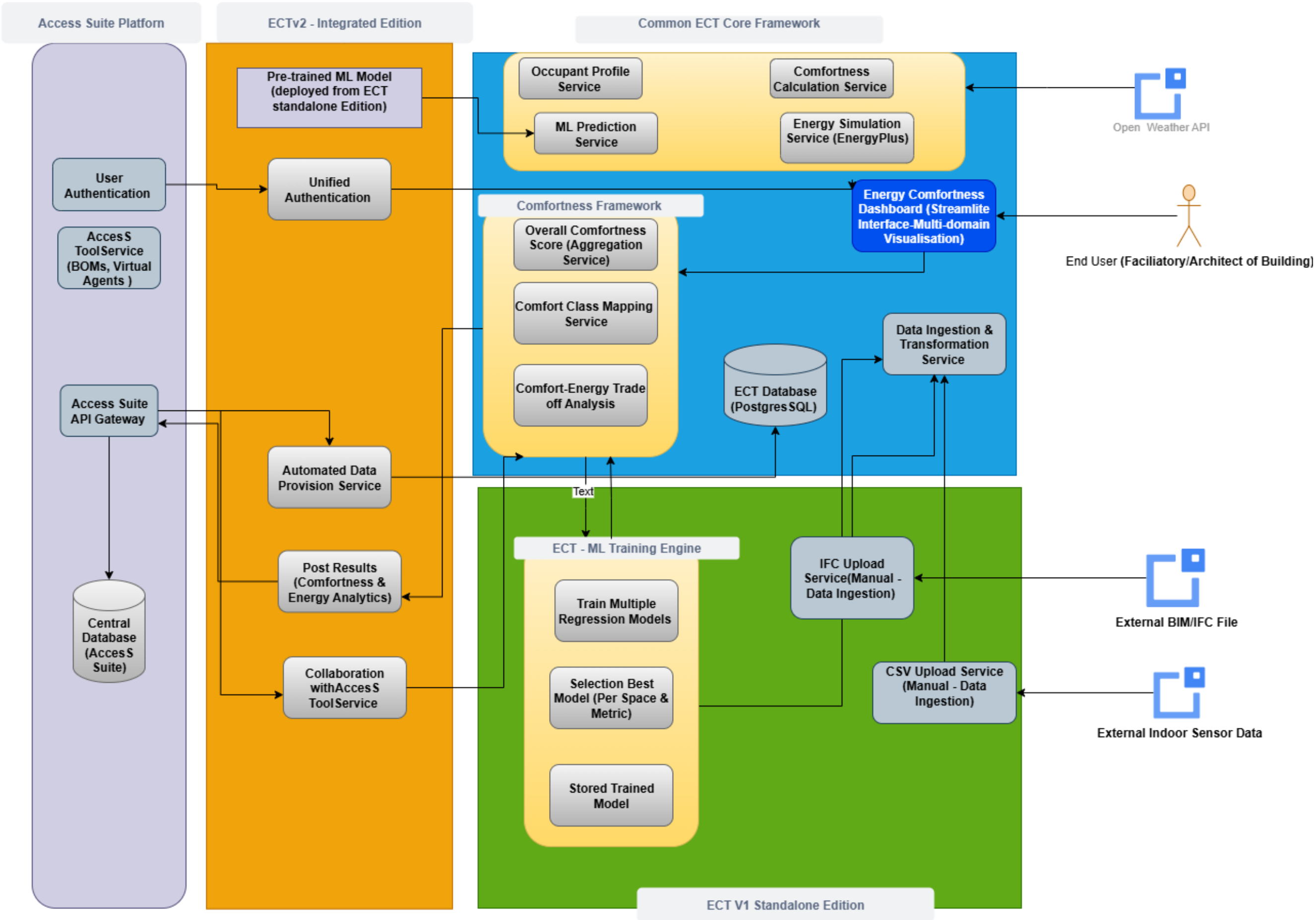

Figure 1. Common Solution Architecture for the Energy Comfortness Tool.

Components are color-coded as follows:

- **Blue:** Common components shared by both ECT (standalone version) and ECT (integrated version)
- **Green:** ECT (standalone version)-specific enabled modules for standalone deployment
- **Orange:** ECT (integrated version)-specific enabled modules for integrated deployment

3.2.1 Common Core Components (Blue)

The common core represents the foundational services and components that ensure consistent "comfortness" evaluation across both tool versions:

Energy Comfortness Dashboard (ECD)

The ECD serves as the primary user interface, implemented as a Streamlit web application that provides comprehensive visualization and control capabilities. It features six analytical tabs:

- *Thermal Comfort*: PMV/PPD indices and environmental trends
- *Visual Comfort*: Luminance levels and EN 12464-1 compliance
- *Acoustic Comfort*: Noise levels with age-adjusted perception modeling
- *Indoor Air Quality*: Multi-pollutant concentration analysis

- *Energy Performance*: Heating/cooling loads from EnergyPlus simulations
- *Energy Comfortness*: Integrated comfort-energy trade-off analysis

Energy Comfortness Engine (ECE)

The computational heart of the platform comprises four specialized services:

- *ML Prediction Service*: Hourly inference of indoor environmental conditions
- *Comfort Calculation Service*: Multi-domain comfort assessment using international standards
- *Energy Simulation Service*: Physics-based building performance simulation via EnergyPlus
- *Occupant Profiles Engine*: Adaptive comfort modeling for diverse user groups (Adult, Elderly, Wheelchair, Low Vision)

Comfortness Framework

This innovative component transforms domain-specific comfort metrics into unified assessments:

- *Overall Comfortness Score*: Weighted aggregation of thermal (31%), visual (19%), acoustic (19%), and IAQ (31%) domains (custom weight per profile)
- *Comfort Class Mapping*: Standardized A-D + NC classification system
- *Comfort-Energy Trade-off Analysis*: Quantitative analysis of energy impact from comfort optimization

Data Management Layer

- *PostgreSQL Database*: Centralized storage for inputs, model outputs, and results
- *Data Ingestion & Transformation Service*: Unified pipeline for processing heterogeneous data sources

3.2.2 ECT (standalone version) Specific Enabled Modules (Green - Standalone Edition)

ECT (standalone version) operates as a self-contained research and validation tool with the following specialized enabled modules:

Manual Data Ingestion Services

- *CSV Upload Service*: Enables manual provision of historical sensor data for model training and validation using standardized CSV formats
- *Manual IFC Upload*: Direct building model import for energy simulation setup

Comprehensive ML Training Engine

ECT (standalone version)'s distinctive capability lies in its robust model development workflow:

- *Train Multiple Models*: Simultaneous training of six regression algorithms (Linear Regression, Extra Trees, Random Forests, XGBoost, LightGBM, CatBoost) per environmental metric and space
- *Select Best Model*: Automated model selection based on predictive performance metrics
- *Store Trained Models*: Persistence of optimized models for deployment and reproducibility

This approach ensures that ECT (standalone version) serves as both a validation platform and a model development environment, establishing the foundation for ECT (integrated version)'s operational deployment.

3.2.3 ECT (integrated version) Specific Enabled Modules (Orange - Integrated/Confidential Edition)

ECT (integrated version) extends the core framework with AccesS Suite integration capabilities that will be further detailed within D4.5 Energy Comfortness Tool v2:

Automated Data Services

- *AccesS Suite API Gateway*: Automated data provisioning from the central platform, eliminating manual data upload requirements
- *Unified Authentication*: Single sign-on integration with Suite identity management
- *Cross-tool Collaboration*: Interoperability with other AccesS Suite tools and services

Optimized Operational Services

- *Pre-trained ML Models*: Deployment of models validated and optimized through ECT (standalone version)'s comprehensive training process
- *Results Publishing Service*: Automated posting of comfortness measurements, energy analytics, and occupant profile assessments back to the AccesS Suite platform

D4.5 will provide further details about the extension of the standalone ECT to the integrated ECT.

3.2.4 Data Flow and Integration Patterns

The architecture supports two distinct data flow patterns:

ECT (standalone version) Development Workflow:

1. Manual CSV sensor data and IFC model upload
2. Comprehensive ML model training and selection
3. Local simulation execution and result storage
4. Interactive analysis through the ECD interface

ECT (integrated version) Operational Workflow:

1. Automated data retrieval via AccesS Suite API
2. Inference using pre-trained ML models
3. Integrated comfortness evaluation and energy simulation
4. Comfortness Analysis publication back to the Suite ecosystem via AccesS Suite API
5. Cross-tool collaboration and reporting (optional)

3.2.5 Architectural Benefits

This unified architecture delivers several strategic advantages:

Consistency & Comparability

The common core ensures that comfortness evaluations remain methodologically consistent across both deployment models, enabling direct comparison between research findings (ECT (standalone version)) and operational assessments (ECT (integrated version)).

Flexibility & Scalability

The version-specific enabled modules allow the toolset to adapt to different user needs and technical contexts without compromising core functionality.

Reproducibility and Validation

ECT (standalone version) serves as a validated reference implementation, while ECT (integrated version) demonstrates the operational scalability of the comfortness concept within a larger smart building ecosystem.

Inclusive Design

The occupant profiles engine ensures that comfort assessments accommodate diverse user needs, aligning with the project's accessibility objectives.

This architectural approach positions the ECT as both a rigorous research tool and a scalable operational platform, effectively bridging the gap between theoretical comfort modeling and practical building optimization while maintaining the unified vision of "Energy Comfortness" as a comprehensive performance indicator.

3.3 ECT (standalone version) Detailed Architecture

ECT (standalone version) has been designed as a modular software tool that combines Machine-Learning (ML) predictions, building energy simulations, and comfort calculations into a unified framework. Its purpose is to provide a holistic assessment of indoor environmental quality and its relation to energy performance in specific spaces of a building. The tool is distributed as a ready-to-use image, which allows users to deploy it without the need to install dependencies or manage a complex software stack. This choice of packaging ensures reproducibility across environments and lowers the barrier for adoption by researchers and practitioners. ECT is divided in two interconnected fundamental units. The Energy Comfortness Engine (ECE) contains all the workflows and algorithms for data ingestion, transformation, model training and prediction, as well as functions for comfort evaluation. The Energy Comfortness Dashboard (ECD) is responsible for exposing the information to the end-user and letting them control simulations.

At the foundation of the architecture lies the data and input layer, which consolidates all information required for comfort and energy assessment. ECT (standalone version) accepts environmental measurements from indoor sensors, including temperature, relative humidity, carbon dioxide (CO_2) and carbon monoxide (CO) concentrations, Particulate Matter (PM2.5 and PM10), Total Volatile Organic Compounds (TVOC) levels, luminance, and acoustic levels. To complement these, the tool retrieves weather forecast information from the Open-Meteo service[19], which provides outdoor conditions that are used consistently by both the ML models and the energy simulation pipeline.

[19] https://open-meteo.com/

Building geometry and materials are introduced through the Industry Foundation Classes (IFC) open format, which is a schema for describing architectural data used in Building Information Modelling (BIM). These files are processed by BIM2SIM [1, 2], an open-source framework that processes IFC files to generate suitable configurations for Building Energy Modelling (BEM). It provides a validated workflow for ingesting architectural data and transforming them to suitable data structures for energy simulation. The energy simulation architecture is completed by feeding the BIM2SIM-generated Input Data Files (IDF) to EnergyPlus [22] for simulating heat and cold loads per building space. In addition, occupant profiles are provided as structured input files in CSV format. These profiles describe personal characteristics such as age, gender, body metrics, clothing insulation, and activity level, as well as visual impairment. They are an essential part of the tool, as they feed directly into comfort calculations by enabling the estimation of metabolic rate and other physiological parameters.

The computation layer transforms the heterogeneous inputs into meaningful assessments of comfort and energy performance. Two processes operate in parallel: machine-learning models estimate the evolution of indoor environmental variables from weather conditions, while Energy Plus simulates the energy behavior of the building using BIM2SIM-derived configurations. These processes remain independent but complementary, as they address different aspects of the problem: the ML branch offers flexibility and speed in predicting sensor-like quantities, whereas the simulation branch provides physics-based estimates of heating and cooling loads per space. Both streams converge in the energy comfortness calculation functions, where standardized indices are derived and normalized into the common four-class system. The integration layer harmonizes the outputs of these processes within a dedicated PostgreSQL database. This layer not only stores measurements, predictions, and simulation results in a consistent format, but also enables the calculation of a weighted overall comfort score that aggregates the four domains (thermal, visual, acoustic, IAQ) into a single metric. By consolidating results from independent computational tracks, it ensures that comfort and energy can be assessed side by side under a unified framework. This overall comfort index, introduced as the “comfortness” concept, is vital for understanding the fully extend of comfort per occupant, under different environments.

The presentation layer exposes these results through a Streamlit-based dashboard. A sidebar guides the user in configuring the scenario by selecting the relevant space, occupant profile, and date range. Results are displayed across six thematic tabs: Thermal, Visual, Acoustic, IAQ, Energy, and Energy Comfortness. The final tab provides both detailed energy results and the overall comfortness score, thus completing the link between domain-specific outputs and the overall assessment. This layered design offers clarity, modularity, and accessibility, presenting advanced analyses in a form suitable for practical use.

3.4 Machine-Learning for Indoor Conditions Assessment

The domain of indoor conditions is a great case-study for the employment of Machine-Learning to infer future observations. Modern systems offer the ability to reliably monitor a space in high resolutions from a multi-parametric standpoint. From more conventional quantities, such as temperature and relative humidity, to more exotic (radiant temperature), Internet-of-Things (IoT) sensors are becoming more popular every year [25], setting up the foundations for data-informed decision-making for managing the indoor environment. ML models, with their ability to capture complex relations between a plethora of parameters and being able to learn new patterns, are ideal to explore the upcoming vast wealthiness of data. For indoor temperature assessment, comprehensive comparative studies have suggested the high accuracy of powerful ensemble regression models (such as XGBoost, Random Forest) to predict based on weather data [26]. IAQ Is, similarly, under heavy research concerning ML applications [27]. Image-based workflows have been suggested to evaluate indoor light conditions and assess visual comfort [28]. Indoor noise, while much harder to predict due to its sensitivity to transient phenomena (e.g. passing traffic) has also been the focal point of specialized studies [8, 9].

ML constitutes the computational backbone of ECT (standalone version). Whereas energy simulation provides physics-based estimates of heating and cooling demands, the ML pipeline is designed to generate high-resolution predictions of indoor environmental variables on an hourly basis. These variables correspond to the quantities that would typically be obtained from a network of indoor sensors, such as air temperature, relative humidity, or luminance. By reproducing these measurable conditions from weather and temporal drivers, the ML models enable comfort assessments even in the absence of dense instrumentation, and provide a flexible means of exploring scenarios across a range of outdoor conditions. The inputs to the models are exclusively derived from weather forecasts retrieved via Open-Meteo and engineered time features. Weather drivers include outdoor temperature and humidity at (2 m resolution), cloud cover, wind speed and gusts (10 m resolution), precipitation, and solar radiation variables (shortwave and direct). These are complemented by sinusoidal encodings of the hour of day and day of year, which capture seasonal and diurnal cycles. The models output predicted indoor conditions in hourly intervals, which are subsequently used as drivers for comfort calculations. The relationship between input drivers and predicted outputs is defined in a feature map, which specifies for each target variable the corresponding set of predictors. Table 10 summarizes this mapping.

Table 10. Input-output feature mapping for ML models

Predicted output (indoor - per space)	Input vector (all outdoor forecasts)
Temperature (°C)	- Temperature (°C) - Relative humidity (%) - Cloud cover (%) - 12-hour - long mean temperature (°C) - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
Relative Humidity (%)	- Temperature (°C) - Relative humidity (%) - Precipitation (mm) - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
Luminance (lx)	- Shortwave radiation - Direct radiation - Cloud cover - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
Peak Noise (dB)	- Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
CO (ppm)	- Wind speed (m/s) - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
CO_2 (ppm)	- Wind speed (m/s) - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal

$PM_{2.5}$ (μg/m^2)	- Wind speed (m/s) - Precipitation - Cloud cover - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
PM_{10} (μg/m^2)	- Wind speed (m/s) - Precipitation - Cloud cover - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal
TVOC (ppb)	- Temperature (°C) - Relative humidity (%) - Shortwave radiation - Hour sinusoidal and cosinusoidal - Day of year sinusoidal and cosinusoidal

The model portfolio of ECT (standalone version) includes a set of algorithms that were selected to balance predictive performance, computational efficiency, and interpretability. The ECT (standalone version) ML pipeline is responsible for transforming the data into a suitable format for model ingestion, train all models (each model per target feature per space) and then select the best-performing one. Trained models are serialized and stored locally for future use, with their metadata being stored in the database. The user may select to retrain models after inserting new data. In this case, newly trained models are compared to existing ones to select the best-performing ones. As prediction of sensor data in our case is a timeseries regression problem, we have models that can tackle this problem efficiently (by also considering that the large amount of data required to train highly-specialized neural networks might not be available). Following we offer an overview of each model trained and evaluated per target.

3.4.1 Linear Regression

Linear regression serves as the simplest predictive model within ECT and functions as a critical baseline against which the performance of more complex algorithms is assessed. Its core assumption is that the relationship between input drivers and indoor conditions can be described as a linear combination of features. While this is rarely the case for environmental processes that exhibit strong non-linearities, linear regression nonetheless has value for specific outputs. For example, predictions of noise levels, which are strongly tied to temporal cycles and are driven primarily by time-of-day encodings, can be effectively approximated by linear models. The transparency of coefficients also provides a direct interpretation of how individual drivers, such as outdoor temperature or cloud cover, contribute to the prediction. Despite its limited capacity for capturing interactions or thresholds, linear regression remains an indispensable reference model, offering interpretability and minimal computational overhead.

3.4.2 Extra Trees Regressor

The Extra Trees algorithm [30] is an ensemble method that constructs multiple decision trees using random feature splits and thresholds. Unlike Random Forests, which rely on optimizing splits, Extra Trees inject randomness at both the feature and threshold selection levels, which often reduces variance and makes the model less prone to overfitting. Within ECT (standalone version), Extra Trees may prove especially effective for predicting indoor temperature and relative humidity, variables that depend on complex and non-linear combinations of outdoor weather drivers. Their ability to handle high-dimensional feature spaces without intensive tuning makes them a practical choice for routine deployment. In addition, Extra Trees are computationally efficient both at training and inference time, which supports their use in scenarios requiring rapid retraining or evaluation.

3.4.3 Random Forests

Random Forests [31] form another tree-based ensemble approach used in the tool. They combine the outputs of many decision trees, each trained on random subsets of features and data samples, to yield stable and generalizable predictions. In contrast to Extra Trees, the Random Forest algorithm chooses optimal splits at each node, which generally results in smoother decision boundaries. In ECT (standalone version), Random Forests may accommodate outputs such as relative humidity and pollutant levels, where smoother relationships are desirable and interpretability of variable importance can guide feature engineering. While slightly more computationally demanding than Extra Trees, Random Forests provide consistent and robust predictions, making them an important component of the modelling portfolio.

3.4.4 XGBoost

XGBoost [32] is a widely adopted gradient boosting framework known for its predictive accuracy and flexibility. It builds trees sequentially, with each new tree correcting the errors of the ensemble built so far. This iterative approach makes XGBoost well-suited for capturing subtle patterns and complex feature interactions. In the context of ECT (standalone version), XGBoost can potentially be preferred for variables with non-linear dependencies on weather conditions, such as indoor luminance and pollutant concentrations. Its ability to handle missing values natively and its extensive hyperparameter tuning options provide additional flexibility for research scenarios. However, its computational cost during training is higher than simpler models, which limits its routine use in production settings.

3.4.5 LightGBM

LightGBM [33] offers an alternative gradient boosting implementation optimized for efficiency and scalability. It uses histogram-based algorithms and leaf-wise tree growth to achieve faster training on large datasets, while maintaining competitive predictive accuracy. Within ECT (standalone version), LightGBM usage may coincide with the same variables as XGBoost, with particular success in handling larger time-series datasets that span multiple seasons. Its efficiency allows for rapid prototyping and comparison of models, making it a valuable option when balancing accuracy with training speed is important.

3.4.6 CatBoost

CatBoost [34] is another gradient boosting library that was evaluated in ECT (standalone version). Its key innovation lies in its ability to handle categorical variables effectively, reducing the need for extensive preprocessing, and in providing stable performance across a range of tasks. Although the feature set in ECT (standalone version) is primarily numerical (weather and time drivers), CatBoost has been useful in testing robustness and reducing overfitting for luminance and pollutant prediction tasks. Its built-in mechanisms for avoiding target leakage and ensuring unbiased handling of categorical features make it a strong candidate for future extensions of the tool, particularly if more diverse input features are introduced.

In summary, the machine-learning module of ECT (standalone version) provides a flexible environment for predicting indoor environmental variables from weather and time drivers. By maintaining a portfolio of algorithms, the tool is able to adapt to different prediction tasks and balance accuracy with interpretability. These predictions are generated on an hourly basis and stored in the integration layer, where they become available for subsequent comfort calculations and aggregation with energy simulation outputs.

3.4.7 Model Validation Example

Herein, we demonstrate the effectiveness of the selected model family by providing information about model training on indoor temperature (°C) using weather data. The demonstration data were provided by CERTH and their Smart House project (located in Thessaloniki, Greece). The initial temperature dataset comprised 9,515 aggregated hourly measurements between 2024-05-01 and 2025-05-01. The initial data were cleaned to remove 483 null records. Then, 80/20 split was used (80% of the data was used in training and 20% in validation), leading to 7,710 measurements used in training and 1,805 in validation. For this performance test, the most effective models were CatBoost, LightGBM, Random Forest and XGBoost. To evaluate the performance of the regression models, several complementary metrics were used. R^2 (coefficient of determination or, in cases of univariate regressions such as ours, the analogous correlation coefficient squared) measures how well the model explains the variance of the observed data, with values closer to 1 indicating a better fit. MAE (Mean Absolute Error) represents the average magnitude of the absolute differences between predicted and observed values, providing an interpretable measure of typical prediction error. MSE (Mean Squared Error) penalizes larger deviations more strongly by squaring the residuals, thus highlighting outlier impacts on model accuracy. Mean residual indicates the average signed difference between predicted and observed values, revealing whether the model systematically over- or underestimates the target. The minimum negative residual (r_{min}) describes the maximum underestimation made by the model. Similarly, the maximum positive residual (r_{mxa}) reflects the maximum overestimation. Following, we provide key metrics for evaluating model performance.

Table 11. Metrics (sorted in descending R^2 order) for the four highest-scoring models for predicting indoor temperature in a space of the CERTH Smart House.

Model	R^2	MAE	MSE	$\bar{r}$	r_{min}	r_{max}
CatBoost	0.56	1.30	2.71	-0.25	-5.36	4.72
LightGBM	0.55	1.33	2.79	-0.21	-6.00	4.93
Random Forest	0.38	1.55	3.87	-0.53	-6.70	4.60
XGBoost	0.35	1.55	4.00	-0.55	-6.80	5.16

To evaluate the performance of the models visually, two types of diagrams were used for each algorithm: residual distributions (top row) and Q–Q plots (bottom row). The residual distributions show how the differences between observed and predicted values are spread around zero - ideally forming a narrow, symmetric bell shape, which indicates accurate and unbiased predictions. The Q–Q (Quantile – Quantile) plots compare the sorted residuals to a theoretical normal distribution acquired from its statistical characteristics (mean and standard deviation). In the displayed figures, when the blue points follow the red line, the errors behave approximately normally, suggesting well-balanced performance. In this case, CatBoost and LightGBM show the most compact and symmetric residuals, indicating the most consistent predictions.

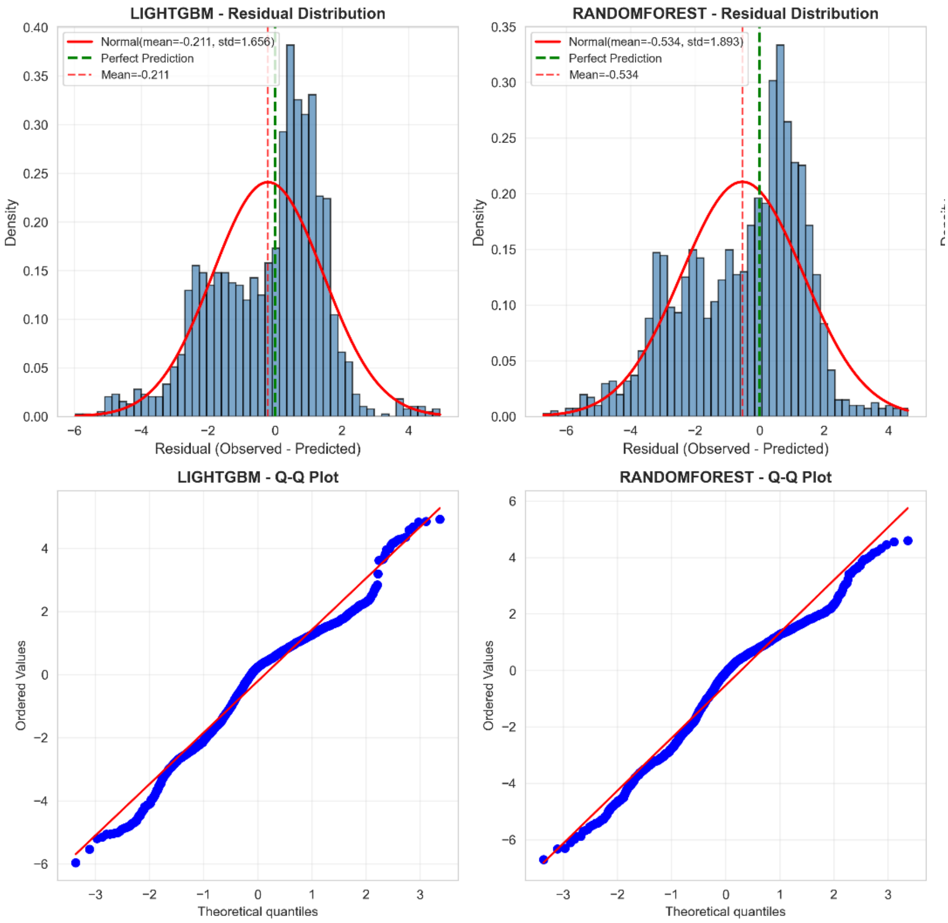

Figure 2. Residual distribution (top) and Q–Q plot (bottom) for the LightGBM and Random Forest models. Both diagrams illustrate the spread and normality of prediction errors, with LightGBM showing a narrower and more symmetric residual pattern compared to Random Forest, indicating slightly more stable and less biased performance.

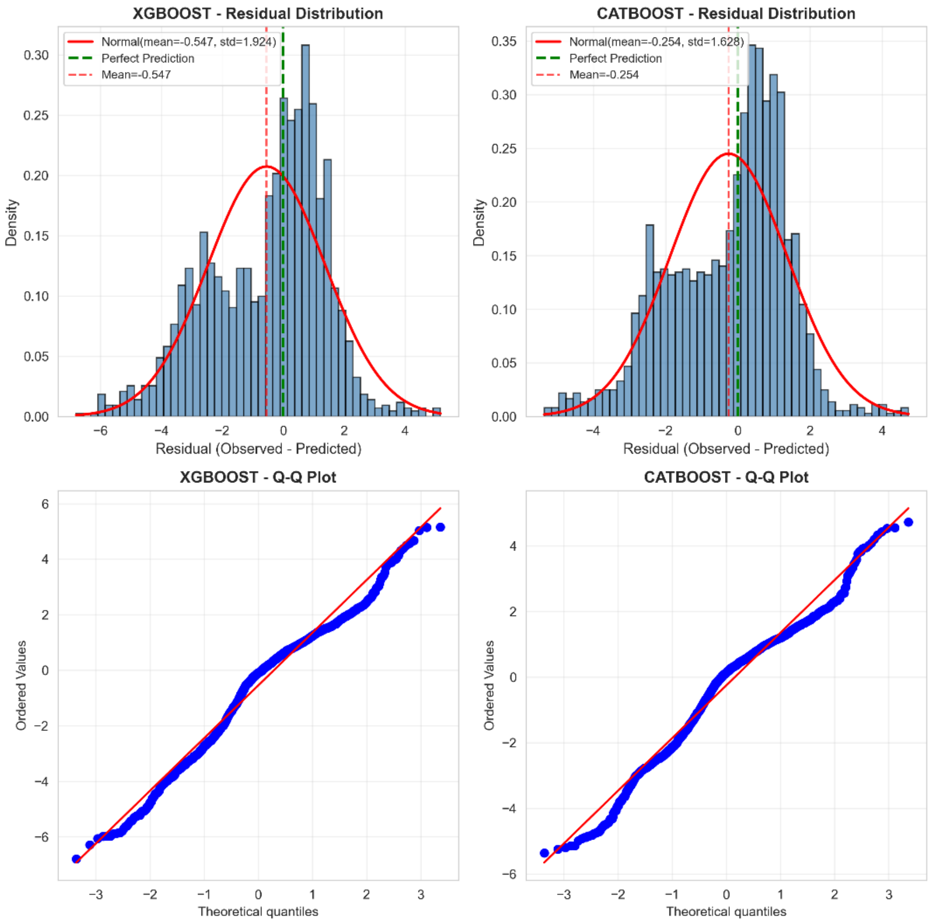

Figure 3. Residual distribution (top) and Q–Q plot (bottom) for the XGBoost and CatBoost models. CatBoost displays the most compact and centered residuals with Q–Q points closely following the theoretical line, suggesting the most balanced and normally distributed prediction errors among all tested models.

To further assess how model accuracy varies across the range of observed values, the absolute prediction errors were plotted against the observed temperatures. Each panel shows a hexbin density map illustrating how frequently specific error magnitudes occur, while the blue line represents the rolling median of the absolute error. This visualization helps identify potential bias or instability in specific temperature intervals. All models show a similar trend, with errors being larger at the lower and higher ends of the temperature range and minimal around the mid-range values, where CatBoost and LightGBM demonstrate the lowest and most stable error behavior.

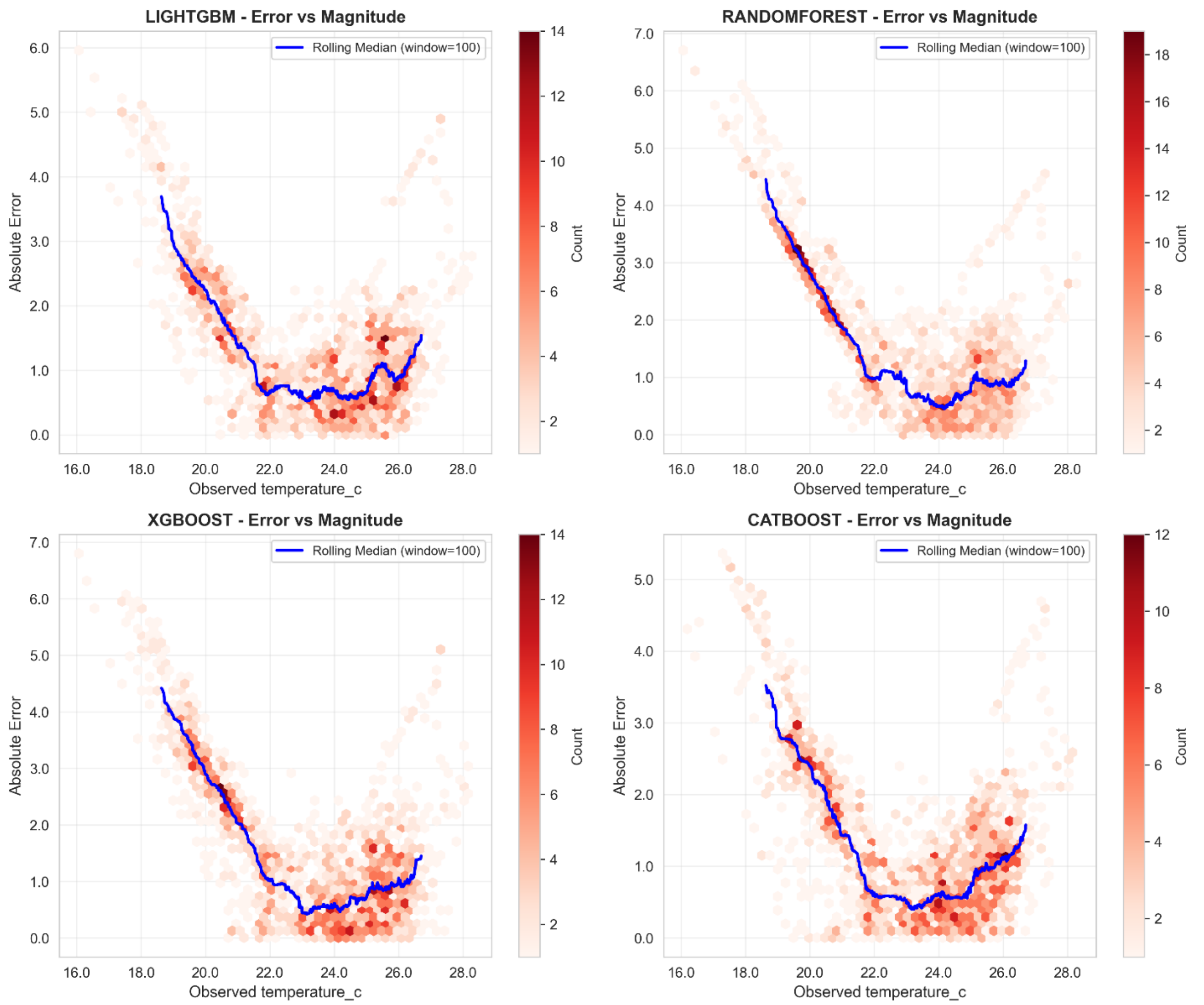

Figure 4. Absolute prediction error as a function of observed temperature for all models. The hexbin shading indicates the density of samples, while the blue line represents the rolling median (with a window of 100 samples). Errors are smallest and most stable within the mid-temperature range (approximately 20 to 25 °C), increasing toward the lower and upper extremes. CatBoost and LightGBM exhibit the lowest overall error variability, indicating more robust performance across the full range of observed values.

Overall, the validation results confirm that the selected ensemble-based models can effectively capture the relationship between environmental drivers and indoor conditions. Among them, CatBoost and LightGBM consistently outperform the others, achieving the highest explanatory power and the most stable residual behaviour. Their performance demonstrates the reliability of this model family not only for indoor temperature but also for other comfort-related parameters such as relative humidity, luminance, noise levels, and indoor air quality indicators. Future developments could broaden this framework by integrating additional contextual features (e.g., occupancy, ventilation rates, or external events) to further improve accuracy and interpretability across all comfort domains.

3.5 Comfort Calculations and Energy Simulation Integration

Comfort in ECT is assessed across four domains (i.e., thermal, visual, acoustic, and Indoor Air Quality (IAQ)) using established international standards and complementary models from literature. Each domain produces a categorical score which is then normalized into the common four-class system (A-

D, best-worst) with an additional "NC" category for non-classified values. These domain-specific classifications are subsequently aggregated into a weighted overall comfort score, ensuring that the most critical aspects of comfort contribute proportionally to the final evaluation. In parallel, energy performance is estimated through building simulations conducted with EnergyPlus [22]. The outputs of both processes are stored in the integration layer, where they can be jointly queried and visualized in the dashboard.

Before addressing comfort itself, it is important to make clear that comfort is occupant-oriented; comfort refers to a person (occupant) and not the space or building. Therefore, we have established a variety of occupant profiles to accommodate the general population and the target groups of the AccesS project.

Table 12. Occupant profiles available in the Energy Comfortness Tool's comfort simulations.

Occupant Profile	Gender	Age	Weight (kg)	Height (cm)	Activity level	Clothing insulation (clo)	Visual Impairment
Adult (M)	Male	40	82	180	1.2	1.0	No
Adult (F)	Female	38	64	165	1.2	1.0	No
Elderly (M)	Male	72	74	172	1.0	1.2	No
Elderly (F)	Female	75	60	160	1.0	1.2	No
Wheelchair (M)	Male	55	70	168	1.0	1.0	No
Wheelchair (F)	Female	53	62	160	1.0	1.0	No
Low vision (M)	Male	50	76	174	1.2	1.0	Yes
Low vision (F)	Female	48	62	162	1.2	1.0	Yes

Thermal comfort is evaluated according to the ISO 7730 standard, which implements the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) model proposed by Fanger [15]. The calculations draw on a combination of environmental variables and occupant-specific parameters, specifically:

- Indoor temperature (T)
- Mean radiant temperature (T_r)
- Air velocity (v_r)
- Relative humidity (RH)
- Metabolic rate (met)
- Clothing insulation (clo)

Indoor air temperature and relative humidity are taken from either sensor measurements or ML-predicted values. Air velocity is fixed at 0.1 m/s, and mean radiant temperature is assumed equal to the indoor air temperature. Occupant metabolic rate is derived from weight, height, gender, and age using the revised Harris-Benedict formula [16, 17], with the activity level and clothing insulation drawn directly from the occupant profile. PMV and PPD values are then computed and mapped into one of the four comfort classes defined in the standard, according to ISO 7730.

Visual comfort is assessed in accordance with the EN 12464-1[20] standard on lighting of workspaces, using luminance values either measured or predicted by ML. Threshold-based classification ensures that illuminance levels correspond to suitable comfort categories. As the standard specifies luminance thresholds per task, we have integrated this to our algorithms assuming light-to-medium luminance requirements, suitable for each occupant profile. For occupants with declared visual impairment, the tool additionally applies the visual score model of [17], which adjusts classification to reflect reduced tolerance to lighting conditions. Unfortunately, literature is quite poor on the subject of visual comfort for persons with visual impairments and, as visual disabilities comprise a wide spectrum of characteristics, it is quite difficult to develop a unified model. The dual approach of using both a standard, for the general population, and the available model for visually impaired persons ensures that both groups are accommodated in the assessment.

Acoustic comfort is evaluated by applying noise level thresholds to indoor acoustic measurements or ML predictions. Classification follows standard noise-level-based comfort categories by NF S31-080:2006[21] but is further refined with an age-dependent annoyance model proposed by [20], which captures differences in perception of noise disturbances across age groups. This allows the tool to better represent the subjective dimension of acoustic comfort for diverse occupant profiles.

Indoor Air Quality (IAQ) is measured through pollutant concentrations, including CO_2 (EN16798-1:2019[22]), CO (EN16798-1:2019), TVOC (EN16798-1:2019), $PM_{2.5}$ (2008/50/EC[23]), and PM_{10} (2008/50/EC). Each pollutant is assessed against established comfort thresholds and mapped to the A-D system. These individual classifications are stored separately, allowing detailed analysis of which pollutant drives the IAQ score.

All comfort classifications are combined into an overall comfort score by applying a weighted aggregation scheme. The weights reflect the relative importance of each domain: thermal comfort (30%), visual comfort (20%), acoustic comfort (20%), CO_2 (15%), TVOC (10%), and PM2.5 (5%). This scheme prioritizes thermal comfort as the most critical contributor, while still incorporating IAQ and other domains into the overall evaluation. The aggregated score is presented in the dashboard under the Energy Comfortness tab and provides a single, harmonized indicator of indoor comfort. If one or more comfort criteria are missing, the weighting readjusts to keep a similar analogy, after removing weights of the missing metrics.

In parallel with comfort calculations, ECT (standalone version) incorporates a dedicated energy simulation pipeline. Building geometry in IFC format is processed using BIM2SIM, which generates the corresponding IDF models required by EnergyPlus. Weather data from Open-Meteo are transformed into EnergyPlus Weather (EPW) files, ensuring consistency between the comfort and energy evaluation streams. EnergyPlus version 9.4 is then executed to simulate the thermal performance of the building, producing outputs of heating and cooling loads expressed in kilowatt-hours for each space (mapped to EnergyPlus thermal zones). These results are stored in the database alongside comfort classifications, enabling integrated analysis of comfort and energy efficiency. Through this combined approach, ECT (standalone version) provides a unified environment where comfort indices and energy loads can be assessed together. Standards-based comfort modelling ensures methodological rigor, while the EnergyPlus simulation framework delivers reliable estimates of building energy performance.

[20] https://www.cibse.org/media/mxymm5no/en12464-2011.pdf
[21] https://www.boutique.afnor.org/en-gb/standard/nf-s31080/acoustics-offices-and-associated-areas-acoustic-performance-levels-and-crit/fa142103/740
[22] https://standards.iteh.ai/catalog/standards/cen/b4f68755-2204-4796-854a-56643dfcfe89/en-16798-1-2019?srsltid=AfmBOorFs-1Hu9hfmeeAranF4xBlTHlaQD2_-EQhandCBl6nl2nH_8jX
[23] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02008L0050-20150918

The integration of these processes allows end-users to explore the trade-offs between occupant comfort and energy efficiency in a systematic and reproducible manner.

3.6 ECT Simulation Dashboard

The user interface of ECT (standalone version) is delivered through a web-based dashboard implemented in Streamlit, which was selected as the development framework because of its simplicity, reproducibility, and compatibility with containerized deployment. Streamlit allows interactive web applications to be written directly in Python, which made it possible to rapidly prototype and refine the dashboard in close alignment with the evolving backend of the tool. This choice also ensures that the same codebase can be executed consistently in different environments, which is crucial for a research-oriented tool. The dashboard acts as the central point of interaction, designed to present complex comfort and energy analytics in a form that is both intuitive and flexible. A fixed sidebar provides global configuration options and is available across all sections of the tool. Through this sidebar, the user defines the space of interest, selects an occupant profile with the relevant physiological and activity parameters, and chooses the time interval for analysis. These inputs serve as global filters that are applied consistently to all visualizations in the main panel, ensuring comparability of results across domains. Once the configuration has been set, the user can navigate through six thematic tabs that correspond to the core analytical domains of the tool: Thermal, Visual, Acoustic, Indoor Air Quality (IAQ), Energy, and Energy Comfortness. Each tab follows a consistent design pattern that combines time-series for dynamic analysis, categorical distributions for classification against standards, and summary indicators for rapid interpretation. In this way, the dashboard makes the results of the tool accessible to researchers and practitioners without requiring them to engage directly with raw data or computational models. Herein, we present demonstrative screens of the tool, with ML models trained with smart sensor data provided by CERTH nZEB Smart House (hourly time-series of indoor temperature, relative humidity, noise level, luminance, CO_2, $PM_{2.5}$ and TVOC concentrations) recorded at their Smart House infrastructure in the period between May 2024 and May 2025 (1-year-long period). For the purposes of energy simulation demonstration, we used the AC20-FZK-Haus.ifc file provided by BIM2SIM, after modifying spaces names to match the ones in the CSV.

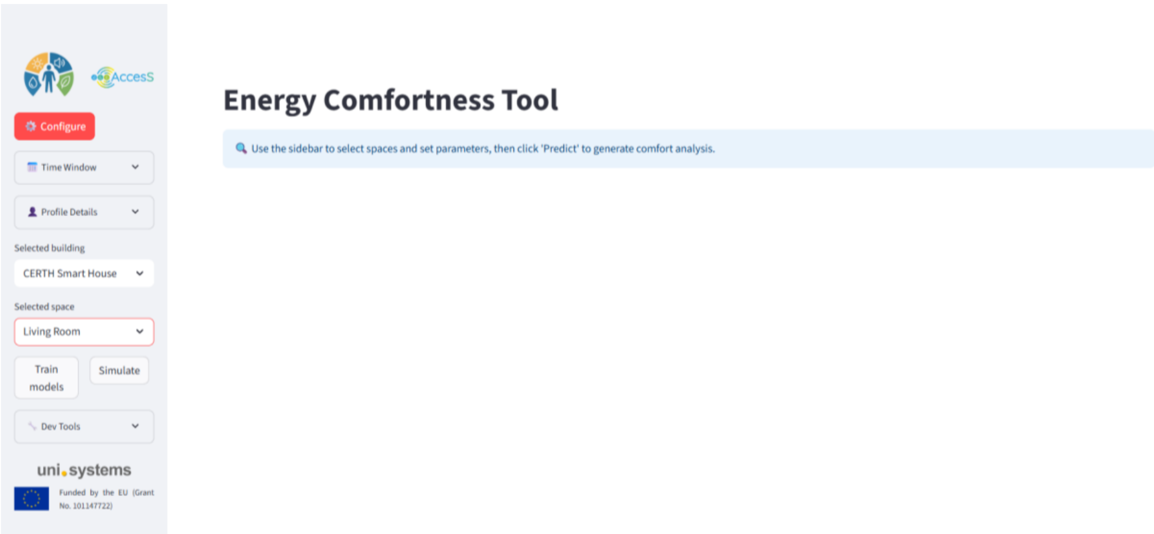

Figure 5. The start screen of the ECT simulation dashboard. The left sidebar acts as the control panel for the application, enabling the user to configure initialization data (training data and IFC) and control the time period, occupant profile and space for which comfort simulations will be ran. The "Train models" and "Simulate" buttons let the user train (or retrain) ML models and simulate data and comfort time-series.

The first tab is devoted to thermal comfort. It displays the hourly evolution of indoor environmental variables such as temperature and relative humidity, accompanied by the calculated PMV and PPD indices. This view highlights the correspondence between these indices and the underlying variables, making it possible to observe how shifts in temperature and humidity affect the predicted comfort level. In addition to the time series, the tab presents a classification of comfort according to ISO7730, assigning each hour to one of the four comfort classes A-D, with the possibility of NC for non-classified values. The distribution of hours across these categories is shown, while periods of discomfort are clearly marked so that the user can identify when and why conditions deteriorate.

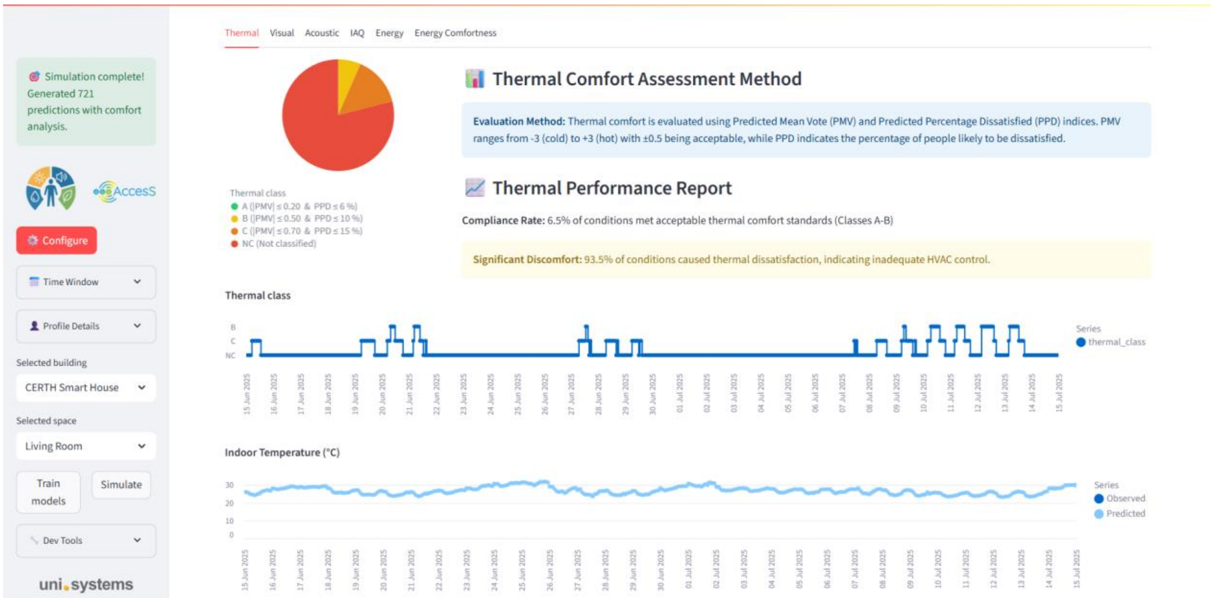

Figure 6. The Thermal tab exhibiting summarized information about the distribution of thermal comfort in the selected space. Sample data for the application were provided by CERTH.

The visual comfort tab presents the hourly values of indoor luminance and evaluates them against the thresholds specified in EN12464-1, the European standard for lighting of workspaces. This enables a direct classification of each period into the established comfort categories. For occupants with visual impairments, as indicated in their profile, the system also applies the model of Yong et al., which adjusts the thresholds to reflect reduced tolerance to glare and lighting variation. In this way, the tab provides a dual view: a standard-based evaluation applicable to the general population, and a personalized evaluation for visually impaired users. The results are shown both as time series and as distributions of hours per category, highlighting times of insufficient lighting or excessive glare.

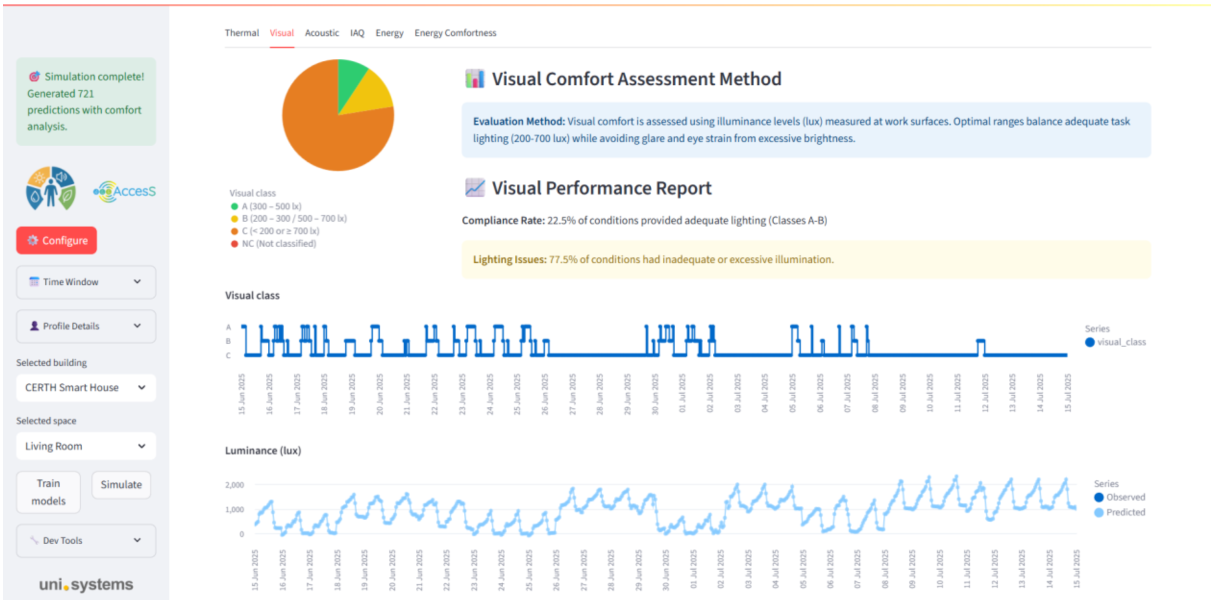

Figure 7. The Visual tab exhibiting summarized information about the distribution of visual comfort in the selected space.

Acoustic comfort is treated in a dedicated tab that combines time series of average and peak decibel levels with classification into comfort categories. The assessment follows standard noise thresholds but is enriched by the annoyance model, which introduces an age-dependent annoyance factor. This addition allows the classification to reflect not only physical noise levels but also the subjective perception of noise across different age groups. The graphical presentation enables the user to see when peaks occur, how they distribute over the analysis period, and whether specific times are more likely to be perceived as disturbing, especially for more sensitive groups.

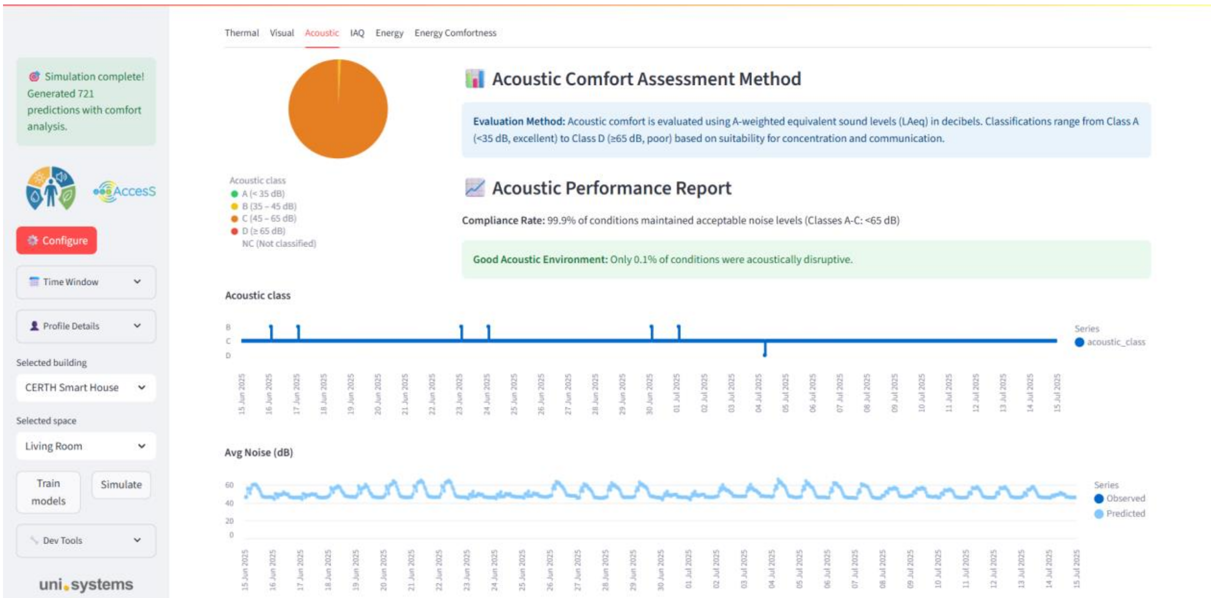

Figure 8. The Acoustic tab exhibiting summarized information about the distribution of acoustic comfort in the selected space.

Indoor Air Quality (IAQ) is addressed in a separate tab that displays pollutant concentrations for CO_2, CO, TVOC, $PM_{2.5}$ and PM_{10}. Each pollutant is evaluated against standard comfort thresholds and mapped into the A-D system, with non-classified values marked as NC. The tab overlays thresholds on the hourly time series and uses color coding to indicate category boundaries, making it immediately visible when conditions exceed recommended levels. Alongside the time series, the distribution of categories over the evaluation period is provided, allowing users to see whether issues are occasional or persistent and which pollutant is primarily responsible for degrading air quality in the space.

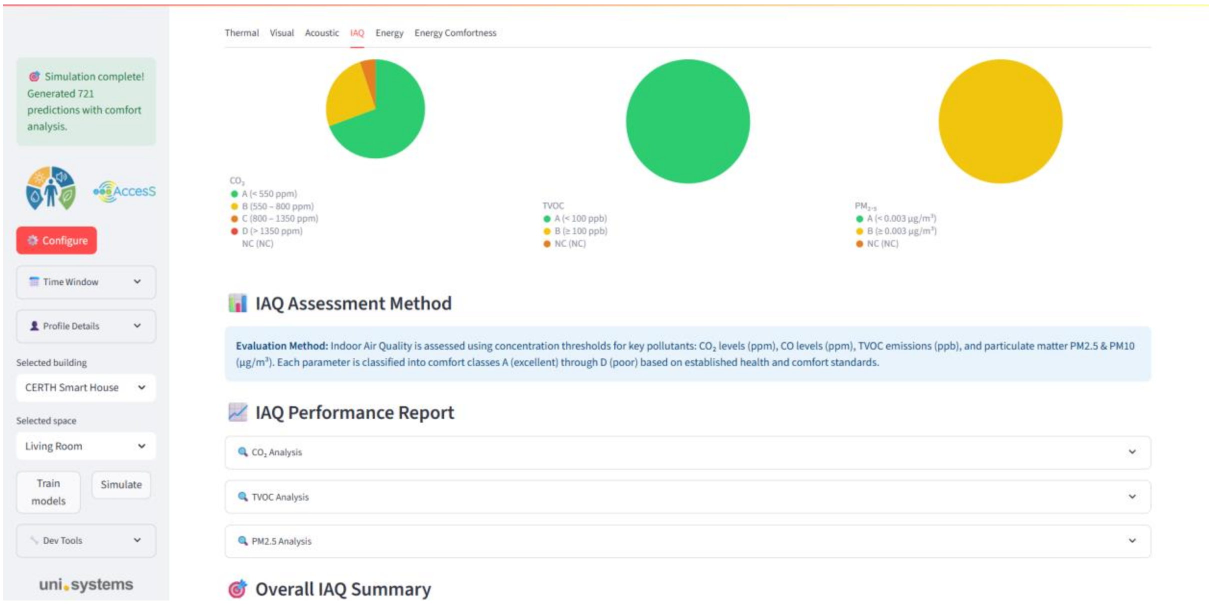

Figure 9. The IAQ tab exhibiting summarized information about the distribution of IAQ in the selected space. Different charts are exhibited for each available IAQ metric.

The energy tab is dedicated to the results of the EnergyPlus simulations. It presents the heating and cooling loads for each space in kilowatt-hours, aggregated on an hourly basis. Users can view the time evolution of loads, examine cumulative totals, and switch between different spaces defined in the simulation. The layout allows the comparison of heating and cooling demands side by side, making it easier to identify periods of high energy requirement and to understand the dynamic balance between the two. In addition, basic logs of simulation runs are displayed to provide transparency in the workflow and to support reproducibility.

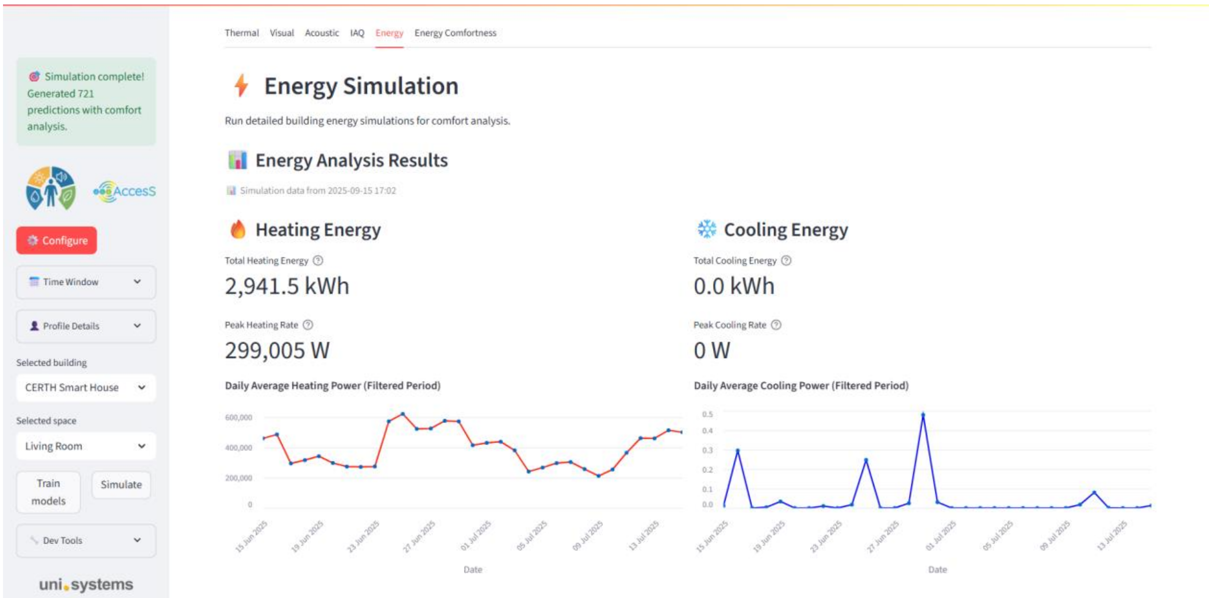

Figure 10. The Energy tab providing control and exhibiting summarized information energy simulation in the selected space.

The final tab, labelled Energy Comfortness, provides a holistic overview by linking comfort with energy performance. It is divided into two subtabs. The first, Energy Timeseries, integrates the hourly heating and cooling loads with comfort variables, offering a combined visualization that enables the exploration of correlations between energy use and comfort conditions. The second, Comfort Analysis, presents the aggregated overall comfortness score. This score is calculated from the weighted contributions of the different comfort domains. The results are displayed in the form of summary indicators and charts that show the proportion of hours in each category for every domain. This makes it clear not only whether the overall comfort is satisfactory but also which specific factor has the greatest influence in lowering the score.

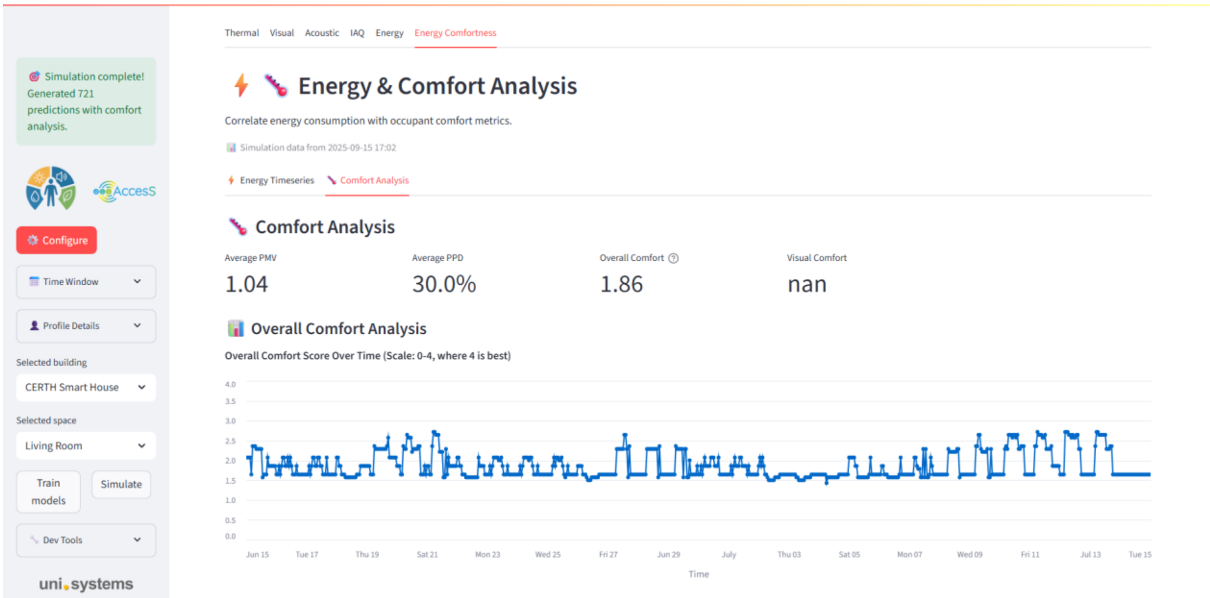

Figure 11. The Energy Comfortness tab exhibiting summarized information about energy and overall comfort (comfortness) in the selected space.

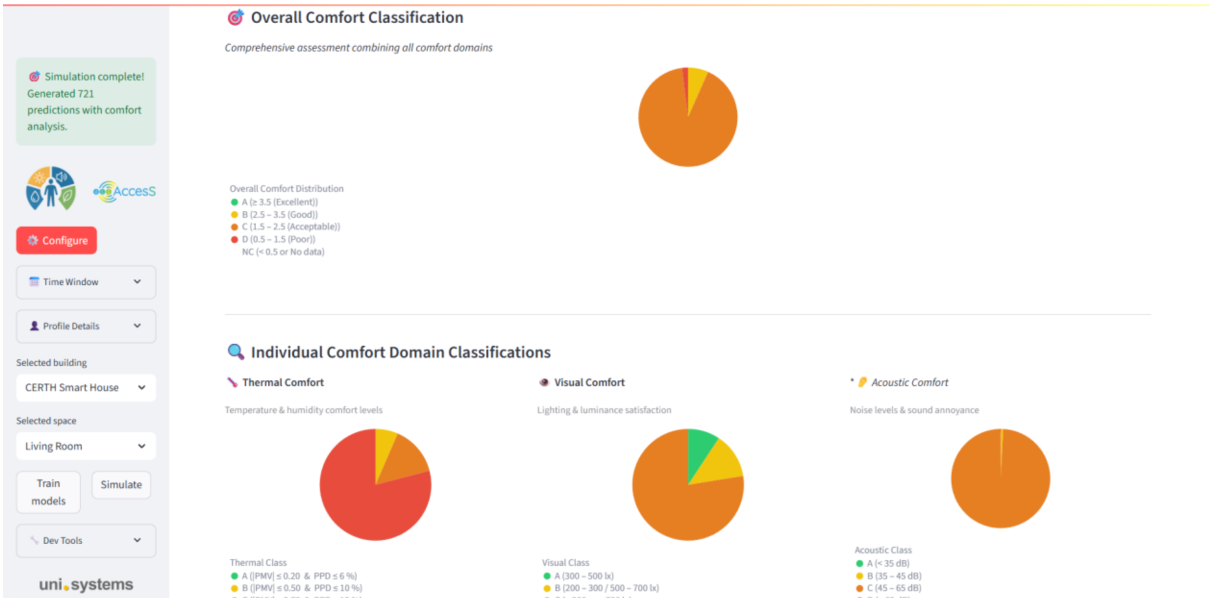

Figure 12. Additional overall comfort analytics shown in the Energy Comfortness tab.

Across all six tabs, the dashboard maintains a consistent visual identity. Time series highlight the temporal evolution of variables, categorical distributions summarize compliance with standards, and compact summary cards provide key indicators at a glance. This uniformity supports both a rapid overview and detailed exploration, enabling users to move seamlessly from general trends to the identification of specific drivers of discomfort or energy demand. The result is a comprehensive and accessible interface that makes the outputs of complex models immediately usable by researchers, designers, and practitioners alike. In summary, ECT (standalone version) represents the standalone implementation of the Energy Comfortness Tool (as opposed to the AccesS-platform-integrated ECT (integrated version) in D4.5), integrating ML predictions, standards-based comfort calculations, and physics-based energy simulations into a unified and modular framework. Its layered architecture ensures that inputs from weather forecasts, occupant profiles, and building models are processed consistently, while maintaining a clear separation between the roles of ML and simulation. Comfort assessment is firmly grounded in established international standards, extended with additional models to account for visual impairment and age-dependent acoustic annoyance, and aggregated into a harmonized classification system. EnergyPlus simulations provide robust estimates of heating and cooling loads per space, complementing the comfort assessment with a reliable measure of energy demand. Finally, the Streamlit dashboard makes these results directly accessible, offering both detailed domain-specific analyses and an overall comfortness score that links energy and comfort outcomes. Together, these components deliver a reproducible, deployable, and user-friendly tool that lays the foundation for further development in subsequent versions.

4 Conclusions

This report presents the development of the Energy Comfortness Tool as a fully functional demonstrator that combines machine-learning predictions, standards-based comfort models, and building energy simulations into an integrated software platform. The tool delivers a holistic assessment of indoor environmental quality and its interplay with energy performance in building spaces, while also offering a user-friendly interface for practitioners and researchers. In this deliverable, we have presented the rationale, architecture, functionalities, and user-facing elements of the standalone version of the tool, together with the stakeholder landscape it is designed to serve. The following conclusions highlight the key achievements of this version, the lessons learned during its development, and the perspectives for its further evolution. One of the most important outcomes of ECT is the establishment of a modular architecture that separates data inputs, computational processes, integration, and presentation. This structure ensures transparency and flexibility, allowing different data sources (weather forecasts, sensor measurements, occupant profiles, and IFC building models) to be combined without conflating their roles. The modularity also supports reproducibility, as each layer has been implemented with clear boundaries and packaged into a containerized environment. By distributing the tool as a ready-to-use Docker image, the project has lowered the barrier for adoption, enabling stakeholders to deploy ECT without extensive technical overhead.

Another major contribution is the implementation of a machine-learning prediction pipeline that generates hourly estimates of indoor environmental variables. By training models on weather data and time features, ECT (standalone version) can reproduce the values that would typically be obtained from a dense network of indoor sensors. This capability enables comfort assessment even in situations where measurements are sparse or unavailable, thereby extending the usability of the tool across a wider range of building contexts. The inclusion of a diverse set of models - ranging from linear regression to ensemble methods such as Extra Trees, Random Forests, and gradient boosting - ensures that the tool can adapt to different tasks, balance interpretability with predictive power, and serve as a benchmark for further research. The integration of standards-based comfort calculations represents another key achievement. Thermal comfort is evaluated according to ISO 7730 using Fanger's PMV/PPD model, with metabolic rate determined from occupant profiles following ISO 8996 and clothing insulation values drawn from ISO 9920. Visual comfort is assessed according to EN 12464-1, with adjustments for visually impaired occupants using the model of Yong et al. Acoustic comfort combines standard noise classifications with the age-dependent annoyance function of Yilmaz et al., while indoor air quality is evaluated through threshold-based categories for CO_2, CO, TVOC, and particulate matter. All results are normalized into a four-class system (A-D, plus NC), enabling consistent aggregation. The introduction of a weighted aggregation scheme - prioritizing thermal comfort while still accounting for IAQ, visual, and acoustic dimensions - produces an overall comfortness score that captures the multidimensional nature of indoor environmental quality.

On the energy side, ECT integrates a BIM-to-simulation workflow based on BIM2SIM and EnergyPlus. Building models in IFC format are transformed into EnergyPlus-compatible IDF files, and weather data from Open-Meteo are converted into EPW format to drive the simulations. The outputs provide detailed heating and cooling loads per space (aligned with EnergyPlus thermal zones), which can be compared with comfort assessments to explore trade-offs between energy demand and occupant well-being. Importantly, the energy simulation branch is implemented independently of the machine-learning pipeline, ensuring that results from physics-based modelling remain distinct while still contributing to the unified framework of the tool. The Streamlit-based dashboard consolidates all these elements into a coherent and accessible interface. By presenting results across six thematic tabs (Thermal, Visual, Acoustic, IAQ, Energy, and Energy Comfortness) the dashboard provides both detailed domain-specific insights and an aggregated overview. The Energy Comfortness tab, in particular, serves as a unifying element, showing how different comfort domains contribute to the overall score and how this relates to simulated energy performance. Consistent visual patterns (time series, categorical distributions, and summary indicators) make the interface intuitive, while the fixed sidebar ensures that configuration options are applied uniformly. This approach allows both technical experts and non-technical users to engage with the tool, fulfilling the inclusiveness principle set out at the start of the project.

From a stakeholder perspective, ECT already delivers tangible benefits. Building managers and operators gain a decision-support system that highlights inefficiencies and provides clear comfort-energy trade-offs. Architects and engineers can use the simulation features to explore design alternatives and assess compliance with standards. Policy makers and regulators can interpret results against established frameworks such as the ISO, and EN standards. Occupants, though not direct users, benefit indirectly through personalized comfort assessments that consider age, health, and impairment factors. Accessibility experts and NGOs can use the outputs to advocate for inclusive environments. Energy consultants and sustainability officers can leverage the integrated comfort-energy framework for certification schemes such as LEED, BREEAM, and WELL. Finally, ICT developers and researchers can treat ECT as a validated prototype to build upon, extending its functionality and integrating it into larger systems. At the same time, the development of ECT as a standalone version has provided valuable lessons and directions for future work. The clear separation between ML-based predictions and energy simulations ensures flexibility, but it also raises opportunities for deeper coupling in subsequent versions, where hybrid models may provide even richer insights. The current focus on a four-class comfort system has proven effective for integration, but it could be refined further to capture subtler gradients of comfort. In addition, while the dashboard currently emphasizes visualization, future versions could expand towards more advanced analytics, such as scenario comparisons, forecasting, or optimization features.

In conclusion, ECT demonstrates the feasibility and value of combining machine learning, standards-based comfort assessment, and energy simulation into a single platform. It addresses the needs of a wide range of stakeholders, from building managers to policy makers, while ensuring inclusiveness for vulnerable groups. By offering a reproducible, containerized, and user-friendly solution, ECT lays the groundwork for scaling and integration in future project phases. Its significance lies not only in the technical achievements presented in this deliverable but also in its role as a catalyst for innovation in the broader field of smart, sustainable, and human-centered buildings.

The tool has been successfully architected as a unifying framework, with a common core for comfort and energy analysis. The standalone version of ECT provides a critical standalone instantiation of this platform, enabled by manual CSV data ingestion, which serves as a validated and reproducible benchmark. This lays the groundwork for the integrated version of ECT, where the unification of data is achieved through seamless integration with the AccesS Suite API, demonstrating the scalability of the ECT concept from a standalone tool to an integrated suite service (details within D4.5).

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ANNEX A: Technical Details

A.1. Requirements

ECT (standalone version) has been packaged and released as a ready-to-use Docker[24] image, which minimises installation complexity and ensures reproducibility across different environments. Nevertheless, certain hardware, software, and data requirements must be met to run the tool successfully.

A.1.1. Hardware Requirements

- Processor: 64-bit CPU (Intel/AMD). Multi-core processors are recommended for faster simulation.
- Memory: Minimum 8 GB RAM; 16 GB RAM recommended for running EnergyPlus simulations with larger IFC models.
- Storage: At least 10 GB of free disk space to accommodate the Docker image, Postgres database, and simulation results. Storage requirements increase depending on the data and IFC model sizes.
- Graphics: No dedicated GPU is required; all calculations are performed on CPU.

A.1.2. Software Requirements

- Operating System: Linux (Ubuntu 20.04+ recommended), Windows 10/11, or macOS.
- Docker Engine: Version 20.10 or later.
- Web Browser: Modern standards-compliant browser (Chrome, Firefox, or Edge) for accessing the Streamlit dashboard.

A.1.3. Data Requirements

Sensor data must be structured in CSV format with the following fields available:

Table 13. Data requirements for input in ECT (standalone version). Fields in italics are optional, but, if not included, will not lead to training models and prediction of relevant metrics.

Field name	Data type (units)	Description	Example
Time_end	timestamp (YYY-mm-dd HH:MM:SS+TZ)	Timestamp of the end of the reference window that characterizes the record	2024-05-01 00:00:00+00:00
Building_id	string	Name of the building	UNIS House
Space_id	string	Name of the space of the building	Living Room

[24] https://www.docker.com/

longitude	float (decimal degrees, WGS84)	Longitude of the building's geolocation	23.7182
latitude	float (decimal degrees, WGS84)	Latitude of the building's geolocation	37.9594
window_seconds	integer (s)	Duration of the window the reference window	3600
temperature	*float (°)*	*Average indoor temperature of reference window*	*24.1*
rh_percent	*float (%)*	*Average indoor relative humidity for reference window*	*48.0*
luminance_lux	*float (lx)*	*Average illuminance for reference window*	*10.0*
average_noise_db	*float (dB)*	*Average noise measurement in the reference window*	*44.0*
peak_db	*float (dB)*	*Peak noise measurement in the reference window*	*66.0*
co2_ppm	*float (ppm)*	*Average CO_2 concentration in the reference window*	*431.33*
co_ppm	*float (ppm)*	*Average CO concentration in the reference window*	*17.2*
tvoc_ppb	*float (ppb)*	*Average TVOC concentration in the reference window*	*1.15*
pm2_5_ugm3	*float (μg/m^3)*	*Average $PM_{2.5}$ concentration in the reference window*	*2.89*
pm10_ugm3	*float (μg/m^3)*	*Average PM_{10} concentration in the reference window*	*1.32*

A.1.4. BIM requirements

Building information must be provided in the IFC4 format, in the architectural (ARCH) domain. The IFC file must be compatible with BIM2SIM v0.2.3 and EnergyPlus v9.4. The maintained BIM2SIM repository at GitHub[25] contains a collection of example compatible IFC files.

[25] https://github.com/BIM2SIM/bim2sim

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