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Occupant-centric building design-Human factors and energy consumption in sustainable offices

A case study of a WELL-Certified Office Building in Gothenburg

Master's thesis in Building Technology

Emil Bodin & David Karlsson

DEPARTMENT OF ARCHITECTURE AND CIVIL ENGINEERING
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EMIL BODIN & DAVID KARLSSON

Academic Supervisor: Quan Jin, Department of Architecture and Civil Engineering, Chalmers University of Technology

Industry Supervisors: Simon Roos & Julia Blom, AFRY AB

Examiner: Alexander Hollberg, Department of Architecture and Civil Engineering, Chalmers University of Technology

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Department of Architecture and Civil Engineering
Division of Sustainable Built Environment
Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

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Abstract

Buildings consistently consume more energy in operation than predicted during design, a discrepancy known as the energy performance gap. A key contributor is the reliance on standardised occupancy assumptions that fail to capture actual occupant behaviour. This study investigates the influence of three human factors on the energy performance of a modern, WELL and BREEAM Excellent certified office building in Gothenburg, Sweden: occupancy patterns, internal electrical loads, and solar shading behaviour.

The Energy-Data-Driven Occupancy Schedule (EDDOS) methodology was applied to derive data-driven occupancy and equipment schedules from one full year of measured tenant electricity data. A sensitivity analysis was conducted on occupancy density, testing scenarios from the SVEBY standard assumption of 20 m^2 per person to 1000 m^2 per person, representing post-pandemic hybrid working conditions. Solar shading behaviour was evaluated using two behavioural archetypes based on the Lightswitch-2002 model, and a glazing sensitivity analysis was performed across three solar heat gain coefficients ($g = 0.26$, 0.40, 0.60).

The results demonstrate that occupancy density is the primary driver of the performance gap, while the temporal variation captured by the EDDOS schedule and solar shading behaviour both have marginal influence on district heating demand. Reducing occupancy density to reflect post-pandemic hybrid working patterns substantially closes the gap between simulated and measured district heating consumption. Solar shading behaviour is found to have negligible energy impact across all glazing specifications tested, consistent with the building's fully automated shading system.

These findings suggest that in modern, highly automated office buildings, occupancy density uncertainty associated with hybrid working represents a more significant source of simulation error than occupant behavioural patterns. Standardised assumptions such as those prescribed by SVEBY may systematically underestimate the performance gap in contemporary hybrid offices.

Keywords: energy performance gap, occupant behaviour, occupant-centric design, building energy simulation, EDDOS, occupancy density, hybrid working, IDA ICE, SVEBY, solar shading.

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Emil Bodin & David Karlsson, Gothenburg, June 2026

Use of AI Tools

In accordance with the guidelines set by Chalmers University of Technology, AI tools were used during the preparation of this thesis. Specifically, Claude (Anthropic) and Gemini (Google) were used as assistive tools for tasks including text refinement, LaTeX formatting, data analysis support, and structuring of arguments.

All AI-generated content has been critically reviewed, revised, and validated by the authors. The authors assume full responsibility for the content of this thesis, including all methodological choices, results, and conclusions. No sensitive or proprietary information was shared with AI tools beyond what is presented in this report.

AI tools used: Claude (Anthropic), accessed via claude.ai; Gemini (Google), accessed via gemini.google.com. Both accessed during 2025–2026.

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AFS	Arbetsmiljöverkets författningssamling (Swedish Work Environment Authority regulations)
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BBR	Boverkets byggregler (Swedish building code)
BMS	Building Management System
BREEAM	Building Research Establishment Environmental Assessment Method
CAV	Constant Air Volume
CV(RMSE)	Coefficient of Variation of the Root Mean Square Error
DNAS	Drivers, Needs, Actions, Systems
EDDOS	Energy-Data-Driven Occupancy Schedule
FoHM	Folkhälsomyndigheten (Public Health Agency of Sweden)
GDPR	General Data Protection Regulation
HVAC	Heating, Ventilation and Air Conditioning
IDA ICE	IDA Indoor Climate and Energy
IEA	International Energy Agency
IEQ	Indoor Environmental Quality
ISO	International Organization for Standardization
NMF	Neutral Model Format
NMBE	Normalized Mean Bias Error
OCD	Occupant-Centric Design
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
SSO	Single Sign-On
SVEBY	Standardisera och verifiera energiprestanda i byggnader (Standardise and Verify Energy Performance in Buildings)
VAV	Variable Air Volume
WELL	WELL Building Standard

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Indices

t	Index for time step (hourly)

Parameters

g	Solar heat gain coefficient of glazing (–)
$E_{min,week}$	Minimum hourly electricity consumption during the week containing time t (kWh)
$E_{max,annual}$	Annual maximum hourly electricity consumption (kWh)

Variables

$E(t)$	Measured tenant electricity consumption at time t (kWh)
$f(t)$	Fractional occupancy and equipment schedule at time t; $f(t) \in [0, 1]$ (–)
$\bar{f}$	Mean fractional occupancy during working hours (–)
PMV	Predicted Mean Vote; thermal comfort index on a -3 to $+3$ scale (–)
PPD	Predicted Percentage of Dissatisfied occupants (%)
NMBE	Normalized Mean Bias Error; measure of systematic simulation bias (%)
CV(RMSE)	Coefficient of Variation of the Root Mean Square Error; measure of dynamic accuracy (%)

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1 Introduction

1.1 Background

To predict the energy performance of a planned building, assumptions need to be made regarding technical systems, climate data, and perhaps most critically, occupant behaviour. Recent studies indicate that human behaviour can lead to large deviations in the energy use of a building when compared to results from standard energy simulations. Sometimes increasing building energy use by up to 80%, or alternatively, through adaptive behaviours and control strategies, reducing it by 20–40% (Ebuy et al. (2023); Hong & Lin (2013)). This deviation is referred to as the performance gap of a building and can simply be explained as the difference between the expectations and the reality. This gap often stems from a fundamental disconnection where simulation models typically assume passive users who follow rigid schedules while real occupants actively interact with the building by adjusting, for example, the thermostats and opening windows to restore personal thermal comfort.

The deviation also results in a difficult challenge for the industry, as it undermines the reliability of the energy use prediction. To mitigate the risk of user complaints regarding indoor climate, HVAC engineers often design for worst-case scenarios rather than typical operation. This frequently results in the oversizing of technical systems which leads to inefficiencies where heating and cooling plants operate at poor partial load ratios.

In traditional older buildings the main challenge has been transmission losses, but as buildings have become more energy efficient the awareness about human behaviour has risen. In modern energy efficient buildings, human behaviours have become much more important since they have a far greater impact on the building's total energy balance. Today a minor fault in the estimation of human behaviour is no longer a marginal error in the overall calculation. It can instead be the factor that decides if a building fulfills its climate goals or not.

For a consulting firm like AFRY AB, understanding and minimizing this gap is crucial for delivering accurate energy models and ensuring that sustainable office designs perform as intended. This requires a move beyond just predicting energy use and more towards a framework that also accounts for occupant satisfaction. As noted by (Roel et al., 2015), the next generation of building simulations must be able to predict how occupants perceive their environment to avoid the performance gap caused by adaptive actions. To address this, there is a need to identify which human factors are most critical, providing a necessary foundation for improving energy calculation methodologies and design strategies. This shift is fundamental for the industry to move toward more robust and reliable building performance predictions.

1.2 Aim

The aim of this thesis is to minimize the gap between building design and operational energy performance, and ultimately to promote occupant-centric building design by placing human factors at the core of the design process. To achieve this, the thesis focuses on two main objectives:

1. Quantifying the Energy Performance Gap: Investigating the discrepancy between design-stage predictions and operational reality through three main comparisons: Baseline Model vs. Real Energy Data, Baseline Model vs. Optimized Model, and Optimized Model vs. Real Energy Data.

2. Evaluating Thermal Comfort: Assessing the thermal accuracy of the baseline model by comparing simulated operative temperatures against in-situ field measurements, and evaluating whether the building maintains thermally comfortable conditions in accordance with ASHRAE Standard 55.

1.3 Limitations

The scope of this study is limited to modern office buildings. Other building types such as residential, educational and industrial are therefore excluded from the study as occupant behaviours and energy profiles differ in these environments. Geographically, the research is based on a case study located in Gothenburg, Sweden. Consequently, the findings regarding occupant-related energy impacts are primarily applicable to locations with similar climate zones and may not be directly transferable to other zones.

Furthermore, this study initially intended to investigate the five most common human–building interactions identified by Ebuy et al. (2023): occupancy, window opening, lighting, solar shading, and thermostat control. In practice, however, the scope of the parametric analysis is further constrained by data availability and building-specific characteristics. The implications of these constraints are discussed in Section 5.5.

Finally, the simulation results are dependent on the technical capabilities and mathematical solvers of the IDA ICE software and the accuracy of the provided data.

1.4 Specification of the issue being investigated

- Research question 1:

How can occupant-controlled electricity data be utilized to derive high-resolution, data-driven behaviour profiles in dynamic building energy simulations?

- Research question 2:

To what extent do occupant-related human factors, including temporal occupancy patterns and total occupancy density, and behavior model contribute to the energy performance gap in a modern, high-performance office building compared to standardised industry assumptions?

- Research question 3:

How does the uncertainty in post-pandemic occupancy density affect the reliability of building energy simulations, and what are the implications for the use of standardised occupancy assumptions in contemporary office buildings?

2

Theory

2.1 The Global Energy Performance Gap

2.1.1 Discrepancies Between Predicted and Measured Energy Use

The energy performance gap refers to the persistent difference between a building's estimated energy performance during the design phase and its actual energy consumption during operation. Despite decades of progress in building technology and increasingly stringent energy regulations, this gap remains a significant and unresolved problem in the built environment. Research has shown that actual energy consumption can deviate from design calculations by up to 300% in extreme cases (Ebuy et al., 2023).

As buildings have become more energy efficient, the nature of the problem has shifted. In older, poorly insulated buildings, transmission losses through the building envelope dominated the energy balance, meaning that occupant behavior had a relatively minor influence on total consumption. In modern, high-performance buildings, the insulated envelope has reduced these losses dramatically, bringing internal heat gains and occupant interactions to the foreground. What was once a marginal source of error in energy calculations has become the decisive factor that determines whether a building meets its energy performance goals or not.

2.1.2 The DNAS Framework: Why Deterministic Models Fail

The primary cause of the performance gap lies in the fundamental mismatch between how occupant behavior is modeled and how it actually occurs. To address this systematically, the IEA Energy in Buildings and Communities Program established the Drivers–Needs–Actions–Systems (DNAS) ontology as an international standard framework for defining and simulating occupant behavior (Yan and Hong, 2018). This framework provides the theoretical foundation for understanding why conventional deterministic modeling approaches are structurally incapable of capturing real occupant behavior.

The DNAS ontology defines the causal chain of occupant interaction as follows. Drivers are the environmental and contextual factors, such as indoor temperature, solar radiation, or poor air quality that stimulate occupants to act. Needs are the physical, physiological, or psychological requirements that must be met to ensure the occupant's satisfaction with their environment. Actions are the interactions with building systems that occupants undertake to fulfill those needs. Systems are the equipment and mechanisms (thermostats, blinds and lighting controls) that occupants interact with to restore comfort. Occupant behavior thereby forms a closed loop: drivers trigger need-fulfillment actions, those actions alter the indoor environment and energy consumption, and the changed environment in turn influences future behavior (Yan and Hong, 2018).

This framework reveals precisely why standard deterministic models fail. Current building performance simulations treat occupants as passive agents who follow rigid, pre-defined schedules, for example, 100% occupancy between 08:00 and 17:00, with fixed equipment loads and automated shading logic. Such models cannot represent the DNAS chain because they eliminate the driver/trigger mechanism entirely. The result is a fundamental disconnection between the simulated occupant and real human behavior, which is inherently event-driven, adaptive, and variable between individuals (Yan and Hong, 2018; Ebuy et al., 2023).

2.1.3 Impact of Human Factors on Building Sustainability

The physical characteristics of a building determine its theoretical energy performance, but actual energy use is largely determined by the people who occupy it. Studies have shown that buildings with identical architecture and technical systems can differ in measured energy use by a factor of three or more, solely due to differences in occupant behavior (O'Brien et al., 2020). Quantitative analyses demonstrate that inefficient user behavior can increase a building's energy use by up to 80%, while conversely, through adaptive behaviors and well-informed control strategies, occupants can reduce energy use by 20–40% compared to standard assumptions (Ebuy et al., 2023; Hong & Lin, 2013).

2.2 Current Building Energy Codes and Standardized Assumptions

2.2.1 International Review of Occupant-Related Standards

Despite the well-documented limitations of fixed schedules, they remain the norm in practice because of regulatory frameworks. O'Brien et al. (2020) conducted a comprehensive review of occupant-related assumptions in building energy codes across 23 regions worldwide. Their analysis found that most codes lack clear guidance on how to represent occupant behavior realistically. Occupancy is almost invariably estimated using a static schedule. These standards are primarily designed to facilitate compliance and comparability between buildings, rather than to provide accurate predictions of operational energy use. Wagner and O'Brien (2024) identify this as a central unresolved challenge in the Annex 79 program, recommending that codes be updated to include occupancy-specific requirements based on recent field studies.

2.2.2 Limitations of Static Occupancy Profiles in Energy Regulations

A major limitation identified by O'Brien et al. (2020) is that energy codes prioritize comparability over accuracy. By mandating rigid schedules, assuming 100% occupancy throughout all designated office hours, regulations force engineers to design for worst-case scenarios rather than typical operation. This systematically leads to the over sizing of HVAC systems, since the stochastic diversity of real occupant behavior is ignored. In a modern, high-performance building where transmission losses are minimized, internal heat gains dominate the energy balance, and a small inaccuracy in the assumed occupancy schedule propagates into a large absolute error in predicted heating and cooling demand (O'Brien et al., 2020).

2.2.3 Evaluation of Swedish Low-Energy Buildings (BBR and SVEBY)

In Sweden, the energy performance of buildings is regulated by BBR and typically modeled using the SVEBY framework, which provides standardized input values for internal heat gains and occupancy schedules (Boverket, 2020; SVEBY, 2013). Empirical studies published by the Swedish Energy Agency (ER 2018:08) demonstrate that actual internal loads in modern office buildings frequently deviate from these standardized values, confirming that the performance gap is an active problem within the Swedish regulatory context. Table 2.1 summaries the key standardized assumptions used as the baseline parameters for the case study simulations in Chapter 4.

Table 2.1: Summary of occupant-related assumptions for office buildings.

Parameter	Standard Value	Source	Impact on Simulation
Legal Law			
Base Vent. (Occupied)	0.35 l/(s·m^2)	BBR	Minimum airflow to evacuate material emissions when in use.
Base Vent. (Unocc.)	0.10 l/(s·m^2)	BBR	Absolute minimum airflow allowed during nights/weekends.
Min. Operative Temp.	18.0 °C	BBR	The building HVAC must be capable of maintaining this at all times.
Authority Recommendations			
Occupant Ventilation	+7.0 l/s per person	AFS	Extra airflow required when people are present to ensure air quality.
CO_2 Limit	Max 1000 ppm	AFS / FoHM	Triggers Variable Air Volume (VAV) systems to increase airflow.
Minimum Temperature	20.0 °C	FoHM	Absolute lowest operational temperature for sedentary office work.
Industry Standards			
Heating Setpoint	21.0 °C	SVEBY	Theoretical baseline used to keep a safe margin above the 20°C law.
Cooling Setpoint	23.0 °C	SVEBY	Theoretical baseline to balance comfort and energy efficiency.
Occupant Density	20.0 m^2/person	SVEBY	Standard assumption for internal heat gains from human bodies.
Operating Schedule	08:00–17:00 (Mon–Fri)	SVEBY	Standard assumption for when the building is fully occupied.
Appliance Power	12.0 W/m^2	SVEBY	Standard assumption for heat gains from monitors/computers.
Lighting Power	10.0 W/m^2	SVEBY	Standard assumption for internal heat gains from ceiling lights.
Blind Control Logic	Auto (> 100 W/m^2)	ASHRAE 90.1	Standard assumption to prevent theoretical overheating.
Metabolic Rate	1.2 met	ASHRAE 55	Used exclusively for calculating PMV/PPD (sedentary work).
Clothing Insulation	0.5 (Sum) / 1.0 (Win)	ASHRAE 55	Used exclusively for calculating PMV/PPD.

2.2.4 Post-Pandemic Occupancy Patterns and the Limits of Standard Assumptions

The validity of standardised occupancy assumptions such as those prescribed by SVEBY is increasingly challenged by structural shifts in office working patterns following the COVID-19 pandemic. Prior to the pandemic, occupancy standards were developed on the basis of traditional full-time, five-day office attendance, where occupant density was assumed to approach design capacity during regular working hours. The widespread adoption of hybrid working models has fundamentally altered this baseline.

Mantesi et al. (2022) demonstrated through building energy simulation that post-pandemic hybrid working patterns is characterised by reduced and less predictable office attendance and could reduce office energy consumption by up to 50% compared to pre-pandemic standards, primarily driven by lower occupant density and more dynamic building service operation. Critically, the study highlights that energy models calibrated against pre-pandemic occupancy assumptions may systematically overestimate internal heat gains and underestimate the performance gap in contemporary office buildings.

This uncertainty is compounded by the dynamic and unpredictable nature of post-pandemic occupancy. Motuzienė et al. (2022) analysed long-term occupancy measurement data across multiple office buildings and found that actual occupancy during the pandemic period dropped to between 12% and 23% of design values, with prediction model reliability strongly dependent on the representativeness of the training data. While occupancy has partially recovered in the post-pandemic period, hybrid working has stabilised as the dominant mode of office work, resulting in average occupancy levels that remain structurally below pre-pandemic design assumptions.

For building energy simulation, these findings imply that the peak occupant density, as prescribed by standards such as SVEBY, may no longer reflect the actual operational reality of contemporary office buildings. The implications of this uncertainty are investigated in Section 4.3.3, where a sensitivity analysis evaluates the influence of the occupant density assumptions on simulated heating demand.

2.3 Occupant-Centric Simulation-Aided Building Design (OCD)

2.3.1 Principles of Occupant-Centric Design

Occupant-centric design (OCD) represents a fundamental reorientation of building simulation methodology from regulatory compliance to the actual needs and well being of building occupants. As O'Brien and Tahmasebi (2023) note, occupant salaries in commercial buildings average approximately two orders of magnitude higher than energy costs, meaning a 1% decrease in worker productivity can rival the entire annual energy bill. Despite this, standard practice has treated occupants primarily as a source of thermal load. The OCD framework instead advocates for integrating high-resolution occupant data throughout the entire building lifecycle, replacing simplified static schedules with realistic models that can represent the dynamic, need-driven patterns observed in real buildings (OBrien and Tahmasebi, 2023), (Wagner and O'brien, 2024).

2.3.2 Adaptive Occupant Behaviours and Indoor Environmental Quality (IEQ)

Within the Occupant-Centric Design (OCD) framework, Indoor Environmental Quality (IEQ), which encompasses thermal comfort, indoor air quality, visual comfort, and acoustics, plays a fundamental role in driving building energy use. According to Roel et al. (2015), predicting occupant satisfaction across these domains is essential for designing robust building systems. Dissatisfaction within any IEQ domain serves as the primary trigger in the DNAS chain, as described in Section 2.1.2. When environmental conditions exceed a physiological or psychological threshold, the probability of an occupant intervening with building controls increases significantly.

These adaptive occupant behaviours are defined as the physical actions taken by individuals to restore their personal comfort. The critical insight is that these actions are reactive, event-driven, and variable, rather than dictated by a static clock. For example, an occupant who lowers blinds in response to glare, or raises a thermostat setpoint in response to feeling cold, alters the system dynamics. A simulation that accurately predicts IEQ and therefore correctly anticipates when occupants are likely to act will more accurately predict the energy consequences of those actions. Conversely, when models fail to account for these reactive interventions, the deviations accumulate across all occupants and zones over a full year, constituting a large portion of the measured performance gap.

2.4 Approaches for Energy Performance Simulation

2.4.1 IDA ICE for Dynamic Energy Consumption Analysis

IDA ICE is a dynamic simulation tool for indoor environment and high-precision energy calculations, widely used in Sweden's building performance sector. Unlike simplified tools relying on steady-state calculations, IDA ICE uses a general-purpose equation solver (NMF) with variable time steps, enabling it to capture the sudden changes to a zone's thermal balance that occupant interactions create. Abdo-Allah et al. (2019) validated this capability in a large-scale case study, demonstrating that IDA ICE can accurately reproduce real building performance when input assumptions are grounded in measured operational data rather than regulatory defaults.

2.4.2 Integration of BMS Data into Building Performance Simulation

Modern Building Management Systems continuously log high-resolution operational data, occupancy status, lighting conditions, blind positions, thermostat setpoints, and energy consumption providing a direct empirical record of the Actions component of the DNAS framework. Integrating this data into building performance simulation is therefore the key step that allows a theoretical design model to be transformed into a calibrated representation of a real building. Abdo-Allah et al. (2019) identified BMS data integration as a critical factor in achieving model-reality alignment, enabling the generation of data-driven input schedules that replace static regulatory defaults.

2.4.3 Model Calibration Using Field Data and Occupant Surveys

Model calibration is the iterative process of adjusting simulation inputs so that predicted outputs match measured operational data. A key challenge is separating physical uncertainties from occupant-driven operational uncertainties. Quantitative BMS data records what happened and when, but rarely explains why. Occupant surveys fill this explanatory gap by identifying the motivations behind observed data patterns distinguishing, for example, whether blind deployments are triggered by temperature, glare, or habit (Abuimara et al., 2019). By integrating the quantitative signal from BMS data with the qualitative context from surveys, calibration can produce behavioural profiles that far better represent the reality of a building's operation than any static schedule (Abdo-Allah et al., 2019).

2.5 Thermal comfort evaluation models

2.5.1 Operative Temperature as a Comfort Metric

While thermal comfort is a complex subjective experience, standard methodologies such as ASHRAE 55 utilize operative temperature as the primary physical metric for evaluating indoor thermal environments. Operative temperature combines the effects of room air temperature and mean radiant temperature, reflecting how the human body actually exchanges heat with its surroundings through both convection and radiation. For standard office environments with sedentary activity levels, ASHRAE 55 defines an acceptable operative temperature range of 20°C to 24°C during the heating season (2020). Using operative temperature rather than simple air temperature provides a more accurate representation of the actual conditions experienced by the occupants.

2.5.2 Linking Thermal Comfort to Simulation Methodology

In building performance simulation, maintaining the operative temperature within established comfort bounds serves as a critical constraint. When evaluating the energy performance gap, it is essential to ensure that any adjustments to input parameters, such as lowering occupancy densities or altering internal loads, do not result in unrealistic indoor environments. By validating the theoretical baseline simulation's operative temperatures against in-situ physical measurements, the thermal accuracy of the model can be confirmed. This validation ensures that the simulated energy demands are based on a building model that practically sustains an acceptable Indoor Environmental Quality (IEQ).

2.6 Mathematical Modelling of Internal Loads and Schedules

2.6.1 Representation of Heat Gains in Simulation

In dynamic simulation environments such as IDA ICE, occupant-driven internal heat gains are categorised into three sources: metabolic heat from occupants, heat from lighting, and plug loads from electronic equipment. Each is mathematically represented by a maximum design load modulated by a time-varying fractional schedule: Q_int(t) = Q_max · f(t), where Q_max is the peak installed load and f(t) is the fractional usage rate at time t, between 0 and 1. Accurate specification of both parameters is essential for reliable energy prediction.

2.6.2 Data-Driven Profiles: Tenant Electricity as a Proxy for Occupancy

In traditional compliance modelling, $f(t)$ is static. A standardized office schedule assumes full occupancy continuously between 08:00 and 17:00, and zero otherwise. This fails to represent the stochastic and need-driven nature of human behaviour described by the DNAS framework. The transition from a deterministic baseline to an OCD model requires replacing this static schedule with a data-driven profile derived from measured operational data. A central theoretical premise of this study is that equipment loads and occupant presence in office buildings are closely correlated, such that a single data-driven schedule derived from tenant electricity can reliably represent both.

Since tenant electricity captures the aggregate plug load of all occupant-controlled equipment, it is simultaneously a measure of occupancy and a direct record of equipment activity. Both factors share the same underlying driver within the DNAS framework: human presence. Al-Saegh et al. (2024) established this empirically by analysing one full year of hourly metered electricity data from an office building, finding a strong correlation between electricity use and time of day with an R^2 value of 0.84. Critically, an equivalent analysis of metered gas consumption showed no such correlation, confirming that electricity is specifically driven by occupant presence and equipment use, while gas reflects weather-dependent heating. Ultimately, these energy-data-driven occupancy profiles reflect actual human behaviour patterns with significantly greater accuracy than static regulatory schedules, reducing annual heating demand estimation errors from 14% to ±2.5% (Al-Saegh et al., 2024).

3

Applied Methodologies

To bridge the gap between calculated and actual energy use, modern research has increasingly moved beyond theoretical standard models. This chapter surveys the scientific methods that previous case studies have established for quantifying, modelling, and reducing the energy performance gap caused by stochastic occupant behaviour. As O'Brien and Tahmasebi (2023) emphasize, the shift from conservative worst-case assumptions towards empirically grounded occupant models is fundamental for designing buildings that perform as intended. Each method described here has been validated in prior research and provides the scientific precedent for the approach applied to the case study in Chapter 4.

3.1 Quantifying the Error Margins of Deterministic Models

A necessary first step in any occupant-centric methodology is to establish the inadequacy of the deterministic assumptions it seeks to replace. O'Brien et al. (2020) provided a comprehensive empirical basis for this in their review of building energy codes across 23 different regulatory regions. They found that assumptions regarding occupant density differed by a factor of nearly three between frameworks which reflects the arbitrary nature of standardized defaults rather than any physical difference between buildings. Their study concluded that codes fundamentally prioritise comparability over predictive accuracy.

The direct consequence of these inaccurate assumptions on simulation outcomes was measured by Abuimara et al. (2019) in a simulation-based case study. Through stakeholder interviews, they collected the specific occupancy-related assumptions that practitioners from different design disciplines would apply to the same building. When tested in a calibrated energy model, these varying assumptions altered predicted energy savings by a factor of five or more, establishing that the performance gap is primarily an occupant-related input parameter problem rather than a physical modelling uncertainty.

3.2 Implementation of Data-Driven Behavior Profiles

Hong and Lin (2013) demonstrated empirically how different occupant profiles directly affect energy use in private office environments. By categorising users along a behavioural spectrum from passive occupants who rarely interact with building controls to active occupants who regularly adjust thermostats, blinds, and lighting they showed that the choice of profile could produce energy use differences as large as the variation caused by physical building parameters. A standard 08:00–17:00 binary schedule was incapable of capturing this range.

This finding is framed within the OCD paradigm by O'Brien and Tahmasebi (2023): rather than asking what schedule should be assumed, the occupant-centric approach asks what behaviour does this specific building and its specific occupants actually exhibit. Answering this question requires empirical data from the building itself which is the methodological principle applied in Sections 3.3 through 3.4.

3.3 Energy-Data-Driven Occupancy Schedules (EDDOS)

Al-Saegh et al. (2024) developed and validated the EDDOS methodology as a computationally practical alternative to both standard based static schedules and computationally expensive stochastic occupancy models. The method is grounded in the empirical relationship between building electricity consumption and occupancy. An analysis of one full year of hourly metered electricity data from an office building demonstrated a strong correlation with an R squared value of 0.84, while an equivalent analysis of gas consumption showed no such correlation. This confirms that electricity specifically reflects occupant presence and equipment activity.

It is important to clarify that this metered tenant electricity encompasses the aggregate consumption across the entire investigated floor plan, including both the open office areas and the enclosed meeting rooms. A theoretically consistent extension of this principle is the application of the same derived schedule to equipment loads in the simulation model. This is directly supported by Al-Saegh et al. (2024). The correlation between electricity and occupancy was established precisely because tenant electricity captures the aggregate behaviour of all occupant controlled equipment. The electricity signal is the equipment signal. Applying the EDDOS derived schedule to equipment loads therefore does not introduce a new assumption, but rather it closes the logical circle from which the schedule was derived.

The EDDOS algorithm translates the measured electricity time series into a fractional occupancy schedule through normalization. The minimum electricity consumption during unoccupied periods is assigned $f(t) = 0.0$, and the maximum annual consumption is assigned $f(t) = 1.0$, with intermediate values derived by linear interpolation within each week's data processed separately. This generates non repeating daily profiles that capture actual seasonal variations in building use, including structural reductions during holiday periods (Al-Saegh et al., 2024).

When validated against measured heating data, EDDOS achieved annual heating demand estimation errors of $\pm 2.5\%$, compared to 14 percent for the standard based schedule and 7 percent for a stochastic model. Notably, the stochastic model, despite its substantially higher computational cost, provided no meaningful improvement over the static schedule, leading Al-Saegh et al. (2024) to conclude that EDDOS offers the best cost benefit ratio for practical design workflows where BMS electricity data is available

While the EDDOS methodology provides a data driven fractional schedule $f(t)$, the peak occupant density determines the absolute magnitude of internal heat gains, which cannot be derived from electricity data alone. Given the documented decline in office occupancy following the COVID 19 pandemic and the widespread adoption of hybrid working models (Mantesi et al., 2022; Motuzienė et al., 2022) , the actual maximum occupancy in contemporary office buildings is subject to considerable uncertainty. The implications of this uncertainty for building energy simulation are investigated through a sensitivity analysis in Section 4.3.3, where three occupancy density scenarios are evaluated to quantify the influence of occupant density assumptions on the predicted performance gap.

3.4 Seasonal Shading Behaviour in Office Buildings

O'Brien et al. (2013) conducted a comprehensive critical review of twelve major observational studies on manual shade operation in office buildings spanning 35 years of research. A key finding is that occupants lower blinds reactively in response to glare but rarely retract them when conditions improve, resulting in a persistent bias towards the closed position that automated radiation-threshold models do not capture. This hysteresis means shades persistently accumulate in the closed position beyond what theoretical models anticipate. Field studies across 42 office buildings confirm this pattern, reporting a mean daily blind adjustment rate of only 15%, with 35% of blinds remaining unchanged over periods as long as four months (Van Den Wymelenberg, 2012). Most occupants were found to change shade position only weekly or monthly, reacting to the gradual sunniness of the preceding 1.5 to 3 hours rather than to instantaneous conditions.

A second key finding is that the dominant motivation for shade operation is visual comfort, specifically glare avoidance rather than thermal comfort. Although occupants frequently cited heat gain as a reason in surveys, observational data showed that indoor temperature was not a statistically significant predictor of shade position in buildings with operational HVAC systems (O'Brien et al., 2013). This means that automated shading logic based solely on a solar radiation threshold correctly models the physical trigger but fails to capture the asymmetric human response.

These findings establish the scientific foundation for a seasonal utilisation factor approach to shading modelling: rather than relying on idealised automated logic, a ratio between actual deployed hours and theoretically warranted hours is used to represent the gap between optimal behaviour and observed human behaviour. The seasonal dimension is justified by the systematic shift in occupant motivation documented across the reviewed studies. Heat rejection and glare avoidance dominating in summer, while daylight admission takes priority in winter and colder periods.

3.5 Sensor-Driven Calibration and Validation Metrics

Once data-driven behavioural profiles have been established, the combined simulation model must be validated against measured data to confirm its accuracy. Abdo-Allah et al. (2019) demonstrated this in a large-scale IDA ICE case study, extracting high-resolution HVAC sensor data and integrating it as direct simulation inputs rather than theoretical design parameters. The resulting model showed high correlation with actual measured energy consumption, confirming that dynamic simulation tools can reproduce real building performance when input assumptions are grounded in measured data.

To ensure that this calibration process is scientifically robust, standardized statistical metrics must be used to evaluate the discrepancy between simulated and measured data. According to ASHRAE Guideline 14, the two primary validation metrics are the Normalized Mean Bias Error (NMBE) measuring systematic overprediction or underprediction and the Coefficient of Variation of the Root Mean Square Error (CVRMSE) measuring dynamic fluctuation accuracy. A model is considered successfully calibrated using monthly data when the NMBE is within $\pm 5\%$ and the CVRMSE is below 15%. These thresholds serve as the definitive quantitative acceptance criteria for the calibrated model in this study.

Sequential calibration, such as updating one parameter at a time and re-simulating, allows the isolated contribution of each human factor to the performance gap to be quantified. As noted by Wagner and O'Brien (2024), this type of post-occupancy data integration is critical not only for closing the gap in the current building but for building the empirical knowledge base that improves occupant-related assumptions in future design-stage simulations. This creates a feedback loop between operational reality and design practice that regulatory compliance workflows currently lack.

4

Case Study

The methods established in Chapter 3, EDDOS for occupancy and equipment scheduling, the seasonal shading utilization factor, and sequential sensor-driven calibration in IDA ICE are applied in this chapter to the case study building Gårda Vesta in Gothenburg. The three human-driven factors identified for investigation are occupancy, equipment loads, and solar shading. Each factor is represented in the simulation using a data-driven approach derived from measured BMS data and, where relevant, occupant survey responses. The goal is to quantify the energy performance gap between the deterministic baseline model and operational reality, and to isolate the contribution of each human factor to that gap.

4.1 Description of the case study office building

4.1.1 Physical and Technical Characteristics

The case study building is Gårda Vesta, a WELL and BREEAM Excellent certified office building located near Svingeln in Gothenburg. As established in the theoretical framework, modern sustainable buildings with highly insulated envelopes are particularly sensitive to internal heat gains and stochastic occupant behaviour. Gårda Vesta, with its advanced high-performance technical systems and strict focus on Indoor Environmental Quality (IEQ), serves as an ideal representative case for investigating the energy performance gap in contemporary commercial real estate.

Architecturally, Gårda Vesta consists of two high-rise towers of different heights connected by a shared base. This study exclusively investigates the taller tower section, which comprises 25 floors with a total heated floor area (A_{temp}) of approximately 32,772 m^2. The investigated tenant occupies a total of eight floors within the building. However, because the floor plans are highly repetitive and the original model relies on multiples of the same layout, analyzing all eight floors was deemed redundant. Therefore, this study specifically focuses on a representative subset of four floors, covering a total area of 2,859 m^2. These investigated floors primarily consist of open-plan office spaces and meeting rooms, accurately reflecting a modern office work environment.

The building is equipped with an advanced BMS that continuously monitors and controls the indoor climate. The HVAC systems operate based on designed for strict regulatory compliance. Critically, the building features sealed windows, meaning that the available human-building interactions are strictly limited to internal controls: thermostat adjustments, blind positioning, and lighting usage. This eliminates window opening as a behavioral variable and focuses the study on the three factors identified in Chapter 3.

4.1.2 The Reference Model and Baseline Assumptions

To evaluate the performance gap, the reference case was built upon an initial IDA ICE model provided by the project partners, which represented the theoretical performance predicted during the design phase. To ensure its validity as a realistic baseline, extensive manual modeling work was required. First, the original model's thermal zoning was restructured to accurately reflect the final as-built spatial layout of the investigated open-plan floors.

Furthermore, when migrating the model from version 4.7 to 5.1.1 of IDA ICE, several operational parameters was lost due to version incompatibilities. A thorough system-by-system review was conducted to rectify this. Where original values remained intact, they were retained. However, missing critical data such as internal heat gain densities, ventilation schedules, and occupancy profiles were manually remodeled and parameterized in strict accordance with SVEBY and BBR guidelines. Finally, the HVAC configuration was verified and updated to reflect the physical reality of the building, ensuring that space cooling is accurately represented exclusively via increased VAV airflow, as the building does not utilize chilled beams.

By redefining the thermal zones and ensuring all theoretical inputs were complete and standardized, a reliable deterministic design model was established. This refined baseline represents the theoretical industry-standard prediction and serves as the fixed reference point against which all subsequent data-driven adjustments are compared. All key standardized assumptions are listed in Table 4.1. A comparison between the baseline model assumptions and the SVEBY standard is listed in Table 4.2.

Table 4.1: Zone groups, HVAC systems, and temperature setpoints in the baseline model.

Zone Group	Zone Types	HVAC System	Heat Setp. (°C)	Cool Setp. (°C)	Notes
Open Landscape	Open plan offices	VAV (Temp + CO_2)	21.0	23.0	Main office areas
Meeting Rooms	Silent rooms, connectors	VAV (Temp + CO_2)	21.0	23.0	Separate schedule
Passage	Corridors, connectors	VAV (Temp + CO_2)	21.0	23.0	—
Small Rooms	Small offices	CAV ($0.35\ \mathrm{l/(s \cdot m^2)}$)	21.0	23.0	No equipment load
Middle (Stairwell)	Trapphus	CAV ($0.35\ \mathrm{l/(s \cdot m^2)}$)	21.0	25.0	Relaxed cooling
Teknik (Fan room)	Fläktrum	CAV ($0.35\ \mathrm{l/(s \cdot m^2)}$)	18.0	25.0	Reduced setpoints

Table 4.2: Baseline model input assumptions compared against SVEBY defaults. Highlighted rows indicate deviations from Table 2.1.

Parameter	SVEBY Default	Baseline Model	Source	Applies to
Heating setpoint	21.0 °C	21.0 °C	SVEBY	All zones except fan room
Fan room heating	21.0 °C	18.0 °C	Project partners	Fläktrum only
Cooling setpoint	23.0 °C	23.0 °C	SVEBY	Office zones
Stairwell/fan room cooling	23.0 °C	25.0 °C	Project partners	Trapphus & Fläktrum
Occupant density	0.05 persons/m²	0.05 persons/m²	SVEBY	Landscape, meeting, passage
Lighting power density	10 W/m²	5 W/m²	Project partners	All occupied zones
Equipment power density	12 W/m²	13 W/m²	Project partners	Landscape, meeting, passage
Blind control logic	Auto >100 W/m²	Auto >100 W/m²	ASHRAE 90.1	All facade zones
Ventilation (office)	VAV, CO_2 controlled	VAV (Temp + CO_2)	BBR / AFS 2009:2	Landscape, meeting, passage
Ventilation (other)	0.35 l/(s · m²)	CAV 0.35 l/(s · m²)	BBR	Small rooms, stairwell, fan room

Two occupancy schedules were included in the baseline model. The open office landscape (Figure 4.1) operates between 06:00 and 18:00, with a dip in occupancy during lunch hours (12:00–13:00). The meeting rooms (Figure 4.2) operate between 09:00 and 18:00 with lower average occupancy. Both schedules are set to zero on weekends and holidays.

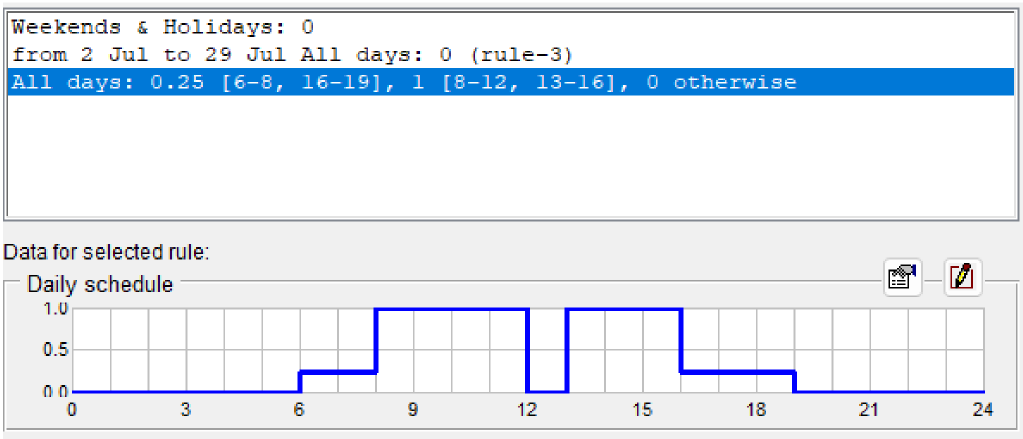

Figure 4.1: Baseline Schedule used for Occupancy and equipment in the open landscape of the office.

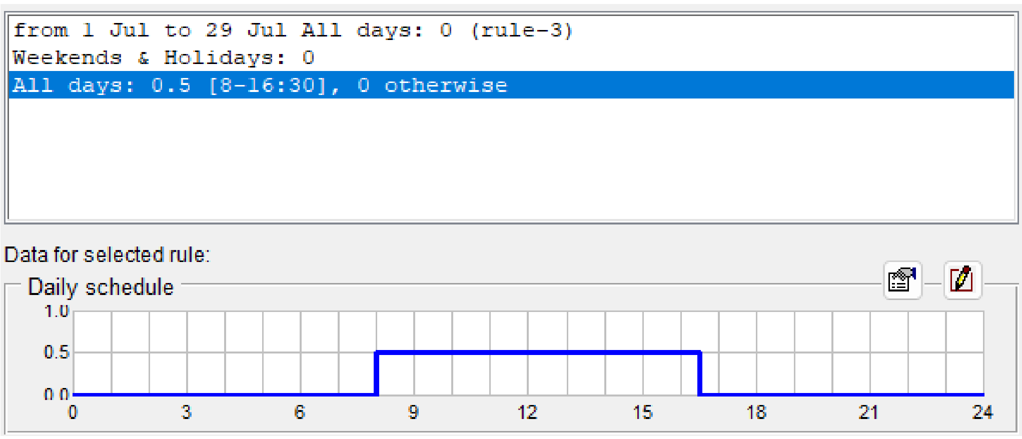

Figure 4.2: Baseline Schedule used for Occupancy and equipment in meeting rooms.

4.2 Data Collection

To go beyond the theoretical assumptions of the reference case, the study draws on two parallel data sources: BMS operational data, and physical in-situ measurements. Together these provide the quantitative inputs needed to both calibrate the simulation model and validate its thermal comfort predictions.

4.2.1 Building Management System (BMS) Data

Operational data was extracted from the building's BMS to support the derivation of data-driven occupancy and equipment schedules. The data collection process revealed significant limitations in the availability and quality of occupant-related BMS signals, which shaped the final methodological approach.

In the case study, the BMS signal with sufficient temporal resolution and direct relationship to occupant activity was hourly tenant electricity consumption for the full calendar year 2025, covering the entire tenancy of one tenant across eight floors. This signal was used as the proxy variable for the EDDOS methodology, as described in Section 4.3.2. It is noted that tenant electricity was available at the tenancy level only as floor-level submetering was not accessible.

Several other BMS signals were investigated but ultimately not used. Occupancy sensors were available per zone across the investigated floors, however the data was logged on a change-of-state basis rather than continuously, and the resulting occupancy curves showed insufficient resolution and reliability for deriving meaningful schedules. CO_2 concentration data was identified at zone level across the investigated floors, however this data was also logged on a change-of-state basis, limiting its applicability for continuous occupancy estimation. Airflow data from the building's air handling units was also considered as an alternative proxy for occupancy, but was deemed unsuitable as the units serve multiple floors simultaneously, preventing isolation of the signal to the investigated zones. Solar shading position data was not available in the BMS.

Monthly heating consumption data was extracted from the BMS for the upper section of the building for the full year 2025, providing a direct basis for performance gap validation of heating energy in Section 4.4.6. Cooling consumption was available only at a more aggregated building-level meter, which limits the precision of cooling-side performance gap validation.

4.2.2 Physical Measurements

In-situ measurements were collected over the winter period across the selected floors and thermal zones within the case study building, near the workstations. Locations were selected to ensure representation across different facade orientations and varying distances from windows. A multi-parameter environmental monitoring instrument were deployed at each workstation to measure the environmental parameters required to operative temperature. This high-resolution physical data provides the real-world baseline for validating the thermal comfort performance of the optimized simulation model.

4.3 Simulation Methodology

The simulation phase is structured as a sequential parametric analysis. Each of the three human-driven factors is updated individually in IDA ICE, allowing its isolated energy impact to be quantified before all adjustments are combined into a final optimized model. Figure 4.4 illustrates the full methodological flowchart.

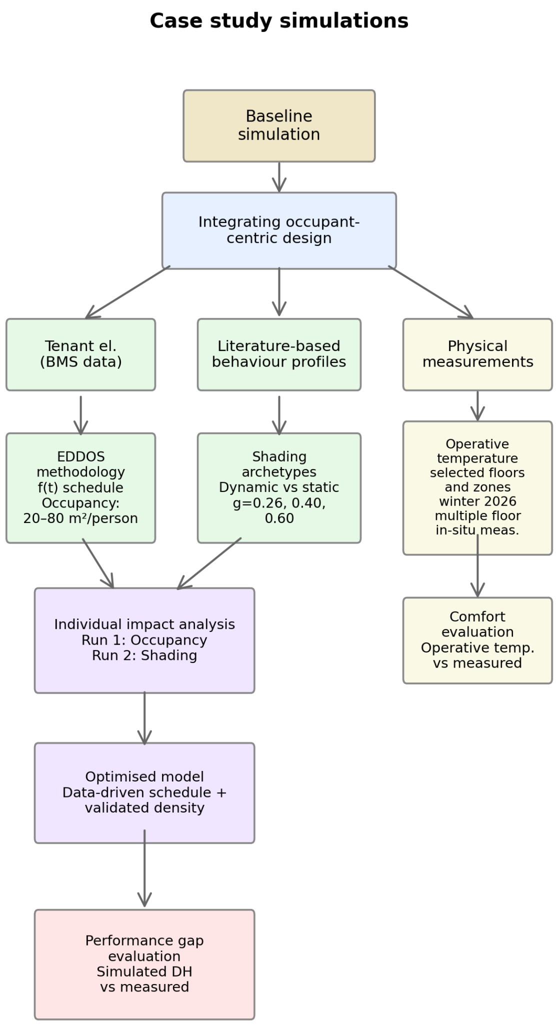

Figure 4.3: Methodological flowchart of the case study simulations, illustrating the transition from a deterministic baseline to an optimized occupant-centric model by merging quantitative BMS data with behaviour triggers.

4.3.1 Baseline Simulation

The first step is to run a full annual simulation of the deterministic reference model described in Section 4.1.2. This generates the theoretical baseline results, establishing the Standardized Industry Baseline for all subsequent comparisons.

While the simulation computes the total building energy balance (including facility electricity, tenant electricity, and HVAC auxiliary power), the primary outputs extracted for this study's performance gap analysis are space heating and space cooling demands. Space heating serves as the critical metric for validation against the measured district heating data, while space cooling is tracked to evaluate the thermal trade-offs introduced by dynamic occupant behavior.

Additionally, the baseline simulation calculates the theoretical PMV and PPD indices for each investigated zone. Based on the standardized SVEBY schedules and setpoints, these indices serve as the theoretical thermal comfort reference and will be validated through the in-situ physical measurements.

4.3.2 Data-Driven Schedule Derivation and Model Adjustment

Due to the absence of high-resolution, direct occupancy data (such as precise headcounts or pass-card logs) from the building's BMS, the EDDOS methodology, validated by Al-Saegh et al. (2024) and described in Section 3.3, was implemented. This method inherently relies on tenant electricity as a reliable proxy variable for human presence. Since tenant electricity was not logged by the central BMS, the hourly metered consumption data for the full calendar year of 2025 was acquired directly from the tenant. Because this data was only available as an aggregated total for their entire tenancy, it was extracted collectively across all eight floors. As established in Section 3.3, this specific electricity signal captures the aggregate plug load of all occupant-controlled equipment including, workstations, lights, coffee machines and other office equipment, allowing both occupancy and equipment schedules to be derived simultaneously from a single empirical data source.

Normalization Procedure

To translate the raw electricity time-series into a fractional occupancy schedule $f(t)$, a two-reference normalization was applied. The lower reference was defined on a weekly basis: for each week, the minimum hourly electricity consumption, representing the overnight idle baseload, was assigned $f(t) = 0.0$. This weekly minimum normalization was chosen specifically to account for observed variations in the baseload across the year, caused by equipment operating independently of occupancy. By defining a week-specific zero reference, these baseload variations are eliminated from the occupancy signal. The upper reference was defined globally across the entire year: the absolute annual maximum electricity consumption was assigned $f(t) = 1.0$. This global annual maximum was deliberately chosen to preserve the relative seasonal differences in peak occupancy between months, ensuring that July, with structurally lower peaks due to summer holidays, correctly receives lower $f(t)$ values than February, which represents full occupancy. All intermediate hourly values were calculated by linear interpolation between the weekly minimum and the annual maximum:

$$f(t) = \frac{E(t) - E_{\text{min,week}}}{E_{\text{max,annual}} - E_{\text{min,week}}} \tag{4.1}$$

Where $E(t)$ is the measured electricity consumption at time t, $E_{min,week}$ is the minimum electricity consumption during the week containing time t, and $E_{max,annual}$ is the annual maximum electricity consumption.

To avoid week-numbering inconsistencies at year boundaries where ISO week numbering can assign late December days to week 1 of the following year, a composite weekly key was constructed by combining the calendar year and week number ($year * 100 + weeknumber$). This ensured that each week received a unique identifier across the full dataset.

Monthly Aggregation and Seasonal Schedule

To identify macro-level seasonal occupancy patterns and generate simulation-ready monthly schedules, the continuous hourly $f(t)$ dataset was aggregated into monthly mean values. Weekends and Swedish public holidays were excluded from this aggregation to ensure that the resulting values reflect typical occupied working days rather than being diluted by consistently low weekend and holiday values. The 13 Swedish public holidays in 2025 were identified and excluded accordingly.

The resulting 12 monthly mean $f(t)$ values, representing the average fractional occupancy on a working day in each month, are presented in Table 4.3.

Table 4.3: Monthly mean $f(t)$ values derived from tenant electricity data (working days only, public holidays excluded).

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.374	0.385	0.385	0.378	0.374	0.358	0.294	0.337	0.365	0.361	0.355	0.308

The seasonal pattern is consistent with expected occupancy behaviour in a modern Swedish office. February and March show the highest occupancy levels, reflecting full staffing with no major holiday interruptions. A gradual decline is observed from May through June, with July recording the lowest value (0.294) which is a 24% reduction relative to the February peak, corresponding to the Swedish summer holiday period. August shows a clear recovery as staff return, and December records the second lowest value (0.308), reflecting the Christmas holiday period. This seasonal pattern strongly supports the validity of tenant electricity as an occupancy proxy, as the observed fluctuations align with known Swedish workplace calendar patterns rather than climatic or technical drivers.

Daily Profiles and Weekday Analysis

In addition to the seasonal dimension, a typical daily occupancy profile was derived from the hourly f(t) data to capture the intra-day variation in building usage. This profile was computed as the mean f(t) for each hour of the day (0–23) across all working days, excluding weekends and public holidays.

To investigate whether a systematic variation exists between weekdays, mean f(t) values were computed separately for each day of the week. The results are presented in Table 4.4.

Table 4.4: Mean $f(t)$ by weekday (all hours, working days only).

Monday	Tuesday	Wednesday	Thursday	Friday
0.375	0.368	0.357	0.365	0.311

Monday through Thursday show closely similar mean values ranging from 0.357 to 0.375, indicating no practically significant difference in building usage between these days. Friday, however, records a markedly lower mean value of 0.311, a reduction of approximately 17% relative to the Monday peak.

Based on this analysis, two distinct daily profiles were derived for implementation in IDA ICE:

Monday–Thursday profile: A single averaged daily profile computed from all Monday–Thursday working days, representing the standard occupied working day. The profile shows gradual ramp-up from 06:00, near-peak occupancy between 09:00 and 15:00, and a gradual decline through the evening hours.

Friday profile: A separate daily profile computed from all Friday working days, reflecting the systematically lower occupancy level observed on this day of the week.

Application to Occupancy and Equipment Schedules in IDA: ICE

The derived EDDOS schedules are implemented in IDA ICE by replacing the static SVEBY baseline schedules for both occupancy and internal electrical loads. Rather than separating equipment and lighting into distinct simulation inputs, the two are combined into a single internal electrical load parameter. This approach is motivated by the nature of the proxy variable: tenant electricity captures the aggregate signal of all occupant-controlled electrical consumption, including both plug loads and lighting, without distinction between the two. Separating them would introduce a false precision unsupported by the data. The average occupant density assumptions used in the simulations are defined in Section 4.3.3. Lighting is set to 0 W/m^2 in IDA ICE, and the full electrical load is assigned to the equipment parameter. Both occupancy and the combined electrical load use the same EDDOS-derived $f(t)$ schedule.

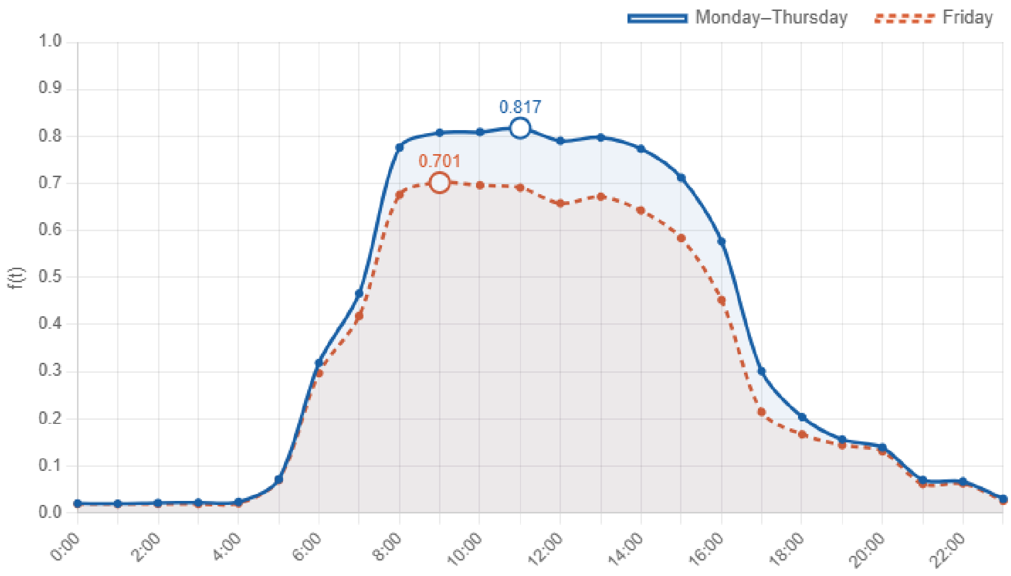

Figure 4.4: Average daily $f(t)$ profiles for Monday–Thursday and Friday, derived from measured tenant electricity data (2025). Weekends and public holidays are excluded. Peak values are indicated for each profile.

In practice, IDA ICE implements this through two layered schedules. The monthly mean $f(t)$ values from Table 4.3 define the seasonal scaling factor, while the daily profiles define the intraday variation. These two schedules are integrated multiplicatively to determine the final operative fraction at any given time during the simulation. The explicit equation used to calculate the final scheduled fraction $f_{sim}(t)$ is:

$$f_{sim}(t) = f_{monthly} \times f_{daily}(t)$$

where $f_{monthly}$ is the scaling factor for the current month and $f_{daily}(t)$ is the hourly fractional value from the applicable daily profile. Monday to Thursday and Friday are assigned their respective daily profiles. Weekends and public holidays retain $f(t) = 0.0$ consistent with the normalization reference. The complete hourly $f(t)$ values and monthly scaling factors used in the IDA ICE implementation are provided in Appendix A.

4.3.3 Occupancy Density Scenarios

While the EDDOS methodology accurately captures the temporal variation in building occupancy through the fractional schedule $f(t)$, it does not determine the absolute number of occupants present at any given time. The total occupancy level, expressed as average floor area per person during working hours, must be defined independently and constitutes a significant source of uncertainty in contemporary office buildings.

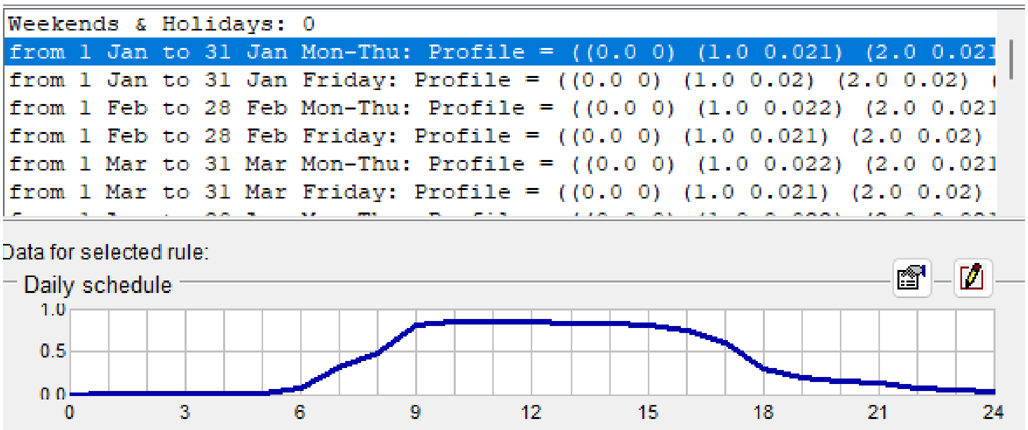

Figure 4.5: The schedule implemented in IDA ICE showing an example from Monday to Thursday in January

As established in Section 2.2.4, the widespread adoption of hybrid working following the COVID-19 pandemic has structurally reduced average office attendance below pre-pandemic design standards (Mantesi et al., 2022; Motuzienė et al., 2022). Standard assumptions such as SVEBY's reference level of 20 m^2 per person were developed on the basis of traditional full-time office attendance and may no longer reflect the operational reality of contemporary hybrid offices.

To investigate the sensitivity of the predicted energy performance to this uncertainty, a range of occupancy density scenarios are defined, representing plausible average attendance levels from SVEBY-equivalent density to significantly reduced post-pandemic scenarios:

- **20 m^2/person,** equivalent to SVEBY's standard assumption, representing full pre-pandemic attendance.
- **30 m^2/person,** representing moderately reduced attendance consistent with partial hybrid working adoption, corresponding to approximately 67% of SVEBY's standard density.
- **40 m^2/person,** representing a high degree of hybrid working corresponding to approximately 50% of SVEBY's standard density, consistent with post-pandemic occupancy observations (Motuzienė et al., 2022).
- **80 m^2/person,** representing an extreme low-occupancy scenario corresponding to approximately 25% of SVEBY's standard density, consistent with the lower end of post-pandemic observations where attendance has been found to drop to as low as 12–23% of design capacity (Motuzienė et al., 2022).

These values represent the average floor area per person during working hours. It should be noted that the baseline model applies this density as a constant value under a binary schedule, while the EDDOS scenarios distribute the same average density dynamically through the continuous $f(t)$ schedule, resulting in different energy outcomes despite identical average occupancy levels.

For the combined internal electrical load, the peak load density is derived directly from the measured annual maximum hourly tenant electricity consumption of 57.93

kW across the full tenancy of 5,718 m^2 (eight floors), yielding 10.13 W/m^2. This value represents the average load during working hours, and the instantaneous load varies dynamically throughout the day and year in accordance with the same EDDOS-derived $f(t)$ schedule as occupancy, consistent with the use of tenant electricity as a unified proxy for both occupancy and equipment activity.

This electrical load configuration is applied identically across all occupancy density scenarios, meaning that only the occupancy level varies between scenarios while the equipment load profile remains derived from the same measured data.

All scenarios use the same EDDOS-derived $f(t)$ schedule, meaning that the temporal variation in occupancy, including the seasonal patterns, daily profiles, and Friday reductions identified in Section 4.3.2, is identical across scenarios. The sensitivity analysis therefore isolates the effect of total occupancy level from the effect of occupancy variation, allowing the two dimensions of occupant behaviour to be evaluated independently. The results are presented in Section 4.4.2.

4.3.4 Modeling of Shading Operation Archetypes

Due to the highly stochastic nature of manual shading overrides, predicting the exact blind positions for the case study building is inherently uncertain. The existing automated logic in the baseline model (Table 4.2) assumes a fully automated system operating optimally, where blinds are deployed exclusively based on a conservative radiation threshold of 100 W/m^2 to minimize cooling loads. However, as established in Section 3.5, occupant interventions frequently disrupt this automation. To accurately evaluate the performance gap and assess the energy implications of automated versus manually operated shading systems, a sensitivity analysis based on archetypes was implemented. Rather than assuming a single deterministic schedule, this study compares the optimal automated baseline against two established extremes of manual shading interaction, based on the Lightswitch 2002 behavioral models defined by Reinhart (2004):

The Dynamic User (Active Manual Control): This archetype represents an occupant who actively operates the blinds on a daily basis, prioritizing daylight and outdoor views. Following Reinhart's definition, this user overrides the automated system to keep the blinds open and only deploys them reactively when direct solar irradiance causes severe visual glare. To simulate this glare avoidance behavior in IDA ICE, the deployment threshold within the automated macro (Control = Sun) was elevated to 250 W/m^2, representing the established upper limit for visual discomfort before manual deployment occurs.

The Static User (Passive Manual Control): This archetype represents an occupant who rarely operates the blinds, typically reacting to a singular glare event and then leaves the shading device permanently deployed in a suboptimal position. This behavior aligns with the hysteresis effect documented by O'Brien et al. (2013). To replicate this lack of dynamic movement, the automated control macro in IDA ICE was disabled entirely. Instead, a static operational schedule (Control = Schedule) was applied during all working hours (08:00 to 17:00). While Reinhart (2004) defines the static user as leaving blinds fully lowered at 100 percent occlusion, this scenario is considered physically unrealistic for Gårda Vesta, where the fully automated shading system limits the extent of manual override. A constant occlusion of 50 percent is therefore applied. This specific value is directly derived from observed mean occlusion rates in office field studies, where mean occlusion consistently falls in the 50 to 60 percent range across multiple buildings and climates (Van Den Wymelenberg, 2012; Rea, 1984).

By evaluating these two distinct behavioral archetypes against the theoretical baseline, the resulting energy tradeoffs between cooling demands (driven by the Dynamic User) and artificial lighting needs (driven by the Static User) can be quantified. It should be noted that these simulations are treated as an exploratory sensitivity analysis rather than a calibration of the optimised model. Given that the case study building operates a fully automated solar shading system with limited occupant override capability, and given the absence of building specific data on override frequency, the blind archetype scenarios are not incorporated into the optimised model. The baseline automated shading logic is retained in the optimised model as the best available representation of actual shading operation. Furthermore, a more comprehensive sensitivity analysis regarding this exact occlusion fraction and its subsequent impact on overall energy consumption is highly recommended for future studies.

4.3.5 Sensitivity Analysis: Solar Shading and Glazing Performance

Building upon the shading operation archetypes defined in Section 4.3.4, a sensitivity analysis is performed on the solar heat gain coefficient (g-value) of the windows. The building's current high-performance glazing ($g = 0.26$) is compared against two alternative scenarios with $g = 0.40$ and $g = 0.60$, representing a modern high-performance office and an older office building respectively.

This analysis investigates whether the impact of occupant-driven shading, specifically the discrepancy between the passive and active user archetypes, becomes more significant when the building facade provides less inherent protection against solar gains. This allows the findings from Section 4.3.4 to be contextualised beyond the case study building's specific glazing specification, investigating whether the conclusions regarding shading behaviour hold across a wider range of building envelope configurations.

In addition to the archetype comparisons, two supplementary simulations are conducted at $g = 0.26$ to bound the theoretical limits of solar shading influence. First, an extreme shading scenario is simulated in which blinds are permanently deployed during the heating season (October to April) and fully retracted during summer (May to September), representing the theoretically optimal seasonal shading strategy. Second, the same extreme shading schedule is repeated with an unconstrained maximum VAV airflow, removing the system capacity limitation identified in Section 4.2.1, to isolate the cooling system's response to increased solar gains without flow restrictions.

4.3.6 Simulations and Isolation of Human Factors

To isolate the energy impact of each human factor, simulations are run in IDA ICE updating one parameter at a time while all others remain at their baseline values.

Three runs are conducted:

Run 1 – Occupancy and Equipment: The EDDOS-derived schedule replaces the standard SVEBY 08:00–17:00 profile for both occupancy and combined electrical loads. To address the uncertainty in total occupancy level described in Section 4.3.3, Run 1 is repeated for a range of occupancy density scenarios from 20 to 80 m^2/person, while the EDDOS $f(t)$ schedule remains identical across all scenarios. All other parameters remain at baseline.

Run 2 – Solar Shading: The deterministic automated blind control logic is replaced by the two scenario-based behavioral archetypes defined in Section 4.3.4, the Dynamic User and the Static User. Each archetype is simulated separately to isolate the energy impact of active versus passive manual overrides. These simulations are treated as an exploratory sensitivity analysis rather than a calibration of the optimised model. In addition, a glazing sensitivity analysis is conducted as described in Section 4.3.5, repeating the archetype simulations for $g = 0.40$ and $g = 0.60$.

Run 3 – Optimised Model: The EDDOS-derived schedule and the 20 m^2/person occupancy scenario from Run 1 are combined. Blind control is retained at the baseline automated setting, as the absence of building-specific override data and the marginal energy impact demonstrated in Run 2 do not justify a departure from the automated logic. This run represents the best available occupant-centric representation of the building's operational behaviour.

By comparing the energy output of each parametric run against the baseline, the isolated contribution of each human factor to the total performance gap is quantified. The occupancy density sensitivity analysis in Run 1 further investigates the influence of post-pandemic occupancy uncertainty on the predicted heating demand, addressing a key limitation of standard-based occupancy assumptions.

4.3.7 Model Validation Against Measured Data

To evaluate how accurately each simulation scenario represents the actual energy performance, the simulated monthly district heating demand was compared against measured consumption data for floors 16–26 for the full year 2025. Rather than serving as a traditional calibration procedure, this validation step quantifies the degree to which each occupancy density scenario closes the performance gap between simulation and reality.

Validation accuracy was assessed using the two statistical metrics defined in Section 3.5: the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error (CV(RMSE)), following the acceptance thresholds prescribed by ASHRAE Guideline 14 for monthly data (NMBE $\leq \pm 5\%$, CV(RMSE) $\leq 15\%$). A scenario meeting both thresholds is considered to statistically represent the measured energy performance of the building. The validation results are presented in Section 4.4.6.

Validation was performed exclusively for district heating, as floor-level measured cooling data was not available for the investigated zones. The available cooling measurement covers the entire building and therefore does not constitute a valid basis for zone-level model validation. Simulated cooling demand is nonetheless reported for all scenarios in Section 4.4, as it constitutes an important component of the overall energy balance and allows for analysis of the trade-off between heating and cooling loads across the investigated scenarios.

4.3.8 Comfort and Performance Gap Evaluation

The final evaluation phase assesses the baseline model's thermal accuracy and summarises the overall energy performance gap across all investigated scenarios.

For thermal comfort, simulated operative temperatures from the baseline model are compared against measurements from a one-week in-situ campaign conducted in 2026, covering six zones across the investigated floors. The comparison aims to assess whether the baseline model produces thermally realistic indoor conditions relative to the ASHRAE Standard 55 comfort range of 20–24°C for typical office environments. The results are presented in Section 4.4.7.

For the energy performance gap, the simulated annual district heating demand is compared against measured consumption data for floors 16–26 across all occupancy density scenarios. Three specific aspects are evaluated: the initial gap between the baseline model and measured data, the progressive reduction in this gap as occupancy density decreases across the EDDOS scenarios, and the residual gap that persists across all scenarios, which is attributed to factors beyond the scope of the investigated human factors. The results are presented in Section 4.4.8.

4.4 Results

4.4.1 Baseline model

The results from the baseline simulation represent the theoretical energy performance of the investigated office floors under standardised SVEBY assumptions, which serve as the fixed operational reference for this study. This model constitutes the primary benchmark against which the performance gap introduced by the data-driven behavioural schedules and shading archetypes is evaluated.

As shown in Table 4.5, the deterministic assumptions yield an annual space heating demand of 21.5 kWh/m², a space cooling demand of 5.4 kWh/m², an HVAC electricity consumption, primarily driven by the HVAC ventilation fans, of 2 kWh/m² and the tenant electricity of 25.7 kWh/m²

These values reflect a perfectly compliant operational state. In this scenario, occupancy and internal electrical loads follow a strict schedule between 08:00 and 17:00, and the automated technical systems function optimally without any manual interference from the occupants.

Table 4.5: Annual energy demand for the baseline model

Energy category	**Annual demand (kWh/m^2)**
District heating	21.5
District cooling	5.4
Tenant electricity	25.7
Total	**54.6**

4.4.2 Occupancy and Equipment Impact

This section evaluates the energy performance impact of replacing the deterministic baseline schedules with the data-driven EDDOS profiles.

Primary EDDOS Implementation

In the primary data-driven scenario, the temporal schedule $f(t)$ was derived from the measured tenant electricity, revealing an average daytime occupancy of $\bar{f} = 0.739$ and a distinct drop on Fridays. The high occupancy scenario of 20 m^2/person, equivalent to SVEBY's standard assumption, was used as the reference density for this implementation (see Section 4.3.3).

As presented in Table 4.6, introducing the realistic temporal profile resulted in some shifts in the energy distribution, despite the total annual heat gains from occupants remaining largely equivalent to the baseline, given that occupancy density is held constant at 20 m^2/person. The space heating demand experienced a marginal increase of 1.8% (from 21.5 to 21.9 kWh/m^2). This stability is physically consistent, as the building primarily requires active heating during unoccupied nights and weekends, periods where both models assume the building is empty.
Conversely, the space cooling demand increased by over 20% (from 5.4 to 6.5 kWh/m^2). The data-driven schedule creates concentrated, dynamic peaks of internal loads during the middle of the day, forcing the cooling system to manage sudden spikes that the temporally uniform deterministic schedule fails to capture.

Table 4.6: Energy simulation results for the four occupancy density scenarios compared to the SVEBY baseline. All values in kWh/m^2.

Scenario	Occupancy (m^2/person)	DH (kWh/m^2)	DC (kWh/m^2)
Baseline (SVEBY)	20	21.5	5.4
EDDOS — 100%	20	21.9	6.5
EDDOS — 67%	30	22.5	6.2
EDDOS — 50%	40	22.9	6
EDDOS — 25%	80	23.5	5.7
Measured (floors 16–26)	—	≈28	—

Sensitivity Analysis: Occupancy Density

A fundamental limitation of utilising aggregated tenant electricity as a proxy for occupancy is the inability to determine the absolute number of occupants present. While the EDDOS method accurately captures the behavioural pattern over time, the total occupancy level remains an estimated variable. To address this uncertainty, a sensitivity analysis was conducted by testing three additional occupancy scenarios ranging from 30 m^2/person to 80 m^2/person, all utilising the same EDDOS-derived $f(t)$ schedule.

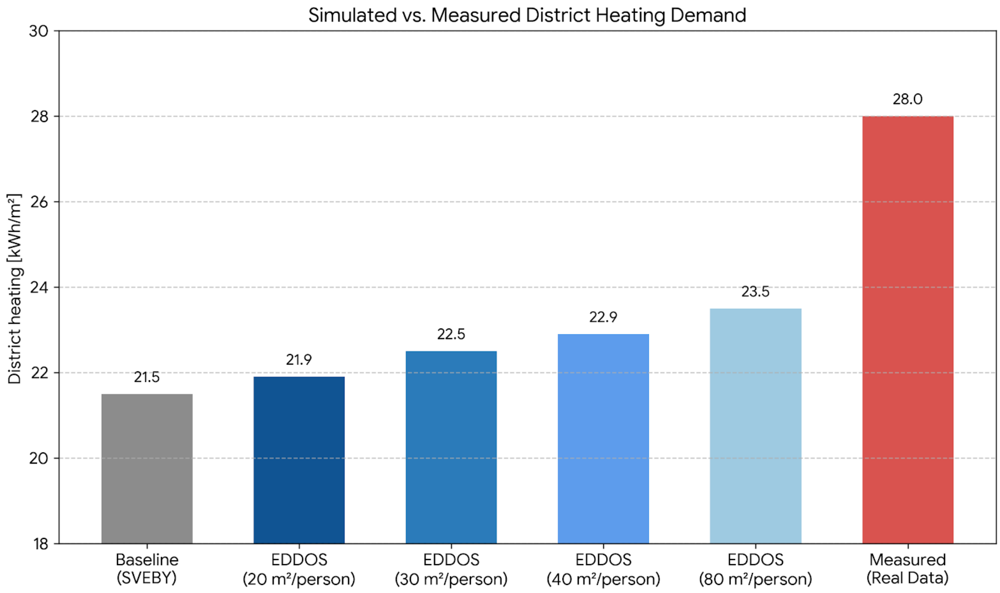

Figure 4.6: Simulated district heating demand for the four occupancy density scenarios compared to the measured annual district heating consumption for the case study. All values in kWh/m^2.

The results of the sensitivity analysis (Table 4.5 and Figure 4.6) demonstrate a clear inverse relationship between occupancy density and space heating. As the average floor area per person increases from 20 to 30, 40 and 80 m^2/person, the building loses a portion of its passive internal heat gains during working hours. Consequently, the active heating system must compensate, driving the heating demand up to 22.5, 22.9

and 23.5 kWh/m^2 respectively. In contrast, the cooling demand steadily decreases from 6.5 down to 5.7 kWh/m^2 as the internal heat gains in the core and perimeter zones are reduced.

This analysis highlights that transitioning to data-driven schedules requires a holistic re-evaluation of occupancy density assumptions. Notably, however, even the extreme low occupancy scenario of 80 m^2/person produces a simulated heating demand of 23.5 kWh/m^2, which still falls short of the measured annual district heating consumption of approximately 28 kWh/m^2 for the upper floors of Gårda Vesta. This suggests that while lowered post-pandemic occupancy levels, consistent with recent observations (Mantesi et al., 2022; Motuzienė et al., 2022), contribute to the performance gap, they do not fully explain it. Other technical or physical parameters likely account for the remaining discrepancy.

4.4.3 Shading Impact

This section presents the energy simulation results for the two manual shading archetypes compared against the fully automated baseline. The Dynamic User archetype applies a higher glare threshold of 250 W/m^2, while the Static User archetype applies a permanent 50% occlusion during working hours (08:00–17:00). Both are compared against the baseline automated threshold of 100 W/m^2.

As presented in Table 4.7, the differences between shading scenarios are small. The Dynamic User profile resulted in a space heating demand of 21.2 kWh/m^2 and a space cooling demand of 5.5 kWh/m^2, while the Static User profile resulted in 21.0 kWh/m^2 and 5.7 kWh/m^2 respectively. These represent deviations of less than 1% in heating and less than 4% in cooling relative to the baseline.

4.4.4 Impact of Glazing Performance on Shading Sensitivity

To investigate whether the observed shading results are specific to Gårda Vesta's glazing specification of $g = 0.26$, simulations were repeated for $g = 0.40$ and $g = 0.60$, representing a modern high-performance office and an older office building respectively.

As presented in Table 4.x, increasing the solar heat gain coefficient results in a consistent reduction in space heating demand and increase in space cooling demand across all shading scenarios. The difference between the Dynamic User, Static User, and baseline scenarios remains small across all g-values tested.
For the higher g-value scenarios, elevated indoor temperatures were observed in the simulation results, particularly during summer months. This suggests that the cooling demand figures for $g = 0.40$ and $g = 0.60$ may underestimate the true cooling requirement, as the VAV system's capacity limits its ability to fully remove the increased solar heat gains.

Table 4.7: Energy simulation results for shading archetypes across three g-values. All values in kWh/m^2.

g-value	Scenario	DH	DC
	Baseline	21.5	5.5
0.26	Dynamic user	21.2	5.5
	Static user	21.0	5.7
	Baseline	20.35	6.41
0.40	Dynamic user	20.06	6.56
	Static user	19.85	6.76
	Baseline	19.03	7.52
0.60	Dynamic user	18.67	7.68
	Static user	18.40	7.88

To further investigate the theoretical maximum impact of solar shading, an extreme scenario was simulated in which blinds were permanently deployed during the heating season (October to April) and fully retracted during summer (May to September) at $g = 0.26$. The resulting space heating demand was 21.5 kWh/m^2 and cooling demand 5.4 kWh/m^2, virtually identical to the baseline.

An additional simulation with unconstrained maximum VAV airflow was conducted under the same extreme shading schedule. Removing the airflow constraint increased the cooling demand from 5.4 to 6.6 kWh/m^2, confirming that the cooling system operates under a capacity constraint in the model configuration.

4.4.5 Optimised Model

From the individual parameter study an optimised model was chosen to represent the most realistic operational scenario for the investigated office floors.

For the internal heat gains, the EDDOS temporal profile was applied paired with the lowest density scenario of 80 m^2/person. This configuration was selected because it yielded a district heating demand of 23.5 kWh/m^2, which represents the closest alignment with the measured consumption of 28 kWh/m^2. While it does not perfectly close the performance gap, it provides the most accurate representation of the building's thermal balance when accounting for post-pandemic hybrid working patterns.

For solar shading, the automated baseline configuration with a deployment threshold of 100 W/m^2 was retained. As demonstrated in Section 4.4.3, manual shading behaviour had a negligible impact on the building's thermal balance, consistent with the fully automated shading system limiting the influence of occupant overrides. The automated baseline was therefore deemed the most robust and representative assumption for the optimised model.

Ultimately, this optimised model represents the limit of what can be achieved through calibrating occupant behaviour alone. The remaining gap between this model and the measured data highlights that while human factors are critical, physical or technical parameters must also be investigated to achieve full model calibration.

4.4.6 Model Validation and Comfort Evaluation

To assess the statistical reliability of each simulation scenario, the simulated monthly district heating demand was compared against measured consumption data following the ASHRAE Guideline 14 criteria established in Section 3.5. The results are presented in Table 4.7.

Table 4.8: Model validation results against measured monthly district heating data following ASHRAE Guideline 14. Acceptance thresholds: NMBE $\leq \pm 5\%$, CV(RMSE) $\leq 15\%$.

Scenario	**NMBE (%)**	**CV(RMSE) (%)**
Baseline (SVEBY, 20 m^2/person)	24.96	35.61
EDDOS 20 m^2/person	23.51	32.24
EDDOS 30 m^2/person	21.51	29.94
EDDOS 40 m^2/person	20.07	28.31
EDDOS 80 m^2/person	17.71	25.75
Dynamic user (250 W/m^2)	25.86	36.07
Static user (50% occlusion)	26.60	36.48

The validation results demonstrate a consistent and systematic improvement as occupancy density decreases, with both NMBE and CV(RMSE) reducing progressively from the baseline value of 24.96% and 35.61% respectively towards 17.71% and 25.75% at 80 m^2/person. However, the investigated scenarios remain somewhat distant from the ASHRAE Guideline 14 acceptance thresholds (NMBE $\leq \pm 5\%$, CV(RMSE) $\leq 15\%$).

The systematic improvement with decreasing occupancy density confirms that occupancy level is a significant driver of the performance gap. Nevertheless, the persistent gap across all scenarios, including the extreme low-occupancy case, suggests that a structural component of the performance gap remains unaccounted for by occupancy-related human factors alone. The shading archetype scenarios show no improvement in validation metrics relative to the baseline, confirming that solar shading behaviour does not contribute meaningfully to closing the performance gap in this building.

It should be noted that the validation was limited to district heating, since floor-level cooling measurements were unavailable for the investigated zones. In addition, the spatial coverage of the measured district heating data only partially corresponded to the zones included in the simulation model. Therefore, the validation was conducted based on the overlapping areas between the measured and simulated zones.

To assess the thermal accuracy of the baseline model, simulated operative temperatures were compared against measurements conducted during a one-week in-situ campaign in winter 2026. The measured values represent zone averages from the campaign, while the simulated values represent the corresponding monthly averages from the 2025 baseline simulation. Baseline model operative temperatures were systematically underestimated across all investigated zones, with deviations ranging from 0.44°C to 1.13°C, as shown in Table 4.9. The simulated operative temperature ranged from 21.4°C to 21.5°C, whereas the measured operative temperature ranged from 21.8°C to 22.5°C. All values remained within the ASHRAE Standard 55 comfort range of 20–24°C, indicating acceptable thermal conditions and supporting the validity of the simulation scenarios from a thermal comfort perspective.
The simulation model represents the building as designed prior to construction, while field measurements were conducted following operational commissioning and optimization. Adjustments to heating setpoints, ventilation parameters, or other operational settings made during commissioning are not reflected in the original design model and likely contribute to the observed temperature differences. Interannual weather variation between the 2025 simulation and 2026 measurement period may also contribute to the discrepancy.

Table 4.9: Operative temperature deviation between simulated and measured values.

Zone	**Deviation (°C)**
Zone 1	+1.13
Zone 2	+1.00
Zone 3	+0.48
Zone 4	+0.44
Zone 5	+0.66
Zone 6	+0.45

This systematic underestimation is consistent with the model's underprediction of district heating demand, suggesting the baseline model is slightly conservative in its representation of the building's thermal balance. The deviations are considered acceptable for this study, as all zones remain within the ASHRAE Standard 55 comfort range and the magnitude of discrepancy is within typical simulation uncertainty bounds.

4.4.7 Performance Gap Summary

This section summarises the energy performance gap between the simulated and measured district heating demand across all investigated scenarios. The measured annual district heating consumption for the upper floors is approximately 28 kWh/m^2, which serves as the reference for all comparisons.

As presented in Table 4.10, the baseline model produces a district heating demand of 21.5 kWh/m^2, resulting in an initial performance gap of 6.5 kWh/m^2. Introducing the EDDOS temporal schedule at 20 m^2/person increases heating demand marginally to 21.9 kWh/m^2, reducing the gap to 6.1 kWh/m^2. This demonstrates that temporal occupancy variation alone has a limited influence on the performance gap.

The occupancy density sensitivity analysis reveals a more substantial effect. As occupancy density decreases from 20 to 80 m^2/person, district heating demand increases progressively from 21.9 to 23.5 kWh/m^2, reducing the performance gap from 6.1 to 4.5 kWh/m^2. Despite this systematic improvement, a residual gap of at least 4.5 kWh/m^2 persists across all occupancy scenarios, indicating that occupancy-related human factors alone cannot fully explain the performance gap.

Solar shading behaviour contributes negligibly to the performance gap, with differences between the Dynamic User, Static User, and baseline shading scenarios not exceeding 0.5 kWh/m^2 across all glazing specifications investigated.

Due to the absence of floor-level measured cooling data, a direct performance gap analysis for cooling is not possible. Simulated cooling demand is therefore reported across scenarios without comparison to measured consumption. The complete monthly simulation data for all scenarios are provided in Appendix B.

Table 4.10: Summary of simulated district heating demand and performance gap relative to measured consumption for all investigated scenarios. Measured district heating consumption for upper floors is approximately 28 kWh/m^2.

Scenario	**DH (kWh/m^2)**	**Gap (kWh/m^2)**
Measured	28.0	0.0
Baseline (SVEBY, 20 m^2/person)	21.5	+6.5
EDDOS 20 m^2/person	21.9	+6.1
EDDOS 30 m^2/person	22.5	+5.5
EDDOS 40 m^2/person	22.9	+5.1
EDDOS 80 m^2/person	23.5	+4.5
Dynamic user (250 W/m^2)	21.2	+6.8
Static user (50% occlusion)	21.0	+7.0

5 Discussion

5.1 EDDOS as a Method for Deriving Data-Driven Behaviour Profiles

The application of the EDDOS methodology to the case study office building demonstrates that tenant electricity consumption provides a practically viable proxy for deriving occupancy and equipment schedules in the absence of direct occupancy measurement. The strong seasonal structure captured in the derived $f(t)$ profile, including the July reduction, the Christmas dip, and the systematic Friday effect, aligns well with known Swedish workplace calendar patterns and confirms that the electricity signal reflects genuine occupant-driven variation rather than technical or climatic noise. This is consistent with the findings of Al-Saegh et al. (Al-Saegh et al., 2024), who reported an R^2 of 0.84 between tenant electricity and occupancy in a UK office building.

When the EDDOS temporal profile is applied at the same occupancy density as the baseline (20 m^2/person), both heating and cooling demand increase relative to the baseline, from 21.5 to 21.9 kWh/m^2 and from 5.5 to 6.5 kWh/m^2 respectively. The cooling increase of approximately 20% is noteworthy and warrants attention. Particularly interesting is the fact that heating and cooling demand increase simultaneously, a result that may appear counterintuitive at first glance. This can be explained by two complementary aspects of the EDDOS profile. First, the monthly scaling amplifies occupancy during the winter months relative to the flat SVEBY schedule, increasing internal heat gains during the heating season and thereby increasing heating demand during these periods. Second, the concentrated midday peaks during summer months create higher instantaneous cooling loads than the temporally uniform SVEBY schedule is capable of capturing. Together these two effects drive both heating and cooling demand upward simultaneously, suggesting that data-driven schedules do not simply redistribute energy demand but fundamentally alter the overall thermal balance of the building, even when total occupancy levels are held constant.

A key limitation of the EDDOS approach as applied in this study is the aggregated nature of the proxy signal. Tenant electricity was available only at tenancy level across eight floors, preventing floor-level or zone-level disaggregation. This means that spatial variations in occupancy and equipment usage within the tenancy are averaged out in the derived schedule, which may not fully represent the actual distribution across the investigated floors. Furthermore, the unified proxy signal does not allow occupancy and equipment loads to be separated, requiring both to be derived from the same temporal profile. While this is consistent with the EDDOS methodology as defined by Al-Saegh et al. (Al-Saegh et al., 2024), it introduces an assumption of proportionality between occupancy and equipment usage that may not hold in all operational conditions.

5.2 The Density Gap: Post-Pandemic Occupancy as the Primary Driver of Performance Gap

The occupancy density sensitivity analysis reveals that total occupancy level, rather than temporal occupancy variation, is the dominant human factor contributing to the performance gap in Gårda Vesta. While the EDDOS temporal profile at 20 m^2/person reduces the gap only marginally from 6.5 to 6.1 kWh/m^2, reducing occupancy density to 80 m^2/person closes the gap to 4.5 kWh/m^2. This represents a reduction of approximately 31% of the initial performance gap through occupancy density adjustment alone.

The systematic improvement in both heating demand and validation metrics as occupancy density decreases points to a fundamental mismatch between SVEBY's standard assumption of 20 m^2/person and the actual operational reality. This is consistent with the post-pandemic hybrid working literature: Mantesi et al. (Mantesi et al., 2022) demonstrated that hybrid working patterns can substantially reduce office energy consumption relative to pre-pandemic standards, while Motuzienė et al. (Motuzienė et al., 2022) documented actual occupancy levels dropping to as low as 12–23% of design capacity in monitored office buildings. The occupancy density range investigated in this study, from 20 to 80 m^2 per person, is directly consistent with this documented range of post-pandemic attendance levels.

It is important to distinguish between two dimensions of occupancy that this study has investigated independently. The temporal dimension, captured by the EDDOS schedule, describes how occupancy varies across hours, days, and months. The density dimension describes the total number of occupants present at peak attendance. The results demonstrate that these two dimensions have fundamentally different magnitudes of influence on the performance gap: temporal variation contributes marginally while density level contributes substantially. This distinction has practical implications for simulation methodology, suggesting that efforts to improve occupancy modelling accuracy should prioritise the determination of realistic peak density assumptions over the refinement of temporal profiles.

Nevertheless, a residual performance gap of at least 4.5 kWh/m^2 persists across all occupancy scenarios, including the extreme case of 80 m^2/person. This is further illustrated by the near-absence of occupants scenario at 1,000 m^2/person, which still yields a district heating demand of 24.2 kWh/m^2, confirming that a structural component of the performance gap exists independently of occupancy-related human factors. This residual gap is likely attributable to physical and technical factors such as thermal bridging, infiltration, or deviations between the design model and actual commissioned system parameters, none of which fall within the scope of the investigated human factors. The systematic underestimation of operative temperatures observed in Section 4.4.6 further supports this interpretation. The baseline model consistently predicted operative temperatures up to 1.13°C below measured values across all investigated zones, suggesting that operational adjustments made during building commissioning, such as an upward revision of heating setpoints, may not be reflected in the original design model. If heating setpoints were raised after the model was finalised, the building would consume more district heating than the simulation predicts, independently of occupancy-related factors. This represents a plausible additional contributor to the residual performance gap that falls outside the scope of the investigated human factors.

5.3 Shading Behaviour and Envelope Performance

The results of the shading archetype analysis demonstrate that manual blind behaviour has a negligible impact on the thermal balance of the case study building under its current glazing specification. Across both the Dynamic User and Static User archetypes, deviations from the automated baseline were less than 1% for heating and less than 4% for cooling. This finding stands in contrast to the broader literature on manual shading behaviour, where blind operation has been shown to carry an energy impact of up to 33% for total energy use in buildings with less performant envelopes (Van Den Wymelenberg, 2012). The explanation lies in the interaction between two building-specific factors: the high-performance glazing with a g-value of 0.26 and the fully automated shading system, which already operates close to the theoretical optimum and therefore limits the energy consequence of manual overrides by either archetype.

The g-value sensitivity analysis clarifies the boundaries of this conclusion. As the g-value increases from 0.26 to 0.40 and 0.60, the overall energy balance shifts substantially: cooling demand rises from 5.5 to 6.41 to 7.52 kWh/m^2 for the baseline, while heating demand decreases from 21.5 to 20.35 to 19.03 kWh/m^2. However, the absolute spread between the Dynamic and Static User cooling demand remains constant at approximately 0.2 kWh/m^2 across all three g-values. This is not indicative of a neutralising effect from the automated shading system, but rather reflects a system capacity constraint: The case study office building relies solely on increased supply air volume for cooling, with no chilled beam capacity. As the g-value increases beyond the building's design specification of 0.26, the system approaches its maximum airflow limit and can no longer fully compensate for the additional solar heat gains. This limitation does not manifest as increased cooling energy but rather as deteriorating thermal comfort, with markedly higher operative temperatures and PPD values at elevated g-values.

This finding has an important practical implication for occupant-centric design in modern automated office buildings. Where high-performance glazing and fully automated shading systems are combined, occupant shading behaviour is largely neutralised as a source of performance gap uncertainty, and the choice of shading archetype has minimal energy consequences. However, this conclusion is specific to buildings whose technical systems are dimensioned for the installed glazing specification. In buildings with higher solar heat gain coefficients, or where cooling systems lack sufficient capacity, occupant shading behaviour would carry more significant energy consequences. Under such conditions, the choice of shading archetype would warrant considerably greater attention in the simulation methodology, not only in terms of energy, but also thermal comfort outcomes.

5.4 Post-Pandemic Occupancy Uncertainty and Simulation Reliability

The shift to hybrid working after the pandemic has permanently changed how offices are used, making traditional occupancy standards outdated. As this study shows, standard assumptions like SVEBY's 20 m^2 per person are based on a pre-pandemic reality of full-time attendance that no longer exists in modern offices. This shift creates a lot of uncertainty about actual peak occupancy, which directly compromises the reliability of building energy simulations if fixed standard values are used without questioning them. The results of the sensitivity analysis confirm this issue as when the simulated occupancy drops to realistic post-pandemic levels, the active heating demand rises significantly to compensate for the lost internal heat from people.

Sticking to these outdated assumptions is especially risky for modern, well-insulated buildings where internal heat gains control the overall energy balance. If energy models assume the building is fully occupied, they will overestimate the free heat and underestimate the actual performance gap. This forces engineers to design HVAC systems for a "worst-case" full office instead of a normal workday, which leads to systems running inefficiently at partial loads. When this happens, energy simulation stops being a useful tool for predicting real-world performance and becomes just a box-ticking exercise for regulatory compliance.

To make energy simulations reliable again, the industry needs to adapt to how offices actually work today. Since modern office attendance is dynamic and hard to predict, treating occupant density as a fixed number is no longer realistic. One effective way to handle this uncertainty is to use scenario-based approaches, such as conducting a sensitivity analysis on occupancy density by testing everything from full design capacity down to extreme low-occupancy levels. While there are various methods to address unpredictable occupant behavior, exploring multiple scenarios allows engineers to properly understand how different attendance levels affect energy use. Ultimately, this flexibility ensures that sustainable buildings are designed to perform efficiently no matter what kind of hybrid working policy a tenant has.

5.5 Methodological Limitations

Although the occupant-centric approach provides a more realistic representation of building performance than static deterministic models, several methodological limitations must be acknowledged. These constraints stem from data availability, model simplifications, and the complexity of monitoring human behaviour.

Data Aggregation and Spatial Scope
A primary limitation concerns the spatial resolution of the measured data. While the investigated tenant occupies eight floors within Gårda Vesta, the simulation model was restricted to a representative subset of four floors to avoid redundant modeling of highly repetitive layouts. However, the tenant electricity data used to drive the EDDOS methodology was only available as an aggregated total across all eight floors. Applying this aggregated data to the subset of four modeled floors assumes a perfectly uniform distribution of equipment and occupancy, which may oversimplify actual spatial variations in building utilization.

Cooling System and Measurement Limitations
Quantifying the total performance gap was significantly constrained by the resolution of the available cooling data. Cooling consumption was only metered at the aggregate building level, meaning no sub-meters were available for the specific zones investigated. Consequently, validation according to ASHRAE Guideline 14 could only be reliably performed for district heating. Furthermore, it should be noted that the actual building is not equipped with chilled beams; space cooling relies entirely on the supply air from the Variable Air Volume (VAV) system. While the simulation model accurately reflects this physical reality, this specific system design inherently caps the maximum cooling capacity. As a result, the building's thermal balance is highly sensitive to the sudden peaks in internal heat gains generated by data-driven schedules, which must be considered when evaluating the cooling demand results.

5.6 Implications for Future Simulation-Aided Design

The findings of this study carry several practical implications for simulation aided building design, particularly for consulting engineers working with modern, high performance office buildings.

The successful application of the EDDOS methodology demonstrates that tenant electricity consumption constitutes a viable and practically accessible proxy for deriving occupancy and equipment schedules in the absence of direct occupancy measurement. Since metered electricity data is increasingly available through standard BMS infrastructure, this approach represents a low cost improvement over static regulatory schedules that requires no additional instrumentation. For engineering practice, this suggests that data driven schedule derivation should be adopted as a default methodology whenever operational electricity data is available, rather than relying on standardised profiles such as those prescribed by SVEBY.

The occupancy density sensitivity analysis further demonstrates that a single fixed density assumption is insufficient for contemporary office buildings operating under hybrid working conditions. A scenario based approach, testing a range of plausible attendance levels from full design capacity to significantly reduced post pandemic occupancy, provides engineers with a more complete picture of how a building will perform across realistic operational conditions. This is particularly important for modern, well insulated buildings where internal heat gains dominate the energy balance and small errors in occupancy assumptions propagate into large prediction errors.

In buildings combining high performance glazing with fully automated shading systems, occupant shading behaviour contributes negligibly to the energy performance gap. In such buildings, simulation resources are better directed towards accurately characterising occupancy density than towards refining shading archetypes. However, this conclusion should not be generalised to buildings with higher solar heat gain coefficients or less sophisticated shading automation, where occupant behaviour may carry considerably greater energy consequences.

Finally, this study highlights the need for future research using real occupancy measurement data, such as access card logs or high resolution sensor networks, to validate and refine the density scenarios explored here. Extending this type of occupant centric analysis to a broader set of buildings and climate zones would further strengthen the empirical basis for updating standardised occupancy assumptions in Swedish and international building energy codes. In this study, the response level from the occupant survey limited the statistical quantification of building specific behavioral triggers. Consequently, factors like thermostat and lighting adjustments were excluded, and the solar shading analysis rely on theoretical archetypes. Therefore, future studies should utilize actual observations and comprehensive data collection from both occupant surveys and operational monitoring. This will help to better understand the true triggers of occupant behaviour and allow their implementation in simulation based building design to further reduce performance gaps.

6
Conclusion

This study investigated the influence of three human factors on the energy performance gap of a modern, WELL and BREEAM Excellent certified office building in Gothenburg, Sweden. The findings are summarised below in relation to the three research questions.

Regarding the first research question, the EDDOS methodology demonstrated that hourly tenant electricity consumption constitutes a reliable proxy for deriving data-driven occupancy and equipment schedules. The derived $f(t)$ profiles captured seasonal patterns, intra-day variation, and a systematic Friday reduction, all consistent with known Swedish workplace calendar patterns. This confirms that tenant electricity data can be used to replace static regulatory schedules with empirically grounded profiles in the absence of direct occupancy measurement.

Regarding the second research question, occupancy density was identified as the primary human factor contributing to the performance gap. Temporal occupancy variation had a marginal influence on heating demand but increased cooling demand by approximately 20%, driven by the higher average occupancy during summer working hours captured by the EDDOS profile and the concentrated midday peaks that the temporally uniform SVEBY schedule fails to capture. Solar shading behaviour had negligible influence across all scenarios, contributing less than 0.5 kWh/m^2 across all glazing specifications tested, consistent with the building's fully automated shading system limiting the energy consequences of manual overrides.

Replacing the static SVEBY schedule with the EDDOS temporal profile at constant density reduced the performance gap only marginally, from 6.5 to 6.1 kWh/m^2. Reducing occupancy density to 80 m^2/person closed the gap further to 4.5 kWh/m^2, representing a reduction of approximately 31% of the initial gap.

Regarding the third research question, a residual performance gap of at least 4.5 kWh/m^2 persisted across all scenarios. This confirms that post-pandemic occupancy uncertainty is a significant source of simulation error in contemporary hybrid offices, and that standardised assumptions such as those prescribed by SVEBY may systematically underestimate the performance gap. The sensitivity analysis further demonstrated that no single occupancy density value can be assumed with confidence and therefore a scenario-based approach is more appropriate than a deterministic single-point estimate.

The thermal comfort evaluation provided an additional perspective on the residual gap. The baseline model consistently underestimated operative temperatures across all investigated zones by up to 1.13°C. This suggests that operational adjustments made during building commissioning, such as an upward revision of heating setpoints, may not be reflected in the original design model, representing a plausible contributor to the residual gap that falls outside the scope of the investigated human factors.

Taken together, these findings suggest that in modern, highly automated office buildings, efforts to improve simulation accuracy should prioritise the determination of realistic occupancy density assumptions over the refinement of temporal profiles or shading archetypes. A scenario-based approach to occupancy density, combined with data-driven schedule derivation using the EDDOS methodology, represents a practically viable and immediately applicable improvement over current standardised simulation practice. Rather than producing a single deterministic energy prediction, this approach allows engineers to present clients with a performance interval. For example, a low-occupancy scenario representative of deep hybrid working, and a high-occupancy scenario approaching full attendance, and thereby communicating the inherent uncertainty of post-pandemic office use in a transparent and actionable way. This shift from a single theoretical answer to a risk-informed range reflects the operational reality of modern offices and represents a more honest and useful basis for sustainable building design.

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Appendices

Appendix A – EDDOS Daily Profiles and Monthly Scaling Factors

The following tables present the hourly mean $f(t)$ values and monthly scaling factors derived from the measured tenant electricity data for the year 2025, as implemented in IDA ICE.

Table 1: Monthly scaling factors applied to both daily profiles in IDA ICE.

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1.050	1.082	1.081	1.061	1.049	1.004	0.827	0.946	1.025	1.014	0.997	0.864

Table 2: Hourly mean $f(t)$ values for the Monday–Thursday profile.

Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)
0	0.020	4	0.023	8	0.466	12	0.817	16	0.712	20	0.156
1	0.020	5	0.072	9	0.776	13	0.790	17	0.577	21	0.139
2	0.021	6	0.319	10	0.807	14	0.797	18	0.301	22	0.070
3	0.022	7	0.466	11	0.809	15	0.773	19	0.204	23	0.067

Table 3: Hourly mean $f(t)$ values for the Friday profile.

Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)	Hr	f(t)
0	0.019	4	0.021	8	0.418	12	0.691	16	0.584	20	0.144
1	0.019	5	0.070	9	0.676	13	0.658	17	0.452	21	0.131
2	0.019	6	0.297	10	0.701	14	0.672	18	0.214	22	0.061
3	0.019	7	0.418	11	0.696	15	0.642	19	0.167	23	0.063

Appendix B – Monthly Simulation Data

The following tables present the monthly simulated district heating (DH) and district cooling (DC) demand for all investigated scenarios. Values are given in kWh/m^2 based on the investigated floor area of 2,859 m^2.

Table 4: Monthly simulated DH and DC demand for EDDOS occupancy density scenarios.

	EDDOS 20 m^2/p		EDDOS 30 m^2/p		EDDOS 40 m^2/p		EDDOS 80 m^2/p	
Month	**DH**	**DC**	**DH**	**DC**	**DH**	**DC**	**DH**	**DC**
January	3.85	0.00	3.95	0.00	4.03	0.00	4.17	0.00
February	3.60	0.00	3.65	0.00	3.71	0.00	3.80	0.00
March	3.02	0.00	3.07	0.00	3.10	0.00	3.16	0.00
April	1.68	0.00	1.72	0.00	1.74	0.00	1.78	0.00
May	0.71	1.30	0.73	1.23	0.73	1.19	0.75	1.14
June	0.24	0.33	0.26	0.31	0.26	0.30	0.27	0.29
July	0.06	2.39	0.07	2.26	0.07	2.19	0.07	2.09
August	0.10	2.28	0.11	2.16	0.11	2.10	0.12	2.00
September	0.53	0.21	0.56	0.19	0.58	0.18	0.60	0.17
October	1.65	0.00	1.70	0.00	1.74	0.00	1.79	0.00
November	2.78	0.00	2.85	0.00	2.90	0.00	2.99	0.00
December	3.67	0.00	3.80	0.00	3.89	0.00	4.03	0.00
Total	**21.88**	**6.50**	**22.46**	**6.15**	**22.87**	**5.97**	**23.54**	**5.69**

Table 5: Monthly simulated DH and DC demand for shading archetype and g-value sensitivity scenarios.

	Baseline		Dynamic user		Static user		Baseline g=0.40		Baseline g=0.60	
Month	**DH**	**DC**	**DH**	**DC**	**DH**	**DC**	**DH**	**DC**	**DH**	**DC**
January	3.78	0.00	3.76	0.00	3.76	0.00	3.73	0.00	3.65	0.00
February	3.58	0.00	3.56	0.00	3.54	0.00	3.47	0.00	3.31	0.00
March	2.99	0.00	2.94	0.00	2.89	0.00	2.73	0.00	2.41	0.00
April	1.64	0.00	1.59	0.00	1.57	0.00	1.43	0.00	1.20	0.00
May	0.71	1.32	0.69	1.33	0.66	1.37	0.63	1.47	0.53	1.61
June	0.30	0.31	0.28	0.31	0.24	0.33	0.23	0.36	0.22	0.40
July	0.12	1.33	0.11	1.37	0.10	1.48	0.09	1.81	0.09	2.43
August	0.13	2.28	0.12	2.32	0.12	2.36	0.12	2.55	0.11	2.83
September	0.63	0.19	0.60	0.20	0.57	0.20	0.54	0.22	0.47	0.25
October	1.62	0.00	1.60	0.00	1.59	0.00	1.51	0.00	1.35	0.00
November	2.67	0.00	2.66	0.00	2.64	0.00	2.58	0.00	2.47	0.00
December	3.32	0.00	3.32	0.00	3.31	0.00	3.28	0.00	3.22	0.00
Total	**21.5**	**5.42**	**21.2**	**5.53**	**21.0**	**5.73**	**20.35**	**6.41**	**19.03**	**7.52**

DEPARTMENT OF ARCHITECTURE AND CIVIL ENGINEERING
CHALMERS UNIVERSITY OF TECHNOLOGY
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